Measuring the Impact of Tourism on Water Resources: alternative frameworks

by

Michalis Hadjikakou

Submitted for the degree of Doctor of Philosophy

Centre for Environmental Strategy
Faculty of Engineering and Physical Sciences
University of Surrey

February 2014

© Michalis Hadjikakou 2014
Abstract

Tourism is a highly important and diverse economic sector. All tourism activity relies directly and indirectly on water resources. While direct water use in hotels, golf courses and other tourism establishments is relatively well researched, the more substantial volumes of water used indirectly to produce goods which cater for tourism demand are poorly understood. The thesis develops and tests three innovative approaches as part of its overall aim of comprehensively quantifying total (direct and indirect) water demand and water productivity (water use in relation to economic output) across different tourism products. The first approach is based on the water footprint concept and uses readily available data from the UN Food and Agriculture Organization and the Water Footprint Network. The second approach uses statistical segmentation and secondary tourism expenditure data, along with Environmental Input-Output (EIO) analysis, to create distinct tourist groups whose water use and productivity is subsequently compared. The third approach employs primary survey data along with a novel EIO model, in order to quantify the specific impacts of tourist dietary choices. The water scarce island of Cyprus, a popular tourism destination, serves as the central case study.

The contribution of the thesis is primarily methodological, producing three methods of differing complexity thus offering a previously unavailable choice to academics and policy makers. Additionally, the approaches generate results with important theoretical and policy implications. Firstly, when both indirect and direct water use is taken into account, cheaper mass tourism is shown to have a higher water productivity compared to higher-spending tourists. With many destinations currently investing in attracting the latter group, this finding is of immediate relevance. Secondly, the findings highlight the importance of obtaining accurate information on dietary preferences in order to better manage the supply chain of key products which account for a significant amount of water consumption.
Statement of Originality

"This thesis and the work to which it refers are the results of my own efforts. Any ideas, data, images or text resulting from the work of others (whether published or unpublished) are fully identified as such within the work and attributed to their originator in the text, bibliography or in footnotes. This thesis has not been submitted in whole or in part for any other academic degree or professional qualification. I agree that the University has the right to submit my work to the plagiarism detection service TurnitinUK for originality checks. Whether or not drafts have been so-assessed, the University reserves the right to require an electronic version of the final document (as submitted) for assessment as above."

Signed ..............................................

Name: MICHALIS HADJIKAKOU

Date of final submission: 10 FEBRUARY 2014
# Table of Contents

Abstract .................................................................................................................. ii

Table of Contents ..................................................................................................... iv

List of Figures .......................................................................................................... vi

List of Tables ............................................................................................................ vii

List of Abbreviations and Acronyms ....................................................................... viii

Acknowledgements ................................................................................................... ix

**PART I - Water and Tourism: methodological challenges** .............................. 1

Chapter 1: Introduction .......................................................................................... 2
  1.1 Background – water and tourism ..................................................................... 2
  1.2 Motivation and problem statement ................................................................. 5
  1.3 Aim and scope .................................................................................................. 6
  1.4 Thesis objectives and structure ...................................................................... 11

**PART II - Estimating total tourism water consumption using available data** ...... 15

Chapter 2: Estimating direct and indirect tourism water use in the Mediterranean - 16
  2.1 Chapter 2 outline ............................................................................................ 16
  2.2 Understanding the nature of tourism water consumption ............................... 18
  2.3 Establishing a methodology to estimate tourism water consumption .......... 32
  2.4 Results and discussion ................................................................................... 44
  2.5 Refining tourism water use estimates ............................................................. 54

**PART III - Estimating water productivity for different market segments.** ........ 58

Chapter 3: Combining market segmentation and EIO Analysis .......................... 59
  3.1 Part III outline ............................................................................................... 59
  3.2 The importance of yield ................................................................................ 62
  3.3 Distinguishing between different tourist types .............................................. 70
  3.4 Estimating water use intensity - Environmental Input-Output Analysis ........ 79
  3.5 EIO model for Cyprus tourism ...................................................................... 99
  3.6 Summary of methodology ............................................................................. 102

Chapter 4: Segmentation and EIO results and discussion ..................................... 103
  4.1 Chapter outline ............................................................................................... 103
  4.2 Market segmentation ...................................................................................... 104
  4.3 Economic impact and water use for each segment ....................................... 110
  4.4 Discussion and appraisal of the framework .................................................. 122

Appendix A - Alternative EIO techniques .............................................................. 134
List of Figures

Figure 1.1 Map showing the location of the island of Cyprus ........................................ 9
Figure 1.2 Water supply sources with a breakdown into different uses ............................ 11
Figure 1.3 Conceptual diagram of the five main objectives of the thesis ........................... 12
Figure 1.4 Thesis structure diagram showing ................................................................. 14
Figure 2.1 Direct and indirect ways in which tourism exerts pressure on water ................ 17
Figure 2.2 Average global water footprints for selected agricultural products ............... 29
Figure 2.3 Daily per capita water footprints for residents of Cyprus, Greece and Turkey ... 42
Figure 2.4 Chart showing relative contribution of blue and green water ......................... 48
Figure 2.5 Green and blue water ‘savings’ from trade ..................................................... 49
Figure 2.6 Local and global WF disaggregated into the five main food groups ................ 50
Figure 2.7 Total WF for residents compared to the four tourist scenarios ......................... 52
Figure 3.1 Figure showing the structure and principal tasks of Part III of the thesis ......... 61
Figure 3.2 The Integrated Tourism Yield framework ......................................................... 65
Figure 3.3 Matrix plot showing estimated water use per visitor night ............................... 67
Figure 3.4 Segmentation procedure followed in the study ............................................... 78
Figure 3.5 Diagram showing a structural path ................................................................. 85
Figure 3.6 Matching to reconcile TSA and expenditure categories ............................... 101
Figure 4.1 Country contributions to arrivals and to total expenditure ............................ 106
Figure 4.2 Total segment contribution to arrivals and to total expenditure ..................... 109
Figure 4.3 Daily direct and indirect water for the main country markets ......................... 112
Figure 4.4 Daily direct and indirect water for different segments of the UK market ......... 115
Figure 4.5 Water use intensity for all tourist segments and residents ............................ 117
Figure 4.6 Value added per USD of tourist expenditure ............................................... 119
Figure 4.7 Total (direct and indirect) employment (jobs FTE) per one million USD ........ 119
Figure 4.8 Linear correlation between expenditure and water use ................................ 129
Figure 5.1 Hybrid accounting framework compared to a conventional I-O framework .... 172
Figure 5.2 Associations across different classification systems .................................. 185
Figure 5.3 Overview of the disaggregation procedure for the agricultural sector .......... 187
Figure 5.4 Map of Cyprus showing tourist sampling locations ..................................... 218
Figure 5.5 Conceptual model of the framework ......................................................... 219
Figure 6.1 Water use associated with the production of agricultural commodities ........ 226
Figure 6.2 Water use intensity for all groups ............................................................... 227
List of Tables

Table 2.1  Estimated global average use per tourist per day .................................................. 31
Table 2.2  Holiday package characteristics........................................................................... 34
Table 2.3  Accommodation water footprint (AF) for each of the holiday scenarios.................. 35
Table 2.4  Activity water footprints for each holiday scenario................................................. 37
Table 2.5  Distances used to calculate the fuel footprint (FF). ............................................... 40
Table 2.6  Results table containing breakdown for each holiday scenario............................. 44
Table 2.7  Basic input-output table for a hypothetical two-sector economy. ............................. 81
Table 3.1  Results of the COO segmentation for the five main country market segments............. 105
Table 3.2  Results of the expenditure-based segmentation and cluster analysis .......................... 108
Table 3.3  Direct water use in accommodation for main COO segments ............................... 110
Table 3.4  Direct water use in accommodation for all UK sub-segments................................. 114
Table 3.5  Economic impact indicators for all tourist segments.............................................. 120
Table 3.6  Direct and total water use and economic contribution coefficients ........................... 121
Table 5.1  Hypothetical two-sector economy ........................................................................... 163
Table 5.2  Sector b disaggregated into two new sectors, b₁ and b₂ .......................................... 163
Table 5.3  20-sector agricultural classification used in the disaggregated matrix ....................... 186
Table 5.4  Summary of results for the five different modelling possibilities ............................. 204
Table 5.5  Sectoral water use breakdown showing direct and indirect water use coefficients ......... 207
Table 6.1  Food expenditure (y₂) breakdown for different tourist groups ............................... 223
Table 6.2  Expenses (y₁) breakdown for different tourist groups ............................................. 224
Table 6.3  Value added per tourist segment in USD per capita per day .................................... 227
### List of Abbreviations and Acronyms

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABS</td>
<td>Australian Bureau of Statistics</td>
</tr>
<tr>
<td>ANOVA</td>
<td>Analysis of variance</td>
</tr>
<tr>
<td>COICOP</td>
<td>Classification of individual consumption by purpose</td>
</tr>
<tr>
<td>COO</td>
<td>Country of origin</td>
</tr>
<tr>
<td>CPI</td>
<td>Consumer price index</td>
</tr>
<tr>
<td>CTO</td>
<td>Cyprus Tourism Organisation</td>
</tr>
<tr>
<td>CYSTAT</td>
<td>Cyprus Statistical Service</td>
</tr>
<tr>
<td>EIO</td>
<td>Environmental Input-Output</td>
</tr>
<tr>
<td>EU</td>
<td>European Union</td>
</tr>
<tr>
<td>FAO</td>
<td>Food and Agriculture Organisation (UN)</td>
</tr>
<tr>
<td>FBS</td>
<td>Food balance sheet</td>
</tr>
<tr>
<td>FTE</td>
<td>Full-time equivalent</td>
</tr>
<tr>
<td>GDP</td>
<td>Gross domestic product</td>
</tr>
<tr>
<td>GVA</td>
<td>Gross value added</td>
</tr>
<tr>
<td>I-O</td>
<td>Input-Output</td>
</tr>
<tr>
<td>IOPC</td>
<td>Input-Output Product Classification</td>
</tr>
<tr>
<td>IOT</td>
<td>Input-Output Table</td>
</tr>
<tr>
<td>ISIC</td>
<td>International Standard Industrial Classification</td>
</tr>
<tr>
<td>LCA</td>
<td>Life cycle assessment</td>
</tr>
<tr>
<td>LOS</td>
<td>Length of stay</td>
</tr>
<tr>
<td>MRIO</td>
<td>Multiregional Input-Output</td>
</tr>
<tr>
<td>NACE</td>
<td>Nomenclature statistique des activités économiques dans la Communauté européenne</td>
</tr>
<tr>
<td>NAS</td>
<td>National Accounts Statistics</td>
</tr>
<tr>
<td>OECD</td>
<td>Organisation for Economic Co-operation and Development</td>
</tr>
<tr>
<td>ONS</td>
<td>Office for National Statistics (UK)</td>
</tr>
<tr>
<td>RSE</td>
<td>Relative standard error</td>
</tr>
<tr>
<td>SITE</td>
<td>Small island tourism economy</td>
</tr>
<tr>
<td>SNA</td>
<td>System of National Accounts</td>
</tr>
<tr>
<td>SUT</td>
<td>Supply and Use Table</td>
</tr>
<tr>
<td>TSA</td>
<td>Tourism Satellite Account</td>
</tr>
<tr>
<td>UN DESA</td>
<td>United Nations Department of Economic and Social Affairs</td>
</tr>
<tr>
<td>UNEP</td>
<td>United Nations Environment Programme</td>
</tr>
<tr>
<td>UNWTO</td>
<td>United Nations World Tourism Organization</td>
</tr>
<tr>
<td>VWC</td>
<td>Virtual water content</td>
</tr>
<tr>
<td>WDD</td>
<td>Water Development Department (Cyprus)</td>
</tr>
<tr>
<td>WEBT</td>
<td>Water Embodied in Bilateral Trade</td>
</tr>
<tr>
<td>WF</td>
<td>Water footprint</td>
</tr>
<tr>
<td>WFN</td>
<td>Water Footprint Network</td>
</tr>
<tr>
<td>WIOD</td>
<td>World Input-Output Database</td>
</tr>
<tr>
<td>WTTC</td>
<td>World Travel &amp; Tourism Council</td>
</tr>
<tr>
<td>WWF</td>
<td>World Wide Fund for Nature</td>
</tr>
</tbody>
</table>
Acknowledgements

As my long and arduous journey draws to a close, I realise that what has so often in the last three years felt like such a painfully solitary task, has in truth been aided greatly by the help and support of many individuals and organisations. I would like to take this opportunity to offer my sincere appreciation to everybody who has directly or indirectly contributed towards making this thesis a reality.

To my supervisors, Jonathan Chenoweth, Graham Miller and Angela Druckman; I am deeply grateful for everything you have given me, on an academic and personal level. Since the very beginning, you have all offered me nothing but encouragement and also the freedom to pursue my ideas.

To my friend and colleague, Christos Zoumides; thank you for generously sharing data and ideas. Our collaboration has been very fruitful so far and I am sure there is more to come!

To Gang Li; thank you for meticulously sharing your statistics and tourism knowledge as well as your insightful comments on certain aspects of my work.

Marilyn and Barbara; thanks for your generous administrative support during my PhD.

To people in Cyprus who helped satisfy my demanding data needs; Constantinos Chappas and Alexis Saveriadis, from the CTO. I also want to thank Maria Euthimiou, Marilena Kythreotou, Lucy Panagidou, Isidoros Kypridakis and Vasilis Hailos from CYSTAT as well as Athena Papanastasiou from the Ministry of Agriculture, Natural Resources and the Environment.

To everyone in Cyprus who helped me with my surveys; Demetris Demetriou from Aphrodite Hills, I am very grateful that you gave me a whole afternoon to interview guests in your resort. Katie O’Hara from Minthis Hills, thank you for responding to my emails and giving me guest numbers for your golf courses. Stelios Kizis and Evros Arakapiotis from the Columbia hotel (Pissouri), I am very grateful for your detailed information on food menus and portions.

To my friends in Guildford; Andy and Richard, you have both been great friends and housemates. I will never forget the time we spent together in our legendary Rupert Road
abode. Val and Foivos, thank you for the good food and company, and for keeping the Cypriot spirit alive! Shane and Scott, watching football games was a completely different experience when it was with you. Thanks for being great friends as well. Murat, Marie and Inka, I only got to know you for a year but Guildford was never the same without you.

All the great people I met in various workshops and conferences; Fiona from the ICOT 2012 conference in Crete, thank you for kindly driving me to Archanes every morning and also for your great company. Didem from IAFOR Brighton, thank you for the stimulating and heated conversations. Finally, thank you to all the PhD students (too many to name!) from Surrey, NCSU and USP who attended the 2013 UGPN Doctoral Seminar in Sao Paulo, what a wonderful experience that was.

I would also like to thank the The Leventis Foundation and the Roger and Sarah Bancroft Clark Charitable Trust for their generous financial support at crucial moments of my PhD.

My last acknowledgements are reserved for the most important people in my life:

Brenna, mon amour; your endless love, support and encouragement means so much to me. I am so thankful that you are in my life. You have been the person that has experienced first-hand all my ups and downs during the thesis. I can’t even imagine how depressing I must have been at times! You are also the best proof-reader in the history of humanity! Je t’aime trop!

The biggest thank you has to go to my family. Firstly to my parents, Marina and Yiorgos, this thesis is dedicated to you (don’t worry, that doesn’t mean you have to read it!); without your boundless love and support I would have never been able to get to this stage. You have both inspired me greatly from a very young age to always pursue knowledge, to work hard and to appreciate what I have. Lastly, a big thank you goes to my sister, Angeliki, thank you so much for your encouragement and invaluable contribution in finding and addressing all kinds of errors in the revised document.
PART I

Water and Tourism: methodological challenges
Chapter 1: Introduction

1.1 Background – water and tourism

Most economic activity relies on the input of environmental resources. One such input is water, a resource which is not only a vital necessity for satisfying everyday needs such as drinking, washing and cooking, but which is also required for growing the food that we depend on for survival and for economic development (Chenoweth, 2008). Water issues have been gaining importance on the global political agenda in recent years (UN-Water, 2006; 2010; UNDP, 2006). There has been talk of an impending ‘global water crisis’ (Biswas, 1999; Hanjra & Qureshi, 2010; Lopez-Gunn & Llamas, 2008), fuelled by the significant numbers of people in developing countries who still lack access to drinking water and sanitation (Montgomery & Elimelech, 2007; UNDP, 2006), an ever-increasing global population (Lutz & Samir, 2010; UN DESA, 2013), increases in water demand as nations become wealthier (Oki & Kanae, 2006; Rosegrant & Cai, 2002), and the possible impacts of climate change on water availability (Arnell, 2004; Bates et al., 2008; IPCC, 2013). The increasing realisation that water is a finite resource raises the urgent issue of how we may use it most efficiently but also how we could save water by minimising our consumption of goods produced using water. Ideally, each drop of water must be used to generate the maximum amount of utility.

Water is an issue of global importance, yet water scarcity issues are inherently local. There is enough water on a global scale to satisfy human needs, as withdrawals account for less than 10% of available renewable freshwater resources (Oki & Kanae, 2006). However, global water resources are very unequally distributed in space and time (Postel et al., 1996; Shiklomanov, 2000). Furthermore, it is often difficult to ascertain whether water is truly scarce in the physical sense or whether it is scarce because of excess demand (Rijsberman, 2006). In the same way that physical availability of water varies in space and time around the globe, demand for water also varies in different places, as it is a factor of development, societal values and human behaviour (Molle & Mollinga, 2003).

Agriculture is globally the largest water user with a 70% share of all withdrawals, followed by industry (19%), with household use responsible for the remaining 11% (FAO, 2011a). Included in these volumes of water is water required for goods and services beyond our basic needs (Gleick, 2003b). Tourism may be considered as one such additional water
demand. At first glance, tourism appears to have a negligible impact on water resources, as global figures suggest that international tourism accounts for less than one per cent of national water use in the majority of countries (Gössling et al., 2012). Nonetheless, water demand from tourism tends to be extremely concentrated in space and time (De Stefano, 2004; Essex et al., 2004; Holden, 2008). Tourism thus poses a challenge akin to a significant increase in the population of a certain destination at a certain time of year. This exerts additional stress on local water resources, often accounting for a significant percentage of domestic water use in places where tourism is an important economic activity.

Tourism has a two-way relationship with natural resources at the destination known as the ‘resource paradox’ (Williams & Ponsford, 2009). It not only exerts a significant stress on natural resources (Hunter & Green, 1995) through infrastructure development, resource consumption and waste generation, but, at the same time, requires a sustainable use of these resources since they are core ingredients of the tourism product. According to the United Nations World Tourism Organization’s (UNWTO) Secretary General, water is one of tourism’s most precious resources as it powers all tourism industries, from hotels to restaurants, leisure activities and transport (UNWTO, 2013a). A single day of insufficient water supply could severely affect the public image and reputation of any tourist destination. Climate change could pose a serious threat to future water availability in many areas (Bates et al., 2008), with severe economic consequences in formerly popular tourism destinations (Gössling, 2006; Simpson et al., 2008). In many cases, tourists are often unaware of local water scarcity issues and cannot be depended on to compromise the quality of their holiday by making pro-environmental choices. Improving the inherent efficiency with which the tourism sector uses water thus becomes key to not only minimising the impact of the sector on the environment, but also to ensuring its survival through continued use of the resource.

The issue of water use by the tourism industry has been attracting attention in recent years, exemplified by the fact that the theme for this year’s UN World Tourism Day (27 September 2013) was “Tourism and Water”. Research and management efforts have so far concentrated on tourist facilities such as hotels, golf courses and swimming pools which directly use large amounts of water (Charara et al., 2010; De Stefano, 2004; Gössling, 2001; Kotios et al., 2009; Mangion, 2013). However, the concepts of embedded or ‘virtual’ water (Allan, 1996, 1998)
and the ‘water footprint’ (Hoekstra, 2003) have succeeded in raising awareness of the fact that the majority of water consumption takes place indirectly through purchases of agricultural and industrial products (i.e. in the supply chain).

For an average consumer, an estimated 86% of their daily water footprint comes from products originating in the agricultural sector (Hoekstra & Chapagain, 2008). This realisation is of immediate relevance to tourism, where approximately one-third of all tourist expenditure is used to purchase food (Telfer & Wall, 2000; Torres, 2003). Tourism may consequently have a much more substantial impact on water consumption than previously thought, particularly on the percentage that is commonly associated with agriculture (Cazcarro et al., 2014; Gössling et al., 2012; Hadjikakou, Chenoweth, & Miller, 2013; Yang et al., 2011).

Tourism is one of the world’s largest industries, supporting one in eleven jobs worldwide and generating more than 9% of global GDP in 2012 (WTTC, 2013b). Tourism is also one of the world’s fastest-growing industries, with new destinations constantly emerging and tourism arrivals worldwide expected to increase by an average of 3.3% per annum from 2010 to 2030 (UNWTO, 2013c). Given tourism’s undeniable role in generating economic output, any efforts to conserve water must be geared towards maintaining or even increasing (where possible) industry profits. An element which adds a degree of complexity is that tourism is highly diverse, offering a plethora of products that cater for different tastes and budgets at different times of the year. These products differ in terms of the revenue generated but also in terms of their demand for water. The ‘water productivity’\(^1\) or ‘water use intensity’\(^2\) of different products, should therefore be considered as an important metric of environmental sustainability in water scarce destinations.

Estimating water productivity in the tourism sector is methodologically challenging, as it involves estimating the total (direct and indirect) contribution of tourism to the economy and comparing this to the total water demand of the sector. The difficulty is that tourism is characterised by a large number of indirect and induced linkages to other economic sectors.

---

\(^1\) Water productivity is defined as the amount of measurable output per unit of water used, where the output is usually measured in economic units such as the value in money of the good or service produced per m\(^3\) of water (Gleick, 2003b).

\(^2\) This indicator is defined as cubic metres of water used per unit of value added (UNESCO, 2009). It is essentially the inverse of water productivity.
(Briassoulis, 1991; Hara, 2008). The same linkages also disperse water demand to several other economic sectors, creating a water demand multiplier effect (Emmanuel & Spence, 2009), in order to cater for tourism purchases, activities, infrastructure and meals.

1.2 Motivation and problem statement

1.2.1 Present research gaps and needs

The complexity of the tourism sector’s interactions with the rest of the economy has in the past prevented attempts to measure the total environmental impact of tourism in the form of carbon emissions or water consumption (EEA, 2009). Whilst attempts to comprehensively quantify and compare carbon emissions and economic output between different tourism products are now fairly prominent in the literature (Becken & Simmons, 2008; Dwyer et al., 2010; Gössling et al., 2005; Jones & Munday, 2007; Munday et al., 2013), approaches to do the same for water use are currently absent. This is, in some part, due to insufficient data in many destinations (Gössling, 2006). Arguably, however, the main reason has been a lack of in-depth understanding and quantification of the indirect component of water use.

Developing such approaches is particularly relevant and timely for established tourism destinations looking to diversify their product base. In the last decade there has been much talk of upgrading or diversifying tourism in the Mediterranean (Bramwell, 2004; Rico-Amoros et al., 2009), an area traditionally associated with ‘sun and sand’ mass tourism (Aguiló et al., 2005; Alegre & Cladera, 2006), with the purpose of maximising tourism revenue. Yet research has shown that the higher end of the tourism market tends to use considerably more water, mainly as a result of a larger abundance and size of water-intensive facilities (Hof & Schmitt, 2011; Rico-Amoros et al., 2009; Tortella & Tirado, 2011). The aforementioned studies have made a valuable contribution to the diversification debate, providing much-needed food for thought. Nonetheless, the existing research has only considered direct water use and has not attempted to compare the economic impact of different kinds of tourism, thus generating only partial conclusions on which to base management decisions.

---

3 Emerging destinations are more challenging because statistics on water use and economic output from tourism tend to be poor.
1.2.2 Advancing current approaches

Given tourism’s global extent, tourism management has an immediate obligation to look beyond direct water use (Gössling et al., 2012). This is not to say that ongoing efforts to minimise direct water use in tourism facilities such as hotels, swimming pools and golf courses are unimportant, but that these should not be pursued at the expense of improving water use efficiency and productivity in the supply chain. Current recommendations based on simplistic frameworks and assumptions remain too generalised to ensure sustainable water use management in the tourism sector. There is thus an urgent need to develop specialised frameworks for quantifying total (direct and indirect) tourism water use that are flexible enough to cope with different settings and scales, and that also allow for comparisons of water productivity between different tourist products.

Management practices geared towards increasing water productivity in tourism should be tailored to the needs and characteristics of different tourist types. This is in line with previous research in the area of sustainable tourism yield, which highlights the need for a better understanding of trade-offs between economic and environmental objectives (Becken et al., 2003; Lundie et al., 2007). Whilst in the vast majority of cases higher-spending tourists are targeted from an economic perspective (Dwyer & Forsyth, 1997, 2008), the notion of an ‘optimal’ tourist type is elusive from an environmental perspective (Becken & Simmons, 2008). For this reason, novel approaches are required. These must combine water productivity estimates with rigorous techniques to classify tourists into distinct segments based on their trip characteristics and spending behaviour, as part of a single integrated framework. Only then can policy and management formulation develop customised practices to improve water productivity for all tourist types.

1.3 Aim and scope

1.3.1 Aim of the research

The present thesis aims to develop novel approaches to comprehensively estimate and subsequently compare total water consumption and water productivity by different tourist types. The intention is to develop three different alternative approaches on a continuum of simplicity to complexity, in order to cater for different levels of data availability and expertise. To this end, the thesis explores the potential of several techniques – namely water
footprinting (Hoekstra et al., 2011), market segmentation (UNWTO, 2007), Environmental Input-Output (EIO) analysis (Lenzen & Foran, 2001; Leontief, 1970; Miller & Blair, 2009), and tourist surveys – to enhance quantification of the indirect component of water use in the tourism sector, in order to complement existing knowledge of the direct component. A secondary aim is to explore the potential of the proposed approaches to generate results with insightful theoretical and policy implications for tourism management.

1.3.2 Thematic scope of the research

The study concentrates on the previously understudied topic of indirect water use in the supply chain of tourism, with a specific emphasis on food consumption and its associated water use impacts. The focus is on making a novel methodological contribution which relates to an existing body of literature on sustainable tourism yield (Becken & Simmons, 2008; Lundie et al., 2007; Northcote & Macbeth, 2006), by delivering frameworks geared towards water use impacts. Improving in-house (direct) water use efficiency in hotels and other tourist establishments is acknowledged in the thesis for its significant role in achieving water savings throughout the tourism supply chain, but is not integral to the present work.

The thesis argues that at this early stage the priority, at least from an academic perspective, should be to acquire a better understanding of tourism consumption patterns and their relation to water use by collecting more data and developing appropriate methodologies. Although some useful management implications emerge from the results and are briefly discussed, generating a list of precise recommendations for tourism establishments falls outside the scope of the present study. This would certainly represent a future goal once methodological frameworks are refined sufficiently to allow dependable policy and management initiatives to be drafted.

1.3.3 Geographical scope – the island of Cyprus

The Republic of Cyprus (hereinafter Cyprus) in the eastern Mediterranean (see Figure 1.1, p.9) provides an ideal case study area to fulfil the aims of the present study for a number of reasons.

Firstly, Cyprus is a popular destination with an economy largely reliant on tourism. Similarly to other islands in the Mediterranean, a favourable climate, natural beauty and rich
history have made the island an attractive tourism destination. Cyprus first became a tourism destination in the 1960s following its independence from Britain. Since then, the development of tourism has been a remarkable success story, with the establishment of tourism as the dominant economic sector since the early 1980s (Sharpley, 2001). In 2012, around 2.5 million international tourists visited Cyprus, which is almost three times the resident population of 860,000 (based on the 2011 official census) (CYSTAT, 2013). In the same year, the tourism sector made an estimated total (direct and indirect) contribution of 19.4% to GDP and supported 26% of total employment in the country (WTTC, 2013a).

Secondly, Cyprus is water scarce. With an annual precipitation of around 460mm, the climate regime is classified as semi-arid – making Cyprus one of the European Union (EU) member states experiencing the highest levels of water stress (Cyprus WDD, 2009; Hochstrat et al., 2009). The water scarcity problem is further compounded by the extremely unequal spatial distribution of water resources, as well as the fact that around two-thirds of annual rainfall falls during the winter months (Kampanellas et al., 2003). As in other Mediterranean islands, water demand can often exceed natural water availability during the summer months as this is when most tourists visit and is also a time when natural flows are lacking (Gikas & Angelakis, 2009).

In addition to the substantial intra-annual variability in rainfall, there is also significant inter-annual variation, with the island frequently experiencing droughts. Consequently, the island has become highly reliant on water abstraction from groundwater, reservoirs (surface water stored in dams) and desalination (see Figure 1.2, p. 11). Desalination plants presently supply up to 50% of the water used in the residential sector during drought years (Kaimaki, 2010). This includes water used in tourism establishments. Furthermore, future water availability on the island is expected to be severely affected by climate change. The eastern Mediterranean region in general is considered to be an extremely sensitive ‘hotspot’ for climate change (Giorgi, 2006; Giorgi & Lionello, 2008; Ludwig et al., 2011). For Cyprus, recent studies using regional climate models suggest that, by mid-century, average temperature is likely to increase in the range of 1.3°C to 1.9°C (Giannakopoulos et al., 2010), and precipitation will decrease by 20% (Chenoweth et al., 2011).

Thirdly, tourism has long been recognised as an important water user on the island. Tourism is directly responsible for around 16.9% of domestic water use in Cyprus, which corresponds
to 5% of the total annual water use\textsuperscript{4} (Kaimaki, 2010). As the most prominent environmental issue on the island is water scarcity, it is commonly accepted that tourism has exacerbated the problem (Boukas et al., 2011; Sharpley, 2003). This is especially so during the summer months where peak tourism demand coincides with full irrigation requirements in agriculture (Iacovides, 2011a). The extremely high guest-to-host ratio which frequently exceeds 1:1 in some parts of the island, such as Ayia Napa in the southeast and Paphos in the west (Ayres, 2000), has undoubtedly contributed to an increase in water demand over the years, with experts warning that tourists are consuming considerable amounts of water at prices which do not reflect its actual value (Adamou & Clerides, 2009).

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{map.png}
\caption{Map showing the location of the island of Cyprus (green circle) and the Republic of Cyprus as the southern part of the island in dark green shown on the left of the image (source: Wikimedia Commons - http://commons.wikimedia.org/wiki/Main_Page).}
\end{figure}

\textsuperscript{4} This figure only refers to direct water use by tourism.
Fourthly, Cyprus, traditionally a sun and sand resort particularly popular with British tourists, is in the midst of an attempt to upgrade its product base. The government and the tourism sector alike have shown an eagerness to diversify the tourism product in order to attract higher-spending clientele (Adamou & Clerides, 2009; Clerides & Pashourtidou, 2007). Since releasing its revised tourism policy plans in 2000, the Cyprus Tourism Organisation (CTO) has actively encouraged developments such as golf courses, water parks and marinas in an attempt to attract higher-spending tourists (Louca, 2011). Nevertheless, academics have argued that it may be more prudent to focus on maintaining and improving the current mass tourism product as part of a more flexible adjustment strategy (Ayres, 2000; Sharpley, 2003). Whilst diversifying the existing tourism product could potentially increase the economic yield of the sector, there is uncertainty with respect to its likely impacts on water demand on the island.

Finally, Cyprus is a small island nation⁵ and is a member of the EU. The small geographic area⁶ means that the need to account for inter-regional differences is minimised. The importance of the tourism sector to the local economy, along with its EU membership, also means that the country has comprehensive data on tourism, including Tourism Satellite Accounts (TSAs). With the current economic downturn in the EU and the recent collapse of Cyprus as an offshore banking centre, the President of Cyprus has stressed the importance of tourism to the economy (UNWTO, 2013b). The present study is therefore a timely attempt to, for the first time, comprehensively quantify the total (direct and indirect) water consumption and water productivity of the tourism sector, and compare the different tourism types currently present on the island.

---

⁵ Cyprus is classified as a Small Island Tourist Economy (SITE) which is a country characterised by its small size, its nature as an island and its economic dependence on tourism (Shareef et al., 2008).

⁶ The area of the whole island is 9250 km².
Figure 1.2 Water supply sources with a breakdown into different uses (data source: CYSTAT, 2013). The figure does not capture the significant inter-annual variability between drought and wet years.

1.4 Thesis objectives and structure

1.4.1 Specific objectives

Following the overall aim defined in section 1.3.1, the thesis is divided into the following series of objectives:

1. Consider how freely available data could be employed to estimate direct and indirect water use for different kinds of tourism in different destinations as part of a simple, intuitive framework.

2. Perform market segmentation to create diverse tourist groups in order to improve understanding of consumption patterns and their associated impacts on water use and productivity.

3. Develop an integrated approach that can estimate total water use and productivity for inbound tourism in Cyprus based on the market segments established in the previous objective, with the intention of performing comparisons between segments.
4. Design a novel modelling framework for quantifying the water use and economic impact of diverse dietary preferences.

5. Test the model developed as part of the preceding objective, using primary data collected in different parts of Cyprus, for a selection of tourist types.

Figure 1.3 below shows how different data are used to meet each of the objectives listed above.

![Diagram of objectives and datasets](image)

**Figure 1.3** Conceptual diagram of the five main objectives of the thesis along with the principal datasets.

### 14.2 Navigating the thesis

The structure of the thesis closely follows the five principal objectives of the study. The thesis consists of five Parts (see Figure 1.4, p. 14). These are the Introduction (Part I), the three approaches developed (Part II, Part III and Part IV), and the Conclusion (Part V). Including this introductory chapter, there are a total of seven chapters. Part III (Chapters 3 and 4) and
Part IV (Chapters 5 and 6) each consist of two chapters owing to the complexity of the methods. All other Parts are shorter and consist of a single chapter. The literature review and methodology of the thesis are distributed across Chapters 2, 3 and 5, whereas the results and discussion are distributed across Chapters 2, 4 and 6. The chosen structure is thematic as opposed to the more conventional thesis structure with a single literature review chapter followed by methodology, results and discussion chapters. This allows each approach to be assessed in its entirety before moving onto the other approaches. The Conclusion (Part V) finally brings everything together to allow the reader to consider the individual and combined contribution of the different parts of the thesis.

Parts II, III and IV each have their own unique research focus and each includes relevant Appendices. Although each Part can also be read independently, it is preferable to follow the thesis in the way it is written as each method builds on the previous one – starting from the simplest approach (Part II) and moving onto the more complex methodological frameworks (Parts III and IV). Parts II and III of the thesis are partly based on previously peer-reviewed publications (specified in the relevant chapters).

In Part II, Chapter 2 develops and tests a simple framework using readily available data, based on the water footprint concept (the first approach). This chapter contains the general literature on water and tourism, and develops concepts and ideas that form the basis of the following, more complex, two methods.

In Part III, Chapter 3 reviews the literature on tourism market segmentation, sustainable yield and Environmental Input-Output (EIO) analysis. It then develops an integrated framework for distinguishing between the water use and productivity of different tourist types (the second approach). Chapter 4 presents estimates of water use and water productivity for different markets segments. It subsequently discusses the findings, before evaluating the performance and usefulness of the approach and the need to address some of its weaknesses and limitations.

In Part IV, Chapter 5 is the longest in the thesis as it documents the process of constructing an innovative EIO model for quantifying the water use impact and water productivity associated with different dietary choices. This chapter reviews technical literature on Input-Output Table (IOT) disaggregation and rebalancing, generating final demand vectors, and
primary data collection. It subsequently describes how the Cyprus IOT is disaggregated and sets up the model for use (the third approach). Chapter 6 demonstrates how the tourist survey data is used to run the model in order to compare tourist groups based on their dietary preferences. The last section of the chapter discusses the findings along with their implications and limitations.

In Part V, Chapter 7 finally evaluates all three methods, including a discussion of their respective strengths and weaknesses and potential applications. The chapter also offers a synthesis of the findings and their implications. To conclude, the chapter discusses future research avenues and reiterates the contribution of the thesis.

Figure 1.4 Thesis structure diagram showing the different parts and chapters of the thesis. The bubbles represent the thesis objectives.
PART II
Estimating total tourism water consumption using readily available data
Chapter 2: Estimating the direct and indirect water use of tourism in the eastern Mediterranean

2.1 Chapter 2 outline

2.1.1 Aim and scope

This chapter presents a basic approach to estimate the total water resource demand exerted by tourism in a destination. The chapter relates to work previously published in Hadjikakou et al. (2012, 2013). By employing the water footprint methodology, the proposed approach makes use of existing data from the United Nations Food and Agriculture Organisation (FAO) and the Water Footprint Network (WFN), along with estimates for different components of the tourism infrastructure from published literature. The method is designed to be intuitive and to not require any major resources, and also serves as an essential precursor by setting the scene for the more elaborate methods to follow in Parts III and IV. It is mostly intended as a means to obtain approximations of the total water used for tourism in a country or region, based on the consumption patterns of a hypothetical average tourist. As mentioned in the Introduction (Part I), direct water use in hotels and other tourism establishments (the domestic or direct component in Figure 2.1, p. 17) has attracted considerable attention in recent years and general awareness on the topic is improving. However, there have been few attempts to understand and quantify the water used indirectly in the supply chain (the indirect component of water use in Figure 2.1) in order to cater for tourism consumption of goods.

A significant body of literature from the water resources domain as well as the general field of sustainability points to the importance of accounting for the resources being used in the production of goods (as part of a life cycle approach) – which, in most cases, are more substantial than the resources used directly by consumers. In terms of water resources, research has shown that food consumption accounts for the vast majority of supply chain water use. Thus, the proposed approach considers both direct and indirect water use by adding them together to arrive at an estimate of total water use. Moreover, owing to the complexity of modern trade patterns in food commodities, food consumed at a certain locale may have not been produced locally. Estimates of imports must therefore be considered an integral component of any attempt to quantify both the local and global water use impacts of
tourism consumption. It is also likely that the choice of what and how much food to import varies enormously between different countries or regions (and in effect, tourism destinations) which suffer from different degrees of water stress. This is a further nuance that the method tries to capture. It is envisaged that the work presented in this chapter will contribute to the growing body of literature considering the environmental and sustainability impacts of tourism food consumption.

Figure 2.1 Figure showing the direct and indirect ways in which tourism exerts pressure on water resources, along with key factors driving tourism water demand.

2.1.2 Objectives and structure

The first objective (section 2.2) of the chapter is to understand the use of water in tourism destinations through an extensive review of the literature, in order to ascertain how the water footprint methodology can be applied to the tourism sector. This also involves an explanation of the water footprint concept, and an assessment of some of its strengths and limitations. The second objective (section 2.3) is to propose a methodology that involves
establishing what kinds of data are available and selecting the most suitable datasets for the purposes of the study. A key component of this objective is the use of trade data from the FAO in order to distinguish between pressure on local water resources and the water embedded in imports. The third objective (section 2.4) is to implement the approach and to generate estimates for Cyprus and some other Mediterranean tourism destinations. The final objective (section 2.5) is to critically assess the usefulness of the approach and the implications of having more detailed and accurate information with respect to water use in the tourism supply chain. Lastly, the limitations of this approach, and the need for more comprehensive approaches which can consider economic impact alongside water, are examined.

2.2 Understanding the nature of tourism water consumption

2.2.1 Section summary

Researchers in the past have argued that too little attention has been given to water use in the tourism sector (Gössling, 2006; Pigram et al., 1995). According to Gössling (2002), at the time there were no available data to allow for detailed calculations of water use in the tourism sector on broad regional levels. This appears to have improved in recent years as water is fast-becoming a scarcer resource. However, the quality of the data remains far from optimal, partly because water demand by tourism is often dispersed through various branches of the economy (Eurostat, 2009). Nevertheless, recent studies and interest in the issue have enriched tourism water demand estimates to a degree which allows an understanding of the heterogeneity in direct water use within the tourism sector. The literature on this topic has been growing in recent years (especially since 2010) and provides useful insights on the enormous range of water volumes being consumed by different types of tourist accommodation.

The direct component of water use is relatively well understood, with the present chapter focusing on both academic and non-academic research that has yielded a sufficient amount of direct water use estimates in different contexts. It is the indirect component that has been largely ignored, with the exception of a small number of studies that explicitly provide estimates of this type of water use (Cazcarro et al., 2014; Gössling et al., 2012; Hadjikakou, Chenoweth, & Miller, 2013; Lundie et al., 2007; Yang et al., 2011). The present study argues
that more comprehensive frameworks capturing total water use (direct and indirect) are required, in order to enhance our understanding of how different tourism products perform with respect to their water use demand. This section reviews the literature in order to unpack the key components of tourism demand as well as the role of different tourist choices, in an attempt to explore the conditions that can make tourism’s impact on water resources consumption a serious problem. This will allow an appreciation of which data are best suited for the subsequent analysis.

2.2.2 Direct water use

Spatial and seasonal concentration can exacerbate water scarcity

As shown in Figure 2.1 (p. 17), direct water use refers to the component of water directly used in hotels, swimming pools and other tourism establishments. This kind of water demand from tourism can exacerbate existing water scarcity problems and create conflict over water resources, even where water resources may appear to be abundant in a climatic sense (Cole, 2013). Where some degree of physical water scarcity is already present, as in most Mediterranean destinations, tourism may compound this by adding further pressure on local water resources. An in-depth review of the literature, mostly focused on Mediterranean and Caribbean destinations, has identified the key reasons for which direct water demand from tourism deserves considerable attention.

The first of these is the spatial and seasonal concentration of tourism activity. Although tourism water use figures appear to be insignificant compared to those of other uses such as agriculture and industry at the global scale, water demand from tourism tends to be very concentrated in specific areas at specific times of year. In islands where tourism is the predominant industry, tourism can be responsible for a substantial percentage of the overall water use. Saito recently estimated that on the Big Island of Hawaii, water consumption by the tourism sector accounts for 44.7% of the island’s total water consumption (Saito, 2013). This is a phenomenally high figure, with other islands such as Malta and Barbados having lower percentages, with 7.3 and 2.6% respectively (Gössling et al., 2012). In Cyprus, around 16.9% of domestic water corresponding to 5% of the total island-wide water demand is used.

---

7 Note that this could be sourced from groundwater, surface water, desalinated water and/or treated wastewater.
by tourism (WDD, 2011). In larger countries, tourism’s share of overall water use may not appear that impressive. However, the annual figures cannot portray the pressure exerted by tourism water demand in certain places during specific periods of the year.

The seasonal and spatial concentration of tourism demand is most evident in Mediterranean countries. There, tourism tends to concentrate in coastal resorts, creating pockets of extremely high population density during the summer months. Water demand from tourism essentially becomes a problem analogous to that of overpopulation. Statistics from different areas of the Mediterranean such as the Provence-Côte d’Azur region in France, the Cyclades island group in Greece and the Costa Brava in Spain show that the population in tourist resorts can increase by more than ten-fold during certain times of the year (De Stefano, 2004), with associated increases in water demand. According to estimates the guest-to-host ratio should ideally never exceed 1:6, but coastal towns in Cyprus often have ratios close to 1:1 (Ayres, 2000). The problem is exacerbated in places where local residents are also more likely to live along the coastal strip, which commonly occurs in Caribbean islands such as Jamaica and Barbados (Goodwin & Walters, 2007).

In the Mediterranean region, where most countries (or parts of countries) suffer from some degree of water scarcity, the climate is characterised by marked seasonality in precipitation with the majority of the rainfall falling during the winter months (Kent et al., 2002). Incidentally, tourists are attracted to Mediterranean resorts largely because of the warm and sunny climate (Holden, 2008), with summer months being the most popular, as the period coincides with the summer holiday period in the northern hemisphere. As a result, in many resorts, water demand frequently surpasses water availability during the summer months (Essex et al., 2004; Gikas & Tchobanoglous, 2009; Kent et al., 2002). A frequently cited example that demonstrates the intense seasonal water demand from tourism is during July 1999 in the Balearic Islands, where the tourism sector’s consumption in that month alone represented 20% of the year’s total domestic consumption (Ecologic, 2007). De Stefano (2004) argues that such intense water demand peaks can only be handled through investments in infrastructure that will then remain underused during the rest of the year. In Cyprus, as in other semi-arid island destinations, the summer deficit in water demand is met through storage of winter rainfall in dams and reservoirs, transfers from more humid parts of the
island, desalination of seawater and an overexploitation of coastal aquifers (Koundouri & Birol, 2011).

Tourism may also contribute to water quality problems. Where unsustainable pumping of groundwater takes place, this can induce water quality problems due to saltwater intrusion (where saline water from the sea is drawn into the aquifer). The main cause for this phenomenon is groundwater over-abstraction for public water supply (Nixon et al., 2003), a large proportion of which comes from tourism in certain areas. This can pose serious problems for water security in islands with very permeable geology, where groundwater is the only conventional source of water (Kent et al., 2002; Manoli et al., 2004; Sapiano, 2008). The quality of groundwater and surface water may also be impaired by significant increases in sewage effluents due to the high accommodation densities in tourist resorts. Moreover, where sewage receives inadequate or no treatment, the ecology is at risk due to the possibility of eutrophication. Pollution of aquifers and coastal waters from fertilisers and herbicides used on golf courses and hotel gardens has also been reported in the literature (Shaalan, 2005).

It is therefore evident that, even if tourism is hardly ever the primary cause of water scarcity, its spatially and temporally intense manner of water consumption creates problems in water scarce localities. Gössling (2006) claims that when tourists travel abroad, the water saved in the source regions partly compensates for overuse of local water resources in the destination regions. He does, however, also acknowledge that tourism on a global level tends to shift water consumption from water-rich to water-poor areas (as people tend to move from colder climates in search of sun and sea). Since water use in most holiday destinations (at least in the Mediterranean), occurs where water availability is low, this implies a high impact on scarce local water resources. The fact that water is saved elsewhere can do little to help alleviate local water scarcity.

In places where the water situation is already critical, climate change is expected to aggravate the situation (Tekken et al., 2013). The Mediterranean, in particular, has been identified as a climate change and water scarcity ‘hotspot’ (Scott et al., 2008). This infers an area where climate models display a robust signal of warming and drying at a rate that exceeds the global average. At the same time, tourism arrivals worldwide are expected to
maintain an increasing trend in the long term (UNWTO, 2010b). This leads Perry (2005) to argue that endemic water scarcity is a very likely future scenario in many popular tourist destinations, which could possibly lead to rising tensions between local people and tourist authorities. Along the same lines, Becken and Hay (2007) conclude that increased stress from both tourism and climate change could eventually make certain destinations extremely water stressed, to the extent that further growth in their tourist industries will not be possible. Climate change is therefore another factor that could aggravate water scarcity even though its effect on seasonality is hard to predict.

**Equity issues – tourists vs. other users**

As a high value user of water where a single day of insufficient water supply could severely affect the public image and reputation of any destination, tourism commonly takes priority over other water users. As a result, tourists are allowed to consume water freely, which often results in conflict over water resources, especially during drought years when local residents and farmers have restricted access to water while the supply to tourist establishments remains unaffected (Holden, 2008). An additional problem is the fact that most tourists come from developed temperate countries where water is fairly abundant. Many tourists, therefore, have little appreciation of where their water comes from or how their use compares to that of the local population – and may also be unwilling to sacrifice the quality of their hard-earned holiday by taking shorter showers or avoiding water-intensive activities. When in ‘holiday mode’ and in the absence of financial incentives to promote more prudent use, pro-environmental behaviour by tourists is rare (Miller et al., 2010). In a recent survey in Malta, the majority of tourists (83%) interviewed said they had three or four showers a day (Mangion, 2013). This is significantly higher than local residents who tend to shower once or twice daily. Tourists therefore not only use more water than locals, but they are also likely to use more water when on holiday compared to what they would use at home.

---

8 According to Perry (2005), areas where temperatures are set to rise significantly such as the Mediterranean could become unpopular during the summer months if temperatures rise to the point where tourists cannot venture outside in comfort. A smaller number of tourist arrivals in the height of summer could, in theory, have positive repercussions with regards to water consumption, even though this would ultimately depend on tourist arrivals during the rest of the year.
Several studies demonstrate that tourists use considerably more water on average compared to the domestic population (Emmanuel & Spence, 2009; Essex et al., 2004; Gössling, 2005). Estimates of tourist water use in the Mediterranean range from 300 to 850 litres per capita per day (hereinafter l/cap/day) (De Stefano, 2004). These figures are high compared to the volume of water necessary to satisfactorily meet human and environmental needs (excluding dietary requirements), which Chenoweth (2008) estimates at 132 l/cap/day. According to the FAO (2011a), the global average in domestic water consumption is currently around 161 l/cap/day. In developing countries where the national per capita use is even lower, there is often a stark contrast between tourist and local water consumption. Gössling (2001) found that the average per capita daily water use in hotels in Zanzibar corresponds to around 15 times the daily per capita demand from the local population. In Cyprus, the average consumption by tourists is estimated at 465 l/cap/day, as opposed to only 222 l/cap/day consumed by urban dwellers (Iacovides, 2011b). This shows that the average tourist consumes around twice the amount needed by an average local.

The increase in local water demand from tourism is sometimes satisfied at the expense of local communities, leading to water inequity. According to Tourism Concern (2011), in the Indonesian island of Bali, villagers in some parts of the island are forced to walk up to 3 km to obtain water whereas the island’s golf courses use around 3 million litres of water daily. The topic of tourism and water inequity in the developing world has attracted more interest in recent years (Cole, 2012, 2013; Tourism Concern, 2012), with such issues likely to persist as tourism development intensifies or expands into new destinations. In developed destinations like Cyprus, tourists may use significantly more water than local residents, but there are very few reports of locals being affected in such adverse ways. Instead, one of the main concerns in southern Europe appears to be tourism competing for water resources with agriculture (Rico-Amoros et al., 2013). The potential clash between tourism and agriculture becomes even more serious when factoring in the indirect aspect of tourism water demand for food (discussed in the following sub-section), which may create complex demand feedback loops.
**Forms of tourism associated with higher direct water demand**

Averaged tourism consumption figures for whole areas or resorts hide the fact that water use varies enormously depending on the type of accommodation and the recreation facilities available. Despite the consensus that tourists use more water compared to local residents, it is also apparent from the wide range of estimates in the literature that the tourism sector is extremely diverse in terms of both the amounts of water consumed and the specific uses of this water (Kotios et al., 2009; Rico-Amoros et al., 2009). The general pattern appears to be that increased luxury leads to increased water consumption in hotels and other types of accommodation, mainly as a result of the greater size and range of facilities on offer in luxury establishments.

Saito (2013) finds that, in Hawaii, the number of guest rooms is the most important variable in determining water use at an accommodation. This confirms Gössling’s (2001) earlier findings from Zanzibar of a correlation between hotel size and water use (both total and per capita). According to the author this mainly occurred due to the larger hotels also having larger pools and larger gardens requiring extensive irrigation. These findings are further supported by a study of the hotel sector in Barbados, where annual consumption showed a strong positive correlation with the number of employees working for a hotel and reflects both the absolute size and the service level of the hotel (Charara et al., 2010). Hotel size therefore appears to be a robust determinant of overall and per capita direct water use throughout the world.

A number of other factors have been identified as being crucial in terms of their influence on tourist per capita direct water use. Gardens, swimming pools and golf courses are all popular attractions that generate tourism revenue and are seen as prerequisites for attracting higher-spending tourism, yet are all extremely water intensive. According to Hof & Schmitt (2011), garden irrigation is the single main cause of high water consumption in ‘quality’ tourist areas, accounting for more than 70% of total water consumption during summer months. The presence of a swimming pool is estimated to increase consumption by up to 60 l/cap/day (Kotios et al., 2009; Tortella & Tirado, 2011), while the existence of café or bar facilities leads to a further 35 l per capita increase (Tortella & Tirado, 2011). Finally, a golf course in Cyprus is estimated to require 10,000 to 15,000 cubic meters per hectare per year
(Mangion, 2013). Although water golf course water requirements are likely to vary significantly depending on the locality⁹, the estimated range given for Cyprus is likely to be applicable to other Mediterranean resorts, an area where golf courses require extensive irrigation.

The density of accommodation is another important factor, also partly related to garden irrigation and swimming pool presence. Rico-Amoros et al. (2009) find that in Benidorm (Alicante coast, Spain), lower consumptions per capita are found in campsites and hotels (ranging from as low as 140 l/cap/day) whereas higher consumption rates are more characteristic of single houses and resort developments (often more than 600 l/cap/day). These results are in agreement with low density ‘quality’ tourism areas in Mallorca where water use can exceed 700 l/cap/day (Hof & Schmitt, 2011). Another study in Mallorca found that the range can vary from 156 l/cap/day to as much as 2425 l/cap/day, with a mean value of 541 l/capita/day (Tortella & Tirado, 2011).

These results lead the aforementioned studies from Mallorca and Benidorm in Spain to the conclusion that the mass tourism product, so often associated with its negative aesthetic impact on the landscape, actually registers much lower direct water consumptions per capita compared to so-called ‘quality tourism’ (Hof & Schmitt, 2011; Rico-Amoros et al., 2009; Tortella & Tirado, 2011). This is explained by the fact that there is an inherent efficiency in the mass tourism product, characterised by limited tourist spending, the optimisation of water supply networks due to concentrated accommodation facilities, and easier management (Rico-Amoros et al. 2009).

Tortella & Tirado (2011) find that the recent proliferation of all-inclusive deals could also increase water use because of higher consumption in meals and kitchens as well as through more frequent use of water-intensive facilities and services (as it encourages guests to spend more time on the hotel premises). These results are consistent with earlier studies showing that the more meals a hotel serves, the higher the water consumption per guest because of more water required in the kitchen (Bohdanowicz & Martinac, 2007; Deng & Burnett, 2002). Activities in hotels are certainly more likely to be water-intensive compared to going to the

---

⁹ According to Gössling et al. (2012), a standard golf course may have an annual consumption of 80,000 m³ to 100,000 m³ in the North of France and 150,000 m³ to 200,000 m³ in Southern France.
beach or sightseeing. However, the literature does not consider in which respects hotel meals or buffets differ compared to meals that the tourists would have consumed outside the hotel.

Chain affiliation is also shown to have a significant impact on water consumption in hotels. In Tortella & Tirado (2011), hotels belonging to small chains tend to have significantly (18%) lower water consumption levels than independent hotels, whereas the hotels that are part of larger international chains display significantly higher (34% higher) levels of water consumption compared to independent hotels. The authors’ possible explanation for this is the fact that larger chains have higher profit margins and, given the low share of water in the overall running costs (around 4%), the larger the chain the lower the incentives to invest in water efficient practices.

The influence of tourist choices such as class of hotel, type of board, and engagement in water-intensive activities, reveals a highly heterogeneous pattern of water consumption. This implies that it is possible, by making certain assumptions, to estimate direct water use on the basis of various trip characteristics. Moreover, the high degree of diversity in water consumption figures has extremely relevant implications for the current study, where one of the main objectives is to compare different types of tourism. The fact that many mature destinations, including Cyprus, are pursuing diversification and upgrading of the tourist product, may have adverse effects on water use by the tourism sector (Hof & Schmitt, 2011). In order to adequately understand the possible influence of these future trends on total water consumption, the indirect component associated with different accommodation and other trip attributes must also be quantified. The evident heterogeneity in direct water consumption patterns is also expected to apply for indirect water consumption but the determining factors are likely to be different. The following sub-section explores the elements that determine indirect tourism water consumption.

2.2.3 Indirect water use

The ‘virtual water’ and ‘water footprint’ concepts

‘Virtual water’ is the volume of water required to grow, produce and package agricultural commodities as well as consumer goods, measured at the place of production (Hoekstra & Chapagain, 2007). Most of this water is not usually present in the final version of a product since it has been used up during production. As an example, although a standard can of soft
drink in Europe only appears to contain 0.35 litres of liquid, it actually requires an average of 200 litres in order to grow and process the sugar contained in the beverage (A. K. Chapagain & Orr, 2008). Similarly, a kilogram of steak requires, on average, 15,000 litres due to the water needed to grow the necessary feed for a cow plus the water directly consumed by the animal and, finally, water used in processing the meat (Hoekstra & Chapagain, 2008).

The term ‘virtual water’ was coined by Allan (1996, 1998) in order to explain the high percentage of cereal imports in countries of the Middle East. His argument was that by importing grains from more humid parts of the world, these water stressed countries are also importing embedded water (which would have been required had these grains been produced locally), thus freeing up water to be used for other uses such as the domestic and industrial sectors. Ever since the introduction of the concept, virtual water trade has featured prominently in considerations of global, regional and national food and water security (Dalin et al., 2012; Lenzen, Moran, Bhaduri et al., 2013; Yang et al., 2003, 2007).

A little over a decade ago, in an attempt to quantify ‘virtual water’ flows, Hoekstra and Hung (Hoekstra & Hung, 2002) developed the notion of a ‘water footprint’. Inspired by the already established ecological footprint (Rees, 1992; Wackernagel & Rees, 1997), the water footprint was primarily intended as a consumption-based indicator. Even though it is numerically equal to the virtual water content of any given product (Zhang et al., 2012), the water footprint provides more information with respect to the type of water, as well as where and when that water is being used (Hoekstra et al., 2009). The total water footprint of any consumer is thus equal to water directly consumed for drinking, washing and cooking (operational footprint) plus the virtual water content of all the products consumed (supply-chain or indirect footprint) (Hoekstra et al., 2011). Technical aspects and components involved in calculating a water footprint are reviewed in section 2.3.

The water footprint concept has succeeded in highlighting the large volumes of water required to satisfy modern consumption patterns, especially in the developed world. In almost every study considered, indirect water use worldwide far exceeds direct use by around an order of magnitude (Ridoutt & Pfister, 2010b; Sophocleous, 2004), as 86% of the

---

10 15,000 litres is an averaged global value – in more humid regions this is likely to be less while in water scarce regions this may often be more.

11 A consumer can be a nation, a corporation, an activity or service, or an individual.
water footprint of humanity is estimated to come from the agricultural sector (Hoekstra & Chapagain, 2008). This stresses the importance of considering food consumption and dietary patterns as the driving factor of global and regional water demand. Diets rich in meat and dairy products are associated with the highest water footprints because of the large amounts of feed crops, drinking water and service water required by the animals (Vanham, Mekonnen et al., 2013). Figure 2.2 (p. 29) shows how the average water footprint of beef, (15,415 m³/ton) compares to the average water footprints of widely consumed vegetal products such as tomatoes (214 m³/ton), wheat (1,827 m³/ton) and soya beans (2,145 m³/ton).

From an academic perspective, the water footprint concept has provided a useful tool with which to explore inter-linkages between water use, food security and consumption (both in terms of different diet types as well as the increasing quantities of food produced and consumed worldwide) (Vanham et al., 2013; Cazcarro et al., 2012). It has revealed great disparities between different countries as well as between the origins of the water we consume. According to Hoekstra & Mekonnen (2012), the average consumer in the United States has a water footprint of 7800 l/cap/day, whereas the average citizens in China and India have water footprints of 2900 l/cap/day and 2985 l/cap/day, respectively. Water footprint studies also stress the importance of trade, with many import-dependent nations exerting significant impacts on water consumption in other parts of the world. The concept has also been attracting interest at the corporate level (Mason, 2013), enabling companies to begin to quantify the impact of their water use, as well as at the national level, with countries like Spain (Aldaya, Garrido et al., 2010) and Germany (Flachmann et al., 2012) already employing water footprint estimates in official policy documents. The ever-growing literature on the topic is testament to the appeal of the concept.
The water footprint of tourism

Tourism, characterised by its strong backward linkages (purchasing links) with other sectors (Briassoulis, 1991; Dwyer & Forsyth, 2008; C. Jones & Munday, 2004), is not an economic sector in the traditional sense. Tourists incessantly purchase and consume many types of goods. Tourism growth can often induce a water demand multiplier effect as tourism has close linkages to other sectors of the economy (Emmanuel & Spence, 2009). Due to the manner in which water use statistics are recorded and water resources are currently managed, water demand is divided into domestic, industrial and agricultural categories, with demand from tourism treated only as a percentage of domestic water. As a sector where products and services are purchased from other sectors and are often shipped in or imported from other regions or countries, tourism appears to be ideally suited to the water footprint concept. Llamas et al. (2010) and Velázquez et al. (2011) strongly argue that the virtual water and water footprint concepts should be applied to specific services such as tourism activities. This sub-section identifies the key components of indirect water use in the context of tourism.

Approximately one-third of all tourist expenditure is used to buy food (Telfer & Wall, 2000; Torres, 2003). Food is required not only as a biological necessity but is often considered to be an important part of the cultural experience of visiting countries and is increasingly used as a form of destination brand identity (Kim et al., 2009; Lin et al., 2011; Smith & Xiao, 2008). Fostering economic linkages between tourism and agriculture is often seen as an opportunity.
to enhance the benefits of tourism to the local community (Telfer & Wall, 1996; Torres, 2003). Producing food locally is considered as a way to reduce any economic leakage that would occur if the food is imported. However, as previously ascertained in section 2.2.2, food has a high virtual water content and is therefore likely to make up the bulk of the tourist water footprint.

Gössling et al. (2012) offer the most comprehensive account of the sources of both direct and indirect water demand from tourism, providing estimates of average daily water use as shown in Table 2.1, p. 31. The estimates shown in the table highlight not only the huge possible ranges in daily direct water use discussed in the previous section, but also the even more significant contribution made by indirect water uses such as fuel and diet to the total daily water use, with the overall total essentially corresponding to a daily water footprint per tourist. Using an estimate of 1 l of water for 1 kcal of food it is estimated that daily water requirements to support human diets range from 2000 to 5000 l/cap/day (Gössling et al., 2012). Yang et al. (2011) arrive at an estimate of 3587 l of water consumed indirectly in food by an average tourist in northwest Yunnan, compared to only 144 l/cap/day of direct water use. In the only other study to explicitly provide estimates for the water footprint of tourism, Cazcarro et al. (2014) fail to estimate per capita consumption. Nonetheless, their total tourism figures for Spain clearly indicate that food consumption accounts for the majority of total water use.

Gössling et al. (2012) also establish that the water embedded in tourism infrastructure as well as that required for energy and fuel production is likely to be significant. Roselló-Batie et al. (2010) report that the use and construction of buildings are responsible for 17 per cent of water consumption worldwide. Gössling et al. (2012) argue that tourism, given the extent of its infrastructure worldwide, must contribute substantially to this consumption. Nevertheless, they do not offer a figure for this type of water consumption (see Table 2.1). Evidently, arriving at an estimate for water embedded in infrastructure in any per capita water footprint would be fraught with uncertainty.
Table 2.1 Estimated global average use per tourist per day broken down into the main components of direct and indirect use (adapted from Gössling et al., 2012).

<table>
<thead>
<tr>
<th>Water use category</th>
<th>Water use (l/cap/day)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Direct water use</strong></td>
<td></td>
</tr>
<tr>
<td>Accommodation</td>
<td>84 – 2000</td>
</tr>
<tr>
<td>Activities</td>
<td>10-30</td>
</tr>
<tr>
<td><strong>Indirect water use</strong></td>
<td></td>
</tr>
<tr>
<td>Infrastructure</td>
<td>n.a.</td>
</tr>
<tr>
<td>Fossil fuels</td>
<td>750 (per 1000 km by air/car)</td>
</tr>
<tr>
<td>Biofuels</td>
<td>2500 (per 1 l)</td>
</tr>
<tr>
<td>Food</td>
<td>2000 – 5000</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>2000 – 7500</td>
</tr>
</tbody>
</table>

Data is generally better with regards to the water required for fuel production. Fuel production has been identified as a particularly water intensive process, even though the virtual water content of fuel varies widely depending on its origin (Wu et al., 2009). Based on an estimate that it takes 18 l of water to produce 1 l of gasoline and 4.1 l of fuel for 100 km of flight distance, Gössling et al. (2012) calculate that for every 1000 km travelled around 750 l of water are required, meaning that an average international air-based tourist trip of 7600 km (return distance) would have a virtual water content of 5600 l. Biofuels are known to be a very water-intensive energy source and, according to Gössling et al. (2012), the production of 1 l of liquid biofuels requires, on average, 2500 l of water. Nevertheless, biofuels only account for a very small percentage of total fuel use in most tourist destinations, especially in the Mediterranean.

It can therefore be concluded that, in addition to the direct demand from accommodation and activities, the two major forms of indirect water use (that are also possible to quantify based on available data and reasonable assumptions) are the virtual water contents of food and fuel. Based on the water footprint literature, food is likely to make up the majority of the water use in any holiday and for this reason it has been given a central role throughout this thesis. Similarly to direct water use, the type and amount of food is likely to vary significantly between destinations, tourist types, and accommodation classes, as well as seasonally. The argument that people eat whether they travel or not (Gössling et al., 2012; UNEP-UNWTO, 2012) may be valid but differences in the quantity, type, origin, and
production efficiency of food, along with a high degree of local water scarcity, could mean that tourism food consumption has a much higher impact on water resources at the destination. It is precisely for this reason that more detailed assessments such as the ones presented in this thesis, which take into account region- or country-specific dietary information, are required for a more complete understanding and management of tourism’s supply-chain water use.

2.3 Establishing a methodology to estimate tourism water consumption

2.3.1 Overview of the methodology

Four holiday scenarios have been constructed (Table 2.2, p. 34) and their associated water footprints have been calculated using existing secondary data sources. The use of hypothetical illustrative examples (scenarios) follows the approaches in WWF (2002), Hunter and Shaw (2007) and Chenoweth (2009). The computation of the water footprint relies on a component-based framework introduced by Gössling et al. (2002b), later refined by Hunter and Shaw (2007), to outline the potential use of the ecological footprint in tourism research. Chenoweth (2009) also adopts a similar approach to estimate the carbon footprint of a holiday. Although the holiday scenarios are hypothetical and should only be seen as indicative, they have been designed in such a way as to allow the reader to appreciate how a range of different choices in terms of transport, accommodation, diet and leisure activities affect water use. Varying the duration of the holiday scenarios also allows for a comparison between the daily water footprint and the total water footprint of each holiday.

Scenario one (luxury golf holiday) is a high-end tourism example, whereas scenario two (hiking holiday) is the more intuitively low impact example. Both take place in Cyprus, which is the default case study location for this thesis (see section 1.3.3 on Cyprus). Scenarios three (budget beach holiday) and four (up-market beach holiday) are considered to fall between the first two examples in terms of luxury and price, and are in line with commercially available packages offered by travel agencies in the UK. For purposes of comparison, Greece and Turkey, two other popular semi-arid destinations in the eastern Mediterranean region, are chosen as the destinations for these holidays. The study also seeks
to contrast the estimated figures for the four holiday packages with figures of average resident direct and indirect consumption in these countries (see section 2.3.3).

Paphos (Cyprus), Bodrum (Turkey) and Mykonos (Greece) are all highly diversified mature resorts, especially popular with UK tourists. Turkey, Cyprus and Greece were all in the top ten most searched-for destinations for UK summer departures for 2011, according to the Skyscanner website (Skyscanner, 2011). Polis (Cyprus) is a popular camping destination in the region. All chosen destinations already suffer from some degree of water scarcity with serious questions regarding future availability (Chenoweth et al., 2011).

Cyprus has available renewable water resources below the water scarcity threshold of 1500–1700 m³/capita (Falkenmark et al., 1989; Yang et al., 2003). Greece with 7000 m³/capita (Iglesias et al., 2007) and Turkey with 3280 m³/capita (Yang et al., 2007) appear to be considerably above this threshold value at the country level. However, most Aegean islands including Mykonos are extremely water scarce (Gikas & Angelakis, 2009; Gikas & Tchobanoglous, 2009; Sofios et al., 2008). Bodrum has been one of the prime international tourism destinations in Turkey in the last two decades (Gezici et al., 2006; Tosun, 2001) and is increasingly faced with water issues. These destinations have also been chosen to allow an appreciation of the role of trade and its potential to minimise impact on local water resources. Cyprus is amongst a group of water-scarce countries that have a large external water dependency (Hoekstra & Mekonnen, 2012), with Greece also being a net importer of grains and water-intensive animal products (FAO, 2010). On the other hand, Turkey has a very low ratio of virtual water imports to renewable resources (Yang et al., 2007). Turkey is, in fact, one of the largest blue virtual water exporters in the world (Hoekstra & Mekonnen, 2012).

The basic water footprint methodology for calculating industrial footprints (Hoekstra et al., 2009; Hoekstra et al., 2011) is applied to tourism by using four principal direct and indirect water use categories as identified by Gössling et al. (2012) in Table 2.1, p. 31. The associated water footprint in l/cap/day for each of the four holiday examples is calculated using:

\[ WF = WF_{direct} + WF_{indirect} = (AF + ACF) + (DF + FF) \]  \hspace{1cm} (2.1)
where $WF$ = total water footprint, $AF$ = accommodation footprint, $ACF$ = activity footprint, $DF$ = diet footprint and $FF$ = fuel footprint.

The assumption is that tourists will be travelling from the UK. The city of Manchester was chosen as the point of origin, for two reasons. Firstly, most people in the UK do not live immediately adjacent to a major international airport such as London Heathrow, and thus the selection of a non-London starting point better represents the type of journey the majority of tourists are likely to take. Secondly, the south of the UK is technically water scarce as a result of a very high population and limited water resources. By choosing a source region in the north of the country, one can safely assume that the tourist is travelling from a water plentiful area to a water scarce area, as is normally the case for tourists in Europe (Gössling et al., 2012). Section 2.3.2 specifies the sources of secondary data used as well as methodological considerations and assumptions involved in the estimation of each of the terms in (2.1).

<table>
<thead>
<tr>
<th>Table 2.2 Holiday package characteristics.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Scenario 1</strong> Luxury golf holiday</td>
</tr>
<tr>
<td>LOCATION</td>
</tr>
<tr>
<td>ACCOMMODATION</td>
</tr>
<tr>
<td>LOCAL TRAVEL</td>
</tr>
<tr>
<td>DIET</td>
</tr>
<tr>
<td>DURATION</td>
</tr>
</tbody>
</table>


2.3.2 Water footprint calculations and assumptions

Direct water footprint

$WF_{direct}$ is composed of the water intensity of the accommodation ($AF$) and the water footprint of any activities pursued by the tourist ($ACF$). Section 2.2.2 has established that accommodation footprint ($AF$) is the term on which most research has focused to date, with many estimates available in the literature for different types and classes of accommodation. Even where there are no existing figures, it is usually possible to obtain a value for $AF$ through a combination of room numbers and occupancy rates from hotel surveys along with total water consumption from water authorities (see Charara et al., 2010 for a detailed explanation).

The estimates for the accommodation footprint ($AF$) for scenario one have been estimated using 2011 occupancy rates and total water consumption figures (O. Markides, personal communication, 16 October, 2012) for the largest golf resort in Paphos. The accommodation footprint ($AF$) estimates for scenario two are based on average figures from campsites in Benidorm12 (Rico-Amoros et al., 2009), while those for scenarios three and four are based on Eurostat (2009) (see Table 2.3 below). The estimates, with the exception of the estimate for the golf resort (scenario one) which is based on real figures, are likely to be conservative, but all fall within the 84–2000 litres per person per day range suggested in Gössling et al. (2012) as well as the ranges estimated in Mallorca (Hof & Schmitt, 2011; Tortella & Tirado, 2011) and Benidorm (Rico-Amoros et al., 2009).

<table>
<thead>
<tr>
<th>Holiday option</th>
<th>l/cap/day</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1 (luxury resort)</td>
<td>1260</td>
<td>Personal communication</td>
</tr>
<tr>
<td>Scenario 2 (campsite)</td>
<td>84</td>
<td>Ricos-Amoros et al. (2009)</td>
</tr>
<tr>
<td>Scenario 3 (2* apartment)</td>
<td>180</td>
<td>Eurostat (2009)</td>
</tr>
<tr>
<td>Scenario 4 (4* hotel)</td>
<td>400</td>
<td>Eurostat (2009)</td>
</tr>
</tbody>
</table>

Table 2.3 Accommodation water footprint (AF) for each of the holiday scenarios.

---

12 No such data were available for any campsites in Cyprus.
An attempt is also made to account for the water footprint of certain activities that are likely to be pursued in each holiday package through the activity footprint (ACF) (see Table 2.4, p.37). Attributing water use from activities such as golf and water parks to individual tourists is challenging, not least because of the difficulty in apportioning responsibility – for example to each golfer for the water use of a golf course that caters for thousands of tourists and non-tourists over the course of a year. A reasonable choice is to adopt a consumption perspective (given that the water footprint is indeed a consumption indicator) and to assume that the water used by a golf course over the year can be divided by the number of players during the year. This is a crude estimate, but is based on the logic that catering for each golfer requires a certain volume of water which the golfer is indirectly consuming to obtain the benefit of playing golf. This logic is compatible with consumption-based accounting (Davis & Caldeira, 2010; Wiedmann, 2009). It could be argued that this water should be part of the indirect water footprint (as it is not directly consumed by the tourist), but it was decided to keep this as direct water use because golf courses do not represent a hidden water demand such as the water embedded in food or fuel.

Based on published figures for golf courses along with some estimated figures of visitors and rounds played, it becomes apparent that the range of 10-30 l/cap/day for the activity footprint (ACF) given in Gössling et al. (2012) is too conservative when it comes to golf, since golf courses in tourist destinations will cater almost exclusively for tourism demand. Scenarios two and three do not entail water-intensive activities and are assigned an average activity footprint of 10, while scenario four is assigned an activity footprint of 30 to reflect possible visits to water parks and swimming pools. Scenario one, where golf is the predominant activity, uses annual irrigation volume (for the golf course) and visitor numbers obtained from the same golf course resort in the Paphos area of Cyprus (O. Markides, personal communication, 23 January 2013). Dividing total golf course irrigation volume by number of visitors gives an activity footprint of 1096 l per visitor. The length of stay (LOS) in scenario one is 7 days, so this equates to 157 l/cap/day.

---

13 This is confirmed by the high ratio of tourists to permanent members.
Table 2.4 Activity water footprints for each holiday scenario.

<table>
<thead>
<tr>
<th>Holiday option</th>
<th>l/cap/day</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1 (golf)</td>
<td>157</td>
<td>Personal communication</td>
</tr>
<tr>
<td>Scenario 2 (hiking)</td>
<td>10</td>
<td>Gössling et al. (2012)</td>
</tr>
<tr>
<td>Scenario 3 (beach)</td>
<td>10</td>
<td>Gössling et al. (2012)</td>
</tr>
<tr>
<td>Scenario 4 (water park, pool)</td>
<td>30</td>
<td>Hof &amp; Schmitt (2011)</td>
</tr>
</tbody>
</table>

**Indirect water footprint**

The diet footprint (DF) is the term which requires significant assumptions to estimate. The simplest approach would be to assume tourists eat the same food as a local would do. However, this is rarely true, given that tourists mostly eat in restaurants and are more likely to take a pleasure approach to their meals (Boniface, 2003). According to Gössling et al. (2012), they are likely to consume a greater share of higher-order, protein-rich foods with higher water footprints than locals. Nevertheless, the average local water footprint per capita can still be used to compare tourists to non-tourists as will be shown later on (see Figure 2.3, p. 42).

The present study devised hypothetical daily menus suited to each holiday example (see Table 2.6, p. 43). The menus should only be seen as a simplification of the tourist diet, which would be more varied in reality as the tourist would not be expected to consume the same foods every day. Moreover, we assume that the calorie consumption of each example equals around 3442 kcal\(^{14}\), which is the average daily calorie consumption for the UK for 2005-2007 according to the FAO (2011b). This ignores differences in nutritional needs of individuals as well as the fact that, when on holiday, individuals may indulge more in food than they would back at home. However, an average value was required in order to allow comparisons between the different examples.

The menus are made up of ingredients such as eggplants, tomatoes, olive oil, chickpeas, and lentils in addition to grains and meats which regularly feature in popular eastern

---

\(^{14}\) This may appear to be a very high figure given that, according to most dietary guidelines the recommended caloric intake is around 2000-2500 kcal but the FAO figure appears to account for waste.
Mediterranean dishes. It is assumed that tourists consume mostly local dishes. Considering the recent familiarity and popularity of Mediterranean dishes in the UK, this appears to be a reasonable assumption. Using the open source dieting software CRON-O-Meter\textsuperscript{15}, the quantities were adjusted to ensure the set caloric intake was met for each example.

In order to perform the calculations, the study uses the virtual water content (VWC) for each ingredient (see Table 2.6, p. 43) as estimated in Mekonnen & Hoekstra (2010a, 2010b, 2011). These figures are expressed in m\textsuperscript{3} per ton and include estimates of blue, green and grey water for each agricultural product in each country taking into account local climatic conditions and production efficiencies, as well as the origin of imports. Blue water refers to water in rivers, lakes and aquifers (Savenije, 2000). It is the visible component of the water footprint and includes all irrigation water in addition to any direct water used in industry and homes, minus any return flows (Chapagain & Tickner, 2012). Green water is the soil moisture in the unsaturated soil zone (Falkenmark & Rockström, 1993) and is the main source of water in rainfed agriculture. This is essentially rainwater trapped in the soil, which many plants and grasses use to grow. Grey water is defined as the volume of water needed to dilute the load of pollutants associated with the production of a certain good or service and is used as an indicator of pollution (Ercin et al., 2011). The grey component of the WF essentially attempts to measure water quality impairment.

In the present study only the blue and green water components are considered. Grey water has been excluded for two reasons. Firstly, water quality is outside the scope of the study. Secondly, grey water is a theoretical rather than an actual measured volume (Morrison et al., 2010) which relies heavily on assumptions and estimations (Galli et al., 2012). Several authors have questioned the use of the grey water footprint, raising valid arguments against its inclusion as part of the water footprint (Chenoweth et al., 2013; Gawel & Bernsen, 2011a; Jeswani & Azapagic, 2011; Thaler et al., 2012). Since Mekonnen & Hoekstra (2010a, 2010b, 2011) provide a breakdown of each water footprint, it was possible to select only the blue and green components.

\textsuperscript{15} Available at http://cronometer.com/
The daily diet footprint (DF) is given by adding up all the individual VWCs of each ingredient consumed (multiplied by the quantities shown in Table 2.6, p. 43), following equation (2.2):

\[ DF = \sum_{i=1}^{n} P_n (BW + GW) \]  

(2.2)

where \( P_n \) = weight of each food product consumed (g), \( BW \) = blue water (l/g) and \( GW \) = green water (l/g).

The diet footprint (DF) requires further manipulation as the study seeks to calculate the local water footprint component in order to distinguish between food products sourced from within the country and products imported from abroad. The VWC of imported goods is assumed to be equal to that of goods produced within the destination country, which is consistent with the savings perspective defined in Renault (2002). This is a significant assumption, as there are important variations in the virtual water content of individual food products depending on climate and agricultural efficiency (Hoekstra & Chapagain, 2008). Nevertheless, this assumption is commonly employed in national and regional water footprint studies (Zhang, Yang et al., 2011; Zhao et al., 2009) and allows for consideration of the extra amount of water required had the food not been imported.

The local diet footprint (LDF) is calculated using the ratio of locally-produced food products as shown in (2.3) below. It is estimated by dividing the locally-sourced available quantity of a good (local production minus any exports) by the total quantity of a good available in the country (locally-sourced available quantity in addition to imports)\(^{16}\). The study uses data on production, exports and imports from the FAOSTAT trade balance sheets for 2007 (FAO, 2010)\(^{17}\). The LDF is found by multiplying the diet footprint by the ratio indicating food produced locally, RLP, as shown in (2.3) below:

\[ LDF = DF \times RLP = DF \times \left( \frac{LP - E}{LP - E + I} \right) \]  

(2.3)

\(^{16}\) Note that for animal products an additional correction was also made for the ratio of local to total (including imported) feed with the exception of goat and lamb which were assumed to have been raised on pastures.

\(^{17}\) More recent datasets for 2009 have recently become available following the completion of the study but the difference between 2009 and 2007 is very small.
where $LDF = \text{local diet footprint, } RLP = \text{ratio of locally-produced food products, } LP = \text{locally produced food (tons), } E = \text{exports (tons)} \text{ and } I = \text{imports (tons)}$.

An important assumption made is the use of the national trade balance. In reality, the ratio of locally-produced food products ($RLP$) is likely to vary depending on the region as well as between different restaurants and hotels. Furthermore, for pulses, vegetables and fruit, the study has used averaged values for the most commonly eaten products instead of individual commodity values in order to capture a possible range of tourist choices, and also to ensure that the method does not become overly cumbersome. The drawback of this choice is that these averages cannot account for the wide range of VWCs between products. With regards to animal product consumption, tourists in Cyprus and Greece are assumed to consume equal amounts of all kinds of commonly eaten meat (pork, chicken, beef, lamb and goat) whereas tourists in Turkey would consume equal amounts of all meat excluding pork which is not eaten in Muslim countries. This ignores personal preferences by providing an averaged value.

The final component of the total WF is the WF associated with fuel, given by $FF$ in equation (2.1). The study uses the estimate given in Gössling et al. (2012) of 750 l for every 1000km of travel by air or car. The fuel footprint ($FF$) is calculated using these estimated figures along with the distances travelled by air (return trip) and public transport or car at the destination shown in Table 2.5 below.

<table>
<thead>
<tr>
<th>Holiday option</th>
<th>Origin</th>
<th>Destination</th>
<th>Return distance (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1</td>
<td>Manchester</td>
<td>Larnaca</td>
<td>6920</td>
</tr>
<tr>
<td></td>
<td>Larnaca</td>
<td>Paños</td>
<td>260</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>Paños</td>
<td>Polis</td>
<td>80</td>
</tr>
<tr>
<td></td>
<td>Manchester</td>
<td>Paños</td>
<td>6800</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>Manchester</td>
<td>Bodrum</td>
<td>5800</td>
</tr>
<tr>
<td>Scenario 4</td>
<td>Manchester</td>
<td>Mykonos</td>
<td>5500</td>
</tr>
</tbody>
</table>

Table 2.5 Distances used to calculate the fuel footprint ($FF$) (Source: www.webflyer.com for international flights and www.mapcrow.info for intra-country travel).
Distinguishing between global and local water footprints

The total (global) water footprint for each holiday scenario is estimated using equation (2.1).

Using the local diet footprint \((LDF)\) (see equation 2.3), the present study distinguishes between total water footprint and local water footprint \((LWF)\). The accommodation footprint \((AF)\) and the activity footprint \((ACF)\) are assumed to come from local blue water and require no further manipulation. The fuel footprint \((FF)\) is not considered to be part of the local water footprint as all countries in the region rely heavily on foreign sources of oil. The local water footprint \((LWF)\) is, therefore, calculated using equation (2.4).

\[
LWF = LDF + AF + ACF
\]  

(2.4)

2.3.3 Direct and indirect water footprint of local residents

The last aspect of the approach presented in this chapter is a comparison between the results of the holiday scenarios with water consumption by local residents for 1996-2005 estimated by the Water Footprint Network (WFN) (Mekonnen & Hoekstra 2011). A data breakdown is available in the appendices of the report by Mekonnen & Hoekstra (2011) which has been used to plot (see Figure 2.3, p. 42). The figures presented include green and blue water but exclude the grey water component for the reasons elaborated previously. Domestic water (violet-coloured bars) represents the direct component of water consumption whereas industrial (blue-coloured bars) and agricultural (red-coloured bars) water make up the indirect component.
Figure 2.3 Average daily per capita water footprints for residents of Cyprus, Greece and Turkey (data for 1996-2005, from Mekonnen and Hoekstra 2011).

2.3.4 Summary of methodology

This section has established a simple framework that allows for a comparison of the water footprint of different tourists, depending on some of their key trip characteristics. The approach presented above makes a series of assumptions and is reliant on secondary data which have their own significant degree of uncertainty. The final sub-section of this chapter (section 2.5) will expand on these issues in order to pave the way for the other two approaches in Parts III and IV of the thesis.
Table 2.6 Simplified daily food menus for the four scenarios taking into account local dishes where appropriate.

<table>
<thead>
<tr>
<th></th>
<th>Scenario 1 - Cyprus</th>
<th>Scenario 2 - Cyprus</th>
<th>Scenario 3 - Turkey</th>
<th>Scenario 4 - Greece</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Breakfast</strong></td>
<td>200g bread + 2 eggs + 150g milk + 50g cheese</td>
<td>200g bread + 50g olives + 40g nuts + 200g fruit + 250ml soy milk</td>
<td>200g breakfast cereal + 200g milk + 250g orange juice</td>
<td>200g bread + 2 eggs + 150g milk + 50g cheese + 250g orange juice</td>
</tr>
<tr>
<td><strong>Lunch</strong></td>
<td>200g meat + 120g salad + 10g olive oil + 200g potatoes + 100g yoghurt</td>
<td>200g bread + 120g salad + 100g hummus&lt;sup&gt;2&lt;/sup&gt;</td>
<td>100g meat + 100g lentils + 200g tomatoes + 150g onions + 100g beans + 100g bread</td>
<td>200g bread + 120g salad + 100g ham + 100g cheese</td>
</tr>
<tr>
<td><strong>Afternoon snack/drink</strong></td>
<td>200g ice-cream + 1 pint (570g) beer</td>
<td>100g dried fruit + 50g dark chocolate</td>
<td>200g fruit + 200g ice-cream</td>
<td>200g ice-cream</td>
</tr>
<tr>
<td><strong>Dinner</strong></td>
<td>200g meat (pork/lamb/chicken/beef) or fish + 100g bread + 100g onions + 100g eggplants + 200g wine + 200g fruit</td>
<td>50g lentils + 200g tomatoes + 150g onions + 50g beans + 50g chickpeas + 150g bread + 200g cooked rice + 200g fruit</td>
<td>200g meat (chicken/lamb/beef) + 50g bread + 20g garlic + 100g chickpeas + 50g eggplants + 100g yoghurt + 1pint (570g) beer</td>
<td>200g meat (pork/lamb/chicken/beef) or fish + 50g bread + 100g yoghurt + 20g garlic + 100g onions + 100g eggplants + 2 pints (1040g) beer</td>
</tr>
<tr>
<td><strong>Total calories</strong>&lt;sup&gt;1&lt;/sup&gt; (kcal)</td>
<td>3317</td>
<td>3388</td>
<td>3462</td>
<td>3392</td>
</tr>
<tr>
<td><strong>Total water footprint</strong> (l)</td>
<td>6697</td>
<td>6417</td>
<td>5057</td>
<td>4696</td>
</tr>
<tr>
<td><strong>Water footprint per calorie</strong> (l/kcal)</td>
<td>2.02</td>
<td>1.89</td>
<td>1.46</td>
<td>1.38</td>
</tr>
</tbody>
</table>

Notes:
1 Calorie values were obtained using the open source dieting software CRON-O-Meter v0.9.7.
2 100g hummus is assumed to contain 60g chickpeas, 20g sesame paste, 10g lemon juice and 10g olive oil.
2.4 Results and discussion

2.4.1 Total water footprint for each holiday scenario

Table 2.7 presents the total (global) water footprint results for all four scenarios along with the percentages in relation to the total of each component of the water footprint as identified in equation (2.1). The results are first analysed with respect to each scenario before attempting to contrast different holiday scenarios.

Table 2.7 Results table containing breakdown for each holiday scenario. DF = diet footprint, AF = accommodation footprint, FF = fuel footprint and ACF = activity footprint.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>DF</th>
<th>AF</th>
<th>FF</th>
<th>ACF</th>
<th>Total WF</th>
<th>WF/ day</th>
<th>Local WF/ day</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>m³</td>
<td>%</td>
<td>m³</td>
<td>%</td>
<td>m³</td>
<td>%</td>
<td>m³</td>
</tr>
<tr>
<td>1</td>
<td>46</td>
<td>75</td>
<td>8.8</td>
<td>14</td>
<td>5.3</td>
<td>9</td>
<td>1.1</td>
</tr>
<tr>
<td>2</td>
<td>56.6</td>
<td>91</td>
<td>0.6</td>
<td>1</td>
<td>5.1</td>
<td>8</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>45.3</td>
<td>87</td>
<td>1.6</td>
<td>3</td>
<td>5.2</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>56.3</td>
<td>86</td>
<td>4.6</td>
<td>7</td>
<td>4.6</td>
<td>7</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: 1m³ = 1000 l

Scenario one (luxury golf holiday in Paphos, Cyprus)

Scenario one has the highest percentage of direct water footprint (hereafter WF) and is also the scenario with the lowest percentage of DF in relation to the total. This is a result of the luxury accommodation and the activities (golf), which together contribute 16% to the total WF. Scenario one has the highest daily total WF of all the examples with 8880 l per day, only 3514 l of which has an impact on local water resources.

Scenario two (Camping holiday in Polis, Cyprus)

This scenario has the highest percentage of indirect use (91% DF plus 8% FF giving a total of 99%). Scenario two has by far the lowest local WF (only 1000 l per day) as a result of a lack of animal products in the diet in addition to the budget accommodation and lack of water-intensive facilities. The total daily WF is the second highest at 7080 l per day.
Scenario three (Budget beach holiday in Bodrum, Turkey)

In the Turkey scenario, accommodation only contributes around 3% to the total WF, the rest coming from DF (87%) and FF (10%). The daily total WF of scenario three is low at only 5790 l (with only scenario four having a lower daily total WF). Nonetheless, this scenario also has the highest daily local WF with 4750 l (82% of the total WF).

Scenario four (Up-market beach holiday in Mykonos, Greece)

The Greece example has the second highest percentage of direct WF with 7% of the total WF. Scenario four has the highest total WF (65 500 l) but has the lowest daily total WF (5460 l) even though the accommodation was 4-star, mainly because of a low daily diet footprint. The overall diet footprint is fairly high because of the long stay (12 days). The daily diet footprint in this case was the lowest of all examples, mainly because of moderate meat consumption.

Total water footprint components - discussion

The range of daily WFs (5790 – 8880 l) estimated in this study is fairly consistent with the figures proposed in Gössling et al. (2012), who suggest a daily WF of 5000-7500 L, with the only exception being scenario one (golf holiday) which has a daily WF (8880 l) that exceeds the suggested range. The final results for each holiday (Table 2.7, p. 44) show that indirect water use dominates the WF in all illustrative examples. Most of this comes from the diet footprint which ranges from 75% to 95% of the total WF. Owing to the importance of this component, it is discussed separately in section 2.4.2.

The AF is typically much lower in absolute terms than the diet footprint, with around 1-14% of the total WF. Nevertheless, it can still be an important component, especially in cases where tourists choose up-market accommodation, as in scenario one and, to a lesser extent, scenario four. Furthermore, the accommodation footprint component is always local and requires blue water\textsuperscript{18}, which has a higher opportunity cost than green water (Aldaya et al., 2010), as it can be used for both agricultural and non-agricultural activities (Renault, 2002). The factors at play for these high daily accommodation footprint figures are the ones

\textsuperscript{18} This may include treated wastewater and/or desalination water.
identified earlier (see section 2.2.2) from the literature: gardens, large swimming pools, and generally a greater range of facilities on offer.

A substantial body of literature (including many of the studies reviewed previously) is already focusing on management solutions to reduce direct water use in the tourism sector, so this issue is only discussed briefly here. The first step usually recommended is a detailed water audit which can identify key areas for improvement (Becken et al., 2013; Smith et al., 2009). A combination of technological, organisational, and behavioural interventions and benchmarking can subsequently be used to considerably lower water use in hotels (Becken et al., 2013; Gössling et al., 2012; UNEP-UNWTO, 2012). Extensive experience in the Australian hotel industry suggests that it is possible for hotels to reduce water consumption by an average of 20-40 per cent without compromising guest comfort (M. Smith et al., 2009). In terms of outdoor water use, identified by most studies as the factor accounting for the bulk of direct water use (Gössling, 2001; Hof & Schmitt, 2011; Rico-Amoros et al., 2009; Tortella & Tirado, 2011), the use of plant species better adapted to the local climate as well as use of pool covers and more extensive water reuse in swimming pools should be encouraged through appropriate legislation and economic incentives (Hof & Schmitt, 2011). Golf course water use can also be limited using similar interventions: hardier grass, irrigation using reused water and mobile desalination plants are all possible options.

With regards to indoor water use, good housekeeping practices, especially in the kitchen and laundry, can reduce water use by 15% (Deng & Burnett, 2002). According to Deng (2003) and Deng & Burnett (2002), the benefits to hotels are evident since cost savings in water often equate to savings in energy as well. An excellent example is the Hilton LightStay Programme, launched across Hilton hotels worldwide to support the sustainability commitments of the company. The results from 2009 showed that properties using LightStay reduced energy use by 5 percent and water use by 2.4 percent compared to 2008, which translates into savings of more than 29 million USD (Hilton Worldwide, 2011). Gössling et al. (2012) argue that strong policy in the form of added economic incentives and appropriate water pricing are required because of the comparatively low cost of water in comparison to other operational costs, something which is also echoed in Tortella & Tirado (2011).
Any attempt to promote prudent water use in tourism must also be complemented with raising public awareness on the issue of water scarcity, especially at destinations already suffering from water shortage. Guest education is therefore key to curbing profligate water use, although this could be difficult to achieve given that the rate paid by the guest does not vary with water consumption. The present study has shown that the accommodation footprint is most significant (as a percentage of total tourist water use) in luxury resorts. Even then, though, it is still less than 15% of the total. Exploring ways such as the ones mentioned above to limit water use in hotels is certainly desirable and if that is achieved at the destination scale or national scale then the water saving may add up to be substantial. Nevertheless, it is imperative that water audits look at the water use impacts outside the hotel as there is little value in maximising in-house water use efficiency if the supply chain water use efficiency, which accounts for most of the water use, remains low.

The last component of tourist water use, the fuel footprint, may account for up to 10% of the total WF as in the case of scenario three; however this water is rarely local water and the water use impacts associated with its use are unknown. The only possible way to manage this issue, other than oil production and vehicle efficiency improvements, is flying shorter distances or preferring public transport at the destination where available. This is consistent with other sustainability targets such as limiting the ecological footprint (Gössling et al., 2002b) and carbon emissions (Gössling et al., 2010) associated with travel and tourism. Promoting the use of biofuels in global transports also needs to be scrutinised (Gossling et al. 2012), particularly where these are grown in water scarce locations. Further discussion on the fuel footprint is beyond the scope of this study.

2.4.2 Exploring the diet footprint

Green-blue distinction and the impact of trade

This section focuses on the daily diet footprint of the four scenarios. In Figure 2.4 (p. 48) the total WF has been split into its constituents in order to distinguish between local green water, local blue water, total (global) green water and total (global) blue water. The graph shows that, with the exception of scenario two, the green water content of food exceeds blue water by around ten times. Blue water use is still significant in all scenarios (the lowest is scenario three with 454 l), with scenario two (Cyprus camper) standing out in this respect as it
requires a total of 2574 l out of which 594 are drawn from local resources. Figure 2.4 highlights the fact that Cyprus (scenarios one and two) and Greece (scenario four) import a significant percentage of the food they consume since their local green WF is much smaller than their total (global). The difference between scenarios one and two also demonstrates that a different diet in the same destination can result in varied water use impacts. The figure also shows an important difference between blue and green water. Blue water is more likely to be local whereas, with the exception of scenario three (Turkey), the vast majority of green water is imported.

Subtracting local blue water and local green water from total blue water and total green water respectively reveals the amount of local water ‘saved’ from importing food, as shown in Figure 2.5 (p.49). The graph further highlights that scenario three (Turkey) registers much lower savings from trade compared to the other examples, which results in a higher degree of water use impacts within the country. Figure 2.5 also highlights the significant savings in local blue water which occur in scenario two.

Figure 2.4 Chart showing relative contribution of blue and green water for all holiday scenarios.

Even though the import of virtual water cannot actually result in real water savings, the option to import food products is assumed to provide water scarce countries with improved food and water security (Antonelli et al., 2012).
Dietary components

In order to better understand the diet footprint, it is useful to examine the WF of its constituent dietary components. Figure 2.6 (p. 50) shows the WF contribution of the five main food groups: meat, dairy, grains, fruit & vegetables, and pulses (legumes). The results include both green and blue water. In all holiday scenarios apart from scenario two (vegan diet), meat and dairy account for over 75% of the diet footprint. Grains follow as the next most water-intensive element. Focusing on the local WF in Figure 2.6 (a) against the total WF in Figure 2.6 (b) of scenarios one and four shows how imported water is primarily associated with meat and grains.

According to Vanham et al. (2013), southern European countries are net importers of cereals. In Cyprus and Greece, most of the meat consumed (pork and chicken) may be locally raised but almost all of it is grain-fed, which is common in semi-arid countries where industrial systems of animal production dominate (Gerbens-Leenes et al., 2013; Mekonnen & Hoekstra, 2012). Cyprus and Greece essentially use very little of their own water to locally raise animals for meat. This is correlated to the significant green water savings in scenarios one
and four previously shown in Figure 2.5, as grain production relies heavily on green water (Falkenmark et al., 2009; Siebert & Döll, 2010).

Fruit and vegetables in the vegan example (scenario two) appear to have a high total WF, most of which is imported. Cyprus produces vegetables and fruit when in season but also needs to import a significant amount from other southern European countries to cater for additional demand from tourism in the summer. Scenario two has the second highest overall WF, despite only including vegetal products. The unexpectedly high diet footprint in this scenario is mostly a result of pulses and vegetables in Cyprus having very high WFs (especially blue WF) according to the figures in Mekkonen & Hoekstra (2010a, 2010b, 2011). These crops require extensive irrigation in semi-arid climates, which means that most of the water associated with these crops is blue water (Aldaya, Garrido et al., 2010). Furthermore, the quantities of vegetal food required to equal the daily calorie counts of the other diets which include dairy and meat are very large (see Table 2.6, p. 43), perhaps unrealistically so.

![Figure 2.6 Local and global WF disaggregated into the five main food groups.](image-url)
2.4.3 Tourists compared to local population

Figure 2.7 (p. 52) compares the average daily per capita WF in each of the destination countries to the estimated WFs for each of the scenarios. The results show that in all cases the tourist WF is higher than that of an average resident. With an average per capita WF of around 5500 l/cap/day, Cyprus and Greece have significantly higher per capita WFs compared to an average global consumer who consumes around 3800 l/cap/day (Hoekstra & Mekonnen, 2012). This is explained by a high meat intake and the fact that the water footprint in l/kg of many domestically produced products is higher in southern Europe than in other areas of the world, especially due to climatological conditions (Vanham et al., 2013).

However, the WF of the two tourist scenarios in Cyprus is considerably higher than that of residents, even for the vegan scenario. This is of course subject to the assumption that all diet menus add up to the same daily calorie totals, which is discussed further in the section on uncertainty.

Given that 7% of the total WF of scenario four (Greece) is made up of the fuel footprint, it can be assumed that a tourist in Greece uses approximately the same quantity as a local resident. This is because in this scenario the tourist is assumed to eat only moderate quantities of meat (see Figure 2.6, p. 50). With a diet footprint of around 4700 l/cap/day, this is even slightly lower than that of the average Greek resident (4822 l/cap/day, see Figure 2.3, p. 42) though the 4-star accommodation makes up for that difference. A less water-intensive accommodation option in this case could have even meant a lower total WF for the tourist compared to a resident. This example also shows the positive impacts on the WF of lowering meat consumption. Possible ways to promote this are discussed in the following section.

The Turkey holiday (scenario three) has a substantially higher (42%) WF compared to that of an average resident. This is unsurprising considering the fact that an average resident of Turkey has a WF which is very close to that of an average global consumer (3800 l/cap/day). This highlights the potential inequity between tourists and residents in most developing destinations, especially since the holiday in Bodrum is a budget holiday. The scenario assumes a moderate amount of meat. On average, meat in Turkey has a similar virtual water
content to meat in Cyprus and Greece\textsuperscript{20}. However, the key difference is that almost all of the food consumed in Turkey is produced in the country. This means that the impact on local resources is even more significant that in the other scenarios.

The issue of inequitable water consumption between tourists and locals in developing countries, as discussed in the literature with respect to the direct WF component (Cole, 2012; Gössling, 2001), is likely to be amplified when the total WF is considered. In this case, the AF is only 180 l/cap/day (because of the cheap accommodation) which is almost equal to the 190 l/cap/day average domestic WF of a Turkish resident. A large percentage of the difference in the total WF between a tourist and a local is therefore accounted for by diet. Contrary to the Greece scenario, in this case the accommodation already has a low WF, meaning that only the overall WF can be lowered significantly through strategies to manage the diet footprint. The next sections discuss some options available for managing the diet footprint and the need for better data and methodologies to improve present understanding.

![Figure 2.7 Total WF for residents compared to that estimated for the four tourist scenarios. The percentages represent percentage increases compared to residents. Cyprus: Tourist 1 (Scenario 1), Tourist 2 (Scenario 2), Greece: Tourist 1 (Scenario 4) and Turkey: Tourist 1 (Scenario 3).](image)

\textsuperscript{20} This may vary widely between different locations in Turkey which is a large country with different climatic zones some of which are water-rich (Unal et al., 2003).
2.4.4 Managing the diet footprint - discussion

Unlike the direct component of the water footprint, the dietary aspect is highly complex. Every individual tourist would be expected to have different impacts depending on their personal preferences. Nevertheless, each destination is likely to have certain characteristics with respect to popular foods or delicacies, the supply chains of products, agricultural practices and the amounts of blue and green water, and the ratios of locally grown to imported food. It is therefore important to consider the water footprint of tourists’ diets as a highly location-specific parameter. Sourcing local food is usually seen as a means to promote economic linkages between tourism and agriculture, thus enhancing the benefits of tourism to the economy (Mak et al., 2012; Telfer & Wall, 1996; Torres, 2002, 2003). However, attempts to boost local production and reduce economic leakage could contribute to water shortage at the destination, especially where tourists demand products that are unsuitable to local environmental conditions.

Based on the water footprint concept, destinations in arid places can maximise economic return in certain cases by importing water-intensive agricultural products from abroad to complement investments in more water-efficient accommodation. Assuming most food imports such as grain come from water-rich countries where agriculture is rain-fed, the impacts abroad should remain low. Nevertheless, there will always be trade-offs that would need to be examined before embracing such an option. Firstly, there are trade-offs with other environmental targets such as carbon emissions. High energy embodied in imported products could result in a large additional supply chain carbon footprint (Gössling et al., 2011). Secondly, choosing to source a higher percentage of food from abroad may have an adverse impact on the local economy in terms of revenue and employment.

Limiting the demand for water-intensive food products could reduce water withdrawals from the agricultural sector. The WF literature has generally succeeded in highlighting the fact that animal products such as meat and dairy are significantly more water-intensive compared to plant-derived products (Hoekstra & Chapagain, 2007; Hoekstra, 2012; Hoekstra & Mekonnen, 2012; Vanham, Mekonnen et al., 2013). Another prominent argument is that a more efficient agricultural sector would allow for tourism-related food demand to be satisfied using less water (Yang et al., 2011). Nevertheless, the origin of water is not always
local, because the feed is often imported, especially in areas with scarce land and/or water. The WFN data and estimates suggest that, in general, recommendations from Gossling et al. (2011) aimed at lowering tourism’s food-associated carbon footprint such as promoting vegetarian dishes, reducing portions, minimising waste, buying less rice and beef while buying more potatoes, chicken and pork in their place would, in most cases, also lead to a lower water footprint. However, a better understanding of the environmental and economic impacts of these choices would need to be ascertained.

2.5 Refining tourism water use estimates

2.5.1 Limitations and uncertainty

The approach presented in this chapter was designed to be simple to understand and to rely on freely available datasets. While it is appropriate for a quick estimate of total water use and some preliminary discussion on ways to reduce it, it has several important limitations which can only be addressed using more comprehensive approaches, such as those developed in Parts III and IV of the thesis.

The principal sources of uncertainty are the direct water use data (accommodation and activity footprints) as well as the hypothetical menus that form the basis for estimating the diet footprint. Accommodation water use figures can be estimated through hotel surveys (in the way this was performed for Cyprus in section 2.3.2). Activity footprints require substantially more research to establish accurate estimates of the water footprint associated with different activities at the destination scale, instead of relying on regional estimates. Estimates should ideally take into account the percentage of reused or desalinated water, as these types of water have different opportunity costs and impacts compared to conventional water sources.

The food menus represent a major assumption since they do not take into account the variety of meals consumed during a holiday or personal dietary preferences. These assumptions were necessary because the considering that tourists have a similar diet footprint to locals is potentially more erroneous in most cases, as demonstrated in section 2.4.3. The average daily intake of 3442 kcal, which is the average for the UK according to the FAO, is likely to be an overestimation considering average recommended values of 2500 kcal per day for men and 2000 kcal daily for women in most countries. However, the latter figures do not include
waste and would also not necessarily apply for a holiday. Using the water footprint per calorie estimates shown at the bottom of Table 2.6 (p. 43) it is possible to estimate the virtual water content for every 500 kcal in each of the scenarios: scenario one (1010 l), scenario two (945 l), scenario three (730 l), and scenario four (690 l). This could be used to provide a range of possible water footprints for all four scenarios depending on total calorie intake. Future research could be used to ascertain calorie intakes of tourists and how they are likely to vary from their non-holiday diet. Ideally, knowing exact dishes and portions could offer invaluable insight in terms of estimating water use and other environmental impacts of food consumption.

Significant limitations of the present framework stem from the fact that the method relies heavily on the water footprint concept. The water footprint concept provides a useful indicator of water consumption and some of its merits have already been discussed in section 2.2.2. Nonetheless, despite its popularity and the expansive literature on water footprinting in recent years, several authors have raised concerns with respect to its limited usefulness as a policy tool (Chenoweth et al., 2013; Gawel & Bernsen, 2011b; Wichelns, 2010a, 2010b, 2011; Witmer & Cleij, 2012; Yang et al., 2013). An in-depth discussion on the weaknesses of the water footprint concept is beyond the scope of the present study (and is further discussed in Chenoweth et al., 2013), but three important flaws are especially pertinent.

Firstly, a water footprint does not account for the opportunity cost of water use or give any indication of water productivity. This offers limited insight when comparing different types of tourism, where the priority should be to minimise water use whilst also ensuring high economic returns.

Secondly, the above analysis includes green water, which is not water in a conventional sense since it refers to water trapped in the soil. According to Yang et al. (2011), providing detailed information on the consumption of green water to tourists could contribute towards improved awareness and acceptability of less water-intensive food options. This, however, assumes willingness to understand and implement recommendations on what is not likely to be an intuitive concept for most people. Ridoutt & Pfister (2010b) argue that green water use does not contribute to water scarcity from a water management perspective as green water is
PART II – Chapter 2

not accessible for uses other than agriculture. It therefore creates inconsistencies between water content figures for agricultural products compared to those of non-agricultural products (Zhang, Yang et al., 2011). In the context of tourism, blue water used in accommodation has a much higher opportunity cost than green water embedded in food. Food also contains a substantial amount of blue water (irrigation water) which is most relevant to water scarcity (Antonelli et al., 2012).

Thirdly, the readily available figures produced by the WFN (Mekonnen & Hoekstra, 2010a, 2010b, 2011) are 10-year averages (1996-2005) estimated using a global soil water balance model with 5-by-5 arc-minute resolution (approximately 10-by-10 km depending on latitude). The low spatial and temporal resolution has recently been criticised, with studies showing that the WFN values deviate substantially from those derived using higher resolution models calibrated for local conditions (Finger, 2013; Zoumides et al., 2012). This implies that, even though results derived using the WFN global model figures are still valuable for performing cross-country comparisons (as in the present case), the figures would need to be interpreted with caution when it comes to policy formulation (Zoumides et al., 2012).

Finally, the approach outlined in this chapter uses the savings principle (Renault, 2002) which assumes that imported goods have the same virtual water content as goods produced locally. This represents a substantial additional simplification because, in reality, imported goods are not likely to have the same virtual water content as locally produced goods. For countries in the Mediterranean, where semi-arid climatic conditions prevail (Yang et al., 2007), it is highly probable that imported grains and meat, in particular, would have significantly lower water footprints than local produce. It is possible, using trade data from FAO, to address this problem by considering the origin of imports and to subsequently use the correct national WF estimates multiplied by import amounts by each country. However, this was avoided in this chapter because the method would become significantly more cumbersome.

2.5.2 Conclusions

The impact of tourist diets on water use stands out as an area that warrants further attention and research. This echoes the suggestion made by Gössling et al. (2012) that management in
tourism should look beyond direct water use. Improving water use efficiency in hotels, pools, golf courses and other tourist facilities is certainly desirable as well, but this would be of limited value if the more substantial indirect component is ignored. Moreover, diet is, perhaps, easier to modify compared to flight or accommodation choices, and large volumes of water could potentially be saved with only minor adjustments and some understanding on behalf of the tourist. Some of these adjustments are revisited in Part IV and the concluding chapter. As things stand, improved data collection and methodological approaches to better understand and quantify the indirect component should be regarded as a priority.

The significant number of assumptions and simplifications made in the approach developed in this chapter highlight that this methodology is somewhat simplistic and should only be seen as a first step in the right direction. As Hunter & Shaw (2007) previously concluded with regards to the ecological footprint, this study highlights the need to collect ‘real world’ primary data for water resources consumed along the whole supply chain of tourism products and services. Estimating the diet footprints for different tourist groups would require extensive interviewing to determine food preferences, something visitation surveys currently do not cover in sufficient detail. Furthermore, a more comprehensive quantification of the potential economic impacts along the supply chain is required for agricultural commodities consumed by tourists at different destinations. Only then can water productivity from different tourist types be fully compared in a comprehensive manner and any trade-offs involved in dietary modifications taken into account. Ideally, an approach designed to capture water use and water productivity in tourism should also be flexible enough, offering the option to either perform a national-scale estimate of how much water is being used by tourism in an economy whilst at the same time allowing the scaling down of estimates for different tourist types and different resorts.

Based on the findings and limitations of the approach discussed in this final section, the remainder of the thesis attempts to develop more comprehensive frameworks for quantifying water use and economic impact for different tourist types, using Cyprus as a case study.
PART III

Estimating water productivity for different market segments.
Chapter 3: Combining market segmentation and Environmental Input-Output Analysis

3.1 Part III outline

3.1.1 Aim and scope

This part of the thesis aims to improve on the water footprint approach by developing a framework for estimating and comparing the water use and economic impacts of different market segments of inbound tourism in Cyprus. The chapter relates to a recently accepted journal article (Hadjikakou et al., in press) and work presented in an international conference subsequently published as a proceedings title (Hadjikakou, Chenoweth, Miller, & Druckman, 2013).

As set forth in the Introduction, one of the key priorities for water scarce tourism destinations should be to use the least amount of water possible whilst also maintaining maximum economic revenues from tourism activities. This idea of minimising environmental impacts whilst maintaining high economic benefits is prominent in the sustainable tourism literature. Concepts such as eco-efficiency (Becken & Patterson, 2006; Gössling et al., 2005; Peeters & Schouten, 2006) and sustainable yield\(^{21}\) (Becken & Simmons, 2008; Lundie et al., 2007; Northcote & Macbeth, 2006) advance the traditional measures of tourism yield (Dwyer & Forsyth, 1997; Dwyer & Forsyth, 2008), solely focused on economic benefits, to include environmental (and, in some cases, social) impacts. This chapter discusses how marrying these concepts together with the notions of water productivity (Gleick, 2003a, 2003b; Molden et al., 2003) and water use intensity (OECD, 2004; SADC, 2014; UN DESA, 2007; UNESCO, 2009), both of which originate from the more general sustainability and water management literature, can create water-specific indicators of sustainable yield currently lacking in the tourism literature. Used as part of an approach that considers water use along the whole supply chain, such indicators could provide useful management insights.

\(^{21}\) The original notion of sustainable yield, first mentioned in Hunter (1997), was more theoretical and closely linked to that of ‘carrying capacity’ (the maximum environmental load an area can withstand without suffering lasting damage). In recent work, such as the studies cited above, the meaning of sustainable yield has evolved towards a quantification of environmental impact in relation to economic impact or benefit to a destination.
From a management perspective, a prominent goal is to compare different tourism products. The Cyprus Tourism Organization (CTO) currently only distinguishes between different tourists based on their country of origin (COO). COO forms an intuitive basis for segmentation and is widely used worldwide (Andriotis et al., 2008; Dolnicar, 2008). Nevertheless, existing COO segmentation needs to be supplemented with tourist typologies based on additional tourist characteristics and consumption patterns, especially when it comes to environmental impact considerations where information with respect to distinct tourist types is highly desirable (Becken et al., 2003). One of the backbones of Part III, and also one of the key objectives of the thesis, is thus to explore alternative ways to segment tourists using a large dataset of passenger survey data obtained from the CTO. Following the segmentation, the framework then proceeds to compare economic and water use performance of the newly formed as well as existing COO segments. The approach presented here is also innovative in the sense that it considers segmentation and sustainable estimates as part of an integrated framework, whereby tourists are segmented in order to improve our understanding of how their trip characteristics and behaviour shape their water use (and, potentially, vice versa).

In an attempt to overcome some of the major shortcomings of the approach presented in Part II, the framework presented in this Part uses a top-down form of economic-environmental modelling known as environmental input-output (EIO) analysis, which captures total (direct and indirect) water use and economic impacts. The approach is more data-demanding and technically complex than the method presented in Part II. Nevertheless, it still relies on secondary information, namely tourism survey data, an Input-Output table (IOT), sectoral water use data, and Tourism Satellite Accounts (TSAs), all of which are frequently available through national statistical offices. The added degree of complexity offers two key advantages. Firstly, the framework presented here can be used to quantify the total water use associated with tourism in a national economy and, secondly, it also quantifies trade-offs and synergies between water use and economic impact for different tourism products. The outputs of the model can eventually be used not only to determine which tourism market segment provides maximum productivity, but also to consider ways to maximise yield from each segment, depending on its characteristics.
3.1.2 Objectives and structure

This Part of the thesis has three objectives. The first is to perform segmentation of the tourism market in Cyprus in order to enhance the current COO distinction. This involves a literature review on statistical segmentation methods and establishing a statistical methodology that is applicable to the survey data available through CYSTAT and the CTO. The second objective is to make use of TSAs and EIO in order to estimate water productivity for each of the major market segments in Cyprus. The third objective is to compare different markets and assess their performance and potential for improving water productivity.

Part III is comprised of two chapters including the current one (see Figure 3.1 below). The present chapter (Chapter 3) is a theoretical chapter which reviews the literature and describes the methodologies, datasets and model set-up (steps 1 and 2 in Figure 3.1). The second chapter (Chapter 4) presents the results of the segmentation and EIO model and their implications.

Figure 3.1 Figure showing the structure and principal tasks of Part III of the thesis.
3.2 The importance of yield

3.2.1 Economic contribution of tourism

As the principal factor driving tourism development, the economic impact of tourism has received considerable attention in policy and academic circles. The scale of interest may range from estimating tourism revenue for a single business, to the economic performance of a resort or region and, finally, to estimating total economic contribution to an entire national economy (Northcote & Macbeth, 2006). A commonly used term for the economic productivity of tourism is that of ‘tourism yield’. Yield from any economic activity is defined as ‘the rate of return earned from investment undertaken in the relevant sector supplying the activity’ (Salma & Heaney, 2004, p.74). While the exact notion of tourism yield is not fixed and may vary depending on the circumstances (Becken & Simmons, 2008; Dwyer & Forsyth, 2008; Northcote & Macbeth, 2006), a fairly comprehensive definition of tourism yield is given by Dwyer et al. (1997) who describe it as the net economic gain from tourism, whilst taking into account the benefits and costs of tourism activity. The use of net benefit is crucial because it acknowledges that there is also a cost in providing goods and services to tourists which needs to be subtracted from any incoming revenue.

Economic impact is almost synonymous with visitor spending (Wilton & Nickerson, 2006). Visitor spending typically includes expenditure on transportation, lodging, food and beverages, gifts and souvenirs, and entertainment and recreation (Jang et al., 2004). The narrowest possible definition of yield is simply to consider that it is equivalent to total expenditure (Dwyer & Forsyth, 2008). However, it is well established that, depending on which kinds of products or services are being purchased and the direct and indirect linkages of the respective economic sectors, the same amount of overall expenditure can have a totally different economic impact (or yield) (Dwyer & Forsyth, 1997; Pratt, 2012; Salma & Heaney, 2004).

The same amount of expenditure can generate different amounts of value added or employment depending on the specific services and products being consumed (Salma et al., 2004). The net economic contribution of tourism is therefore correlated to both the total expenditure and the economic linkages of the various sectors involved.

---

22 Broader definitions of yield, which include social and environmental costs and benefits in addition to economic value, are discussed later.
amount spent and the composition of the expenditure and its repercussions in the economy. In addition to the more apparent direct effects of tourist expenditure on suppliers who sell goods and services directly to tourists, there are indirect or induced economic effects which occur as the initial tourist money is spent and re-spent in the economy by firms and households (Dwyer et al., 2010). Expenditure injection from tourism therefore creates a ripple effect of spending in an economy, known as the ‘tourism multiplier’ (Wanhill, 1994).

Tourism is an unusual economic sector in that it relies on purchases of many diverse products from other economic sectors (Cai et al., 2006). According to Hara (2008), the vast number of indirect and induced linkages to other economic sectors often leads to the underestimation of the sector’s importance in national statistics. The complex nature of interactions with other sectors means that effectively quantifying yield from tourism requires the use of reliable information on the economic linkages with other sectors in the form of demand for goods and services. This can ultimately inform residents, consumers, businesses, and governments with regards to the most effective marketing and planning of facilities and amenities (Dwyer & Thomas, 2012; Frechtling, 2006; Mok & Iverson, 2000).

Boosting tourism yield appears to have become a popular mantra for destinations (Dwyer et al., 2009). Although higher tourist numbers and longer stays remain desirable, it is the big spending markets that are seen as more profitable for most tourism stakeholders (Dwyer & Forsyth, 2008). This has spurred an interest in moving away from mass tourism towards ‘higher-yield’ types of tourism, commonly associated with luxury, higher-spending tourists. Mature resorts in the Mediterranean have been investing heavily in the diversification of their tourism industries in the last decade, with an aim of attracting tourists from the higher end of the market in order to maximise yield (Bramwell, 2004; Chapman & Speake, 2011; Farsari et al., 2007; Ioannides & Holcomb, 2003; Kozak & Martin, 2012). However, this is rarely based on comprehensive measures of yield or any studies quantifying the net benefits of tourism spending at the destination.

---

23 Tourism is rarely distinguished as a distinct sector in economic statistics or national accounts because it sells products and services that are traditionally assigned to other sectors such as hotels and restaurants.
As previously mentioned in the Introduction (Chapter 1, section 1.3.3), the CTO sees targeting the higher end of the market as a way to compensate for a fall in tourism arrivals and loss in profitability from the mass tourism end of the market in recent years. However, the argument that luxury tourism contributes more positively to the economy is based solely on total tourism expenditure, with no consideration of indirect or induced economic impact. Furthermore, a purely economic definition of yield (no matter how comprehensive or technically rigorous) that ignores any impacts on the environment and society remains incomplete. It should therefore not be employed for making decisions, as these could compromise the present and future sustainability of the destination.

3.2.2 Sustainable yield, water productivity and water use intensity

In recent years, there has been an increasing realisation that maintaining a certain economic output (or yield) from tourism also entails the use of certain social and environmental resources which sustain the industry. This is exemplified by studies estimating carbon emissions (Becken & Patterson, 2006; Gössling et al., 2005), ecological footprints (Gössling et al., 2002a; Hunter & Shaw, 2007), water footprints (Cazcarro et al., 2014; Hadjikakou, Chenoweth, & Miller, 2013), and combinations of carbon, water and ecological footprints (Lundie et al., 2007; Patterson & McDonald, 2004) at different destinations. There have also been attempts to expand the more conventional financial or economic notion of yield to that of ‘sustainable yield’, in order to include non-market costs (externalities) of tourism such as environmental and social impacts (Becken & Simmons, 2008; Dwyer et al., 2006; Lundie et al., 2007; Northcote & Macbeth, 2006).

Northcote & Macbeth (2006) argue that yield must be understood as a larger resource-based system, where both inputs (resources) and outputs (productivity) are considered in terms of costs and benefits. In this context, yield becomes a matter of trade-offs between economic returns and environmental impact and a sustainable tourism yield is closely connected to the concept of triple bottom line accounting (Foran et al., 2005; Tyrrell et al., 2013). The challenge therefore becomes how to quantify environmental, social and economic impacts in a comprehensive manner. As previously expanded upon in Part II, the chosen method for this kind of analysis must capture both direct (onsite) and supply-chain economic and environmental impacts.
Northcote & Macbeth (2006) also introduce the Integrated Tourism Yield (ITY) concept. This is based on a systems perspective, in which all resources that can be valued are considered as interdependent. In this context, a sustainable yield is defined as a tourism yield where all respective constituents of the overall yield (as defined by their current yield level) shown at the bottom of the pyramid in Figure 3.2 below fall between their required (minimum) and potential (maximum) values. What becomes apparent from this framework is that many of the decisions as to what constitutes a potential and required yield level are ultimately arbitrary and subjective. Although the ITY concept is an insightful attempt to bring together many variables and consider their trade-offs in an inclusive manner, it is still rather idealistic and thus more valuable as a conceptual rather than an empirical quantitative framework.

![Figure 3.2 The Integrated Tourism Yield framework (source: Northcote and Macbeth, 2006).](image)

Furthermore, the idea of calculating a social yield and comparing this to an economic yield, although appealing, poses methodological problems. Dwyer et al. (2006) explore ways that can be used to assess the vulnerability of communities and how tourist characteristics and the activities they pursue impact the destination. They propose a series of questionnaires and surveys to gauge public perception of tourism activities and the understanding of their consequences for the community. Nevertheless, social impacts remain very hard to quantify due to the subjectivity of perceptions, whereas the use of environmental resources lends itself better to quantitative analysis in the form of resource use (or pollution) in relation to expenditure or some other indicator of economic yield (Dwyer et al., 2007). For this reason, Lundie et al. (2007) propose a combination of economic and environmental yield. They
subsequently demonstrate a framework which quantifies onsite and supply chain energy use, water use, greenhouse gas emissions and ecological footprint in relation to tourist expenditure per night.

Several studies have compared estimates of carbon emissions or ecological footprints with expenditure for tourism in different destinations (Becken & Patterson, 2006; Becken & Simmons, 2008; Gössling et al., 2005; Peeters & Schouten, 2006). Similarly to Lundie et al. (2007), the aforementioned studies essentially contrast the environmental impact (tons of CO$_2$ or hectares of land) with tourist expenditure or turnover in monetary terms. The principal goal of the studies is to compare different kinds of tourists in order to ascertain their different impacts and environmental-economic trade-offs. Lundie et al. (2007) and Becken & Simmons (2008) stress the importance of considering each tourism market segment as being associated with its own set of economic and environmental impacts as a result of its activities and purchases. This is illustrated in Figure 3.3 below, taken from Dwyer et al. (2006), where estimated water use and expenditure for different tourist ‘niche’ markets are plotted against each other. In theory, tourist groups in the bottom right quadrant represent the best performing niche markets due to higher than average expenditure per night and a lower than average environmental impact.

The sustainable yield literature provides a suitable theoretical foundation for the current study because it allows for the incorporation of environmental externalities which arise from the use of scarce resources, like water, in the same framework as economic impact considerations. It also has the potential to link well to existing water management indicators. One such commonly used indicator is ‘water productivity’. Physical water productivity is the ratio of product output (goods and services) over water input. In relation to agriculture, there are usually large disparities in water productivity between different crops as well as between different times of the year (Soler, 2008). Increasing productivity of water in agriculture by producing more agricultural output with the same amount of available water is a common policy goal in water scarce areas (FAO, 2003; Molden et al., 2001).
Economic water productivity is defined as the amount of measurable economic output per unit of water used (Gleick, 2003b). This is a more versatile indicator than pure ‘water productivity’, as the monetary numerator allows comparisons between different sectors not necessarily related to agriculture. Economic water productivity tends to vary markedly between different sectors of the economy as well as over time (Gleick, 2004). The Pacific Institute (2004) has estimated that economic productivity of water in the US has more than doubled since the 1970s, with water use per capita finally falling below 1950 levels in 2000, thus implying significant improvements in water use efficiency that offset increases in population. In the case of tourism, economic water productivity would be expected to vary in relation to different types of tourism product, and to also show significant spatial, seasonal and temporal variations.

Another commonly used indicator is ‘water use intensity’. Water use intensity of an economy is a measure of the amount of water required by the economy to produce one unit of currency (SADC, 2014). According to the UN, it is generally used as an indicator of
pressure exerted by the economy (or different sectors of the economy) on the water resources. It is also a widely accepted indicator of sustainable development (OECD, 2004; SADC, 2014; UN DESA, 2007; UNESCO, 2009). The OECD (2004), UNESCO (2009), and the UN DESA (2007), consider water intensity to be an important indicator for policies of water allocation among different sectors of the economy, especially in water-scarce regions, where there is more competition for water among various users. According to UNESCO (2009), monitoring water use intensity over time can also be used to assess whether a country has decoupled water use from economic growth. UN DESA (2007) specifically recommends its use for countries which rely heavily on seasonal tourism, often coinciding with periods of high water scarcity, stipulating that it may be particularly useful in identifying the most relevant economic activities for tourism (such as accommodation and food service activities). This last point highlights the appropriateness of water use intensity as an indicator for the present study.

The concepts of water productivity, water use intensity and sustainable tourism yield are very similar in principle. All three provide a measure of monetary value in relation to environmental resource use. In a mathematical sense, water use intensity (or a water-specific sustainable yield) is the inverse of water productivity. Whereas water productivity expresses economic output per unit of water use (for example, $/m^3), water use intensity measures resource use per unit of economic output (for example, m^3/$). The two concepts are two sides of the same coin, with both capable of providing a solid basis for considering trade-offs between economic output and water use across different tourism products.

Being numerically similar to sustainable yield, water use intensity is more consistent with previous work on tourism (Gössling et al., 2005; Lundie et al., 2007; Munday et al., 2013), where the reasoning is usually to minimise resource consumption per unit of economic output. For this reason, the remainder of the thesis focuses will use the term water use intensity when referring to mixed units combining water use and economic output. Whilst arguably the most suitable indicator for water use impact is the volume of water used, there are numerous possible indicators for economic impact in monetary and non-monetary terms. This issue will be revisited in section 3.5.2.
Becken & Simmons (2008) are opposed to aggregating environmental and economic impacts into one single index, on the grounds that this is prone to oversimplification and misleading results. They argue instead that it should be left to the decision makers to assess different tourist types based on the original estimates. This is a valid argument on the grounds that considering water productivity or water use intensity in isolation could hide a very high water use value in cases where economic impact is also very high. For this reason, it is best to consider the two values separately as well as in a single indicator form. The graphical matrix form (Dwyer & Forsyth, 2008; Dwyer et al., 2010; Lundie et al., 2007) used in Figure 3.3 (p. 67) is thus an effective way to present and contrast any two types of indicator.

### 3.2.3 Improving sustainable yield estimates

There are some important shortcoming in the studies mentioned thus far. Firstly, none of the studies reviewed in this section, with the exception of those concentrating exclusively on economic yield (Cai et al., 2006; Dwyer & Forsyth, 2008), considers indirect or induced economic impact. Considering the nature of tourism as a sector with far-reaching economic connections to other sectors, this is a significant omission. Recent tourism studies using EIO analysis (Collins et al., 2012; Jones & Munday, 2007; Munday et al., 2013) have partly filled this gap by providing comprehensive estimates of economic and environmental yield, even though they do not explicitly associate themselves with the sustainable yield literature. The ability of EIO to trace both environmental and economic impacts in a top-down manner throughout the supply chain provides a more solid methodological framework for the purposes of the present study. Furthermore, the EIO structure is flexible enough to allow comparisons between different consumption patterns. The methodological aspects of EIO are further expanded upon in section 3.4.

Secondly, there are no established yield indicators for water use in relation to economic output in the tourism literature. Similarly to the approach presented in Part II of the thesis, Cazcarro et al. (2014) focus on tourist water footprints in isolation from their economic contribution. Furthermore, Cazcarro et al. (2014) make no attempt to differentiate tourist types, other than the fundamental distinction between home tourists and foreign tourists, thus providing no insight with respect to tourist choices and their associated water use.
impact. The concept of water use intensity, explained previously, is highly appropriate for filling this gap.

Thirdly, no previous study has performed tourist segmentation with the purpose of comparing water use and economic impact trade-offs. The studies considered above either use COO segments (Gössling et al., 2005; Peeters & Schouten, 2006), or other previously established segments (Becken & Simmons, 2008; Collins et al., 2012; Dwyer et al., 2006; Jones & Munday, 2007; Lundie et al., 2007; Munday et al., 2013), and thus do not treat segmentation and yield estimation as part of an integrated framework. Becken et al. (2003) appears to be the only study which segments tourists by their travel patterns with the purpose of estimating their energy use. However, they do not attempt to consider economic yield in their study, which leaves an opening for potential improvement.

Given the heterogeneity of tourism in most destinations, there is a need for more sophisticated segmentation of tourist market segments – not only with the purpose of better understanding which tourist types are linked to the highest environmental impacts (Lundie et al., 2007), but also to develop specialised management strategies to improve yield (economic and environmental) for all tourist types (Becken et al., 2003; Becken & Simmons, 2008). In an attempt to address this gap, one of the objectives of the thesis is to use sophisticated segmentation techniques alongside water use intensity estimates in order to understand and compare water use by different tourist types. The following sections detail how this is to be achieved.

3.3 Distinguishing between different tourist types

3.3.1 Tourism market segmentation

Utility as a management tool

Tourism as a sector offers an incredible array of products which cater for different tastes, budgets and times of the year. This diversity is partly the result of different destinations possessing distinct physical features (climate, topography, geology) or cultural characteristics (history, archaeology, cuisine). It also reflects the fact that tourists are not homogeneous in terms of their desires and behaviour (Hsu & Kang, 2007; Mok & Iverson, 2000). Even within the same destination, several types of tourist may be present at the same
time, attracted by different services or sites. Forming and exploring market groups or segments has become a popular managerial practice known as ‘market segmentation’ (Chen, 2003).

Market segmentation is defined as an ‘attempt to pinpoint specific customer groups within larger undifferentiated populations in order to develop and implement marketing programmes specifically defined for their needs’ (UNWTO, 2007, p. 3). Market segmentation originates from the broader domain of marketing and encompasses the choice of techniques and statistical procedures that allow the division of a heterogeneous market into relatively homogeneous sub-groups (Dolnicar, 2004; Mok & Iverson, 2000). The objective is essentially to create groups in which members are as similar as possible to each other, and as dissimilar as possible to members of other groups (Dolnicar, 2008). This kind of knowledge subsequently allows a prioritisation of marketing efforts and offers invaluable guidance with regards to how different consumers are to be effectively targeted and satisfied (Hanlan et al., 2006; Kotler, 1999).

Market segmentation relies on data from tourism surveys based on responses to questions referring to their expenditure (spending patterns), purpose of visit, socio-demographic characteristics, and type of accommodation, all of which can be used to form different groups that share similarities with respect to the aforementioned parameters. Depending on the available data and desired outcomes of the study, one or more segmentation criteria may be used. Popular approaches in the literature include geographical segmentation (such as COO segmentation) (Becken & Gnoth, 2004; Flögnerdt, 1999a; Kotler, 1999), benefit segmentation (needs and wants sought) (Frochot, 2005; Jang et al., 2002; Loker & Perdue, 1992), demographic segmentation (Juaneda & Sastre, 1999), psychographic segmentation (activities and opinions) (Galloway, 2002; Schewe & Calantone, 1978), and behavioural segmentation (consumer knowledge and motivation) (Bigné et al., 2007; Kozak, 2002; Park & Yoon, 2009).
An expansive literature exists on tourism market segmentation for different destinations\textsuperscript{24} which falls outside the scope of the present study. The focus of the rest of this section is on the aspects of segmentation relevant to the thesis.

**Methodological options for segmentation**

Two principal approaches to carrying out segmentation are recognised in the literature: a priori segmentation, and post-hoc (data-driven) segmentation (Dolnicar, 2004). In a priori or ‘common-sense’ segmentation, the researcher chooses a variable or variables of interest and then classifies customers according to those pre-defined criteria (Hanlan et al., 2006). Dolnicar (2008) offers a step by step outline of the standard procedure. An initial segmentation criterion such as COO or purpose of trip is used to group respondents into segments. The selection of the segmentation criterion is based on previous knowledge and underlying assumptions of the important marketing stimuli (Hanlan et al., 2006). The segments are then explored using difference tests such as analyses of variance (ANOVA), t-tests or chi-square tests depending on the scale and distribution of the data. This step is known as ‘profiling’ as it allows for the testing and establishment of the characteristics in which tourists differ significantly. The final step is an assessment of whether the common-sense segments meet the predefined criteria in order to be of managerial value. Targeted marketing activities and investment can then take place for different segments.

The fundamental difference between a priori (common-sense) and post hoc (data-driven) segmentation lies in the method employed to group tourists into segments. While a priori segmentation uses one single criterion variable, post hoc segmentation uses several variables and forms groups with respondents who have similar characteristics through the use of quantitative (statistical) techniques of data analysis (Najmi et al., 2010). Dolnicar (2008) again offers a step by step outline of post hoc segmentation. Firstly, a number of critical variables are chosen as the segmentation base. As with the selection of the criterion variable in a priori segmentation, selection of these variables involves subjective judgements – such as priorities at the destination and/or objectives of the study. A statistical algorithm is then chosen to group the tourists. Most tourism studies use hierarchical clustering procedures such as Ward’s clustering or partitioning techniques such as k-means clustering (see Dolnicar, 2002,

\textsuperscript{24} The *Journal of Travel Research* is a regular outlet for segmentation work.
Once the clusters have been formed, the following step is stability analysis. This consists of performing repeated computations and then selecting the number of clusters that give the most stable results. The last two steps, profiling and assessment of the segments, are identical to a priori segmentation.

The two approaches can also be combined to give rise to hybrid segmentation techniques. This typically occurs where a common-sense segment is further split into data-driven subgroups (Dolnicar, 2004). Nevertheless, in destinations where prior knowledge of the significance of different variables is deemed inadequate due to a lack of previous studies, it may be preferable to initially employ a data-driven approach in order to extract some preliminary patterns and then follow this up with common-sense segmentation (Najmi et al., 2010). According to Dolnicar (2004), combining a priori and post hoc segmentation in creative ways allows a much more original segmentation of tourists, thus creating niche markets that have yet to be exploited. The present study aims to explore and combine different segmentation techniques.

### 3.3.2 Developing a segmentation approach for Cyprus

Many tourism boards around the world, including the CTO, use COO as their main segmentation criterion. The advantage of this straightforward a priori approach is the creation of segments which may be targeted through a common language and national media channels (Andriotis et al., 2008; Dolnicar, 2008; Reid & Reid, 1997). According to Park & Yoon (2009), the purpose of segmentation is to promote improved efficiency in supplying products which meet the identified needs of target groups, with the ultimate objective usually being to make the most money from selected target markets (Jang et al., 2002). COO segmentation may capture some cultural differences in preferences and spending patterns between tourists (Becken & Gnoth, 2004; Kozak, 2002). Nevertheless, the inter-group variation is often considerable, and placing too much emphasis on comparing different nationalities can often lead to other important descriptors being overlooked (Flognfeldt, 1999b; Moscardo et al., 2001).

This last point is highly relevant to established destinations that tend to already have significant numbers of repeat visitors (Alegre & Cladera, 2006), typically from large single-country source markets with a preference for the destination due to factors such as
proximity, affordability or other historical links. Some prominent examples are Caribbean and Mexican destinations for American tourists, New Zealand for Australians, Thailand, Taiwan, Macau and Hong Kong for the Chinese, and Malta, southern Spain and Cyprus for the British. In such cases, it could be argued that enhancing COO with other segmentation techniques is not only beneficial but essential. In the case of Cyprus, grouping and targeting all UK tourists, who have accounted for between 37 and 55% of inbound tourism to Cyprus in recent years (CYSTAT, 2012), ignores the considerable heterogeneity within this large and important market segment.

In order to eventually better examine and understand the factors that dictate water use and water use intensity, it is necessary to consider alternative options of segmentation. One of the principal objectives of the study, as defined in the Introduction (section 1.4), was to explore possible ways in which currently available tourism data in Cyprus could be used to supplement existing COO segmentation with tourist typologies based on other tourist characteristics and consumption patterns. This is subsequently employed to compare water use across different tourist groups segmented on the basis of their expenditure patterns. The next section explains the approach, also recently used in Hadjikakou et al. (in press).

### 3.3.3 Segmentation methodology

**Datasets and pre-processing**

In the present study, the purpose of the segmentation procedure is to deliver tourist groups that can subsequently be compared in terms of economic and water use impacts. It was therefore important to take the necessary precautions to ensure that the results would be suitable for this purpose. For this reason, the study uses the latest edition of the Cyprus TSAs (see Box 3.1 on the next page for explanation) from 2007, along with the corresponding passenger survey data (which includes expenditure) for the same year. Both were supplied by the Cyprus Statistical Service (CYSTAT).

The survey data had to be obtained in a raw format in order to allow alternative methods of segmentation not previously pursued by CYSTAT and the CTO. The data thus required substantial processing and recoding. In the pre-processing stage, all desired variables were merged into one dataset for the whole year, all expenses were converted from reported foreign currencies to Cypriot pounds (used in the 2007 TSA) based on monthly currency
exchange rates for 2007 provided by the CTO, and selected variables were recoded into categorical and continuous variables. The outcome of the pre-processing was a spreadsheet with a total sample size of 30,849 cases (corresponding to 60,456 individuals). The categorical variables kept were COO, age, month, sex, reason for visit, area, package or non-package and accommodation type (class). The continuous variables kept were party size, length of stay (LOS) and all available expenditure categories.

Passenger survey data that includes expenditure is typically collected through exit surveys: tourists are asked to provide an estimate of total and detailed expenditure during their entire visit, or, alternatively, an estimate of what they spent on the last day of their trip (Wilton & Nickerson, 2006). In this case, the exit surveys were administered through questionnaires at the island’s two major airports (CYSTAT, 2011c). Expenditure categories in the survey data were eventually matched to those of the TSAs (see section 3.5.1) to ensure a common classification. The area, accommodation type and month variables serve the additional purpose of allowing segment-specific direct water use (discussed in section 4.3).

**Segmentation procedure**

The study uses two types of *a priori* segmentation (COO and expenditure-based) as well as a data-driven technique (see Figure 3.4, p. 78). The objectives of the segmentation stage were to explore the diversity within the UK market segment, and to create sub-segments of a size that would allow yield comparisons within this segment and with other COO segments. Costs of travelling to the destination were removed as these are more likely to benefit international companies and firms within the tourist’s COO rather than the destination economy (Legohérel & Wong, 2006). For package tourists, local expenditure consists of the cost of the package (minus 15% to reflect foreign agency profits), plus any additional expenses, minus estimated journey costs. For non-package tourists, local expenditure consists of all costs minus journey costs. Data analysis was carried out using SPSS version 19.0.
Box 1 - Tourism Satellite Accounts (TSAs) – brief explanation

TSAs are satellite accounts used as an adjustment to a country’s national accounts to measure the economic significance of tourism activities. Tourism accounts exist in the form of a satellite account because conventional national account framework do not consider tourism as an important economic sector, and it was only in response to the surge in the relative importance of the tourism industry in the late 20th century that TSAs were launched (Hara, 2008). As tourism is not considered to be a conventional industry owing to its diverse range of inter-linkages to other sectors, including specific information on tourism within the actual national accounts would seriously overburden and imbalance the accounts. Therefore, creating a specific framework for tourism was seen as a more practical solution (Frechtling, 2010).

TSAs are constructed using a combination of demand data from tourism surveys with data on the supply of goods and services taken from the System of National Accounts (SNA) framework (Smith et al., 2011). TSAs essentially aggregate the share of overall activity in an economy that is directly linked to tourism demand.

Through effectively linking tourism supply and demand in a consistent and balanced framework which uses the same definitions and approaches as those agreed for the measurement of other economic activities (Bryan et al., 2006), TSAs provide a consistent tool for measuring the performance of the tourism sector and are also used to identify the more profitable types of tourism, providing valuable insight that may then be used to inform and improve tourism policy (Dwyer et al., 2010; Jones et al., 2003). Despite methodological discrepancies between different national TSAs, most countries in the EU have fully-fledged TSAs (Eurostat, 2010). According to the UNWTO (2010a), 60 countries worldwide had already produced or were in the process of developing TSAs as of early 2010, with more countries likely to have been added to this list since then.

TSAs typically consist of a set of inter-related tables that show the size and distribution of the different forms of tourism consumption in a country and contributions to gross domestic product (GDP), national income, employment, and other macroeconomic measures of a national economy (for detailed description see Frechtling, 2010; Smith et al., 2011; TSA RMF, 2008). By using the appropriate tables in TSAs, several measures of tourism yield can be
estimated – such as direct contribution to GDP and contribution to employment in tourism industries. The main limitation of yield estimates derived directly from TSA statistics is that they do not include indirect or induced effects (inter-industry and economy-wide impacts) on income and employment, which can only be estimated through economic modelling approaches (Ahlert, 2008; Dwyer et al., 2007). For this reason, the method presented here uses Input-Output (I-O) modelling in order to capture total (direct and indirect) yield, which is an improvement over the direct estimates previously published in Hadjikakou et al. (in press).

The first *a priori* segmentation performed was the traditionally used COO segmentation which created tourist groups based on their COO (see Figure 3.4, p. 78). Cross-tabulation of variables allowed for profiling of the main COO segments to determine their mean expenditure in each of the spending categories. The UK market segment was then further segmented into three groups using expenditure-based segmentation (shown in Figure 3.4, top right). This is a popular *a priori* technique which divides visitors into three equal-sized segments based on the frequency distribution of the total expenditure variable (Craggs & Schofield, 2009; Dixon et al., 2012; Mok & Iverson, 2000; Shani et al., 2010; Spotts & Mahoney, 1991). Following the recommendation by Legohérel & Wong (2006), daily expenditure was chosen as the preferred segmentation criterion. This provides a more solid base of similarity as opposed to accumulative expenditure for the whole trip which is strongly influenced by the length of stay (see Becken et al., 2003, with reference to travel behaviour). ANOVA and chi-square ($\chi^2$) tests were used to confirm that there are significant differences in the means between the spending groups for all spending categories as well as for all the other categorical and continuous variables.

Finally, a data-driven segmentation of the UK market was performed using the SPSS TwoStep® cluster analysis (see Figure 3.4, bottom right). This technique was chosen because it can simultaneously handle both categorical and continuous variables, and was also specifically designed to handle large datasets (SPSS, 2001). It consists of pre-clustering cases into many small sub-clusters, followed by grouping the sub-clusters into the desired number
of clusters (Hsu et al., 2006). In the pre-clustering stage, observations are read and processed to decide whether they should be combined with an existing pre-cluster, or whether a new pre-cluster should be created, based on a Log-likelihood distance measure. In the subsequent clustering stage, pre-clusters are then grouped through an agglomerative clustering algorithm (Huang & Han, 2008).

Since expenditure-based segmentation already provides a separation on the basis of expenditure that would allow correlating expenditure to water use, the goal of the clustering procedure was to use variables other than the expenditure categories in order to appreciate their effect on economic impact and water use. A number of variable combinations were tested before arriving at a consistent solution with a good degree (0.65) of intra-group cohesion and inter-group separation. As shown in Figure 3.4 below, the best results were achieved with a total of three clusters. ANOVA and chi-square ($\chi^2$) were used to confirm that there are significant differences between the groups across all expenditure categories.

![Figure 3.4 Segmentation procedure followed in the study. Cross-tabulation of variables was used to create COO segments. The UK segment was subsequently segmented in two different ways.](image)

---

25 The silhouette measure of cohesion and separation is a measure of the overall goodness-of-fit and is based on the average distances between the objects and can vary between -1 and +1. Values of more than 0.50 indicate a good solution (Mooi & Sarstedt, 2011).

26 Note that there could theoretically be an overlap with the expenditure-based segments.
Summary results of the segmentation procedure are presented in Chapter 4, section 4.2. Having established market segments, the next section explains how EIO is used to capture direct and indirect (supply-chain) economic and water use impacts for each of the segments shown in Figure 3.4 above.

3.4 Estimating water use intensity - Environmental Input-Output Analysis

3.4.1 Section summary

This section firstly explains the basic structure and modelling elements of Input-Output (I-O) analysis before introducing Environmental Input-Output (EIO) analysis, which combines environmental and economic accounts in order to expand the basic I-O structure. The focus of the section subsequently shifts to studies that have used EIO to estimate freshwater use in an attempt to extract methodological elements appropriate for the purposes of the present study.

Studies using EIO to estimate the economic and environmental impacts of tourism are also reviewed, as this allows for special methodological and data considerations when dealing with the tourism sector. Finally, a tailor-made approach for estimating water use in the tourism sector in Cyprus is developed based on the available data.

3.4.2 Basic Input-Output (I-O) model

EIO analysis is a top-down economic technique that allows for the association of economic accounts with environmental accounts of resource use or pollution. It is based on the I-O model, an analytical framework developed by Leontief in the 1930s that makes use of sectoral monetary transactions to account for interdependencies between industries in modern economies (Munksgaard et al., 2005). Leontief (1973) reasoned that any process, from the manufacture of steel, to the education of youth, to the running of a family household, generates outputs and absorbs a specific combination of inputs. The output of one process is often the input for another, thus creating a network of links which depend upon each other directly, indirectly or both (see Figure 3.5, p.85, explained in detail further on).
The fundamental starting point for performing an I-O analysis is having information on the flows of products from each economic sector to each of the other sectors, based on observed economic data for a particular geographic area\textsuperscript{27} (Miller & Blair, 2009). This is typically available in the form of an input-output table (IOT) of the economy (see simplified version in Table 3.1, p. 81). Today, most statistical agencies worldwide regularly produce IOTs as part of their System of National Accounts (SNA). In the inter-sectoral transactions matrix (shaded area in Table 3.1), rows represent the distribution of a producer’s output throughout the economy whereas columns describe the composition of inputs required by a particular industry.

The appeal and apparent simplicity of the I-O model, for which Leontief was awarded a Nobel Prize in Economic Science in 1973, is that economy-wide interdependencies in inputs are modelled as a set of linear simultaneous equations (Joshi, 1999), that capture both direct and indirect effects of production in the economy. A short explanation follows on how these linear equations are derived and then solved as part of the basic I-O model structure.

Assuming the simplest possible format of a two-sector economy where each sector produces a single good for which an input-output table of inter-sectoral flows is available (Table 3.1 below), the total output for the two sectors can be expressed by:

\begin{align}
x_1 &= z_{11} + z_{12} + y_1 \\
x_2 &= z_{21} + z_{22} + y_2
\end{align}

where \( x_1 \) and \( x_2 \) refer to total output for each sector, \( y_1 \) and \( y_2 \) are demand for finished goods by households, government and foreign trade (known as final demand), and \( z_{11}, z_{12}, z_{21}, z_{22} \) represent transactions between pairs of sectors – known as intermediate demand, i.e. demand for inputs (inter-industry sales) to products as opposed to demand for finished products. The numbers used as subscripts in inter-sectoral transactions \( (z) \) denote the specific transaction in each case (see Table 3.1). As an example, \( z_{12} \) refers to output from sector 1 used as an input to production in sector 2. Total output for each sector is, therefore, assumed to

\textsuperscript{27} This is usually a nation (country) but can also be a region or state.
equal the sum of inter-industry sales to all other sectors (including itself) and final demand for finished products by consumers.

Table 3.1 Basic input-output table for a hypothetical two-sector economy.

<table>
<thead>
<tr>
<th>Sector 1</th>
<th>Sector 2</th>
<th>Final demand (y)</th>
<th>Total output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sector 1</td>
<td>$z_{11}$</td>
<td>$z_{12}$</td>
<td>$y_1$</td>
</tr>
<tr>
<td>Sector 2</td>
<td>$z_{21}$</td>
<td>$z_{22}$</td>
<td>$y_2$</td>
</tr>
<tr>
<td>Imports</td>
<td>$m_1$</td>
<td>$m_2$</td>
<td></td>
</tr>
<tr>
<td>Value added</td>
<td>VA$_1$</td>
<td>VA$_2$</td>
<td></td>
</tr>
<tr>
<td>Total inputs</td>
<td>$x_1$</td>
<td>$x_2$</td>
<td></td>
</tr>
</tbody>
</table>

The next step in deriving the Leontief I-O model is to replace the inter-industry sale terms (denoted by $z$) in equations (3.1) and (3.2) with technical coefficients. These are also known as input-output coefficients or direct input coefficients (R. E. Miller & Blair, 2009) and are interpreted as the monetary input value per monetary unit of output for each sector and are described using the ratio:

$$a_{ij} = \frac{z_{ij}}{x_j} \quad (3.3)$$

As an example, the technical coefficient of $z_{12}$, $a_{12}$, would be given by $z_{12}$ divided by $x_2$. These technical coefficients highlight one of the major assumptions of the I-O model. $a_{ij}$ is assumed to be a constant, measuring a fixed relationship between a sector’s output and its inputs which also means that sectors use inputs in fixed proportions (R. E. Miller & Blair, 2009). Any change in output will lead to proportional changes in all inputs in order for the technical coefficients to remain unchanged. Table 3.1 can then be expressed using the technical coefficients. This is known as the operational form, and is shown in Table 3.2 below.

Table 3.2 Input-output table for a two-sector economy with inter-industry transactions (shaded area) in operational form.

<table>
<thead>
<tr>
<th>Sector 1</th>
<th>Sector 2</th>
<th>Final demand (y)</th>
<th>Total output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sector 1</td>
<td>$a_{11}$ $x_1$</td>
<td>$a_{12}$ $x_2$</td>
<td>$y_1$</td>
</tr>
<tr>
<td>Sector 2</td>
<td>$a_{21}$ $x_1$</td>
<td>$a_{22}$ $x_2$</td>
<td>$y_2$</td>
</tr>
<tr>
<td>Imports</td>
<td>$m_1$</td>
<td>$m_2$</td>
<td></td>
</tr>
<tr>
<td>Value added</td>
<td>VA$_1$</td>
<td>VA$_2$</td>
<td></td>
</tr>
<tr>
<td>Total inputs</td>
<td>$x_1$</td>
<td>$x_2$</td>
<td></td>
</tr>
</tbody>
</table>
The linear equations (3.1) and (3.2) can also be expressed in terms of the technical coefficients:

\begin{align*}
    x_1 &= a_{11}x_1 + a_{12}x_1 + y_1 \quad (3.4) \\
    x_2 &= a_{21}x_2 + a_{22}x_2 + y_2 \quad (3.5)
\end{align*}

At this point, and assuming that all of the technical coefficient terms as well as the final demand terms are given (known), this pair of simultaneous linear equations can be solved by straightforward algebraic manipulation in order to solve for \( x \) (Proops et al., 1993). As a first step all the \( x \) terms are brought to the left side:

\begin{align*}
    (1 - a_{11})x_1 - a_{12}x_2 &= y_1 \quad (3.6) \\
    -a_{21}x_1 + (1 - a_{22})x_2 &= y_2 \quad (3.7)
\end{align*}

Solving for \( x \) finally gives:

\begin{align*}
    x_1 &= \frac{(1 - a_{22})y_1 + a_{12}y_2}{(1 - a_{11})(1 - a_{22}) - a_{12}a_{21}} \quad (3.8) \\
    x_2 &= \frac{a_{21}y_1 + (1 - a_{11})y_2}{(1 - a_{11})(1 - a_{22}) - a_{12}a_{21}} \quad (3.9)
\end{align*}

Although these solutions may appear fairly simple, the equations become very complex in the real world, where economies comprise many more than two sectors. To overcome this issue, equations (3.4) and (3.5) are transformed into their more compact matrix form. In element form this becomes:

\[
\begin{pmatrix}
    a_{11} & a_{12} \\
    a_{21} & a_{22}
\end{pmatrix}
\begin{pmatrix}
    x_1 \\
    x_2
\end{pmatrix} +
\begin{pmatrix}
    y_1 \\
    y_2
\end{pmatrix} =
\begin{pmatrix}
    x_1 \\
    x_2
\end{pmatrix}
\quad (3.10)
\]

Equation (3.10) can then be expressed in condensed matrix form:

\[
Ax + y = x
\quad (3.11)
\]
where A is the direct requirements matrix whose elements are all the technical coefficients (a terms) for a given economy. Equation (3.11) expresses what was contained in equations (3.1), (3.2), (3.4) and (3.5) in matrix form, i.e. that the sum of inter- and intra- industry flows (Ax) and final demands (y) equals total output (x). The Leontief inverse matrix can then be derived by solving for x in equation (3.11). Subtracting Ax from both sides rearranges the formula in terms of Y.

\[ y = x - Ax \]  

Equation (3.12) simply states that final demand is equal to total output minus intermediate goods. Factorising for x then gives:

\[ y = (I - A)x \]  

where I is the identity matrix (where the I-matrix is equivalent to 1 in normal algebra). Finally, rearranging the equation in terms of x (total output) gives:

\[ \frac{y}{(I - A)} = x \]  

This is usually expressed as:

\[ (I - A)^{-1}y = x \]  

where \((I - A)^{-1} = L\), the total (direct and indirect) requirements (‘Leontief inverse’) matrix. Equation (3.15) is the most commonly used expression of the basic Leontief I-O model. \(L\) represents the total production generated by each economic sector in order to satisfy final demand in the economy by describing the relationship between \(x\) (total output or total demand) and \(y\) (final demand) (Velazquez, 2006). This makes \(L\) a central tool in multiplier analysis which seeks to quantify the impact that changes in \(y\) (\(\Delta y\)) have on \(x\) (\(\Delta x\)) as well as other aspects of the economy such as income or employment (Sova, 2011). As inter-industrial transactions are contained in \(L\), total increase in output always exceeds the initial increase in final demand, as connected industries are also forced to increase their output in order to
satisfy the increased level of final demand (Hara, 2008). \( L \) is known as the total (direct and indirect) requirements matrix precisely because it captures both the direct increase in industrial output as well as the indirect increase which takes place due to inter-industry linkages. It is this ability of the Leontief model to estimate the potential multiplier effects across the whole economy of any anticipated changes in one of more final demand components that makes it such an invaluable tool for policymakers. The model is also often used to answer ‘what if’ questions relating to changes in policies and consumer demand (\( \Delta y \)).

\( L \) captures, in each of its elements, the total sum of an infinite series of round-by-round direct and indirect effects exerted by a given final demand vector \( (y) \) on the output of each and every industrial sector (Miller & Blair, 2009). These direct and indirect effects can be better understood if equation (3.15) is solved by employing the power series approximation of \((I - A)^{-1}\) instead of using a matrix inversion which allows for the separation of direct and indirect (round-by-round) effects (3.16). This approach was commonly employed during the early years of I-O studies when computer power did not allow the inversion of large matrices and is explained in more detail in Miller & Blair (2009, p.31-34). Using this alternative form:

\[
x = (I - A)^{-1}y = (I + A + A^2 + A^3 + \cdots + A^n)y
\]

(3.16)

The direct and indirect output terms can then be expressed, by removing the parenthesis in equation (3.16), as:

\[
x = y + Ay + A^2y + A^3y + \cdots
\]

(3.17)

where \( y \) is the direct increase in final demand, \( Ay \) is the first-round indirect increase in output associated with increased production to allow the production of \( y \), \( A^2y \) is the second-round indirect increase in output associated with increased production to allow the production of \( Ay \), and so on. The expansion of equations (3.16) and (3.17) obeys the elementary scalar theory of infinite series and is only valid if the column sums of \( A \) are less than one (Proops et al., 1993). According to Miller & Blair (2009), this is almost certainly the case in any open model of a real economy under the reasonable assumption that each sector uses inputs from the payments sector (value added – shown in Table 3.1, p. 81 and Table 3.2,
Value added components are omitted when calculating the $A$ matrix which means that any given column sum of input-output coefficients should always add up to less than one. The power series approximation will be reconsidered in Chapter 5, section 5.4.3.

By turning an infinite sequence of additions into a single matrix inverse, Leontief ensured that I-O analysis can cover all supply chains at an infinite length (Murray & Lenzen, 2010). Nowadays, any personal computer can easily handle inverse matrix operations, ensuring that the ‘boundary issue’ problem, commonly encountered in environmental audits, does not occur in I-O analysis. Whereas audits usually need to set strict a priori limits in terms of the depth of the analysis (with most audits concentrating entirely on local or on-site effects) due mainly to time and financial constraints, there is no boundary issue in I-O analysis since it accounts for all upstream linkages to production/demand. The decomposition of the I-O model solution into its direct and indirect components, shown in equations (3.16) and (3.17), may be even better understood when presented in the form of a diagram. This is depicted in Figure 3.5 below with reference to the inputs required to satisfy the demand for a train journey by a resident of Melbourne, Australia. The diagram illustrates how demand for any service initiates a process of upstream industrial interdependence that can be thought of as the branches of an infinitely extensive tree (Munksgaard et al., 2005). Only the first four upstream layers (rounds) are depicted here. In reality, the supply chain carries on indefinitely with each round yielding diminishing outputs, something which is captured by the $L$ matrix.

![Figure 3.5 Diagram showing a structural path through the supply chain of a train journey by a resident of Melbourne, where industrial dependencies in a hypothetical five-sector economy are shown as a series of upstream production layers (after Foran et al., 2005).](image_url)
3.4.3 Environmental Input-Output (EIO) model

Basic formulation

The extension of the basic economic I-O model to include links between economic and environmental data first began in the late 1960s (Perman et al., 2003). It was Leontief (1970) himself who first realised and explained how environmental externalities such as pollution can be incorporated into the conventional I-O structure. Consumption of any service or good involves the use of resources and the emission of pollutants. The volume or mass of resources or pollutants associated with the production of a product or service can be seen as a function of consumer demand for that product or service. Resources and pollutants directly linked with a consumption activity are called direct requirements whereas resources and pollutants embedded in the supply chain of a product or service are called indirect requirements (Munksgaard et al., 2005). By making use of the Leontief matrix ($L$) which accounts for all monetary inter-industry transactions, both direct and indirect environmental pressures (resource use or pollution) for any given consumption pattern can be estimated. The logic behind this is that all monetary flows in the supply chain of a product or service are associated with the use of resources or the emission of pollutants.

The most commonly used approach to EIO involves the use of an exogenous vector of environmental coefficients (denoted by $u$ in this case) also known as direct impact coefficients (this is also known as generalised I-O; see Appendix A for alternative EIO frameworks). This is a vector of environmental impact (resource use or pollution) per unit of currency of output for each sector or commodity considered within the I-O framework, calculated as:

$$ u_i = \frac{e_i}{x_i} \quad (3.18) $$

where $e_i$ is a vector of direct resource use or pollution attributed to each economic sector or commodity and $x_i$ is a vector of total sector or commodity outputs. Once the $u$ vector is calculated, it can then be employed in a variety of ways to estimate total resource use or pollution per economic sector associated with a given final demand vector, or a change in final demand expected to result from a certain policy or event. In technical terms, conventions differ as to how the final expression for calculating total resource use should be
presented and also with regards to the order of operations that are performed as part of the equation. \( u \) may be kept as a vector or can be used to form a diagonal matrix \( U \), which is a matrix whose diagonal elements are the elements of the \( u \) vector and whose other elements are zero values (Hendrickson, 1998).

Lenzen & Foran (2001) first multiply \( u \) by \( L \) in order to calculate a multiplier matrix \( M \) which is then multiplied by a final demand vector to give total resource use. Perman et al. (2003), on the other hand, simply multiply the \( u \) vector by \( x \) (total output vector). The outcome in both cases is the same, a vector whose elements represent total environmental pressure (resource use or pollution generation) associated with each economic sector. The generalised expression for calculating the total resource use (direct and indirect) for any given final demand vector is given by the vector of environmental outputs (\( E \)):

\[
E = u x = u(I - A)^{-1}y
\]

which, as mentioned in the above paragraph, may also be expressed as:

\[
E = uL y = M y
\]

where \( M \) is a multiplier matrix obtained by multiplying sectoral production factor usage (\( u \)) by the Leontief Inverse Matrix (\( L \)). \( M \) is often used to encompass multiple production factors (both environmental and non-environmental such as labour or value added) within the same I-O operation (Lenzen & Foran, 2001; Munksgaard et al., 2005; Turner et al., 2007). The form and level of aggregation of the \( M \) matrix will depend on whether \( u \) is kept as a vector or used as a diagonal matrix (\( U \)). If \( u \) is kept as a vector, the \( M \) matrix will also, in fact, be a vector. The advantage of using \( U \) is that it yields a matrix that contains disaggregated total environmental requirements per monetary unit, which allows an appreciation of how each input or output of a certain sector contributes to the overall environmental impact of the sector.

In a similar way, the \( y \) vector can also be used to form a diagonal matrix, \( Y \), which also provides a detailed breakdown of the overall environmental impacts of each sector (Wiedmann et al., 2006). \( y \) can also be split into separate final demand column vectors to reflect different final demand categories such as expenditure from households, government,
or non-profit organisations (see for example Druckman et al., 2008; Jackson et al., 2007). In studies that are mostly concerned with the final outcome in the form of the $E$ vector or, in many cases, only the sum of the $E$ vector, these finer methodological details are rarely a point of concern.

**Applications of the EIO model**

EIO can be used to model the use of resources or emission of pollutants in a supply chain. EIO allows for the estimation of not only the total environmental impact associated with a product or service, but also to trace the origin and destination responsible for the environmental impact (Duarte & Yang, 2011). In a similar way to the basic I-O model, EIO can also be employed to answer ‘what if’ questions referring to changes in final demand and their environmental repercussions and to make comparisons between different consumers or consumption patterns. The ability of EIO models to trace resource use or pollution through the whole supply chain means that they are ideally suited and are often employed in life-cycle assessment (LCA) and environmental footprint considerations in academia and government/policy circles.

Common applications of EIO in the literature include carbon emissions (Druckman & Jackson, 2008, 2009, 2010; Lenzen et al., 2004; Minx et al., 2009; Munksgaard et al., 2005; Weber & Matthews, 2008), ecological footprint considerations (Turner et al., 2007; Wiedmann et al., 2006) and water use/water footprinting (Cazcarro et al., 2012; Duarte et al., 2002; Wang et al., 2009; Zhang et al., 2011; Zhao et al., 2010). However, the method is flexible enough to handle a variety of environmental pressures relating to resource inputs such as electricity, fuels, ores and fertilizers, and to environmental outputs such as toxic emissions, waste generation, air pollutants, global warming potential and ozone-depleting substances (Hendrickson, 1998). Furthermore, EIO offers the possibility to model environmental impacts from a variety of perspectives: per sector, per product of final consumption activity, or as correlated to the use of a natural resource (Tukker et al., 2006).

**Accounting for trade and direct resource use - alternative frameworks**

According to Miller & Blair (2009), the smaller the economic area, the more dependent the area’s economy is on trade with outside areas. The EIO model formulation provided thus far (3.19) is for a single-region model which does not consider trade. This kind of model cannot
therefore account for interconnections between regions (Lenzen et al., 2004; Wiedmann, 2009). Cyprus is a very small island nation where a significant amount of both food and non-food products consumed by tourists and residents are imported, implying that significant amounts of water are also imported through trade (as previously seen in section 2.4.2, chapter 2). Furthermore, a high degree of dependency on imported products acts as a constraint on the size of the multiplier effects from tourism consumption (Dwyer et al., 2010).

The simple single-region model (3.19) must therefore be expanded to account for trade between Cyprus and the rest of the world. There are several alternative ways to achieve this, depending on the quality of data available as well as the objectives of the study.

The ideal solution to this problem would be to use an interregional input-output (IRIO) model, first proposed by Isard (1951). This kind of model assumes that there is a full set of information available on both intraregional flows and interregional flows between sectors (Miller & Blair 2009). This means that a complete coefficients matrix (equivalent to A in the single-region I-O model) for a two-region interregional model consists of four submatrices $A_{rr}$, $A_{rs}$, $A_{sr}$, and $A_{ss}$ – where $A_{rr}$ is the intraregional input coefficient matrix for region r, $A_{ss}$ is the intraregional input coefficient matrix for region s, $A_{rs}$ is the interregional input coefficient matrix showing exports from region r to region s and $A_{sr}$ is the intraregional input coefficient matrix showing exports from region s to region r. The A matrix consisting of these four individual matrices (this matrix will have dimensions $2n \times 2n$ where n equals the number of economic sectors in each region) can then be solved as before using the regular Leontief I-O model (for a detailed explanation and numerical example see Miller & Blair, 2009, p.76-86).

Of course, such a model assumes that extensive surveys of firms in both regions have been conducted to capture locally produced and imported inputs between each sector (Miller & Blair, 2009). It also requires a full set of environmental coefficients (as in 3.18) for all the regions (or countries) being modelled. The full interregional model has rarely been implemented empirically (Hewings & Jensen, 1986), mainly because of the enormous amounts of data required. However, according to Miller & Blair (2009), it has inspired modifications and simplifications that have resulted in more operational frameworks.

One such framework is multiregional input-output (MRIO) analysis. The major difference between a multiregional and an interregional model is that when building a coefficients matrix (A) in a multiregional model, the origin of a given input is ignored. What is required
is information on the input from each sector (irrespective of region) to each other sector in each of the regions. As a result, the A matrix is simply composed of $A^r$ and $A^s$ which are then placed on the diagonal of a $2n \times 2n$ matrix, with the remaining two matrix elements being zeroes. In order to then capture interconnections among regions, the multiregional model uses trade flows of each good from one region to another, without taking into account the sector of destination in the receiving region. These flows are denoted by a matrix $C$, which in a two-region model would be composed of submatrices $C^r_r$, $C^r_s$, $C^s_r$ and $C^s_s$, where the diagonal elements of $C^r_s$ indicates the proportion of each good used in each region $s$ which comes from region $r$ and $C^s_r$ indicates the proportion of each good used in each region $r$ which comes from region $s$. $C^r_r$ and $C^s_s$ are the proportions of each good sourced locally from within the region (where $C^r_r + C^s_r = 1$ and $C^r_s + C^s_s = 1$). In this case, the solution of the I-O model is given by:

$$x = (I - CA)^{-1}Cf \quad (3.21)$$

Note that because the interregional shipment data include both sales to producing sectors (intermediate demand) and final-demand users in a receiving region, $f$ also needs to be adjusted by multiplying by $C$ (for a detailed explanation and numerical example see R. E. Miller & Blair, 2009, p.87-96). The multiregional model offers a cruder representation of flows between sectors and regions compared to the interregional model, but is ideally suited to the significantly reduced data that is available when two or more regions are being considered. Extending this multi-national framework with environmental coefficients allows for links to be established between the location of environmental impact and the demand and consumption of goods and services elsewhere in the world (Wiedmann & Barrett, 2013). Recent years have seen an explosion of MRIO databases which contain national and global IOTs along with environmental extensions such as greenhouse gases, water use and land use (Tukker & Dietzenbacher, 2013), thus opening up various possibilities for research and policy-related applications of EIO. Popular examples are Eora (Lenzen, Kanemoto, Moran, & Geschke, 2012a; Lenzen, Moran, Kanemoto et al., 2013), the World Input-Output Database (WIOD) (Dietzenbacher et al., 2013; Timmer et al., 2012) and EXIOPOL (Tukker, de Koning, Wood, Hawkins et al., 2013).
A third option, the unidirectional trade model, is simpler than the MRIO framework and has also been shown to produce adequate results when it comes to estimates of carbon emissions (Lenzen et al., 2004; Tukker, de Koning, Wood, Moll et al., 2013). In this case, a domestic IOT as well as IOTs for the main trading partners of the country of interest are used to estimate embedded pollution and resource use in bilateral trade with these specific countries. The major simplification of this model in relation to the MRIO model is that it requires only trade coefficients between one focal country and its (main) trading partners, whilst ignoring trade among the trading partners. It therefore assumes that an imported product is made in full in the country that exports it (Tukker, de Koning, Wood, Moll et al., 2013). As with the previous models, environmental coefficients are ideally required for the focal country as well as all its main trading partners. Nevertheless, even when environmental coefficients or IOTs of trading patterns are not obtainable or available in very different classifications, an assumption known as the ‘domestic technology assumption’ (Druckman et al., 2008; Druckman & Jackson, 2009; Tukker, de Koning, Wood, Moll et al., 2013) allows for an estimate of environmental impacts exerted outside the domestic realm. Proops et al. (1993) introduced a framework based on the domestic technology assumption to overcome the absence of information on the emission (resource) intensity and economic structure of the rest of the world. The emission (resource) intensity vector and the Leontief inverse for the rest of the world were therefore taken to be the same as that for the UK, which was one of the focal countries in the study.

Proops et al. (1993) also apply a second simplification, that of the small country assumption, which allows one to ignore the amount of resources or emissions embedded in products exported by the focal country which could then be used to eventually produce goods for intermediate or final demand in the focal country (Jackson et al., 2007). Following these assumptions, the following identities hold true:

\[ E_P = u^1(I - A_1)^{-1}y^{11} \]  \hspace{1cm} (3.22)

\(^{28}\) A common problem faced by EIO modellers is the mismatch between the sector classifications used in economic accounts in relation to those used in environmental accounts. In these cases, assumptions are required in order to aggregate or disaggregate the available data in a way as to ensure compatibility between the two types of accounts. This topic is further elaborated in Part IV of the thesis.
where $E_P$ = environmental footprint associated with the flow of goods produced locally to meet final demand in the focal country, $E_Q$ = environmental footprint associated with the flow of goods produced abroad (rest of the world) to meet intermediate demand for goods consumed in the focal country, $W_R$ = environmental footprint associated with the flow of goods from abroad for direct consumption (to meet final demand in the focal country), $u^1 =$ vector of water intensity coefficients for each sector (calculated by dividing estimated water use in each sector by the output of the sector), $B_{21} =$ matrix which describes the flow of intermediate goods from the rest of the world to the focal country (import use coefficients), $y^{11} =$ vector of final demand in the focal country met by local production and $y^{21} =$ vector of final demand in the focal country met directly through imports. The derivation of the formulae is provided in Proops et al. (1993), and Jackson et al. (2007).

Based on (3.22), (3.23), (3.24) and Munksgaard et al. (2005), it follows that the total resource or emission consumption for a given final demand vector ($y$), will equal:

$$E_T = (E_P + E_Q + E_R) + E_D$$

where $E_T$ = total resource consumption and $E_D$ = direct consumption (this could be energy or water use at household level). The terms in the parenthesis ($E_P + E_Q + E_R$) represent the indirect environmental footprint, which is the volume of resources or emissions embedded in consumed products. $E_P$ (3.22) is the footprint of goods produced domestically to satisfy the domestic component of final demand ($y^{11}$). $E_Q$ (3.23) is the footprint of products originally produced abroad which serve as inputs to domestic production in order to satisfy $y^{11}$. Finally, $E_R$ (3.24) is the footprint of products produced abroad which are imported in order to satisfy the external component of final demand ($y^{21}$). $E_R$ essentially refers to the products imported and consumed directly without any further processing and associated use of domestic resources.
From a water and tourism perspective, and in the context of the current study, all three approaches outlined above could potentially be applicable. However, even considering that accounting for the differences in embedded water contents from products originating from different countries would enhance the reliability of the analysis, tracing the origin of the water is a peripheral exercise which falls outside the scope of the current research project. The focus in the present framework is on local multipliers and on the need for separating out and accounting for imported (external) water. The last framework is therefore adequate for fulfilling this aim, provided its simplifying assumptions and their likely influence on the results are acknowledged. The following section reviews water-related EIO studies to allow for further elaboration of the model structure as well as to provide an idea of the data required.

3.4.4 Water-related EIO studies

This section reviews EIO studies that have specifically focused on water use. The main aim of the section is to appreciate the goals and scope of previous studies, in an attempt to single out and select the elements of their methodology or other useful assumptions that may suit the purposes of the current study. According to Duarte and Yang (2011), water was never a major issue in I-O analysis in the past because of several reasons: poor availability of water data in many parts of the world, a general lack of concern for water in advanced economies due to relative abundance, a lack of interest in water quality aspects in the majority of water management models, and the general belief that water was essentially an agricultural issue. However, although water use data is usually more difficult to obtain and place into the desired aggregation level, estimating water use through the EIO structure is methodologically identical to energy or ecological footprint calculations.

Increasingly, as awareness over water issues has become more widespread, there has been renewed interest in coupling the study of water resources with EIO. This is illustrated by a notable increase in publications on the topic over the last decade (Duarte & Yang, 2011). The emergence of the virtual water (VW) and water footprint (WF) concepts, an increased consideration of water aspects in Environmental National Accounts, and the creation of online MRIO databases have all contributed to this apparent trend. A number of countries including Australia, Denmark, France, the Netherlands, New Zealand and Spain have
already developed their own water accounts in ways that allow their use alongside existing economic accounts (Vardon et al., 2007).

Earlier water-related EIO studies (Duarte et al., 2002; Lenzen & Foran, 2001; Llop, 2008; Velazquez, 2006) highlight the fact that the agricultural sector has high direct water use and low indirect use, as opposed to service sectors (such as hotel and catering or food and beverages) that are associated with low direct use and high indirect use (this is consistent with findings in Part II). This stresses the importance of using methods that allow for the estimation of total water consumption and which include both direct and indirect water consumption, especially for sectors such as tourism that are highly dependent on inputs from agriculture.

The Lenzen & Foran (2001) study is the most pertinent to the present objectives since the authors investigate the relationship between the water use, income and expenditure of Australian households. However, the authors are mostly focused on estimating water use under different future scenarios. Furthermore, none of the above-mentioned studies explicitly considers virtual water imports through trade as they focus solely on water originating within a certain region or country. This inevitably ignores a highly significant volume of water when considering a country’s water use from the consumption perspective. Combining I-O analysis with the WF concept appears to offer more flexibility to do so.

Increasingly, there has been an emphasis on the impacts of consumption on water use and sustainability in other regions through considering inter-regional trade using MRIO models (Cazcarro et al., 2013; Daniels et al., 2011; Ewing et al., 2012; Lenzen, Moran, Bhaduri et al., 2013; Steen-Olsen et al., 2012). These studies provide a useful illustration of the potential of MRIO to better understand and trace water use in trade flows between countries, but a detailed discussion on their outputs remains outside the scope of the present study. The focus is instead on elements from studies that have used the WF concept alongside EIO in order to estimate regional and national water use (Wang et al., 2013; Yu et al., 2010; Zhang, Yang et al., 2011; Zhao et al., 2009, 2010).

Zhao et al. (2009) develop a framework that allows for an estimation of the national WF of China for 2002 using an EIO approach. The national WF is calculated as the sum of the internal WF and the external (imported) WF. The external WF is estimated based on the
assumption that the virtual water content of imported goods is the same as if they had been produced in China. This is consistent with the savings perspective defined in Renault (2002) which considers the volume of local water saved through international trade. This assumption ensures that a single-region I-O model without interregional or multi-regional extensions is enough to provide an estimate of the national WF.

Zhao et al. (2009) also distinguish between the water imported for the purpose of final consumption as opposed to the water embodied in intermediate inputs (only a fraction of which is consumed by domestic final demand, as some of it is re-exported in the form of finished goods). Thus, in many ways the method is similar to Proops et al. (1993). Zhao et al. (2010) make use of the same model this time applied to a specific basin in China. The main difference is the temporal focus of the study which looks at changes in the WF intensity\(^{29}\) over time. The studies illustrate how estimates of the WF of different economic sectors can be made by employing a single-region basic EIO model. The second study also demonstrates the use of indicators such as water footprint intensity which is very similar to water productivity.

Zhang et al. (2011) use an interregional model setup with separate IOTs for different regions of China. They also adopt Renault’s (2002) savings perspective, as the sectoral water requirement quotas of the other regions are assumed to be identical to those of Beijing for which water consumption data are available and which serves as the focal region in the study. In another recent study, Yu et al. (2010) adopt a multi-regional I-O framework to assess the WF of the UK. This framework includes UK trade with three world regions, EU OECD countries, non-EU OECD countries and non-OECD countries. An important methodological consideration made in this study is that it also adds the domestic water footprint (water used directly in homes) to the WF used to satisfy intermediate and final demand within the I-O framework. The equation for total WF therefore becomes very similar to the equation proposed by Munksgaard et al. (2005) to include direct factor usages as well as all indirect factors embodied in inputs of any functional unit. Yu et al. (2010) express total WF as:

\[^{29}\] WF intensity is defined as the total WF of a sector divided by the domestic final demand of the sector. This is similar to the concept of water productivity as defined in (Gleick, 2003b).
where \( e \) is the water consumption coefficient and \( w_{hh}^{d} \) is the direct water consumption by households in the UK. Of course (3.26) only refers to the domestic component, and adding the imported component (see 3.23 and 3.24) is necessary to complete the framework. This is referred to by Feng et al. (2011) as the Water Embodied in Bilateral Trade (WEBT) approach which is identical to Proops et al. (1993).

All WF studies discussed above make the same assumption when it comes to the virtual water content of imported goods, based on Renault’s (2002) savings perspective. In one of the earlier water I-O studies for the Australian economy, Lenzen & Foran (2001) acknowledge that as a consequence of such an assumption, embodiments in imports of textiles and food would tend to be overestimated for a country with a climate like that of Australia. This is because most products, when produced overseas, are likely to require significantly less water than if they had been produced in Australia. This assumption would be expected to hold true for Cyprus and any other semi-arid country where agricultural production is heavily reliant on irrigation water. However, this appears to be inevitable in the absence of water use data in other regions or countries, especially when considering multiple regions within the same model.

With regards to the water use coefficients, water-related EIO studies usually make use of sectoral water withdrawals. This is essentially the same as blue water. As per the earlier discussion in Chapter 2, section 2.5.1, many authors appear to be in favour of excluding green water and grey water from the analysis (Steen-Olsen et al., 2012; Zhang, Yang et al., 2011; Zhao et al., 2010). First of all, blue water has a much higher opportunity cost as it can potentially be used for any purpose, whereas green water is only relevant to the agricultural sector and often its alternative uses are difficult to deduce (Zhao et al., 2010). Including green water in the assessment would create inconsistency between water content figures for agricultural products compared to non-agricultural products (Zhang, Yang et al., 2011). Moreover, according to Ridoutt & Pfister (2010b), green water needs to be considered in terms of land resource requirements, something that would further complicate the analysis. As for grey water, its usefulness as an indicator is still under debate and is therefore best excluded as already explained in Chapter, section 2.3.2.
In addition to looking at current water consumption from different countries or regions, two studies have also used EIO analysis to make future projections (Hubacek & Sun, 2005; Hubacek et al., 2009). Both studies make use of forecasts for future economic growth, population dynamics and urbanisation, consumption patterns (diet) and expected technical changes (such as water-saving measures) to estimate changes in water consumption in the Chinese economy. Even though the accuracy of the findings in these studies is subject to significant uncertainties and assumptions of the forecast data, they do illustrate how altered final demand \((y)\) vectors may be ‘fed’ into an EIO model to ascertain how different demand patterns impact the use of water resources in the economy. A comparison of different tourist groups for example, may be accomplished in a similar way. The challenge of deriving these final demand vectors is the subject of section 3.4.5.

In conclusion, this section has demonstrated that the use of I-O alongside the consumption-based WF concept (with some modifications such as the exclusion of green and grey water components) provides a framework that is capable of considering differences in water productivity between tourist groups by considering water use and economic impacts in the whole supply chain, whilst also taking into account imports of water from abroad using a simple model setup which requires the minimum amount of information for foreign economies that export goods to Cyprus.

### 3.4.5 EIO models and tourism – comparing tourists

Having established a suitable EIO model structure, there still remains the issue of estimating final demand \((y)\). The majority of EIO studies on consumption patterns use the household final demand vector which usually comes as part of the IOT and is derived using household expenditure. However, tourism consumption rarely has a ready-made final demand vector that can be used to ‘force’ the EIO model. Tourism-related EIO studies (Cazcarro et al., 2014; Collins et al., 2012; Jones & Munday, 2007; Lundie et al., 2007; Munday et al., 2013) are examined here to seek a solution to this issue.

Cazcarro et al. (2014) is the only study that has used EIO in order to estimate the water footprint of tourism at a country level. According to the authors, since tourism is a multi-sector activity, spending in each of the relevant sectors must be considered. The authors explain how they distributed the total sum of tourism consumption given in the Spain IOTs
to obtain new values for imports, exports and household column vectors. Even though they acknowledge the use of the TSA in order to perform this procedure, they do not provide sufficient explanation as to how this was achieved. Moreover, they only produce two final demand vectors, one for local tourists and another for foreign tourists, thereby not accounting for more fundamental differences between tourist groups.

The other studies appear to make an effort to compare different tourist segments with different expenditure patterns. Lundie et al. (2007) use expenditure data for existing market segments in Australia which they re-classified and compressed into the Australian I-O classification in order to generate $y$ vectors. This was carried out with the aid of data on food statistics and household expenditure surveys. This implies that the authors assume that tourists eat and shop like locals for some expenditure categories in which tourism expenditure data are too aggregated in order to match with the I-O classification.

Jones & Munday (2007) follow a similar procedure for Wales, guided by the availability of TSAs which are integrated into the IOTs, allowing for the distribution of the initial expenditure into the IOT sectors to generate final demand vectors. A similar model structure is used in Collins et al. (2012) and Munday et al. (2013). With the exception of the Collins et al. (2012) study which concentrates on event goers, the other two studies consider different market segments, with Jones & Munday (2007) distinguishing between day visitors, UK visitors and overseas visitors and Munday et al. (2013) making use of the same distinctions with an added segmentation based on length of stay.

A standardised procedure for distributing initial tourism consumption in the I-O classification appears to be lacking. From earlier economic I-O studies (Briassoulis, 1991; Fletcher, 1989) to the more recent studies reviewed in this section, the issues and uncertainties involved in generating final demand vectors using tourism expenditure data are re-examined in Chapter 4, section 4.4.2, and Chapter 5, section 5.4. The availability of TSAs in Cyprus offers the possibility to reclassify tourism expenditure in a similar way to Lundie et al. (2007) and Jones & Munday (2007).

The subsequent section elaborates on the specifics of the EIO model setup for Cyprus.
3.5 EIO model for Cyprus tourism

3.5.1 Datasets and model set up

Based on the preceding discussions of the key methodological elements, this section details how the available data are used to run the EIO model based on the outputs of the segmentation procedure (section 3.3.2). In order to facilitate the explanation, the section relates each dataset used with terms in the EIO model equation. The second part of the section (3.5.2) explains the indicators used to estimate economic impact from each segment.

To facilitate analysis, equations (3.22-3.26) are merged into one to yield (3.27):

\[
W_T = u^1(I - A_1)^{-1}y^{11} + u^1(I - A_1)^{-1}B_{21}(I - A_4)^{-1}y^{11} \\
+ u^1(I - A_1)^{-1}y^{21} + w_{hh}^u
\]  

where \(W_T\) refers to the vector of total water use, \(u^1\) is the vector of sectoral water coefficients, \(B_{21}\) is the import matrix of products to Cyprus and the rest of the terms remain as previously defined.

The study requires two main kinds of data to perform EIO: (a) economic data in the form of an IOT for Cyprus along with imports per sector, TSAs and tourism expenditure data, and (b) water use data (sectoral water use data and household water use estimates). The data are all for the year 2007, which corresponds to the latest edition of the Cyprus TSAs. Below is a brief description of the datasets in relation to the terms in (3.27).

(a) Economic data – IOTs, tourism expenditure data and TSAs

As Cyprus does not currently release its own official IOTs, the study uses IOTs for Cyprus from the World Input-Output Database (WIOD)\(^{30}\). The IOT is a square 35 by 35 matrix and is based on the NACE\(^{31}\) (NACE Rev.2) classification. The WIOD table was selected after performing quantitative comparisons with other available options (such as Eora) against the Cyprus National Accounts (see Appendix B). The WIOD IOTs are used to estimate \((I - A)^{-1},\)

\(^{30}\) IOTs for all EU countries in addition to some other from non-EU countries are available at [http://www.wiod.org/](http://www.wiod.org/).

\(^{31}\) NACE stands for ‘Nomenclature statistique des activités économiques dans la Communauté européenne’ and is the standard statistical classification of economic activities in the European Community.
the ‘Leontief inverse’ matrix and also to give the values for $y^{11}$ and $y^{21}$ for Cypriot households, which are used as a basis for comparison with the tourist segments. In order to estimate $y^{11}$ and $y^{21}$ for the tourist segments, the expenditure patterns of the segmented groups (based on the original tourism survey – section 3.3.3) were matched to the TSA classification as shown in Figure 3.6 below. Once in the TSA classification, the Cyprus TSAs contain a table (‘production accounts table’) which allows for the allocation of the initial expenditure into economic sectors which closely match those of the IOT classification. Price base conversions (see Box 2 in Appendix B) were performed using additional data from the Cyprus Supply and Use Tables (SUTs) (Eurostat, 2011b) and all final demand vectors were finally converted to 2007 basic prices in USD using exchange rates provided by the WIOD (Timmer et al., 2012).

(b) Water use data

The Cyprus WDD (2011) and the Cyprus Statistical Abstract (2011b) provide the most accurate information on annual water withdrawals and estimated water demand for different sectors of the economy for any given year. Following sector matching and basic aggregations, the water withdrawal and demand data provide the vector $e$ which then allows the calculation of $u^i$; in equation (3.27). Furthermore, the WDD provides information with respect to domestic water use, taken as $w_{hh}^u$ in (3.27), for households. The figure used in this study for the local population is 217 litres per capita per day (WDD, 2011). For tourists, the segmentation data on area and accommodation type and class for each segment were used to pro-rate spatially- and temporally- specific water use figures for tourism accommodation from Savvides et al. (2001). This exercise provides segment-specific $w_{hh}^u$ values taking into account the accommodation preferences and spatial distribution of each segment on the island in 2007.
Figure 3.6 Sector aggregation and matching to reconcile TSA and expenditure categories.

3.5.2 Indicators of environmental and economic impact

Whereas the indicator of choice for water use impact is litres of water per capita per day, the situation is more complex with respect to economic impact indicators. Different measures of economic yield are unlikely to provide consistent rankings for different market segments (Becken & Simmons, 2008; Dwyer et al., 2007). An analysis using a combination of different yield measures therefore provides a more complete understanding of economic impact. Recent yield studies (Dwyer & Forsyth, 2008; Lundie et al., 2007; Munday et al., 2013) propose several alternative options.

The following indicators of total (direct and indirect) economic contribution have been estimated using the EIO model in the present study:

1. Total gross value added (GVA). This is defined as the value of output less the value of intermediate consumption (OECD, 2001). GVA is a measure of contribution to GDP, since the total GVA in an economy plus taxes and minus subsidies on products is equal to the GDP (ONS, 2013). GVA per sector is given in the IOT. Value added
coefficients can be estimated and used in the same way as water use coefficients in the EIO model, as seen in Munday et al. (2013).

2. **Total employment contribution as number of full-time jobs equivalent (FTE).** This is the number of jobs in the economy directly or indirectly supported by tourist spending (Dwyer et al., 2010). This is a commonly used economic indicator in tourism research. It is chosen to complement GVA because it is a non-monetary indicator with stronger social welfare implications. Furthermore, economic sectors with a high GVA do not necessarily employ many people. The WIOD ([http://www.wiod.org/](http://www.wiod.org/)) provides estimates of employment per sector based on the Cyprus National Accounts.

3. **Total GVA per American dollar (USD) spent** – This is a more composite indicator which allows for an appreciation of the GVA generated per dollar of expenditure. It is dependent on the pattern of expenditure as opposed to the total sum of expenditure. This indicator has previously been used in Salma & Heaney (2004).

4. **Total employment contribution per million USD spent** – Similarly to the above, this allows for an estimation of the number of jobs generated for each million USD spent in the economy, and has previously been used in Salma & Heaney (2004) and Dwyer et al. (2010).

Total GVA per segment is then used to estimate the water use intensity (inverse of water productivity – see section 3.2.2) by dividing GVA by water use per segment. Matrix plots (such as Figure 3.3, p. 67) are also used to explore the synergies and trade-offs in water use and economic impacts between different segments in relation to the performance of the average tourist.

### 3.6 Summary of methodology

This chapter has established an integrated segmentation-water use intensity methodology for estimating water use and economic impact for tourism in Cyprus. A review of previous literature on market segmentation and EIO has allowed for an understanding of the assumptions that needed to be made in order to make use of available data. The following chapter will present the results generated using the approach explained in this chapter. The penultimate section of Chapter 4 (section 4.4.2) provides an appraisal of the framework which links back to many of the methodological aspects discussed in the present chapter.
Chapter 4: Segmentation and EIO results and discussion

4.1 Chapter outline

Following a detailed explanation of the overall framework and the model setup in Chapter 3, the present chapter presents and evaluates the results obtained, firstly from the market segmentation procedure (section 4.2), and, secondly, from running the EIO model for each of the segments (section 4.3). The chapter brings a selection of the findings together to allow the reader to appreciate the value of the approach. These findings are subsequently used as the basis for evaluating the effectiveness of this framework, and to discuss useful policy or management implications. The chapter focuses on how the approach developed in this part of the thesis improves on the approach in Part I, and also discusses the main limitations of the findings presented here – which essentially provide the basis for subsequent chapters.

The layout of the segmentation results follows the method presentation in section 3.3.3. Results for the main COO segments are first presented, before results from the segmentation of the UK market. Section 4.2 presents only those results of the segmentation that are directly relevant to the EIO analysis. More detailed segmentation and direct economic contribution based on the TSAs can be found in Hadjikakou et al. (in press).

The EIO model results (section 4.3) follow a similar order, with results for COO segments presented followed by UK segments. This section builds on results from Hadjikakou et al. (2013). The last section compares water use intensity for all segments and examines the potential to improve water use intensity for different segments.
4.2 Market segmentation

4.2.1 Initial COO segmentation results

Table 4.1 below shows the average characteristics for each of the main COO segments. The mean value is used for the expenditure categories and continuous variables, whereas the mode (and its percentage within the segment) is used for categorical variables. The analysis concentrates on selected findings.

The COO segmentation reveals that the average UK tourist is fairly similar to the average inbound tourist. This is unsurprising given that UK tourists made up 53.1% of inbound tourism in 2007. Nevertheless, the UK tourist is more likely than the average to be a repeat visitor, over 40 years old, travel with family or friends, and visit the island for a holiday; they also stay slightly longer and spend slightly less per day than the average tourist. Their overall spending per trip is higher than average because of their longer stay. Greeks (5.8% of total inbound tourism) appear to have the lowest mean daily expenditure out of the other main COO segments and also spend fewer days in Cyprus. They tend to visit alone for business and stay with family or friends. The average Swedish tourist spends less than the average tourist, with the majority of Swedish tourists (5% of total inbound tourism) visiting on a package summer holiday and staying in a predominantly mass tourism resort (Ayia Napa). The German tourists (5.7% of total inbound tourism) appear to have a similar average expenditure to the average tourist, even though they are likely to spend less on food/drink/tobacco and stay for less time than the average tourist. Finally, the Russian segment (6% of total inbound tourism) spends more overall compared to the average tourist. The Russians tend to visit Lemesos, which has a large Russian community, and stay longer than average. Russian, Swedish and German tourists are more likely to be visiting for the first time.
Table 4.1 Results of the COO segmentation for the five main country market segments

<table>
<thead>
<tr>
<th></th>
<th>Average tourist</th>
<th>UK</th>
<th>German</th>
<th>Greece</th>
<th>Sweden</th>
<th>Russia</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample (N)</td>
<td>30 849</td>
<td>10 841</td>
<td>2 254</td>
<td>1 982</td>
<td>1 413</td>
<td>1 635</td>
</tr>
<tr>
<td>Sample share (%)</td>
<td>100</td>
<td>35.1</td>
<td>7.3</td>
<td>6.4</td>
<td>4.6</td>
<td>5.3</td>
</tr>
<tr>
<td>Actual 2007 (%)</td>
<td>-</td>
<td>53.1</td>
<td>5.7</td>
<td>5.8</td>
<td>5.0</td>
<td>6.0</td>
</tr>
</tbody>
</table>

Mean expenditure in USD per day ($)  
- Accommodation: 34.59, 27.97, 35.61, 27.23, 18.19, 44.75  
- Food/drink/tobacc: 34.39, 40.17, 26.50, 18.71, 40.51, 36.56  
- Recreation/culture: 5.06, 4.11, 8.09, 3.80, 4.27, 10.13  
- Other: 18.86, 14.70, 15.63, 16.22, 18.48, 27.04  

Mean total expenditure in USD ($)  
- Daily expenditure: 106.09, 98.47, 100.28, 79.87, 88.73, 131.84  
- Trip expenditure: 1057.64, 1078.21, 982.76, 592.66, 799.46, 1355.35  

Continuous variables  
- Mean party size: 1.96, 2.15, 1.97, 1.35, 2.48, 1.80  
- Mean LOS (days): 9.97, 10.95, 9.80, 7.42, 9.01, 10.28

Categorical variables (mode)  
- Month:  
  - May-Oct: 62%  
  - May-Oct: 61.6%  
  - Oct-Nov: 22.5%  
  - Dec-Mar: 44.5%  
  - May-Oct: 70%  
  - Jun-Oct: 64.2%  
- Sex:  
  - Female: 54.3%  
  - Female: 56.4%  
  - Female: 50.3%  
  - Male: 51.3%  
  - Female: 58.5%  
  - Female: 62.8%  
- Age:  
  - 20-49: 64.9%  
  - 40+: 68%  
  - 30-49: 53.4%  
  - 20-49: 67%  
  - 20-49: 72%  
  - 20-49: 74.3%  
- First time (Yes/No):  
  - No: 53.5%  
  - No: 67.8%  
  - Yes: 72.9%  
  - No: 76.1%  
  - Yes: 54.4%  
  - Yes: 58.8%  
- Purpose:  
  - Leisure: 77.3%  
  - Leisure: 86.7%  
  - Leisure: 86%  
  - Business: 36.7%  
  - Leisure: 94.1%  
  - Leisure: 81.8%  
- Area:  
  - A. Napa: 19.6%  
  - Pafos: 25.4%  
  - A. Napa: 27.5%  
  - Lefkosia: 41.8%  
  - A. Napa: 53.3%  
  - Lemesos: 41.4%  
- Alone (Yes/No):  
  - No: 66.2%  
  - No: 80%  
  - No: 75.6%  
  - Yes: 73.8%  
  - No: 84.1%  
  - No: 57.7%  
- Package (Yes/No):  
  - Yes: 50.9%  
  - Yes: 51.4%  
  - Yes: 72.6%  
  - Yes: 90.7%  
  - No: 88%  
  - No: 65%  
- Accommodation:  
  - 4-star: 21.8%  
  - 4-star: 20%  
  - 4-star: 44.4%  
  - Friends: 46.8%  
  - App. A: 32.6%  
  - 3-star: 26.5%  

32 Only the segments accounting for 5% of arrivals or more are considered, the rest are in the ‘other’ category (not shown in this table).
Figure 4.1 below shows the total contribution of each of the main COO segments in terms of arrival numbers and contribution to total expenditure. The numbers in green indicate segments which have a higher than average contribution to expenditure, whilst the numbers in red indicate segments which have a lower than average contribution to expenditure. Figure 4.1 highlights the fact that the UK, Germany and ‘Other’ segment have a very close to average total expenditure. On the other hand, tourists from Greece and Sweden spend significantly less (45% and 24% respectively) than the average tourist.

![Figure 4.1 Country contributions to arrivals and to total expenditure (data source: CYSTAT, 2013).](image)

**4.2.2 Segmentation of the UK market**

In the expenditure-based segmentation of the UK market (see Table 4.2), ‘low spenders’ are defined as those who spent less than 43.10 USD per day, ‘medium spenders’ as those who spent between 43.10 and 84.87 USD per day, and ‘heavy spenders’ as those who spent more than 84.87 USD per day. All ANOVA and chi-square results for differences between segments in all variables were significant at the 0.01 level. ‘Low spenders’ mostly visit Cyprus on a package holiday during the high season and stay in mass tourism resorts (Paralimni). ‘Medium spenders’ and ‘high spenders’ share similar characteristics; these tourists predominantly visit family holiday resorts and tend to be over 40 years old. Most
‘high spenders’ travel non-package, and spend more in all categories compared to the other two segments – with the most significant difference in spending occurring in the accommodation category.

Table 4.2 (p.108) also shows the results of the cluster analysis. The best combination of clustering variables was achieved using the variables with an asterisk. The largest segment (cluster 3), which represents 49% of the UK market (26% of total inbound tourism), is composed only of package tourists and can, therefore, be considered representative of UK package tourists. The characteristics and spending patterns of cluster 3 appear to be a mix of those of the ‘low spenders’ and ‘high spenders’ segments established previously. Cluster 3 is given the name ‘budget mass tourism’ to reflect its characteristics and spending patterns.

Cluster 1 (18% of the UK market and around 10% of the total) is mostly composed of non-package tourists travelling alone. The spending patterns of this segment appear to be quite similar to those of ‘high spenders’. Cluster 1 exhibits less seasonality, and a higher percentage of repeat visitors (80%). Cluster 1 is representative of more upmarket tourism and is thus dubbed ‘luxury tourism’.

Cluster 2 (33% of the UK market and slightly over 17% of the total), has characteristics which are more similar to those of the average tourist or the average UK tourist shown in Table 1. Cluster 2 tourists are mostly repeat visitors (81%), come in season with family or friends, and are not on package deals. This cluster is labelled ‘non-package UK’ to reflect the highly average nature of this cluster.

With regards to expenditure, luxury tourists (cluster 1) spent double on ‘accommodation’ compared to average non-package UK tourists (cluster 2) and more than four times as much as budget tourists (cluster 3). They also spent considerably more in the ‘transport’ category (112% more than cluster 2 tourists and 180% more than cluster 3 tourists) and in the ‘other’ category (84% more than cluster 3 tourists and 107% more than cluster 3 tourists), which includes various kinds of shopping. By contrast, spending in the ‘food and beverage’ category is only 33% higher than in cluster 2 and only 29% higher than in cluster 3.
Table 4.2 Results of the expenditure-based segmentation and cluster analysis of the UK market segment. Variables with an asterisk (*) were used for clustering.

<table>
<thead>
<tr>
<th>EXPENDITURE-BASED UK</th>
<th>CLUSTER ANALYSIS UK</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Medium</td>
</tr>
<tr>
<td>Sample (N)</td>
<td>3594</td>
</tr>
<tr>
<td>Sample share (%)</td>
<td>33.3</td>
</tr>
<tr>
<td><strong>Mean expenditure in USD ($) per day</strong></td>
<td></td>
</tr>
<tr>
<td>Accommodation</td>
<td>9.50</td>
</tr>
<tr>
<td>Food/drink/tobacco</td>
<td>34.18</td>
</tr>
<tr>
<td>Transport</td>
<td>6.97</td>
</tr>
<tr>
<td>Recreation/culture</td>
<td>3.54</td>
</tr>
<tr>
<td>Other</td>
<td>9.24</td>
</tr>
<tr>
<td><strong>Mean total expenditure in USD ($)</strong></td>
<td></td>
</tr>
<tr>
<td>Daily expenditure</td>
<td>63.43</td>
</tr>
<tr>
<td>Total trip expenditure</td>
<td>888.02</td>
</tr>
<tr>
<td><strong>Continuous variables</strong></td>
<td></td>
</tr>
<tr>
<td>Mean party size*</td>
<td>2.21</td>
</tr>
<tr>
<td>Mean LOS (days)</td>
<td>14.00</td>
</tr>
<tr>
<td><strong>Categorical variables (mode)</strong></td>
<td></td>
</tr>
<tr>
<td>Month</td>
<td>May-Oct</td>
</tr>
<tr>
<td></td>
<td>(74.8%)</td>
</tr>
<tr>
<td>Sex</td>
<td>Female</td>
</tr>
<tr>
<td></td>
<td>(60.2%)</td>
</tr>
<tr>
<td>Age</td>
<td>40+</td>
</tr>
<tr>
<td></td>
<td>(65%)</td>
</tr>
<tr>
<td>First time (Yes/No)</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>(65.2%)</td>
</tr>
<tr>
<td>Purpose*</td>
<td>Leisure</td>
</tr>
<tr>
<td></td>
<td>(88.5%)</td>
</tr>
<tr>
<td>Area*</td>
<td>Paralimni</td>
</tr>
<tr>
<td></td>
<td>(29.1%)</td>
</tr>
<tr>
<td>Alone (Yes/No)*</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>(83.4%)</td>
</tr>
<tr>
<td>Package (Yes/No)*</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>(64.3%)</td>
</tr>
<tr>
<td>Accommodation*</td>
<td>Friends</td>
</tr>
<tr>
<td></td>
<td>(23.5%)</td>
</tr>
</tbody>
</table>
Figure 4.2 (p.109) shows the results of the expenditure-based segmentation with respect to the total UK segment contributions to arrival numbers and expenditure. Similarly to the COO segmentation results, the total UK segment contribution was grossed up using CYSTAT figures for 2007 in order to ensure that the total contribution of the segment was consistent to published figures. The relative differences in expenditure breakdown between the segments, derived by the segmentation procedure (see Table 4.2), are kept intact. Figure 4.2 highlights the heterogeneity present in the UK market segment. The expenditure-based segments ('low', 'medium' and 'high') show that nearly half (45%) of the total expenditure comes from the high-spending segment ('high'), with the other two segments contributing fairly similar amounts.

The segments emerging from the cluster analysis ('luxury', 'average non-package' and 'package') exhibit an even higher degree of heterogeneity, with the 'luxury' segment (cluster 1) contributing 31.1% of the expenditure even though it only accounts for 18.1% of arrivals. ‘Average non-package’ (cluster 2) contributes slightly more (+13%) than the average UK tourist. Lastly, the ‘package’ segment only makes a 31.8% contribution to expenditure despite comprising around half (49.1%) of UK tourists.
4.3 Economic impact and water use for each segment

4.3.1 COO segments

Direct water use

Based on area and accommodation data from the passenger survey for each tourist country market, direct water use is estimated as shown in Table 4.3 below. The range of 267 l/cap/day to 330 l/cap/day, which suggests small differences between different nationalities, is at the lower end of previous estimates (De Stefano, 2004; Gössling et al., 2012; Hof & Schmitt, 2011; Rico-Amoros et al., 2009; Tortella & Tirado, 2011). Swedish tourists are associated with the lowest per capita direct water use because a high percentage (78.1%) rent cheap apartments. Russians, on the other hand, have the highest direct per capita water use because of their tendency to stay in 4-star and 5-star hotels. None of the country markets consumes substantially more than the average resident (225 l/cap/day) as estimated by the Cyprus WDD (2011). This occurs because the majority of tourists stay in apartments or local houses all of which are associated with an average water use close to that of the average resident.

Table 4.3 Direct water use in accommodation for main COO segments
(source: author estimates based on Savvides et al., 2001).

<table>
<thead>
<tr>
<th>Accommodation</th>
<th>Germany</th>
<th>Greece</th>
<th>UK</th>
<th>Russia</th>
<th>Sweden</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>5-star (%)</td>
<td>14.9</td>
<td>11.9</td>
<td>10.9</td>
<td>26.5</td>
<td>11.6</td>
<td>14.8</td>
</tr>
<tr>
<td>4-star (%)</td>
<td>44.4</td>
<td>19</td>
<td>19.8</td>
<td>21.3</td>
<td>8.6</td>
<td>21.4</td>
</tr>
<tr>
<td>3-star (%)</td>
<td>14.6</td>
<td>9.4</td>
<td>10.6</td>
<td>22.4</td>
<td>1.7</td>
<td>14.2</td>
</tr>
<tr>
<td>Apart/House (%)</td>
<td>26.1</td>
<td>59.7</td>
<td>58.7</td>
<td>29.8</td>
<td>78.1</td>
<td>49.6</td>
</tr>
<tr>
<td>Water use (l/cap/day)</td>
<td>323</td>
<td>283</td>
<td>282</td>
<td>330</td>
<td>267</td>
<td>296</td>
</tr>
</tbody>
</table>

Even though there is evidently a difference in the direct water consumption between tourists and residents, this is considerably less than that suggested in the literature reviewed in Chapter 2, section 2.2.2.
**Total water use**

Figure 4.3 (p. 112) displays total (direct plus indirect) daily water use for the main country markets in comparison to the average tourist and the average resident (households). Figure 4.3 also shows what percentage of the water use is direct or indirect, and further divides supply-chain water use into domestic water and imported water.

Figure 4.3 shows a considerable range in daily total water use between tourists and households, with the average tourist consuming almost twice as much water (1426 l) as the average Cypriot (719 l), with some tourists groups (Russia and Other) consuming around 1750 l. It is the indirect water use that accounts for the range in total water use between segments, since the absolute differences in direct water use are relatively small (as shown in Table 4.3). The findings support the hypothesis that tourists consume substantially more water than locals when indirect water use is considered, mainly because they spend more money on meals and other purchases.

Excluding residents, direct water use accounts for 17-25% of total water use, with indirect water use accounting for 75-83%. The direct water use contribution is higher than in Part I (where it was only 7-14%) mainly because green water is omitted from the present analysis, for reasons previously detailed in Chapter 2 section 2.5.1 and Chapter 3 (section 3.4.4). It is also significantly higher than in Lundie et al. (2007) who find that direct water use amounts to around 4% of total water use. However, bearing in mind that their water use figures are excessive (18 000 l/cap/day for some segments), and also that they do not explicitly acknowledge whether they factor in green water or not (which they must), theirs is not a reliable estimate with which to perform a comparison. Cazcarro et al. (2014) do not make an attempt to compare the ratio of direct to indirect water use hence they do not provide a basis for comparison. According to the WFN, indirect water use tends to account, on average, for around 92% of total water use (Hoekstra & Mekonnen, 2012), which supports the present findings.
Blue water footprints for residents of Cyprus or the wider geographical area are available from process-based (Mekonnen & Hoekstra, 2011; Vanham, Mekonnen et al., 2013) and EIO studies (Arto et al., 2012a; Steen-Olsen et al., 2012). The estimates range from 605 l/cap/day (Mekonnen & Hoekstra, 2011) to 821 l/cap/day (Steen-Olsen et al., 2012), with the other estimates (Arto et al., 2012b; Vanham, Mekonnen et al., 2013) falling in between. The estimate for residents in this study (719 l/cap/day) falls in the middle of this range.

Local indirect water use makes up 36-41% of total water use, with imported water making up 39-42%. Slight variations exist between segments are related to differences in spending patterns. When direct water use (all of which is local) is also considered, local water use accounts for 59-61% of the total, implying that well over half the water consumed is from within Cyprus. This is close to the 66% estimate by Mekonnen & Hoekstra (2011) with respect to the ratio of local (internal) to total (local and imported) blue water use in Cyprus.
4.3.2 UK market segments

Direct water use

Table 4.4 below shows the results for direct water use in the UK sub-segments. The spread of 249 – 314 l/cap/day is again smaller than anticipated based on the literature, with UK segments all showing high percentages of tourists staying in apartments, with friends or family, or on their own property. The exception is the package segment where a higher proportion of people stay in hotels on various flight, hotel and meal deals. For this reason, this segment records the highest per capita direct water use. The ‘luxury’ and high-spending segments have surprisingly low direct water use figures, reflecting the fact that a high percentage of these tourists stay in houses or apartments. This is somewhat contrary to expectations, but there are two likely reasons for this.

Firstly, Cyprus is unique in the sense that a very high percentage (37.5% based on author estimates) of UK tourists either own a local property or have friends or family who live here permanently or who might opt to rent out their property during the high season. As previously seen in Chapter 2, section 2.2.2, apartments tend to be associated with lower water use compared to hotels as they usually lack large gardens, laundry facilities and large swimming pools. Secondly, the water demand survey (Savvides et al., 2001) only distinguishes between two different classes of apartment/house which means that villas and luxury apartments are considered to have an average annual water use of 333 l/cap/day which is that of an “A-class” hotel apartment. For these reasons, direct water use in accommodation in Cyprus appears to be low in general (see Appendix C for island-wide figures).
Table 4.4 Direct water use in accommodation for all UK sub-segments
(source: author estimates based on Savvides et al., 2001).

<table>
<thead>
<tr>
<th>Accommodation</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
<th>Luxury</th>
<th>Non-Package</th>
<th>Package</th>
</tr>
</thead>
<tbody>
<tr>
<td>5-star (%)</td>
<td>10.4</td>
<td>13.2</td>
<td>9.2</td>
<td>5.2</td>
<td>4.4</td>
<td>17.3</td>
</tr>
<tr>
<td>4-star (%)</td>
<td>8.8</td>
<td>25</td>
<td>25.7</td>
<td>11.7</td>
<td>6.9</td>
<td>31.3</td>
</tr>
<tr>
<td>3-star (%)</td>
<td>1.9</td>
<td>8.5</td>
<td>21.6</td>
<td>8.7</td>
<td>5.2</td>
<td>14.9</td>
</tr>
<tr>
<td>Apart/House (%)</td>
<td>78.9</td>
<td>53.3</td>
<td>43.5</td>
<td>74.4</td>
<td>83.5</td>
<td>36.5</td>
</tr>
<tr>
<td>Water use (l/cap/day)</td>
<td>264</td>
<td>293</td>
<td>288</td>
<td>256</td>
<td>247</td>
<td>314</td>
</tr>
</tbody>
</table>

**Total water use**

Figure 4.4 below shows that, within the UK tourism segment, there is considerably more range in daily per capita water use (892-2142 l/cap/day) than between the different country segments. This highlights the argument made earlier that considerable heterogeneity is lost when only considering different country segments. Again, it appears that those segments that spend the most money (‘luxury’ and ‘high’) are the ones associated with the highest total water use, with both of these segments consuming around three times as much water as an average Cypriot resident.

Nevertheless, the percentages of direct and indirect (local or imported) water use in Figure 4.4 show considerably more variation than in Figure 4.3 (p. 112). A comparison between the two extremes within the UK market demonstrates this observation well. In the ‘luxury’ segment, 87% of total water use comes from the supply chain (43% of which is local and 45% of which is imported), with only 13% of the total water use being directly used on-site. In contrast, in the ‘package’ segment, only 70% of total water use comes from the supply chain (34% of which is local and 36% of which is imported), with 31% of the total water use taking place on-site. Therefore, even though on-site water use in absolute terms does not differ widely between the two segments, overall water use is around double in the ‘high-spending’ segment, owing largely to higher spending to buy food and other goods that require significant inputs of water in their production.
The results presented thus far do not yet consider economic impact (which is discussed later in this chapter), but still produce some interesting implications worth discussing briefly. For the more budget end of the market, it appears that on-site water use can represent up to 35% of the total water use associated with a tourist’s consumption activities. This implies that ensuring water-efficient facilities and practices (discussed in Chapter 2, section 2.4.1) becomes an important priority for budget hotels and other accommodation, as it should be a cost-efficient way to achieve higher water productivity for the lower-spending tourist segments. This contradicts the results in Chapter 2 (section 2.4). The reasons for this are discussed in section 4.4.2.

With regards to the higher-spending end of the market, indirect water use typically accounts for up to 85% of total water use, emphasising the need to consider where agricultural products used in hotels and restaurants originate from and how much water was required to produce them. Even though this issue is important for all types of tourist, it is particularly so for the higher-spending segments. According to estimates for all segments (COO and UK

---

**Figure 4.4 Daily direct and indirect water for different segments of the UK market.**
sub-segments), around 92% of local indirect water use is food-related while 80% of imported indirect water use is food-related.

4.3.3 All segments – water productivity, water use intensity and trade-offs

Introducing economic impact indicators (see Table 4.5, p. 120) significantly enhances the analysis, providing more complete sustainable yield indicators. The results presented in this sub-section consider trade-offs between economic impact and water use for all segments. Numerous comparisons are possible depending on priorities at the destination, with only a selection considered here for reasons of brevity.

Figure 4.5 (below) considers water use intensity (equivalent to the inverse of water productivity). According to the overall results, an average tourist uses 10.6 litres for every USD of total value added generated. This is significantly less than the average Cypriot resident that requires 17 litres in order to generate one USD of value added. This appears to suggest that, even though tourists use significantly more water than local residents, they do contribute considerably more to the economy. It therefore becomes more important to explore the range of values for different tourist types. Once again, taking two extremes as an example, the ‘package’ segment (red bar in Figure 4.5) requires 12.1 litres (14% more than the average tourist) for every USD of value added generated whereas the ‘luxury’ segment (green bar in Figure 4.5) requires only 9.7 litres (8% less than the average tourist) for every USD of value added.

It is evident that the higher-spending (“luxury” and “high”) tourist segments tend to compensate for their higher water use by generating more value added for each litre of water they use (or, inversely, they use less water to produce 1 USD of value added). Greece, Russia, and other nationalities (“other”) also require less water than average (10.6 l per USD value added) for every USD of value added generated. Russia and the “other” segments both have high value added contributions (see Table 4.5, p. 120). Greece on the other hand, is a thought-provoking result, as this country segment has a low per capita expenditure and value added (see Table 4.5). Understanding this result requires exploring some additional indicators and comparing these against the original expenditure results (which indicate the sectors of the economy receiving the initial spending).
Figure 4.5 Water use intensity (inverse of water productivity) for all tourist segments and residents.

Figure 4.6 (p. 119) is a matrix plot, following previous practice in the literature (Dwyer et al., 2006; Dwyer et al., 2007; Dwyer et al., 2010; Lundie et al., 2007) to reveal trade-offs between different indicators. The use of a more composite economic indicator, value added per USD of initial expenditure, essentially considers the influence of a segment’s spending pattern on the economy (without being affected by the magnitude of the total expenditure). The segments in the bottom-right quadrant (Greece, Germany and “medium”) are the ones which perform best in both indicators as they have a lower than average water consumption and higher than average value added per USD. In contrast, the segments in the top-right quadrant (“high” and Russia) perform worst across both indicators, with higher than average water use and lower than average value added per USD.

The good performance of Greece, Germany and the “medium” segment can be explained by their higher proportion of spending in sectors with high value added coefficients and low water use coefficients (see Table 4.6, p. 121). The higher than average proportion of spending on accommodation, transport and other expenditure categories is a characteristic shared by
all three segments. The “medium” segment does have lower spending on accommodation which gives it a lower ratio of value added to USD spent compared to the other segments. An analysis of the I-O sectors receiving the bulk of the initial or first-round expenditure on accommodation, transport and other expenditure categories reveals that these are all sectors with high value added in relation to output such as retail trade, telecommunications, hotels and restaurants, real estate and maintenance of motor vehicles. These are also incidentally sectors with low to moderate water consumption coefficients (see Table 4.6, p. 121) thus allowing the segments to remain below the average water use line.

Figure 4.7 below shows the relation between water use and another composite indicator (number of jobs supported directly and indirectly for every million USD spent). The logic is similar to Figure 4.6 with the only difference being that attention now shifts to employment as opposed to value added. Greece and Germany appear to perform well again but they are also joined by the UK and the “low” spending segment. The presence of Greece and Germany coupled with the absence of the “medium” spending segment (which was also featured in the bottom-right quadrant in Figure 4.6) suggest that the spending on accommodation (which is spread between the retail, hotel and restaurant, and agricultural sectors) contributes significantly to employment. The UK and “low” segments spend a higher percentage of their overall expenditure on food/drinks and tobacco, which are also associated with high employment contribution. Their water use remains low mainly because their overall spending is lower than average.
Figure 4.6 Value added per USD of tourist expenditure (in basic prices) and water use (l/cap/day) in relation to the corresponding values of the average inbound tourist for 2007.

Figure 4.7 Total (direct and indirect) employment (jobs FTE) generated per one million USD of expenditure and water use (l/cap/day) compared to the average inbound tourist for 2007.
Table 4.5 Economic impact indicators for all tourist segments estimated using the I-O model. All prices are in basic prices for 2007 converted into USD.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Daily expenditure ($)</th>
<th>Total Value Added ($)</th>
<th>Employment (per 1000 tourists)</th>
<th>Final demand ($)</th>
<th>Total Output ($)</th>
<th>VA per USD spent</th>
<th>Employment per USD million</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Tourist</td>
<td>106.09</td>
<td>120.27</td>
<td>2.56</td>
<td>146.93</td>
<td>201.92</td>
<td>1.13</td>
<td>24.13</td>
</tr>
<tr>
<td>Germany</td>
<td>100.28</td>
<td>118.26</td>
<td>2.58</td>
<td>144.14</td>
<td>198.27</td>
<td>1.18</td>
<td>25.73</td>
</tr>
<tr>
<td>Greece</td>
<td>79.87</td>
<td>96.94</td>
<td>2.13</td>
<td>117.85</td>
<td>162.36</td>
<td>1.21</td>
<td>26.67</td>
</tr>
<tr>
<td>UK</td>
<td>98.47</td>
<td>109.54</td>
<td>2.30</td>
<td>133.94</td>
<td>183.81</td>
<td>1.11</td>
<td>23.36</td>
</tr>
<tr>
<td>Russia</td>
<td>131.84</td>
<td>148.34</td>
<td>3.17</td>
<td>181.33</td>
<td>249.13</td>
<td>1.13</td>
<td>24.04</td>
</tr>
<tr>
<td>Sweden</td>
<td>88.73</td>
<td>95.87</td>
<td>1.97</td>
<td>117.25</td>
<td>160.63</td>
<td>1.08</td>
<td>22.20</td>
</tr>
<tr>
<td>Other</td>
<td>130.35</td>
<td>152.35</td>
<td>3.33</td>
<td>185.96</td>
<td>256.26</td>
<td>1.17</td>
<td>25.55</td>
</tr>
<tr>
<td>Low</td>
<td>63.43</td>
<td>70.62</td>
<td>1.46</td>
<td>86.12</td>
<td>117.92</td>
<td>1.11</td>
<td>23.02</td>
</tr>
<tr>
<td>Medium</td>
<td>78.59</td>
<td>89.43</td>
<td>1.87</td>
<td>108.93</td>
<td>149.38</td>
<td>1.14</td>
<td>23.79</td>
</tr>
<tr>
<td>High</td>
<td>167.56</td>
<td>185.36</td>
<td>3.92</td>
<td>227.04</td>
<td>311.85</td>
<td>1.11</td>
<td>23.39</td>
</tr>
<tr>
<td>Luxury</td>
<td>157.10</td>
<td>178.48</td>
<td>3.84</td>
<td>218.33</td>
<td>300.34</td>
<td>1.14</td>
<td>24.44</td>
</tr>
<tr>
<td>Non-package</td>
<td>90.91</td>
<td>99.32</td>
<td>2.08</td>
<td>121.77</td>
<td>167.19</td>
<td>1.09</td>
<td>22.88</td>
</tr>
<tr>
<td>Package</td>
<td>71.10</td>
<td>79.25</td>
<td>1.64</td>
<td>96.70</td>
<td>132.48</td>
<td>1.11</td>
<td>23.07</td>
</tr>
</tbody>
</table>
Table 4.6 Direct and total water use and economic contribution coefficients estimated using sectoral output and the Leontief inverse matrix.

<table>
<thead>
<tr>
<th>SECTOR</th>
<th>Direct water use (\text{m}^3/\text{USD})</th>
<th>Total water use (\text{m}^3/\text{USD})</th>
<th>Direct VA (\text{VA}/\text{Output})</th>
<th>Total VA (\text{VA}/\text{Output})</th>
<th>Direct Employment (#) of jobs/1M Output</th>
<th>Total Employment (#) of jobs/1M Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Agriculture, Hunting, Forestry and Fishing</td>
<td>0.1526</td>
<td>0.1671</td>
<td>0.432</td>
<td>0.688</td>
<td>18.574</td>
<td>23.942</td>
</tr>
<tr>
<td>2 Mining and Quarrying</td>
<td>0.0108</td>
<td>0.0110</td>
<td>0.563</td>
<td>0.775</td>
<td>5.739</td>
<td>8.728</td>
</tr>
<tr>
<td>3 Food, Beverages and Tobacco</td>
<td>0.0015</td>
<td>0.0196</td>
<td>0.275</td>
<td>0.663</td>
<td>7.316</td>
<td>16.219</td>
</tr>
<tr>
<td>4 Textiles and Textile Products</td>
<td>0.0002</td>
<td>0.0024</td>
<td>0.377</td>
<td>0.665</td>
<td>22.091</td>
<td>29.150</td>
</tr>
<tr>
<td>5 Leather, Leather and Footwear</td>
<td>0.0002</td>
<td>0.0011</td>
<td>0.485</td>
<td>0.757</td>
<td>14.399</td>
<td>19.935</td>
</tr>
<tr>
<td>6 Wood and Products of Wood and Cork</td>
<td>0.0002</td>
<td>0.0011</td>
<td>0.372</td>
<td>0.659</td>
<td>11.602</td>
<td>18.645</td>
</tr>
<tr>
<td>7 Pulp, Paper, Paper, Printing and Publishing</td>
<td>0.0002</td>
<td>0.0004</td>
<td>0.402</td>
<td>0.689</td>
<td>9.635</td>
<td>14.950</td>
</tr>
<tr>
<td>8 Chemicals and Chemical Products</td>
<td>0.0006</td>
<td>0.0009</td>
<td>0.356</td>
<td>0.586</td>
<td>7.943</td>
<td>12.304</td>
</tr>
<tr>
<td>9 Rubber and Plastics</td>
<td>0.0002</td>
<td>0.0004</td>
<td>0.372</td>
<td>0.567</td>
<td>10.626</td>
<td>14.269</td>
</tr>
<tr>
<td>10 Other Non-Metallic Mineral</td>
<td>0.0037</td>
<td>0.0055</td>
<td>0.307</td>
<td>0.673</td>
<td>4.821</td>
<td>10.363</td>
</tr>
<tr>
<td>11 Basic Metals and Fabricated Metal</td>
<td>0.0002</td>
<td>0.0004</td>
<td>0.337</td>
<td>0.436</td>
<td>8.635</td>
<td>10.203</td>
</tr>
<tr>
<td>12 Machin ery, Nec</td>
<td>0.0001</td>
<td>0.0002</td>
<td>0.357</td>
<td>0.517</td>
<td>9.814</td>
<td>12.677</td>
</tr>
<tr>
<td>13 Electrical and Optical Equipment</td>
<td>0.0001</td>
<td>0.0003</td>
<td>0.223</td>
<td>0.447</td>
<td>5.280</td>
<td>9.495</td>
</tr>
<tr>
<td>14 Transport Equipment</td>
<td>0.0002</td>
<td>0.0003</td>
<td>0.391</td>
<td>0.623</td>
<td>10.064</td>
<td>14.278</td>
</tr>
<tr>
<td>15 Manufacturing, Nec; Recycling</td>
<td>0.0002</td>
<td>0.0007</td>
<td>0.368</td>
<td>0.627</td>
<td>12.921</td>
<td>18.855</td>
</tr>
<tr>
<td>16 Electricity, Gas and Water Supply</td>
<td>0.0001</td>
<td>0.0002</td>
<td>0.428</td>
<td>0.446</td>
<td>1.800</td>
<td>1.984</td>
</tr>
<tr>
<td>17 Construction</td>
<td>0.0000</td>
<td>0.0008</td>
<td>0.459</td>
<td>0.717</td>
<td>10.033</td>
<td>14.522</td>
</tr>
<tr>
<td>18 Sale, Maintenance and Repair of Motor</td>
<td>0.0000</td>
<td>0.0001</td>
<td>0.563</td>
<td>0.864</td>
<td>15.981</td>
<td>18.425</td>
</tr>
<tr>
<td>19 Wholesale Trade and Commission Trade</td>
<td>0.0000</td>
<td>0.0001</td>
<td>0.607</td>
<td>0.802</td>
<td>12.377</td>
<td>16.036</td>
</tr>
<tr>
<td>20 Retail Trade</td>
<td>0.0000</td>
<td>0.0001</td>
<td>0.635</td>
<td>0.886</td>
<td>22.018</td>
<td>24.870</td>
</tr>
<tr>
<td>21 Hotels and Restaurants</td>
<td>0.0000</td>
<td>0.0042</td>
<td>0.522</td>
<td>0.792</td>
<td>15.292</td>
<td>20.673</td>
</tr>
<tr>
<td>22 Inland Transport</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.524</td>
<td>0.694</td>
<td>19.452</td>
<td>22.255</td>
</tr>
<tr>
<td>23 Water Transport</td>
<td>0.0000</td>
<td>0.0001</td>
<td>0.477</td>
<td>0.538</td>
<td>13.607</td>
<td>14.629</td>
</tr>
<tr>
<td>24 Air Transport</td>
<td>0.0000</td>
<td>0.0003</td>
<td>0.249</td>
<td>0.471</td>
<td>3.421</td>
<td>7.455</td>
</tr>
<tr>
<td>25 Other Supporting and Auxiliary Transport</td>
<td>0.0000</td>
<td>0.0002</td>
<td>0.597</td>
<td>0.766</td>
<td>9.556</td>
<td>12.147</td>
</tr>
<tr>
<td>26 Post and Telecommunications</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.629</td>
<td>0.864</td>
<td>5.773</td>
<td>8.363</td>
</tr>
<tr>
<td>27 Financial Intermediation</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.764</td>
<td>0.933</td>
<td>8.970</td>
<td>11.521</td>
</tr>
<tr>
<td>28 Real Estate Activities</td>
<td>0.0000</td>
<td>0.0002</td>
<td>0.732</td>
<td>0.917</td>
<td>1.067</td>
<td>4.422</td>
</tr>
<tr>
<td>29 Renting of M&amp;Eq and Other Business</td>
<td>0.0000</td>
<td>0.0001</td>
<td>0.669</td>
<td>0.890</td>
<td>12.317</td>
<td>15.773</td>
</tr>
<tr>
<td>30 Public Admin and Defence; Compulsory Social</td>
<td>0.0000</td>
<td>0.0001</td>
<td>0.693</td>
<td>0.802</td>
<td>12.861</td>
<td>14.601</td>
</tr>
<tr>
<td>31 Education</td>
<td>0.0000</td>
<td>0.0007</td>
<td>0.874</td>
<td>0.942</td>
<td>17.642</td>
<td>18.663</td>
</tr>
<tr>
<td>32 Health and Social Work</td>
<td>0.0000</td>
<td>0.0002</td>
<td>0.665</td>
<td>0.767</td>
<td>14.355</td>
<td>16.350</td>
</tr>
<tr>
<td>33 Other Community, Social and Personal</td>
<td>0.0000</td>
<td>0.0002</td>
<td>0.663</td>
<td>0.879</td>
<td>28.121</td>
<td>31.456</td>
</tr>
</tbody>
</table>
4.4 Discussion and appraisal of the framework

4.4.1 Segmentation

Contribution

In a similar way to Pratt (2012), this study heeds the call made earlier by Dwyer et al. (2007) for more studies focusing on estimating yield for different destinations and different market segments, using a mature destination with a dominant country market. The segmentation procedure demonstrated that clustering techniques are possible using existing passenger survey datasets, and that this should be pursued by the CTO and other Destination Marketing Organizations (DMOs) in the future in order to enhance the traditional COO approach. Country markets (COO segments) all appear to have their own unique characteristics, both in terms of their spending amounts and patterns and in terms of their demographic and trip-related profile. This is consistent with previous findings (Becken & Gnoth, 2004; Kozak, 2002; Reid & Reid, 1997). Large country markets are also likely to have very high intra-segment heterogeneity, as is the case with the UK market in the present study. This framework is thus particularly pertinent to other mature destinations with large country markets.

The cluster analysis performed in this study is only one example of the ways in which available variables may be employed to distinguish different attributes. Cross-tabulation of variables may be employed to produce any number of desired niche or specialised markets following the example of Tourism Research Australia (Dwyer et al., 2007; Salma & Heaney, 2004; Salma et al., 2004). Further clustering of tourists within specific areas of Cyprus could also be used to study specific resorts or times of the year (since all of this information is contained in the dataset).

Performing segmentation as part of an integrated segmentation-yield framework has several advantages compared to previous work:

1. The outputs of the segmentation procedure will be at the right level of detail and in the necessary classification to perform yield estimates. If using existing segments from previous studies with different objectives, this will rarely be possible.
2. It allows an in-depth appreciation of the differences between diverse tourist groups and a better understanding of the reasons behind dissimilarities in economic impact and/or water use. This kind of knowledge can subsequently provide guidance on how to improve the performance of different segments (Becken & Simmons, 2008; Lundie et al., 2007).

3. The details with respect to type of accommodation, area, and time of year of the visits allow an accurate determination of direct water use using secondary data from Savvides et al. (2001). Direct water use data are often available and provided they cover an adequate geographic area, the method described in this part of the thesis allows spatially and temporally weighted direct water use estimates for any given market segment.

4. In this framework, segmentation research which does not typically trace the impacts of tourism spending (Pratt, 2012) is combined with more elaborate yield measures to compare the economic contribution of groups established on the basis of their total expenditure. This also allows for an assessment of the expenditure variables which contribute most to different measures of economic impact.

Uncertainty and limitations

Uncertainty in the segmentation procedure arises mainly from the statistical approach as well as the underlying dataset. An important source of uncertainty in the expenditure dataset is the commonly cited problem of recall bias (Legohérel, 1998; Mok & Iverson, 2000; Wilton & Nickerson, 2006). In exit surveys, tourists are usually asked to recall their expenses over a period of many days (Frechtling, 2006). Despite a very large sample in this case, there are many missing variables, mostly in the expenditure categories, as a result of many tourists only reporting the types of expenditure they could recall along with estimates of their total expenditure. This means that the responses are biased towards tourists who provided a detailed expenditure breakdown. In order to mitigate this problem, total expenditure was grossed-up to represent the full visitor population, as previously explained in Collins et al. (2012). This essentially means correcting the total expenditure with official statistics for 2007 (CYSTAT, 2008) whilst maintaining the unique spending patterns of each segment from the tourism survey data. The error related to bias is very low with respect to
the other tourist characteristics (excluding expenditure categories) mainly because of the sample size.

Additional collection of data on tourist expenditure at a more detailed product level is certainly required. The 2007 passenger survey dataset is now a bit dated but was chosen as this corresponds to the latest edition of TSAs available for Cyprus. Tourist behaviour is dynamic and the data and results for 2007 should only be interpreted as a snapshot of the situation at the time. Lastly, the simple 5-sector aggregation of expenditure (as a result of the original classification mismatch between the TSA and the passenger survey dataset - see section 3.5.1) highlights the need for improved data collection, something which would also significantly enhance yield estimates.

4.4.2 Water use intensity estimates - contribution and implications

Direct water use

The results confirm previous findings from the literature (Cazcarro et al., 2014; Gössling et al., 2012; Lundie et al., 2007; Yang et al., 2011) and from Part II which show that indirect water use dominates over direct water use for all kinds of tourism consumption. However, direct water use still contributes an important percentage (up to 35% for package tourists) to overall water use. This is contrary to the findings in Part I and occurs because the present method only considers blue water. As stressed in section 4.4.1, an important contribution of the present framework is the option to obtain spatially and temporally weighted direct water use estimate for each segment. Given the fact that direct water use estimates in Cyprus tend to be at the lower end of the range estimated in the literature, the absolute contribution of direct water use would be expected to be even higher in other destinations, especially for the lower end of the market. For this reason, solutions proposed in the literature (Becken et al., 2013; Gössling et al., 2012; Smith et al., 2009; UNEP-UNWTO, 2012), briefly summarised in Chapter 2 (section 2.4.1) may provide the easiest and quickest way to increasing water productivity in segments where the supply chain water use is already low.

Indirect and total water use and origin of water

With respect to the import/export balance, the results reveal a lower percentage of imported water compared to the water footprint estimates in Part II and in secondary sources
(Hoekstra & Mekonnen, 2012). As before, the reason for this is the exclusion of green water, which accounts for the bulk of embedded water in grain imports into Mediterranean countries (Aldaya et al., 2010; Vanham, Mekonnen et al., 2013). The blue water imports are lower because Cyprus tends to produce its own fruit and vegetables, and most of its meat domestically, both of which require substantial amounts of irrigation and service water respectively (Zoumides et al., 2013). Nonetheless, the results presented in this chapter still demonstrate that imports of agricultural products allow Cyprus to ‘save’ more than half of the water that would have been needed if all products which cater for tourism had been produced locally. Importing even more water-intensive crops like fruit and vegetables in lieu of producing them at home may increasingly take place as water becomes scarcer on the island.

Summing up water use across all inbound tourism segments reveals that, according to the model, tourists directly and indirectly consumed around 20.65 MCMs (million m$^3$) or 9.9% of the total water use (208.6 MCMs) in Cyprus in 2007. Direct water use by tourism was around 4% (WDD, 2011), meaning that the supply chain used up around 6% of the country’s annual water resources to satisfy approximately 2.5 million tourists who stayed for around 10 days each. When imported water is also considered, the total is 34.35 MCMs. Following the example of Cazcarro et al. (2014), based on the average household water use in Cyprus of 217 l/cap/day (2011), total tourist (local and imported) water use corresponds to the annual household direct water use for 434,000 people. This is over half the resident population of Cyprus, which highlights the large volume of water used to cater for tourism in an island tourist economy. It also highlights that there is a global dimension to tourism-related water consumption (Cazcarro et al., 2014) because of the imported food component. Moreover, it shows that some key solutions for minimising tourist water use actually lie outside the tourism domain (for example, increasing water use efficiency in agriculture).

---

34 This entails multiplying estimates for the average tourist by the number of tourists and tourist days over the whole year.

35 Hochstrat et al. (2009) estimated direct water use by tourism in Cyprus to be equal to 39,400 residents. This is certainly an underestimation because the authors used lower tourist arrival numbers and shorter lengths of stay. Tourism direct water use for 2007 should equal household water use for around 90,000 people.
Water productivity and sustainable yield

The present framework potentially allows for estimating and visualising the performance of different types of tourism across numerous economic and environmental indicators. Research shows that different indicators of economic contribution often result in a different ranking of the segments (Dwyer & Forsyth, 2008; Dwyer et al., 2010; Lundie et al., 2007; Pratt, 2012). For this reason, the results presented here should only be considered as a demonstration of the model capabilities. Further indicators of economic yield as well as other environmental indicators (carbon emissions, waste, land use) may be investigated using a similar model setup to reveal trade-offs and synergies between policy objectives in any destination. The emphasis here was on water use, value added and employment, as these are important variables in the Cyprus context. Some interesting findings are discussed in this sub-section.

A choice to import more agricultural products in order to save local water is not likely to have a substantial impact on value added as the contribution of the agricultural sector to GDP is low, even when accounting for multiplier effects (Table 4.6, p.121). Nevertheless, the agricultural sector does have a relatively high contribution to employment with respect to the number of jobs it sustains directly and indirectly (see Table 4.6). Employment is an indicator which also encompasses social implications in addition to economic impact, so any potential negative effect on employment should be avoided. Investigating such trade-offs in detail (for specific goods and services) requires a disaggregated EIO model, the need for which is further discussed below.

Adopting the perspective of Lundie et al. (Lundie et al., 2007) and Becken & Simmons (2008), the aim of tourism management initiatives should be to improve sustainable yield (in this case this is equivalent to water use intensity) from all segments. In the context of the present study, this could be interpreted as exploring ways to push segments towards the ‘coveted’ bottom-right quadrant in Figure 4.6 and Figure 4.7. In principle, this is an attractive concept because the matrix graph may allow a prioritisation of management efforts to achieve a higher yield. Segments in the bottom-right quadrant already have lower than average water use so for some (for example “package”, “low” and Sweden) it may simply be a case of increasing expenditure by the right amount (as too much may then increase water use too
much) to ‘push’ them into the bottom-right quadrant. For the ones in the top-right quadrant (especially those close to the average line) it may simply be a case of higher water efficiency in accommodation or encouraging behavioural changes and best practices.

However, translating theory into practice is not straightforward and requires a much better understanding of how tourism money is filtered into the economy. Techniques such as structural path analysis (Defourny & Thorbecke, 1984; Miller & Blair, 2009; Wood & Lenzen, 2003) allow for an ‘opening up’ of the Leontief inverse matrix in order to examine and rank important paths of economic and environmental impact in an economy. This was outside the scope of the present study but would be a necessary addition to any research aiming to examine the implications of increased expenditure or imports related to different tourism segments.

Segments with an otherwise low per capita contribution to value added and employment (such as Germany or Greece), have a low water use impact as well as a high contribution to employment and value added with respect to their expenditure. Boosting expenditure and pursuing more arrivals from these market segments (or other segments with similar characteristics) may represent a sustainable strategy and provide a preferable option to boosting expenditure elsewhere through diversification and attempts to target the higher end of the market. These findings provide a previously unavailable quantification which appears to support the arguments made in previous studies with respect to the environmental and economic advantages of maintaining a healthy mass tourism product in Cyprus (Ayres, 2000; Farsari et al., 2007; Ioannides & Holcomb, 2003; Sharpley, 2003). Nevertheless, any such conclusion should only be made with caution at the present stage because of limitations and sources of uncertainty in the EIO model.

Limitations and uncertainty – improving estimates

A number of sources of uncertainty originate from the use of the EIO model. Some are specific to this study and others are inherent limitations of the I-O model that need to be acknowledged in any EIO study. The general assumptions are discussed first, concentrating on three key concerns: linearity, sector aggregation, and the ‘domestic technology assumption’. Exhaustive reviews of assumptions and limitations in I-O modelling are
available in Eurostat (Eurostat, 2008) and Miller and Blair (Miller & Blair, 2009). The subsection then considers issues of specific importance to the present framework.

Firstly, on the issue of linearity, I-O analysis does not take into account economies of scale in production as it assumes a fixed relationship between sector output and its inputs. As the representation of flows is linear, a doubling in output requires a doubling of inputs, thus ignoring dynamic effects such as behavioural change and response to changes in price (Murray et al., 2010). A further assumption is that each sector uses all inputs in fixed proportions (Miller & Blair, 2009). This means that each commodity is assumed to have a homogeneous production process. The same linear proportionality applies to estimating environmental impacts or pollution through EIO analysis. Even though the underlying environmental processes are often non-linear, the modeller is forced to assume a linear relationship between economic output and environmental impact (Hendrickson, 1998). Figure 4.8 below demonstrates how the linearity problem impacts the present research as there are indeed strong linear correlations between expenditure and water use (Figure 4.8a) and value added and water use (Figure 4.8b).

Secondly, a recurrent concern emerging from the results is the need for more disaggregated economic and environmental impact estimates. According to Joshi (1999), national IOTs have sectors which tend to be broad aggregates and include many products. This does not allow for investigating the effects of changes in demand for certain products if these are lumped into a broader category in the model. The negative impacts arising from sector aggregation have been stressed in previous tourism research (Briassoulis, 1991; Jones et al., 2003; Lundie et al., 2007).

The approach developed in this part of the thesis requires further refinement in order to provide reliable management advice and policy guidelines. It is necessary to use more disaggregated data (IOTs, tourism expenditure and water use) in order to explore the role of different dietary preferences. As indirect water use is clearly associated with food consumption, it is imperative that the analysis is carried out at a level of disaggregation that allows for capturing the impact of different food choices. Only then would the approach be capable of producing more specific recommendations for hotel buffets or restaurant menus.
in order to maximise water productivity for different kinds of tourist consumption. The issue of EIO disaggregation is explored in detail in Part IV of the thesis.

The third inherent assumption of the present framework is the ‘domestic technology assumption’ (Druckman et al., 2008, 2009; Tukker, de Koning, Wood, Moll et al., 2013). According to this simplifying assumption, the production technology of imported goods and services is identical to the local economy (Wiedmann, 2009). According to Tukker et al. (2013)

---

**Figure 4.8 Linear correlation between expenditure and water use.**
this supposition can lead to erroneous results, since impacts of production abroad may be different from the impacts of production of the same products produced domestically. This assumption is related to the water savings perspective (Renault, 2002), previously discussed in Chapter 2, section 2.3.2.

The assumption that the volume of embedded water in imports is the same as that of domestic products was consciously made in the present study, firstly because of a lack of water coefficients for other countries that trade with Cyprus (the WIOD does offer some but these are incomplete) and, secondly, because it allows an appreciation of the water that would have been required in Cyprus had the goods not been imported, in addition to the potential domestic savings of importing more in the future. There is certainly a strong case to be made for reducing the impacts of imports coming from water scarce countries (Lenzen, Moran, Bhaduri et al., 2013; Ridoutt & Pfister, 2010a) but this was outside the scope of the present analysis.

Quantitative assessment of the uncertainty in I-O models involves identifying uncertainty in the source data and its effect on the final result. Attempts to perform uncertainty analysis in I-O models have employed Monte Carlo techniques (Lenzen, Wood, & Wiedmann, 2010b). These tend to reveal that, despite errors from over- or under-reporting from the multitude of different data sources normally used to construct IOTs, these errors are random and result in a reduced final error once all the sources are aggregated (Murray et al., 2010). Although the error of a standard I-O calculation will vary depending on the question being investigated, Lenzen (2000) has estimated that errors in organisation studies lie in the 10-20% range whereas economy-wide studies have potentially lower error margins. The current study is first and foremost concerned with comparisons between tourist segments, therefore the assumption that uncertainties in relative differences must result in a reduced final error should be valid. Furthermore, the water consumption results obtained for residents of Cyprus compare favourably to previous work (Arto et al. 2012a; Mekonnen & Hoekstra, 2011; Steen-Olsen et al., 2012; Vanham & Bidoglio, 2013), which suggests that the water use multipliers and the I-O structure are performing reasonably well.

With respect to study-specific assumptions and limitations, there are two important issues that must be discussed in addition to the aforementioned general considerations. The first
relates to the data used. In the absence of an official Cyprus IOT, the IOT used in the study is taken from the WIOD. Numerous assumptions have been made in order to derive the IOT based on trade data, National Account data and assuming a similar I-O structure to Greece (see Appendix B). The present framework has employed the WIOD table following a systematic comparison with other options (see Appendix B) and it was found that the WIOD table complies best with the Cyprus National Accounts and Eurostat SUTs. Nevertheless, this does not imply that the internal structure of the IOT is accurate, but rather that it was not possible to test as there are no previous IOTs for Cyprus. The other main data issue is the absence of detailed direct water use data for sectors 17-33 of the IOT (See Table 4.6, p. 121). Direct water use in these sectors is unlikely to be significant compared to water use in agricultural and industrial sectors (1-16). In fact, the Cyprus WDD (2011) appears to consider these water uses negligible by considering them as part of domestic water use (i.e. as part of the 217 l/cap/day estimate). Obtaining possible estimates from other sources for these sectors could potentially create a double-counting issue and was hence not pursued.

The final significant assumption in the present framework relates to the reclassification of the initial tourism expenditure into the I-O classification (section 3.4.5). Briassoulis (1991) refers to this issue as the ‘assumed sectoral distribution of tourist spending’ (Briassoulis, 1991). Deciding which sectors are likely to receive the initial injection of expenditure as given in the tourism survey or the TSAs involves a significant degree of subjectivity (C. Jones et al., 2003; Jones & Munday, 2004, 2007). This is a similar problem to the allocation of CO₂ emissions to high level functional uses discussed in Druckman & Jackson (2009) in the sense that there may often exist several alternative (and equally sensible) ways to distribute the expenditure from the TSA classification to sectors in the IOT. This issue is re-examined in section 5.4 in Chapter 5 which investigates how final demand vectors can be generated on the basis of tourism expenditure.
4.4.3 Concluding remarks

Minimising the water use impact of tourism is certainly desirable, but in a competitive industry such as tourism this will never realistically be pursued at the expense of positive economic impact. The use of EIO ensures that both environmental and economic impacts throughout the supply chain of tourism are captured, which allows for an appreciation of trade-offs and synergies using several indicators. The framework developed here also integrates a segmentation procedure which allows for comparisons between tourist market segments, as well for accurate direct water use estimates for any sub-segment of the sample. No previous study has performed such in-depth analysis of water use in relation to economic impact at a tourism destination.

Nevertheless, some important limitations considered in the previous section have considerable consequences with respect to the quality and reliability of the model outputs. In an attempt to improve the first method in Part II of the thesis by adding economic impact estimates, the detail related to diet and food choice was lost because the IOT only has a single agricultural sector. Therefore, even though the framework still clearly underlines the role of agricultural products in overall water use, it cannot, in its present form, differentiate between different diets. It essentially assumes an average diet composed of all foods available in the economy. Disaggregation of the IOT framework would allow a higher degree of detail, although there would still be a problem with the expenditure data from the tourism survey which allocates all food and beverages to one category. Comprehensively addressing this issue consequently entails some form of primary data collection to improve information on dietary choice and related expenses. Collecting more disaggregated expenditure bypasses the need to make assumptions in order to reclassify the initial expenditure because it should theoretically be possible to collect data at closer to the desired level (the classification of the available IOT).

The linearity problem is potentially highly problematic when it comes to food consumption. The price paid for a meal does not necessarily equate to a larger quantity of food being consumed. For this reason, the EIO method must be modified to take into account food portions. This is both an issue requiring additional primary data collection as well as a methodological modification of the conventional EIO framework. Lastly, there is the
‘domestic technology assumption’ which could be addressed using available blue water footprint data at product level along with detailed trade data assuming that the EIO framework is sufficiently disaggregated to allow for the inclusion of this data.

The subject of Part IV is to develop an EIO approach which addresses the aforementioned limitations and which could be used to reliably quantify the total water use of tourist dietary choices, whilst also allowing an appreciation of the associated direct and supply chain economic impacts.
Appendix A - Alternative EIO techniques

Linking inter-industry monetary flows to environmental pressures has been accomplished through a variety of different methods (Hawdon & Pearson, 1995). According to Miller & Blair (2009) these fall into three basic categories of EIO models:

1. Generalised I-O models use additional rows or columns which are added to the technical coefficients matrix in order to include resource use or pollution. This type of model involves the estimation of environmental coefficients along with the use of an exogenous vector of environmental coefficients, also known as direct impact coefficients. One of the first applications of the generalised I-O model is found in Leontief (1970). For a more detailed description of the different forms and extensions of this model see Miller & Blair (2009).

2. Economic-ecologic models extend the inter-industry framework to include ecological commodities as inputs or by-products of production. The basic I-O matrix is split into different quadrants in order to allow for flows within the economy, within the environment and between the environment and the economy. The way these flows are modelled is similar to how inter- and intra-regional transactions are recorded in an interregional I-O model. Daly (1968) appears to be the first to have proposed a conceptual form of this type of model with reference to physical and biological processes. Isard et al. (1972) later offered a more operational form of this type of model.

3. Commodity-by-industry models use the commodity-by-industry format employed in SUTs, which includes additional rows of ecological inputs and columns of ecological outputs. Pioneered by Victor (1972), this kind of model is also known as a limited economic-ecologic model. It essentially limits the scope of the economic-ecologic model by accounting only for flows of natural resources from the environment to the economy and waste from the economy to the environment (R. E. Miller & Blair, 2009), as opposed to accounting for all possible flows as in an interregional model.

In addition to these three categories which involve adding rows/columns/coefficients into the basic I-O matrix, two other model types are worth mentioning. Firstly, there is the hybrid model which substitutes rows of ecological commodities expressed in physical units for rows valued in monetary terms in the I-O table. The Leontief inverse matrix is then recalculated once the units are modified based on the adjusted flows (Machado et al., 2001). This model was first developed by Bullard & Herendeen (1975) to overcome problems encountered by using direct impact coefficients for energy analysis such as the fact that the direct coefficient formulation does not obey the energy conservation law unless uniform energy prices are observed across all industries (Machado et al., 2001). The other main type of model involves the use a completely transformed I-O tables, where the monetary quantities are entirely replaced by physical quantities. Known as physical input-output tables (PIOTs), in contrast to environmental input-output tables which treat resource use and/or waste generation as extensions to the basic monetary I-O flows, these tables use actual material flows in physical terms (Liang & Zhang, 2011). The main advantage of the method is that it does not assume that monetary transactions are proportional to physical transactions (which is what happens when using environmental coefficients to extend the basic I-O module), thus taking into account the fact that use prices may vary between different sectors (Y. Wang et al., 2009). However, even though the use of the physical inverse matrix can better illustrate the
physical structure of the economy (Hubacek & Giljum, 2003), the construction of PIOTs requires data on the physical interactions between sectors, making this kind of model particularly data-demanding.

Despite the attractions of the more complex EIO model structures described above, most of these models are extremely demanding when it comes to data requirements. For that reason, it is hardly surprising that the vast majority of EIO studies employ some form of the generalised I-O model, which involves the use of environmental coefficients added to the basic I-O structure (Hawdon & Pearson, 1995). In the absence of any information to suggest otherwise, it makes sense to assume that there is a linear relationship between the output of each sector and its use of resources, which will also apply to all inter-industry transactions. This part of the thesis makes use of the generalised I-O model.
Appendix B - Assessing available IOT options for Cyprus

Introduction

The aim of this appendix is to examine the available tables for Cyprus and to critically assess their suitability for the purposes of the thesis. As no official IOTs or SUTs currently exist for Cyprus, the only available tables come from international databases, namely Eora and the WIOD. There are also provisional SUTs available, which were submitted by the Cyprus Statistical Service to Eurostat in February 2012. Nevertheless, the SUTs cannot be used directly for performing the analysis since the Use table is only available in purchasers’ prices (see Box 2). The current assessment, therefore, concentrates on assessing how well the Eora and WIOD tables model the Cyprus economy by comparing them against sector output totals in the Eurostat Supply table. This is carried out by briefly comparing the procedures followed in the compilation of national SUTs and IOTs in each case, which also involves a critical assessment of the reliability of the underlying datasets. The subsequent section performs numerical comparisons to compare how well the Eora and WIOD databases model total sectoral outputs. The final section summarises the main findings of the qualitative and quantitative comparison in order to justify the final choice of tables to be used to model the economic and water use impacts of tourism in Cyprus.

Comparisons

The most important issues to be considered when comparing different databases are:

1. To understand how the data have been used to create national SUT and IOTs. This is achieved through a review of the accompanying publications of WIOD, EORA and Eurostat and a brief description of the procedures followed to compile SUT and/or IOTs in each case. The objective of this exercise is to appreciate underlying assumptions and simplifications in each of the databases. This also entails evaluating the nature and quality of the underlying data. As there has never previously been an official Cyprus SUT or IOT to provide a solid foundation, the assumptions are likely to be significant in all cases. This involves looking at the main sources of data such as national accounts, trade statistics and previous tables used in each case along with highlighting major assumptions made in order to accommodate the data in each of the respective databases.

2. Finally, the main aim is to reach some conclusions with regards to how reliable the specific Cyprus tables provided in each case are likely to be. Cyprus, being a small country economy with no official balanced IOTs and no previous editions on which to rely on, presents a significant challenge for any database. As the Cyprus tables are of crucial importance to the present thesis, some numerical comparisons are also made between the different databases to ascertain (quantitatively) how closely the different tables match the most reliable data submitted by Cyprus to Eurostat in December 2011. The aim is to subject each of the IOTs to a robustness analysis in order to compare the absolute and percentage deviations of each of the sectors between the database tables and the Eurostat SUT. It must be appreciated, however, that the results of these comparisons cannot be used to draw generalised conclusions about the overall reliability of each of the databases but are, rather, specific for the

136
Cyprus situation in 2007 and are only meant to serve the purposes of the present study.

**BOX 2 – PRICE BASES**

A common problem in I-O analysis is the need to make conversions between different price bases. This arises due to the fact that price entries in trade statistics or IOTs vary depending on whether transactions are valued at the price at which an industrial seller completes transactions or at the point of purchase of a good or service by the consumer (Druckman et al., 2008; Lenzen et al., 2004; Mahajan, 2007). The three most commonly used price bases are basic price, producers’ price and purchasers’ price. In the glossary of the Eurostat Manual of SUTs and IOTs (2008, p. 551-579) the three price bases as defined as follows:

*The basic price is the amount receivable by the producer from the purchaser for a unit of a good or service produced as output minus any tax payable, and plus any subsidy receivable, on that unit as a consequence of its production or sale; it excludes any transport charges invoiced separately by the producer.*

*The producer’s price is the amount receivable by the producer from the purchaser for a unit of a good or service produced as output minus any VAT, or similar deductible tax, invoiced to the purchaser; it excludes any transport charges invoiced separately by the producer.*

*The purchaser’s price is the amount paid by the purchaser, excluding any deductible VAT or similar deductible tax, in order to take delivery of a unit of a good or service at the time and place required by the purchaser; the purchaser’s price of a good includes any transport charges paid separately by the purchaser to take delivery at the required time and place.*

Basic and producers’ prices only differ in the fact that producer prices include the per unit subsidy that the producer receives and taxes on production (International Monetary Fund, 2004). For this reason, basic prices are also referred to as net producers’ prices. As an illustration, the relationship between the two price bases in terms of final consumption, $y$, is given in equation form by Lenzen and Foran (2001) as

$$y_{bw} + t_d = y_{prp} \quad (1)$$

where $y_{bw}$ is basic price, $t_d$ is commodity taxes less subsidies and $y_{prp}$ is the producers’ price. To then pass to purchasers’ prices from either basic prices or producers’ prices, a margin matrix (denoted by $P$) which describes interindustry margins is required:

$$y_{pp_j} = y_{prp_j} + \sum P_{ij} = y_{bw_j} + t_d + \sum P_{ij} \quad (2)$$

where $y_{pp_j}$ is the purchasers’ price for industry $j$, $y_{prp_j}$ is the producers’ price for industry $j$ and $P_{ij}$ is the margin matrix describing margins supplied by industries $i$ to industries $j$ (Lenzen & Foran, 2001).
It is generally advisable to work in basic prices as they show a higher degree of homogeneity and stability over time owing to the fact that they are not subject to changes in taxes and other margins (Eurostat, 2008; Lenzen et al., 2004). Basic prices are, therefore, considered to be more representative of the production value of a product as opposed to the market value (Hertwich & Peters, 2010). Most IOTs are already in basic or producers’ prices with cumulative margins for all interindustry transactions assigned to a single column. In this way, the trade and transportation sectors are treated as pass-through sectors, something which allows transactions to be depicted as being carried out directly between producers and consumers (Miller & Blair, 2009). Eurostat publishes European IOTs in basic prices whereas the US Bureau of Economic Analysis publishes US IOTs in producers’ prices. Even though most I-O tables are already in basic prices, the need to make conversions arises with final demand vectors and SUTs (especially where these are used in the absence of IOTs to represent interindustry transactions) which can often be in purchasers’ prices. This means that in order to include this information in the analysis, the prices need to be converted to basic prices.

In order to do so, two important steps must be carried out. Firstly, the distributors’ margins (trade and transport margins) need to be subtracted from intermediate and final demand of goods and then added to the wholesale and distribution sectors and, secondly, taxes less subsidies need to be subtracted from products and imports (Druckman et al., 2008). This is essentially the inverse process of what was described in equations (1) and (2). Data on taxes less subsidies and distributor margins are available in the Supply Table but these totals apply to all elements of intermediate and final demand and must therefore be allocated accordingly. In the absence of a detailed matrix which breaks down taxes and subsidies as well as margins available for some countries like Australia, the allocation becomes problematic.

Druckman et al. (2008) outline two possible ways of overcoming the problem of only having a table in purchasers’ prices without a detailed margin matrix. One is to assume that the margins, taxes and subsidies apply in the same proportion as they did for past years, for which the necessary data are available. In their case, they were able to find these proportions for 1995 and apply them to 2004 data. The assumption in this case is that the proportions have remained more or less fixed. An alternative approach is to assume that margins and taxes less subsidies are applied pro-rata across intermediate and final demand for all industries. The advantage of this method is that it can be used where no past data is available on margin and tax less subsidy proportions. However, the pro-rata approach cannot provide any indication of differential margins, taxation rates and subsidies across sectors. Both approaches suffer from obvious limitations making it clear that, where available, tables in basic prices (assuming these come from reputable sources) should be favoured.

The following sub-sections perform a qualitative and quantitative comparison of the two databases.
Characteristics of databases and underlying datasets

WIOD

Funded by the European Commission’s 7th Framework Programme (EC, 2012), the WIOD has been developed in order to help in the analysis of the impacts of globalisation on trade patterns, environmental pressures and socio-economic development (Timmer et al., 2012). The database, which includes national and world SUTs and IOTs, socio-economic accounts and environmental accounts for 40 countries (27 EU and 13 other major countries which are responsible for more than 85% of the world’s GDP) for 1995-2009 is freely available from the WIOD website (http://www.wiod.org/).

According to Timmer et al. (2012), the construction process involved 4 main steps: raw data collection and harmonisation, construction of time-series of SUTs, construction of import use table breakdown by country of origin and, finally, construction of the WIOTs. The present analysis concentrates on the first three steps, with special emphasis on how the final harmonised national SUTs (and, consequently, IOTs) were compiled. Step 1 involved the collection and harmonisation of National Account Data, SUTs and international trade statistics. Only data officially published by national statistical institutes were used. According to Timmer et al. (2012), official government data are more rigorously checked and validated as opposed to data generated for specific research purposes. All data had to be harmonised across time and across countries in order to meet the WIOD classification of 59 products and 35 industries based on the CPA and NACE rev 1 classifications. According to the authors of the accompanying manual, this level of detail was a compromise between the need for a detailed classification and the data availability through national accounts (Erumba et al., 2012).

As countries do not prepare SUT tables using a common classification, correspondence tables were created for each national SUT in order to bridge the level of detail between the country table and the WIOD classification. In some cases this involved straightforward aggregation of sectors. However, in cases where the original tables were too aggregated, additional data from the National Accounts was used to disaggregate tables based on value added and gross output by sub-industry. Common industry-production shares and common use shares were assumed in the disaggregation of the supply and use table, respectively (basically a pro-rata disaggregation divided across all inputs or outputs depending on the value added and gross output of the sub-industry). Where total supply and total use did not balance, differences were distributed across the final consumption categories in order to balance supply and use (Timmer et al., 2012). These manipulations need to be understood in the WIOD’s attempt to use a common classification. Both aggregation and disaggregation of sectors commonly requires making assumptions which fail to capture sector heterogeneity. Even though disaggregation is more complicated and often requires the use of fragmentary information, Lenzen (2011) has recently demonstrated that disaggregation significantly improves the accuracy of input-output multipliers.

The second step involved the revision of SUTs using National Account data in order to create continuous time-series. This was needed as SUTs are not revised very often. This was achieved by benchmarking the SUTs on consistent time-series of gross output, total use, private and government consumption, gross fixed capital formation, total changes in inventories, taxes minus subsidies, total margins, total imports, total exports and final use.
from National Account statistics. These were taken from a combination of sources such as National Statistical Institutes, the OECD and UN National Accounts Statistics (NAS). Using a technique named SUT-RAS (Temurshoev & Timmer, 2011), the data was used to create balanced updated SUTs.

The second step involved a series of assumptions and simplifications, the most important of which are discussed here. Firstly, in the absence of data on changes in inventories by product, total changes in inventories from the NAS were added pro-rata across the different products. Secondly, for years for which SUTs are available, import/export data from the NAs and SUTs are combined with OECD totals to obtain exports/imports by products. For all other years, trade data was interpolated using annual growth rates in international trade statistics. Finally, although the Supply table is always in basic prices, the Use table is only often available in purchasers’ prices (as is the case with the Cyprus Eurostat Use table – see Box 2). As valuation matrices are not available from public sources, WIOD uses net tax rates derived from the Supply tables (derived by dividing net taxes by product by total supply at purchasers’ prices) along with trade margins (unlike net taxes, it is unclear what sources are used for these but it is assumed they are either taken from the Supply table of the NAS). The aforementioned SUT-RAS technique was then used to re-balance the Use tables once margins had been removed. As explained in Box 2, this procedure is likely to have introduced substantial error.

The final step, also linked to step two described above, was to produce a set of bilateral trade in goods and services consistent with the national SUTs. This process used data from the UN Comtrade database (UNSD, 2012). The bilateral data was used to split total imports and exports into end-use categories and to then split up flows of products between countries per end-use category (which is a requirement for separating import use tables from total national use tables). Capturing trade in services is more challenging and requires more assumptions to be made, mainly because the quality of trade data in services is still far away from being comparable to trade data for merchandise goods (Timmer et al., 2012). For this reason, the WIOD used a combination of sources: United Nations data, Eurostat data and OECD data. Trade in services is likely to be one of the main sources of uncertainty in the database and is likely to affect the totals in the national SUTs, especially in years for which official SUTs were not available.

The national SUTs along with bilateral trade data are used to create international SUTs which are also then used to make international IOTs. The database also offers matching socio-economic and environmental accounts, which include estimates of water resource use. However, these appear to be incomplete as they do not offer estimates for most economic sectors, concentrating instead on the large water users such as agriculture (without any disaggregation for different agricultural sub-sectors or products). The water use data comes from secondary sources such as Mekonnen and Hoekstra (2010a, 2010b, 2011).

Eora

Created by a team at the University of Sydney working under Professor Manfred Lenzen and supported by funding from the Australian Research Council (ARC), the Eora tables comprise a time series of high-resolution IOTs along with matching environmental accounts. Similarly to WIOD, the tables are freely available for research purposes from www.worldmrio.com. The tables cover 187 individual countries for 1990-2009 and, unlike
WIOD or any other previous MRIO database initiative, Eora is a heterogeneous MRIO. This implies that country tables are kept in the maximum possible level of detail without any requirement to match the dimensions of the individual country tables (Kanemoto et al., 2011). As a result, tables range from 26 to 500 sectors per country.

The reason for keeping a heterogeneous classification system is that, unlike the WIOD, the main motivation behind Eora was to provide a continuous series of environmentally extended tables (Lenzen, Kanemoto, Moran, & Geschke, 2012a). Homogeneous sector classification requires substantial aggregation and reclassification and also results in loss of information and transparency. According to Lenzen (2011), when matching economic and environmental accounts, it is preferable to use the most disaggregated economic tables possible, even if that requires disaggregation based on few real data points.

The main sources of data used in Eora are IOTs and main aggregates from national statistical offices and/or Eurostat 2009, IDE-JETRO 2006 and OECD 2009, National Accounts Main Aggregates Database and Official Data from the UN, and UN ComTrade and UN ServiceTrade for data on trade of goods and services respectively. The compilation process for NIOTs consists of an initial estimate based on available tables (or a modelled initial estimate where previous tables are not available) followed by an advanced optimisation technique that rates and reconciles information from all available data. The tables are constructed using a serial iterative approach (Lenzen, Kanemoto, Moran, & Geschke, 2012a).

Starting off with the 2000 initial estimate for the year 2000, this is reconciled with all 2000 constraints to give the final 2000 solution. This is then taken as the initial estimate for 2001 and so on (Kanemoto et al., 2011). The only exception is in cases of strong economic growth, where initial estimates also need to be scaled using inter-year ratios adjusted using transactions, final demand, value added and supply tables. At each stage of the compilation process (both before and post-optimisation), standard deviations allow for an appreciation of the reliability of the constituent data and the final tables. The fact that every MRIO and satellite account element is accompanied by corresponding standard deviations is a unique and innovative feature in Eora (Lenzen, Kanemoto, Moran, & Geschke, 2012a).

In order to arrive at the initial estimates (the first table of the time series), the Eora team has tried to use, as much as possible, the same data source for all countries, favouring specific as opposed to proxy data. For countries for which no SUTs or IOTs are available, the three most detailed and diverse tables- USA, Japan and Australia- are used to construct generic 25-sector international SUT proxies (Lenzen, Kanemoto, Moran, & Geschke, 2012b). These country tables have been chosen because of their high sector detail as well as the fact that they cover a wide range of industries and commodities. The idea of using several country tables instead of choosing a single representative country on which to model countries that lack published IOTs, aims at encompassing the potential heterogeneity in economic structure between countries with similar GDPs. This argument is supported by Andrew et al.(2009). For the countries for which previous tables were available, Eora country tables are constructed using any available table (either SUT or IOT) which is closest to the year of valuation (2000 was chosen as the year with the best overall availability of IOTs worldwide). Where data is incomplete, the generic 25-sector tables are also used.

Once initial estimates are established, Eora uses variants of advanced optimisation methods such as Quadratic Programming and KRAS (Lenzen et al., 2009) in order to reconcile all
available information such as national account data and international trade data. According to Kanemoto et al. (2011) reconciling these data sources presents three important problems addressed by Eora. Firstly, national import matrices do not provide information on the exporting country and trade databases do not indicate the using sector. Secondly, the classification for imported commodities is often different from the classification used in national IOTs. Thirdly, there are inconsistencies between import and export data from various sources. These problems are addressed by building intermediate concordance matrices to bridge the different classification systems. Overall, with regards to international trade, national import matrices are treated as ‘superior data’. Priority is given to national imports matrices as the most reliable indicators of absolute trade flow, whereas trade statistics are used for allocating across patterns. The optimisers are also used to address the fact that raw data on domestic transactions and international trade are often expressed in different valuations from basic prices to various combinations of margins and taxes (see Box 2). This is achieved by modelling the MRIO at all levels of valuation. In this way, all available raw data may be used as constraints to the model without requiring any conversion (Kanemoto et al., 2011).

Another novel feature of the Eora database is the fact that every IOT and satellite account is accompanied by corresponding standard deviations. This is achieved by fitting an error propagation formula to standard deviations of the raw data points (Lenzen, Kanemoto, Moran, & Geschke, 2012a) in order to ascertain uncertainties in the initial datasets along with Monte-Carlo simulations to determine uncertainties in the calculated environmental multipliers (Lenzen, Wood, & Wiedmann, 2010a). These are accompanied by graphical representations of uncertainty for each table and every multiplier. Standard deviations of the raw data are estimated on the basis of published data or expert interviews or set according to world views on the uncertainty of various data sets (Lenzen, Kanemoto, Moran, & Geschke, 2012a). It is usually assumed that data from national statistical offices is the most accurate (with small standard deviations) as opposed to UN data which are thought to have larger standard deviations. What appears to be clear from the Eora website and associated publications is that there is a certain level of subjectivity in the initial raw data uncertainty estimates as these rely on personal opinions and other a priori assumptions.

According to the Eora website, when multiple sources of raw data are being used, conflicting data points along with their quality scores are run through the optimization software in order to produce a quality-weighted result (Eora, 2012). The final results on the website are accompanied by adherence reports which show the data sources with the strongest influence on the results as well as violation reports which show the constraints least respected by the optimiser. Adherence of constraints is also shown in the form of rocket plots (Figure B1). Overall, large transactions are better represented because there are usually adequate supporting raw data for these, meaning that the necessary adjustments through the optimisation software are minimal. Lenzen et al. (2012a) conclude that despite many MRIO elements only being supported by few data points, it is still always beneficial to exploit as much information as possible and that small and unreliable elements have very limited influence on input-output multipliers.
Figure B1 Rocket plot of constraints and their adherence estimated for the 2007 Cyprus IOTs (source: Eora, 2012). The rocket plot shows that large transactions are more reliable and have a higher adherence compared to small transactions which are less reliable and less adhered to in the final solution.

With regards to environmental data (satellite accounts), the database uses similar secondary sources to the WIOD. Water requirements are taken from the WaterStat database which has been built using the figures in Mekonnen and Hoekstra (2010a, 2010b, 2011). No optimiser was used in the case of water data because these were only taken from a single source. As a result, minimal corrections to the data in Eora essentially means that both WIOD and Eora are entirely reliant on water footprints published by the same source and no significant differences should be expected (other than differences because of alternative sectoral classifications).

Nevertheless, there has been some validation of the final satellite accounts. In addition to uncertainty estimates and their associated confidence intervals, Eora results have also been validated by comparing national footprints (ecological, carbon and water footprints) using data from Eora against results derived from published footprint studies (Figure B2). The fact that the Eora results are in line with the results of the three other studies is encouraging. It is, however, assumed that these results are reliable in the first place. It is very possible that these previous studies used fairly similar national account and international trade databases which means that a close match between results should be expected. It does, however, provide a confirmation that the complex modelling carried out as part of the compilation of the Eora IOTs and matching satellite accounts gives sensible final footprint estimates.

Figure B2 From left to right, these plots show strong correlation between footprint results from Eora on the y-axis and results from the GFN (2010), Water Footprint Network (Mekonnen & Hoekstra, 2011) and Peters et al. (2011).
Eurostat expects EU member states to submit SUTs annually and IOTs every five years in a standardized format for 60 industries (NACE1 rev. 1.1) and 60 products (CPA) (Eurostat, 2011a). This is required as part of an ongoing project to develop and maintain an Environmentally Extended Input-Output (EE-Io) database for the EU27 (Rueda-Cantuche et al., 2009). However, it does appear from the Eurostat webpage (Eurostat, 2011b) that IOTs are not yet available for some countries and that some of the SUTs and IOTs submitted are provisional. This includes Cyprus which, according to Rueda-Cantuche et al. (2009), had not submitted any statistical information at the time.

The Eurostat database is comprised of the official tables submitted by each of the member countries as well as the EU 27 composite table which sums up all transactions including imports from within and outside the EU in a series of SUTs and IOTs. In order to construct the EU 27 tables, Eurostat had to use all available tables from national statistical agencies and estimate tables for countries that had not submitted their own. In this sense, the tables should be seen as containing the best available information available for European countries. However, various assumptions had to be made in order to produce the composite EU 27 tables in basic prices, because that required all constituent country tables which were only available in purchasers’ prices to be converted into basic prices as well. It is generally considered preferable to work in basic prices as they show a higher degree of homogeneity and stability over time owing to the fact that they are not subject to changes in taxes and other margins (Eurostat, 2008; Lenzen et al., 2004). Balancing of the tables was subsequently achieved using the Euro method as described in the Eurostat (2008) manual.

It is evident from the Eurostat documentation that the project outcomes were not met fully because of several limitations: “In the ideal case, this project would have produced SUTs in basic prices for each member state, estimated bilateral imports and exports, and created a so-called multiregional SUT for the EU27 in which each EU member state would have been visible individually. Crucial for this is insight in valuation data that helps in transforming the Use table in purchaser prices to basic prices. For a large number of EU member states, such data could not be obtained from public sources. Various national statistical offices were able to provide additional data, under the provision they would not be published externally at member state level. This constraint forced the project to concentrate on building consolidated Supply and Use tables for the aggregated EU 27 only” (Eurostat, 2011a, p.6).

The lack of valuation matrices for many countries was addressed by using the valuation matrices of countries that had provided them. Several national statistical offices agreed to provide additional data, under the provision these were to not to be published externally at member state level (Eurostat, 2011b). According to Rueda-Cantuche et al. (2009), these countries were Belgium, Denmark, Austria and Finland, out of which Belgium was chosen as the reference country (the reason for this is not explained in the article but it can be assumed that Belgium has the largest and most diversified economy out of the above countries). For countries that had not supplied any tables, a set of “itineraries” were defined with the aim of estimating missing Use tables in basic prices. However, as the final objective was changed to merely building an aggregated EU 27 table, if any country was not thought to significantly impact the European totals, a neighbouring/similar country table was used instead. (Eurostat, 2011b). This appears to be the case for Cyprus which was modelled using information from the Greece table in order to derive import matrices and SIOTs structure.
These simulated Cyprus tables were not made available and were only used as part of the aggregated EU 27 table.

The Cyprus Statistical Service did finally manage to submit provisional SUTs in February 2012 (for the period 2001-2007) and has an obligation to submit the final series by the end of 2013. However, as mentioned previously in the introduction, the problem with using these SUTs directly for generating multipliers is that the Use matrix is only given in purchasers’ prices, with no valuation matrices provided to assist in making any conversions, apart from the conversion from purchasers’ prices to basic prices for product/industry totals given in the Supply matrix. This makes it extremely hard to convert the Use matrix into basic prices as, in the absence of margins, taxes and subsidies from past years, the only option is to assume that margins and taxes less subsidies are applied pro-rata across intermediate and final demand for all industries (Druckman et al., 2008). However, the pro-rata approach cannot provide any indication of differential margins, taxation rates and subsidies across sectors. This is the main reason for which the Eurostat SUT tables are not used directly in the analysis but have been used to perform a comparison of the databases based on the assumption that the industry supply total in basic prices must be consistent with total output.

Qualitative comparison of databases

Both Eora and the WIOD make important assumptions in order to model country tables, especially those for which minimal previously published data exists. Table B1 below summarises how WIOD and Eora fare in respect to what are the main issues on which the qualitative comparison is based.

The first issue is sector detail. It is obvious that WIOD offers a more detailed sectoral aggregation compared to Eora. Nevertheless, in both cases the agricultural sector is not disaggregated which means that further disaggregation will need to be performed. Furthermore, WIOD may offer a more disaggregated IOT but this is likely to be at the expense of performing disaggregation and aggregation based solely on sector outputs and inputs. On the other hand, Eora keeps all country tables in their most detailed native format in order to avoid disaggregation/aggregation errors. Even though this is a very positive overall characteristic of the database, the modelled Cyprus table lacks sectoral detail. Both databases use foreign country tables as a basis in order to model the Cyprus IOT. This is understandable as no official Cyprus tables exist. Eora uses a combination of USA, Japan and Australia in an attempt to capture the heterogeneity in economic structure whereas the WIOD simply uses SUTs from neighbouring Greece. Despite this not being ideal in either case, Greece should be more representative of the Cyprus economy which is heavily reliant on tourism and services, with a small agricultural sector and small industry and mining sectors.

In terms of the data used for sector outputs and imports/exports, both databases rely heavily on UN data. Eora appears to make use of a richer collection of data when it comes to sector outputs whereas the WIOD appears to use a wider source of trade data. Even though a wider source of data does not necessarily mean a more accurate representation, it should provide more detailed information. Both databases use recently published and accepted methods to balance the final matrices so there is no clear favourite in this issue. The last issue is the quality of the environmental satellite accounts offered by the two databases. Despite Eora being more specialised for EIO and also the fact that most of the environmental accounts
including the water use statistics are validated against previous studies, both databases have very aggregated sectoral water use data, with numerous missing sectors. As a result, they do not offer any advantages compared to official water use estimates/statistics from the Cyprus Water Development Department (WDD) which have a more detailed sector aggregation and are more likely to come from primary sources.

Table B1 Summary of how each of the two databases performs in relation to the other in the most important issues as related to the Cyprus tables.

<table>
<thead>
<tr>
<th>Issue</th>
<th>WIOD</th>
<th>Eora</th>
<th>Verdict</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sector detail</td>
<td>SUTs: 59 X 35</td>
<td>IOTs: 26 X 26</td>
<td>WIOD</td>
</tr>
<tr>
<td>Agricultural sector</td>
<td>Single sector</td>
<td>Single sector</td>
<td>Tie</td>
</tr>
<tr>
<td>Aggregation/disaggregation</td>
<td>Re-classification</td>
<td>Tables kept in native format</td>
<td>Eora</td>
</tr>
<tr>
<td>Error/uncertainty estimates</td>
<td>Not available</td>
<td>Detailed estimates</td>
<td>Eora</td>
</tr>
<tr>
<td>Cyprus economic structure</td>
<td>Greece SUTs</td>
<td>Australia, Japan, USA IOTs</td>
<td>WIOD</td>
</tr>
<tr>
<td>Trade data</td>
<td>Products: UN ComTrade Services: UN, Eurostat, OECD</td>
<td>Products: UN ComTrade Services: UN ServiceTrade</td>
<td>WIOD</td>
</tr>
<tr>
<td>Balancing algorithms</td>
<td>SUT-RAS</td>
<td>Quadratic Programming &amp; KRAS</td>
<td>Tie</td>
</tr>
<tr>
<td>Water use data</td>
<td>Mekonnen and Hoekstra (2010a; 2010b; 2011)</td>
<td>Mekonnen and Hoekstra (2010a; 2010b; 2011)</td>
<td>Tie</td>
</tr>
</tbody>
</table>

Quantitative comparison of databases – robustness analysis

Methodology

Comparing the sectoral configuration and distribution of inter-industry flows of the two databases against the Cyprus SUT provides a quantitative means of assessment of their numerical robustness. There are several variables (inter-industry flow coefficients, final demand, value added, total output) which could potentially be compared and different numerical indicators which could potentially be used to do so (absolute difference, percentage difference). Various numerical comparison possibilities of variable complexity are possible. Nevertheless, the quest is to find a simple indicator in order to complement the qualitative comparison of the databases.
The initial idea was to compare official trade statistics and value added by economic activity (from the National Accounts) provided by CYSTAT with the values in each of the different tables for 2007 (the year of interest). The idea behind this is that official National Account data are considered to be reliable. Nevertheless, it was decided that value added is not a suitable indicator of robustness as it does not provide any comparison with regards to intermediate demand, which is arguably the most important part of an input-output table as it is used to estimate the A-matrix. Moreover, the tables are largely modelled on the national accounts and on value added statistics (as explained above, National Account data are used as constraints in the construction of SUTs and IO tables), which implies that these values are likely to be accurate and not representative of the ability of the table to capture inter-industry relationships.

The method eventually employed to perform a consistency check of the available IOTs is through the use of a ‘monetary error’, in the way described in Druckman et al. (2008). The estimation of this type of error involves a simple comparison between the left and right hand sides of the basic input-output relationship: \( x = (I-A)^{-1}y \). In their study, Druckman et al. (2008) use this consistency test in order to compare the robustness of their results between two different dates. In both cases, it is the official UK IOT that is put to the test. In the present study, the Eora and the WIOD IOTs are to be compared against the total domestic output of products in the Eurostat Supply Table.

The percentage difference between the two sides provides an indicator of the overall accuracy of each of the tables but does not, provide any indication of where the error originates in the industrial coefficients matrix or the final demand categories. Druckman et al. (2008) acknowledges the assumptions and limitations of the given indicator by stating that the monetary error is a simple indicator on which to base any discussions of accuracy. An additional test that would have allowed a comparison between the inter-industry matrices of the different databases would have been to add up total intermediate output for each sector and compare that against total intermediate output in the SUT – in essence this would have been a robustness test for the A matrix or the Leontief Inverse (against, for example, the industry-based technology assumption Leontief \((I-DB)^{-1}\)). However, this is once again not possible because the Use table for Cyprus in only available in purchasers’ prices. According to Wiedmann et al. (2006), in order to transform the use from purchasers’ into basic prices, data is required on direct taxes and trade and transport margins. The procedure by which this can be achieved is detailed in Sova (2011) using the UK SUTs. Nevertheless, as the data currently available for Cyprus only contain information with regards to total taxes and margins for entire product sectors, this option is not explored at the present time.

In order to perform such a comparison in this case, a series of steps must be carried out:

(i) The tables must first be re-classified into a common classification. This implies the aggregation of matrices into the classification that matches the Eora table (25 X 25), which is the most aggregated. Aggregation of sectors is performed by multiplying the Z matrices and the y vectors with appropriate aggregation matrices as outlined in p.161-162 in Miller and Blair (2009). Included in this step are also any necessary currency conversions along with other manipulations necessary in rendering the tables comparable.
(ii) The aggregated (see step i) Leontief Inverse (L) need to be calculated for both the Eora and the WIOD matrices.

(iii) The aggregated (see step i) Leontief Inverse (L) must be multiplied by aggregate final demand (y) in both cases to give total domestic output in both cases.

(iv) Finally, the calculated vectors in step iii are compared to the aggregate (see step i) total domestic supply vector from the Cyprus Supply Table using percentages and total values.

The results of each step are detailed in the following section.

Analysis

(i) Aggregation of inter-industry transaction matrices and currency conversions.

The tables were all converted from their native formats (Eurostat SUTs are 59 X 59, WIOD IOTs are 35 X 35 and Eora IOTs are 26 X 26) to a 19 X 19 industry-by-industry classification (shown in Table 2). The aggregation procedure required a significant number of assumptions and introduces aggregation bias, which is highest for the Eurostat and WIOD tables which initially had a significantly more detailed sectoral classification. It does, however, create comparable tables which have the same number and order of sectors which was the purpose of this exercise.

The aggregation is carried out using $Z^* = S.Z.S'$ (where $S'$ is the transpose of $S$) and $y^* = S.y$ as outlined in Miller and Blair (2009). An example of $S$ is shown in Table B4.

Currency conversions in IOTs are commonly performed using Market Exchange Rates (MERs), even in cases where linking data from different regions to a common currency is required (Hertwich & Peters, 2010). The final demand vectors are all converted to US dollars (this operation is not necessary for the inter-industry matrices as these are only used to calculate L). The WIOD and Eora tables are both in US dollars, whereas the Eurostat domestic supply vectors had to be converted from Euros to US dollars\(^{36}\).

(ii) Calculating L for aggregated WIOD and Eora matrices.

This is carried out using the basic I-O identity: $L = (I - A)^{-1}$ and produces two 19 X 19 matrices.

(iii) Calculating total domestic output (x) for aggregated WIOD and Eora matrices.

This is carried out using the basic I-O identity $x = L.y$. This produces two vectors (one for WIOD and one for Eora) with a length of 19 to be compared with the Eurostat supply vector.

(iii) Database comparison

In the final step of this robustness analysis, the $X_{EORA}$ and $X_{WIOD}$ vectors are compared against total domestic industry supply (TDIS), from the official Eurostat Cyprus Supply Table. The results are presented in Table B3.

---

\(^{36}\) The exchange rate use was 1EUR = 1.2931 US dollars, valid on 27 November 2012.
Table B2 The final aggregated sector classification used to match the WIOD and Eora I-O tables with the Eurostat SUT industry classification.

<table>
<thead>
<tr>
<th>#</th>
<th>Sector name</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Agriculture, hunting, forestry and fishing</td>
</tr>
<tr>
<td>2.</td>
<td>Mining and quarrying</td>
</tr>
<tr>
<td>3.</td>
<td>Food and beverage</td>
</tr>
<tr>
<td>4.</td>
<td>Textiles, leather and all footwear and wearing apparel</td>
</tr>
<tr>
<td>5.</td>
<td>Wood, paper and printed matter</td>
</tr>
<tr>
<td>6.</td>
<td>Petroleum, chemicals, rubber and plastic and non-metallic mineral products</td>
</tr>
<tr>
<td>7.</td>
<td>Basic and fabricated metal</td>
</tr>
<tr>
<td>8.</td>
<td>Machinery, manufactured goods and recycling</td>
</tr>
<tr>
<td>9.</td>
<td>Transport equipment</td>
</tr>
<tr>
<td>10.</td>
<td>Electricity, gas and water</td>
</tr>
<tr>
<td>11.</td>
<td>Construction</td>
</tr>
<tr>
<td>12.</td>
<td>Maintenance &amp; repair and all trade (wholesale &amp; retail)</td>
</tr>
<tr>
<td>13.</td>
<td>Hotels and restaurants</td>
</tr>
<tr>
<td>14.</td>
<td>All transport (inland, water and air)</td>
</tr>
<tr>
<td>15.</td>
<td>Post and telecommunications</td>
</tr>
<tr>
<td>16.</td>
<td>Financial intermediation and other business (real estate, insurance, R&amp;D etc)</td>
</tr>
<tr>
<td>17.</td>
<td>Public administration and defence and compulsory social security services</td>
</tr>
<tr>
<td>18.</td>
<td>Education, health and other services</td>
</tr>
<tr>
<td>19.</td>
<td>Private households</td>
</tr>
</tbody>
</table>
Table B3 Results of comparisons between the Eora and WIOD IOTs against the Eurostat SUT.

| Sector # | TDIS  | X\textsubscript{EORA} | X\textsubscript{WIOD} | TDIS- X\textsubscript{EORA} | TDIS- X\textsubscript{WIOD} % Diff. Eora % Diff. WIOD |
|---------|-------|------------------------|------------------------|-----------------------------|-----------------------------|-----------------------------|
| 1.      | 1163.444 | 687.505                | 527.300                | -475.939                    | -636.144                    | -40.91                      | -54.68                      |
| 2.      | 130.014  | 150.911                | 78.519                 | 20.897                      | -541.955                    | 16.07                       | -39.61                      |
| 3.      | 1675.723 | 1286.778               | 1233.898               | -388.945                    | -441.825                    | -23.21                      | -26.37                      |
| 4.      | 147.694  | 195.929                | 44.116                 | 48.235                      | -103.578                    | 32.66                       | -70.13                      |
| 5.      | 606.713  | 499.760                | 591.353                | -106.953                    | -15.36                      | -17.63                      | -2.53                       |
| 6.      | 1109.891 | 1348.354               | 768.667                | 238.463                     | -341.224                    | 21.49                       | -30.74                      |
| 8.      | 397.862  | 1718.241               | 288.444                | 1320.379                    | -109.418                    | 331.87                      | -27.50                      |
| 9.      | 35.074   | 797.587                | 7.162                  | 762.513                     | -27.912                     | 2174.01                     | -79.58                      |
| 10.     | 833.427  | 1084.808               | 943.821                | 251.381                     | 110.394                     | 30.16                       | 13.25                       |
| 11.     | 3490.287 | 3066.628               | 3742.759               | -423.659                    | 252.472                     | -12.14                      | 7.23                        |
| 12.     | 3862.707 | 4899.743               | 3221.313               | 1037.036                    | -641.394                    | 26.85                       | -16.60                      |
| 13.     | 2263.641 | 2230.723               | 2614.001               | -32.918                     | 350.36                      | -1.45                       | 15.48                       |
| 14.     | 2035.436 | 1375.559               | 723.185                | -659.877                    | -1312.251                   | -32.42                      | -64.47                      |
| 15.     | 803.105  | 1534.049               | 719.858                | 730.944                     | -83.247                     | 91.01                       | -10.37                      |
| 16.     | 5768.786 | 9495.614               | 7088.918               | 3726.828                    | 1320.132                    | 64.60                       | 22.88                       |
| 17.     | 2545.415 | 2969.376               | 2699.543               | 423.961                     | 154.128                     | 16.66                       | 6.06                        |
| 18.     | 3363.162 | 4948.765               | 3397.887               | 1585.603                    | 34.725                      | 47.15                       | 1.03                        |
| 19.     | 156.942  | 63.565                 | 149.762                | -93.377                     | -7.18                       | 59.50                       | -4.57                       |
| TOTAL   | 30873.91 | 38791.57               | 29089.25               | 7917.663                    | -1784.663                   | 25.65                       | -5.78                       |

TOTAL ABSOLUTE DIFFERENCES | 12374.817 | 6229.085 | - | - |

MEAN ABSOLUTE DIFFERENCES | 651.306 | 327.847 | 160.50 | 28.51 |
Table B4 Aggregation matrix (S) for Eora inter-industry transactions table. The dimensions of the table are 19 rows (number of sectors in the to-be-created aggregated table) by 25 columns (number of sectors in unaggregated table). Aggregation takes place where there is more than one 1 in the same row. In the example below, it is easy to see that sectors 1 and 2 have been aggregated into a new sector 1.

**INITIAL (UNAGGREGATED) SECTOR #**

|    | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 |
|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| 1  | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 2  | 0  | 0  | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 3  | 0  | 0  | 0  | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 4  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 5  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 6  | 0  | 0  | 0  | 0  | 0  | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 7  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 8  | 0  | 0  | 0  | 0  | 0  | 0  | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 9  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 10 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 11 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 12 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 13 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 1  | 1  | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 14 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 15 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 16 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 17 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 18 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 19 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 20 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 21 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 22 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 23 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 24 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 25 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
| 26 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  |
The results show that both databases, having to rely on other country tables and complex balancing procedures (which involves reconciling international trade statistics to national tables) in order to build the Cyprus table, do not closely match sectoral output from official sources (Eurostat). Compared to the figures in Druckman et al. (2008) for the UK, where in the worst case (2004 tables) the error was 7%, the errors for both tables are significantly higher in this case. Nevertheless, the WIOD IOT appears to more closely match the Total output of industries from the Eurostat table compared to Eora IOT. This is the case across all comparison criteria:

- The WIOD IOT underestimates total output by 5.78% whereas the Eora IOT overestimates this by 25.65%.
- The WIOD IOT is off by $328,000 on average for each sector with respect to the absolute\(^\text{37}\) difference in sectoral output whereas the Eora IOT is off by an average of $651,000.
- Finally, the WIOD IOT is off by 28.51% in terms of mean percentage absolute differences per sector whereas the Eora IOT is off by 160.50%.

It is obvious, therefore, that despite the WIOD table also showing considerable errors, especially in sectors 1 (Agriculture – arguably the most important sector for the present study), 4 (Textiles, leather and all footwear and wearing apparel – all items the tourists tend to spend some of their money on), 9 (transport equipment – some of this is often included in rental cars so it is slightly relevant to tourism expenditure) and 14 (transport – tourists spend a significant amount on taxis, buses and other public or rented transport). The WIOD IOT underestimates the output of these four aforementioned sectors by more than 50%. As this degree of error is potentially problematic for these important sectors, it was decided to also consider a direct comparison between the Eurostat SUTs and the WIOD SUTs (as the WIOD has also released an SUT for Cyprus) in the hope that the WIOD SUT is likely to more closely match sector outputs compared to the WIOD IOT. In what follows, the analysis (comparison) is extended to the SUTs.

**WIOD SUT**

The WIOD SUT has dimensions of 59 commodities by 35 industries. It essentially has an identical product classification to Eurostat, which implies that the comparison can take place using total product outputs without the need for aggregation (the tables are also both in euros, meaning that no currency conversions are required, which considerably increases the accuracy of the comparison). This can also allow comparisons between exports per product in the SUPPLY matrix and imports as well as final demand categories in the USE matrix. As the WIOD provides a USE matrix in both basic and purchasers’ prices, the WIOD USE table provides a further means of comparison, potentially allowing numerous comparisons between the two databases. The aim of the present analysis is to explore some of these options in order to determine whether there are any advantages to using the commodity by industry classification model compared to the more conventional IO table.

\(^{37}\) Absolute implies the number irrespective of its sign. Negative differences (i.e in cases where the table underestimates a certain sector output) are still treated as positive differences otherwise errors would cancel out in a similar way as they do when considering total economy output.
Comparing total supply values for each product in the two tables reveals that, in addition to the WIOD SUTs having a more detailed classification compared to the IOTs, they are only +2.64% off in terms of total supply compared to the Eurostat SUTs with only a 72.94 EUR deviation with respect to the absolute difference in sectoral output. However, as the values are generally small in some sectors, these absolute differences translate into a large (50.71%) deviation in terms of mean percentage of absolute differences per sector. This percentage is even higher (176.24%) when it comes to the column of total imports per commodity. Exploring the values in detail reveals that selective aggregation of sectors could significantly improve these percentages. Nevertheless, this would only be achieved at the expense of losing the more detailed product classification, which is not advisable in EIO according to Lenzen (2011).

The above considerations suggest that, as things stand, using the commodity-by-industry classification offered by the SUTs does not offer an advantage to using the conventional IOTs. Furthermore, the WIOD SUT classification is orthogonal (35 X 59) which presents a methodological challenge when it comes to disaggregating the agricultural sector and subsequently rebalancing the interindustry transaction tables, both of which are vital components of the present study. An option would be to aggregate the product classification to 35 products in order to produce a square SUT. This would, however, bring the classification detail of the SUTs down to 35 X 35, which is the same detail offered by the WIOD IOTs. As there are no apparent advantages to using the SUT classification instead of the more commonly employed IO classification, it is decided that the analysis will proceed with the WIOD IOTs.

**Conclusion**

The qualitative and quantitative analyses carried out have shown that using the WIOD IOTs appears to be the best option at the moment. In terms of the qualitative comparison, both databases appear to have their own respective advantages and disadvantages owing to the significant assumptions being made. The unavailability of previous Cyprus SUTs or IOTs compromises their ability to accurately model the Cyprus economy. Nevertheless, the WIOD IOTs outperform the Eora IOTs in all three categories considered in the quantitative analysis: total output, absolute difference in sectoral output and mean percentage absolute differences per sector. A further comparison between the WIOD IOTs and WIOD SUTs has revealed that there are no advantages to using SUTs in this particular case. The present analysis has also led to the conclusion that the environmental satellite accounts of both databases are not adequate for the purposes of the study and that water use estimates from the Cyprus WDD are expected to be superior.

The robustness analysis suffers from the fact that an official IOT is lacking, meaning that there is no way to perform a comparison of the robustness of the A-matrix as such and needing to rely, instead, on sectoral totals. The results show that selective aggregation can lead to an improved match in sectoral output totals but there is no way of quantifying how this is likely to affect the validity of individual cell values. Despite the limitations of the comparison, it appears that for the case of Cyprus (for 2007), the WIOD provides the best choice and has subsequently been chosen as the table of choice.
### Appendix C – Direct water use in tourist accommodation

Table C1 Weighted author estimates based on Savvides et al. (2001).

<table>
<thead>
<tr>
<th>PROVINCES</th>
<th>ISLAND</th>
</tr>
</thead>
<tbody>
<tr>
<td>Famagusta</td>
<td>Larnaca</td>
</tr>
<tr>
<td>-----------</td>
<td>---------</td>
</tr>
<tr>
<td>Water use</td>
<td></td>
</tr>
<tr>
<td>5*</td>
<td>357</td>
</tr>
<tr>
<td>4*</td>
<td>330</td>
</tr>
<tr>
<td>3*</td>
<td>229</td>
</tr>
<tr>
<td>Hotel Apartment (Class A)</td>
<td>200</td>
</tr>
<tr>
<td>Hotel Apartment (Class B)</td>
<td>192</td>
</tr>
<tr>
<td>Apartment/house</td>
<td>225</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Number of hotels (sample)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>5*</td>
<td>3</td>
</tr>
<tr>
<td>4*</td>
<td>3</td>
</tr>
<tr>
<td>3*</td>
<td>3</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Number of appts (sample)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Hotel Apartment (Class A)</td>
<td>3</td>
</tr>
<tr>
<td>Hotel Apartment (Class B)</td>
<td>2</td>
</tr>
</tbody>
</table>
PART IV

The influence of dietary choice on water use and economic impacts
Chapter 5: Refining the EIO model to account for dietary choices

5.1 Part IV outline

5.1.1 Aim and scope

This chapter develops and subsequently applies a novel methodological framework whose primary purpose is to explore differences in the environmental and economic impact of different tourist groups, arising from dietary preferences. Previous chapters of the thesis have explored broader frameworks, both of which have highlighted diet as the most critical factor in determining water use multipliers in the economy. This claim is supported by a substantial body of water footprint and virtual water literature, reviewed in earlier chapters. Part III of the thesis used EIO as a tool to quantify the water use and economic impacts of different tourist consumption patterns, identifying strengths and weaknesses in conventional approaches. It concluded that EIO offers an apt approach for comparing different tourist consumption patterns, ideally suited to the nature of tourism consumption, with its long supply chain and high degree of dependence on other economic sectors. Nevertheless, in order to explore the impact of food consumption in detail and arrive at meaningful recommendations for the tourist industry of Cyprus, a higher degree of disaggregation of the agricultural sectors in addition to some modifications to relax some of the assumptions in conventional EIO, are warranted.

5.1.2 Objectives

Part IV seeks to advance the EIO approach by carrying out certain modifications and adding innovative features to overcome some of the shortcomings of the more conventional approach followed in the previous chapter. This is divided into the following objectives:

- The agricultural sector is disaggregated into the major food groups consumed on the island. This allows for taking into account the unique characteristics of each agricultural sub-sectors, such as how it trades with other economic sectors, what and how much it exports or imports from abroad, how much value added it produces and, most importantly, how much water is embedded in its supply chain. To meet this objective, the Cyprus IOT is first disaggregated and then rebalanced into its new classification.
• A novel EIO framework which can take into account the quantity of food consumed in addition to dietary choice is developed. This involves a reconsideration of how final demand vectors are generated and how they are used in the model. The EIO model also uses estimates of the blue water footprints of imported agricultural products, thus eliminating the ‘domestic technology’ assumption.

• Primary data collection is undertaken. The analysis in this chapter is no longer based on secondary tourism expenditure data but makes use of recent primary data instead. These were collected from carefully designed surveys administered in different parts of the island in September 2012, in order to provide final demand vectors at an appropriate classification compatible with that of the modified disaggregated EIO model. Short interviews of tourists in addition to restaurant owners and catering managers coupled with recent agricultural statistics are employed with the intention of estimating representative meal portion sizes.

• Demonstrate the model capabilities. This is achieved by running the ‘refined’ EIO produced on the basis of the aforementioned objectives, in order to compare the impact of consumption by different tourist groups emerging from the surveys. The performance of the model and further potential applications are finally discussed, focusing on implications for future research methodologies and tourism management.

5.1.3 Structure

The structure of Part IV closely follows the objectives set out above. Part IV includes two chapters, the present chapter (Chapter 5) and Chapter 6. As in Part III, the first chapter (Chapter 5) is a theoretical (literature review and method development) chapter. The next section (section 5.2) of the chapter describes the revised model setup and the need for disaggregation through an in-depth review of the literature on disaggregation of IOTs and the advantages this entails with respect to modelling capabilities. This section also reviews the necessary assumptions and procedures to rebalance the resulting matrix and ensure its compatibility with the original aggregated matrix. The following section (section 5.3, p. 184) details how the challenge posed by disaggregation was specifically tackled for the Cyprus 2007 IOT. The ensuing section (section 5.4, p. 191) develops an original modelling framework
in order to make use of the disaggregated table and primary data, along with a detailed description of how tourist responses allow for the generation of suitable final demand vectors. In the last section (section 5.5, p. 208), the primary survey design is established. Assumptions implicit in deriving menus and portion sizes based on tourist responses are also discussed.

Chapter 6 offers a demonstration of the model application, by presenting selected results using the EIO approach developed in Chapter 5. Its purpose is to demonstrate the potential of the model in determining food consumption patterns and their associated water use and economic impacts. The first section presents water use and economic impact results for different segments. The following section discusses implications of the research, including potential applications based on reduced portion sizes and arrival numbers from different years, and suggests ways to further refine the model and the analysis in order to improve accuracy and performance. The final section concludes by exploring specific policy guidelines arising from the present research, as well as avenues of further research and their potential significance for tourism destinations and the tourism industry in general.

5.2 Disaggregating the IOT

5.2.1 Section summary

This section critically reviews available disaggregation techniques and assesses their usefulness for the purposes of the current study. The primary aim is to choose a pragmatic method of disaggregation, well suited to the available economic and environmental data. The chosen approach offers a sensible compromise between the assumptions it makes and the improvement in validity and relevance likely to be achieved as a result of a more detailed sectoral classification of the agricultural sector. The section begins by defining the nature of the problem using a hypothetical two-sector example. It subsequently reviews relevant literature on disaggregation, focusing specifically on possible disaggregation methods. The following sub-section concentrates on the method of choice and describes how the disaggregation of the agriculture sector in the Cyprus IOT is carried out. The section closes with a review of possible methods for rebalancing the disaggregated table followed by a numerical demonstration of the chosen method.
5.2.2 Disaggregation in Input-Output analysis

The nature of the problem

The vast majority of earlier water EIO studies reviewed in Part III used IOTs with a single aggregated agriculture sector. As the present study aims to capture differences in water use resulting from different diets, the agriculture sector needs to be split into various subsectors, each of which are to represent the main agricultural commodities. The process of dividing a single sector into subsectors is given the term ‘disaggregation’. Disaggregation is frequently required in EIO studies where sectors are likely to contain subsectors with very different environmental intensities. Two prominent examples in the literature are the electricity sector in EIO studies focusing on carbon emissions from different electricity production technologies (Lindner et al., 2012a; Liu et al., 2012; Su et al., 2010), and the agricultural sector in EIO studies focusing on water use and/or the ecological footprint associated with different consumption patterns (Cazcarro et al., 2012; Ewing et al., 2012). In both cases, subsectors often have environmental coefficients that differ by several orders of magnitude\(^3\).

Even though it is well understood that aggregation of sectors results in loss of information and implicit compensations, both of which significantly affect the reliability of results (Marin et al., 2012), it still occurs because of several reasons. Firstly, I-O accounts and environmental satellite accounts are generally compiled by different statistical agencies (Lenzen, 2011), each of which is likely to prioritise the most important sectors for its purpose. Secondly, the number of sectors in an IOT tends to be decided in the context of the problem being considered (Miller & Blair, 2009). In the majority of cases, the tables are compiled with economic analysis in mind. Consequently, industries with similar economic structures are usually aggregated because any loss of detail is minimal with regards to economic analysis, thus outweighing the benefit from spending time and resources to ensure adequate disaggregation of all environmentally sensitive sectors (Lindner et al., 2012a). By contrast, service sectors, due to their high value added and employment contribution, are often more

\(^3\) Renewable energy technologies have very different carbon emissions per kilowatt produced compared to fossil fuel energy technologies. Similarly, livestock production tends to be significantly more water intensive than crop production.
disaggregated in the I-O classification than in environmental accounts (Lenzen, 2011)³⁹. Thirdly, in certain cases there are simply no disaggregated raw data available or the data may be deemed confidential (Wiedmann et al., 2010).

When faced with a situation where environmental data are more disaggregated than I-O data, the solution is either to aggregate the environmental data to match the I-O classification or, conversely, to disaggregate the I-O data by using additional information and assumptions. The first option is often the preferred course of action: partly because it is computationally more straightforward, but also because there is a misconception that aggregation is based only on ‘real data’ – unlike disaggregation, which tends to be regarded with more suspicion (Lenzen, 2011). In cases where many different kinds of data must be reconciled, as in complex MRIO models which deal with countries for which minimal data is currently available, aggregation may be an acceptable option. However, there are many cases where aggregation introduces significant error.

Aggregation of sectors often involves significant assumptions, giving rise to what is known as the ‘aggregation problem’ (Miller & Blair, 2009). In earlier I-O work, the lack of computational capability meant that aggregation was considered to be a necessary compromise between the information lost and the ability to work with a smaller, less cumbersome matrix (Fisher, 1958). This led to a wealth of early literature focusing on methods to optimise aggregation and estimate the bias introduced as a result of sector aggregation (Fei, 1956; Fisher, 1958; Harrison & Manning, 1987; Morimoto, 1970). Following tremendous improvements in computational power, recent work has concentrated on quantifying bias, with several recent studies (Lenzen, 2011; Marin et al., 2012; Su et al., 2010) addressing this issue.

The aforementioned studies have shown that aggregating to solve a mismatch situation often introduces severe aggregation bias, especially where the sectors brought together are

³⁹ According to Lenzen (2011), the problem of having more aggregated environmental data is, in the absence of additional environmental data, commonly addressed through pro-rating environmental aggregates across their I-O sector counterparts based on the gross output of these sectors.
heterogeneous in terms of their economic and environmental characteristics\textsuperscript{40} (Lenzen, 2011). Lenzen (2011, 2012a) is a strong advocate of using IOTs at the highest possible disaggregation level when performing EIO analysis. Furthermore, his work appears to strongly support the disaggregation of input-output tables in order to match the sectoral classification of environmental data, in cases where the latter are available in more detail.

Lenzen (2011) compares the relative standard error (RSE) for aggregate multipliers calculated by aggregating environmental data to match the economic data classification, against the RSE from aggregate multipliers obtained by disaggregating the economic data, performing EIO and then subsequently aggregating the results to an identical sectoral detail level. Using Monte-Carlo simulation on an input-output system with random numbers to investigate the propagation of uncertainty in each of the two cases (aggregations versus disaggregation and subsequent aggregation), he empirically demonstrates that, even in the worst case scenario where disaggregation is carried out on a purely random basis, disaggregation of input–output data and aggregation of environmental data results in equally accurate multipliers (Lenzen, 2011).

Lenzen’s (2011) results suggest that when minimal additional information is available, disaggregation of the IOTs should be preferred over aggregation of the environmental data as it is more likely to yield more accurate multipliers. Even when dealing with the opposite case where economic data is available at a more disaggregated level than environmental data, Su et al. (2010) have concluded that disaggregation (of environmental data in their case) improves the accuracy of I-O multipliers. Since the benefits of aggregation are no longer as desirable as they were in the past, aiming for more accurate multipliers should be seen as the priority. These findings are directly relevant to the present study, where the aim is to capture additional detail with respect to dietary preferences through the disaggregation of the economic IOT, whilst ensuring that the quality of the final aggregate multipliers is not compromised.

\textsuperscript{40} The only cases where aggregation has zero bias are where sectors being aggregated have identical production characteristics or where final demand for aggregated sectors does not change (but changes in other sectors are not affected by the aggregation), as defined in Morimoto (1970).
Additional data required

Disaggregation ideally requires a complete set of information with respect to the characteristics of prospective sectors, commonly termed ‘new’ sectors. Firstly, their total output, value added, and total inputs must be known. Furthermore, available data should also allow the estimation of their transactions in the I-O matrix. More precisely, this necessitates information on what inputs they require and where these inputs come from (including imports), and where they sell their outputs (including sales abroad). Inputs may come from other economic sectors that have not been disaggregated, known as ‘common sectors’, but they may also come from abroad or from other new sectors. Transactions between new sectors make up what is known as the ‘intra-matrix’ (Lindner et al., 2012b), which often represents the most challenging element of the disaggregation procedure (see section 5.2.3, p. 163 & section 5.2.4, p. 165).

This ideal set of additional information is only available through detailed business cost sheets and product market shares (Joshi, 1999) or may even require comprehensive collection of such additional data as performed in Foran et al. (2005). Disaggregation needs to use comprehensive survey and financial accounts data from companies that form the sub-sectors of the sector(s) to be disaggregated. However, in most cases there are insufficient resources or time to carry out such data collection. Wolsky (1984) and, more recently, Lindner et al. (2012b) have demonstrated that disaggregation is possible even without complete information, based simply on estimates of the weighted output ratios of the new sectors which are generally known in advance or may be straightforwardly estimated using other available information such as total turnover (as in, for instance, Wiedmann et al. 2011).

Carrying out disaggregation with fragmentary information is not a straightforward task, mainly because there are often a range of possible solutions with regards to the values of the unknown technical coefficients of the disaggregated matrix (Lindner et al., 2012b). The solution is to use the maximum amount of accessible information in any specific case, in addition to making various clearly explained assumptions in order to minimise the range in possible solutions. A hypothetical example is used in the following sub-section to illustrate the challenges posed by disaggregation and define the constraints that need to be met during
the disaggregation process. Following that, a review of the literature selects an appropriate method to satisfy the objectives of the present study.

5.2.3 Disaggregation example for a two-sector economy

In addition to the above literature review and a qualitative description of the disaggregation problem, it is essential that the technical aspects and appropriate algebraic nomenclature are introduced at this stage. For purposes of illustration and simplification of the problem, the example uses a two-sector economy and assumes that additional information such as value added (VA) and imports (m) of new sectors are available. As shown in Table 5.1 below, the inter-industry matrix is a 2-by-2 matrix in this case.

Table 5.1 Hypothetical two-sector economy. The shaded area represents the original intra-matrix.

<table>
<thead>
<tr>
<th></th>
<th>Sector a</th>
<th>Sector b</th>
<th>Final demand</th>
<th>Total output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sector a</td>
<td>Z_a</td>
<td>Z_ab</td>
<td>y_a</td>
<td>x_a</td>
</tr>
<tr>
<td>Sector b</td>
<td>Z_b</td>
<td>y_b</td>
<td></td>
<td>x_b</td>
</tr>
<tr>
<td>Imports</td>
<td>m_a</td>
<td>m_b</td>
<td>y_m</td>
<td></td>
</tr>
<tr>
<td>Value added</td>
<td>VA_a</td>
<td>VA_b</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total inputs</td>
<td>x_a</td>
<td>x_b</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Assume that sector b is to be disaggregated into two sub-sectors. These become sector b1 and sector b2 in the new table (Table 5.2).

Table 5.2 Sector b disaggregated into two new sectors, b1 and b2. The shaded area is the intra-matrix.

<table>
<thead>
<tr>
<th></th>
<th>Sector a</th>
<th>Sector b1</th>
<th>Sector b2</th>
<th>Final</th>
<th>Total output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sector a</td>
<td>Z_a</td>
<td>Z_ab1</td>
<td>Z_ab2</td>
<td>y_a</td>
<td>x_a</td>
</tr>
<tr>
<td>Sector b1</td>
<td>Z_b1a</td>
<td>Z_b1b1</td>
<td>Z_b1b2</td>
<td>y_b1</td>
<td>x_b1</td>
</tr>
<tr>
<td>Sector b2</td>
<td>Z_b2a</td>
<td>Z_b2b1</td>
<td>Z_b2b2</td>
<td>y_b2</td>
<td>y_b2</td>
</tr>
<tr>
<td>Imports</td>
<td>m_a</td>
<td>m_b1</td>
<td>m_b2</td>
<td>y_m</td>
<td></td>
</tr>
<tr>
<td>Value added</td>
<td>VA_a</td>
<td>VA_b1</td>
<td>VA_b2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total inputs</td>
<td>x’a</td>
<td>x’b1</td>
<td>x’b2</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

A set of conditions dictate the range of values in the disaggregated matrix. These conditions (restrictions) follow the rule that the total output and total purchases (inputs) of the disaggregated sectors must equal the total output and total purchases (inputs) of the ‘parent’ sector, as outlined in Joshi (1999) in his EIO-LCA model III. All constraints are defined in the following equations:
In addition to the above, there is also the intra-matrix (grey shaded area in Table 5.2) which must also conform to the following condition:

\[ z_{b1b1} + z_{b1b2} + z_{b2b1} + z_{b2b2} = z_{bb} \] 

Disaggregating the \( z_{bb} \) term requires additional information with respect to how the two newly formed sectors purchase from and sell to each other. Pro-rating inputs and outputs, as can be performed for the terms in (5.1)-(5.6), is no longer an option in the case of the intra-matrix (5.7). Assuming sector b is agriculture, the disaggregation must take into account all information with respect to the characteristics of the target sectors. If sector \( b_1 \) is crops and sector \( b_2 \) is livestock, then sector \( b_2 \) would purchase inputs from sector \( b_1 \) (in the form of feed), with minimal inputs going the other way (only, for instance, manure) and with fairly limited transactions between the sub-sectors themselves\(^{41}\) (\( z_{b1b1} \) and \( z_{b2b2} \) may also be equal to zero under certain circumstances, reflecting the fact that sub-sectors with entirely different characteristics may not purchase goods from each other).

A simple numerical example of the procedure described above is available in Appendix D. In reality, producing a disaggregated matrix has two main further complications. Firstly, sectors often need to be disaggregated into several new sectors (creating a lot more cells to fill and an even larger intra-matrix\(^{42}\)). This is the case in the present study where the agriculture sector is disaggregated into 20 new sectors (see Table 5.3, p. 186). Secondly, and most importantly, disaggregation results in an ‘unbalanced’ matrix, where sectoral row and column sums are no longer equal to each other. Additional manipulations and assumptions

\(^{41}\) Different kinds of livestock are unlikely to trade between them even though there could be some transactions between cattle farmers and dairy farmers for example. The same is true to a large extent with growers of different crops.

\(^{42}\) Number of cells in the intra-matrix = \( n^2 \), where \( n \) is the number of new sectors within an existing sector.
are necessary in order to balance the disaggregated matrix before it becomes fit for use in I-O models. The recommended approach for balancing large disaggregated matrices such as the one in the present study involves the use of a balancing algorithm. However, rebalancing can only take place once a suitable disaggregation method has been carried out. Outlining possible options and justifying the most appropriate choice of disaggregation method is the focus of the next section.

5.2.4 Literature review of possible disaggregation methods

The example in section 5.2.3 (p. 163) has outlined the basic principles of disaggregation. There are, in effect, several possible disaggregation approaches, and choosing the most appropriate one often depends on the amount of additional information available. A systematic review of the literature reveals four principal approaches to disaggregation. These exist on a spectrum, from methods and studies that perform disaggregation based on a minimum amount of information and those that make use of an optimum set of information. Starting with the one that requires the least amount of information, all four possibilities are critically examined below.

Method 1 - Disaggregating an IOT with incomplete information

This approach is capable of disaggregating one sector into two or more sectors based only on the value of total output of each of the newly formed sectors (Lindner et al., 2012b). Initial work by Wolsky (1984), who presented a methodology for disaggregating one sector into two sectors, was recently extended by Lindner et al. (2012a), who applied their approach in order to disaggregate the electricity sector in the Chinese IOT into several sectors. This disaggregation method essentially builds a model to estimate a range of solutions in the absence of detailed information on inter-industry inputs and outputs between newly formed sectors and common sectors.

The original method by Wolsky (1984) estimates a final disaggregated A matrix by combining a first estimate of an augmented\textsuperscript{43} A matrix with a distinguishing matrix (denoted by Δ):

\textsuperscript{43} Augmented in this case stands for an intermediate matrix of equal dimensions to the target disaggregated matrix. It is thus augmented with respect to the original aggregated matrix.
The augmented $A$ matrix is simply a matrix where the disaggregated sectors have technologies that are identical to the technology of the ‘parent’ sector in the aggregated matrix. This is derived by keeping all inputs from common sectors equal to those of the ‘parent’ sector and then pro-rating outputs based on a weighting parameter ($w$) equal to the ratio of the gross output of each new sector in relation to the total output of the ‘parent’ sector. The weight proportionality assumption is also applied to the intra-matrix, to give a crude first estimate. For two new sectors as in Wolsky (1984), $w_1 + w_2 = 1$. The distinguishing matrix ($\Delta$) is a matrix that accounts for the difference between the augmented $A$ matrix and the final disaggregated $A$ matrix. As Wolsky (1984, p.284) aptly describes it, it ‘embodies the other data needed to accurately describe the disaggregated model’. $\Delta$ is necessary because disaggregation requires more information than is embodied in the augmented matrix, according to which newly disaggregated sectors are essentially identical.

$\Delta$ is made up of a series of independent parameters which account for the difference between the two newly formed sectors in terms of their demand for inputs (since $\Delta = A - A$), the departure from what the parent sector supplies to other sectors and, lastly, the differences in the intra-aggregate (intra-matrix) exchanges between $A$ and $A$. In the appendix of the article, Wolsky (1984) presents a method based on sensitivity analysis which allows all the independent parameters to be bounded by setting maximum and minimum possible values based solely on the values of the weights ($w_1$ and $w_2$). Wolsky (1984) points out that the accuracy of estimates of these independent parameters, and hence the accuracy of the final solution, improves with additional information with respect to inputs, outputs and intra-matrix transactions of newly formed sectors.

Lindner et al. (2012a) have recently generalised the approach by Wolsky (1984) in order to allow its use to create an arbitrary number of new sectors. The two main assumptions – that new sectors have identical technologies and that they supply other sectors proportionally to their output weights – are conserved in order to arrive at an initial estimate. The other major contribution of Lindner et al. (2012a) is the use of an algorithm to explore the full range of possible values for parameters which describe the level of departure of the disaggregated I-O

---

44 ‘Other data’ meaning additional to the simple augmented $A$ matrix which would otherwise result in a gross oversimplification of the problem.
table from the initial estimate. As in Wolsky (1984), the conclusion of the study is that when additional information with regards to the new sectors is available (besides their total output which is a given), this must be employed in order to improve the disaggregation.

The method appears promising for cases where the only information available is sectoral outputs of the new sectors. Nevertheless, the method is unnecessarily complicated for cases when there is a wealth of additional data with respect to the new sectors. There is also no mention of how the final matrix is balanced. It is unclear from the text or equations whether the disaggregation process implicitly handles balancing. Another apparent shortfall of the method is the fact that it works only with the coefficients matrix and not the transactions matrix. This does not allow the user to assess its performance against the original aggregate transactions matrix. The aforementioned issues mean that, despite its merits and the fact that the aforementioned seminal papers provide an in-depth understanding of disaggregation constraints to take into consideration, this method is not suitable for the purposes of this study.

**Method 2 - Disaggregating by pro-rating and expert knowledge**

This is perhaps one of the most commonly used disaggregation approaches, especially seen in work which uses disaggregation as a means to an end, and not as the main focus of the study. It offers a sensible compromise between the amount of information utilised and its technical simplicity. Even though this particular approach (as considered in this study) encompasses a variety of subtly different methodologies (depending on the sector being disaggregated, on the country and the data available and other permutations), the main principle is to prorate inputs and outputs from and to common sectors and then deal with the intra-matrix using common sense and additional information with regards to the transactions between the new sectors. Recent manifestations of this approach are seen in Wiedmann (2010, 2011) and Liu et al. (2012), applied to the electricity sectors of the UK and Taiwan, respectively.

In their study, Wiedmann et al. (2010, 2011) sought to determine the indirect GHG emissions of wind power. Using an SUT framework instead of the more conventional IOT, they first split the electricity industry and product sectors into eleven sub-sectors (including a transmission and a distribution and trade sector) using data on total turnover and the
amount of electricity generated. In this first step, the input and sales structure of the sub-sectors is kept the same. It is then refined by using real process-based data, which are converted into expenditure using unit prices of production for domestic and imported goods. The choice of what to include or not and how to modify the initial pro-rated inputs is largely based on common sense, according to the authors. Also, based on ‘common knowledge’ is the fact that wind power does not directly require any significant quantity of fuels for its operation and that its direct emissions are zero (as it is a clean source of energy, with its only impact coming indirectly through the supply chain). The matrices are finally rebalanced using a rebalancing algorithm (see section 5.2.5, p. 173).

Liu et al. (2012) follow a similar approach for the electricity sector in Taiwan (which is disaggregated into six sectors) but also expand this to disaggregate the ‘fossil fuels’ sector into two further sectors and the ‘forestry and agriculture’ into three further sectors. The electricity sector is split using the amount of electricity generated as a weight for pro-rating inputs, whilst the sales structure is kept the same. The final disaggregated matrix is then ‘adjusted to reflect the specificities of the sub-sectors’ (Liu et al., 2012, p.127). This again assumes that many of the transactions in the intra-matrix are set to zero. Examples mentioned in the text are transactions between the ‘wood products’ and ‘paddy rice’ sectors, and the ‘hogs’ and ‘other poultry and livestock’ sectors. Finally, the matrix is rebalanced.

The disaggregation approach described in these articles is pragmatic in the sense that it is highly geared towards a certain objective, whilst minimising the amount of time and technical manipulation required. Adding necessary zero values to reflect the nature of sector transactions and then pro-rating other inputs and outputs is highly functional in the sense that it ensures that a certain amount of ‘real-world’ characteristics of the sectors are effortlessly included in the disaggregation procedure. Furthermore, a balancing algorithm (see section 5.2.5, p. 173) ensures that the resulting matrix is balanced properly, whilst strictly obeying disaggregation constraints as outlined previously. Liu et al. (2012), importantly, also demonstrate that this method can work for disaggregating agricultural sectors and thus is highly pertinent to the present study. A possible disadvantage of the method is that some of the assumptions made with respect to intra-matrix transactions represent oversimplifications. Nevertheless, this is a necessary approximation in the absence of detailed trade data between newly formed sub-sectors.
Method 3 - Disaggregation using detailed industry or farm data

This appears to be one of the most thorough approaches for disaggregating an IOT, and is especially pertinent to performing agricultural sector disaggregation in cases where high-resolution data on transactions between subsectors are available through detailed farm surveys. Arguably the best example of this method is found in Lindberg & Hansson (2009). A slightly more simplified procedure using FAO supply utilisation accounts was also used in the GTAP 7 database which also employs a disaggregated agricultural sector (McDougall, 2008). Within this category of approaches, one can also include the approach used by Allan et al. (2007) to disaggregate the electricity generation sector in Scotland based on detailed industry surveys and face-to-face interviews to determine inputs and outputs of different electricity generation technologies45. The present review focuses on the method described in Lindberg & Hansson (2009) as it is more relevant for agricultural products.

Lindberg & Hansson (2009) perform disaggregation in order to investigate the potential that different agricultural sub-sectors in Sweden have in terms of stimulating output, income and employment. Since their study is highly focused on agriculture and its specific role in the national economy, a meticulously crafted disaggregation approach is merited in order to capture differences in multipliers for different agricultural products. Using an SUT classification, they first use data from the detailed Swedish Farm Accounting Data Network (FADN) which contains profit and loss statements and balance sheets for all medium to large commercial farm units specialised in cattle (milk and beef), pig farming, mixed livestock production and cereal production, as well as other types of production. Another database is also used to supplement information on poultry and sheep farms, for example with gross margin budgets – which contain information on required input quantities of specific commodities.

All flows of inputs into different farm types are then used to disaggregate the USE matrix while all production from different kinds of farms appears in the MAKE matrix. The approach also accounts for all intra-matrix transactions such as purchases of live animals

45 Note that unlike in the previous approach, the Allan et al. (2007) study does not appear to prorate inputs or output based on total turnover but relies on published data along with further data collection which also allows for estimates of imports, labour, capital and taxes for different technologies.
between farms. The authors appear to make two major assumptions in their work. Firstly, that feedstuffs purchased by agricultural sectors from the food and beverage sector as well as those imported from abroad have the same trade and transport margins. Secondly, that the resultant disaggregated matrices are consistent with the original aggregated ‘parent’ matrices. The first assumption is perfectly understandable in the absence of detailed trade and transport margins for subsectors. On the other hand, the authors’ lack of consideration of balancing methods is surprising, especially considering their overall attention to detail. A disaggregated matrix, when subjected to aggregation, must ideally equal the original aggregated matrix (Fei, 1956; Lenzen, 2011; Wolsky, 1984). A balancing algorithm (see section 5.2.5, p. 173) can be used to ensure this is the case. The authors do not appear to have considered this option.

Evidently, the quality of the results obtained using this approach should, in principle, be superior to the other two approaches described earlier. However, in the absence of research comparing different disaggregation approaches, this claim cannot be tested. Furthermore, all the data required in order to comprehensively disaggregate a sector in the manner described in Lindberg & Hansson (2009) is most often unavailable. With regards to Cyprus, some detailed elements based on farm surveys are available in the Cyprus Agricultural Statistics (CYSTAT, 2010) and can be used to infer more details about the purchasing and selling taking place between agricultural sub-sectors. Nevertheless, some inputs and outputs need to be pro-rated because there is insufficient information to consistently disaggregate all sectors based on this last approach. Furthermore, this approach uses a SUT classification as opposed to the IOT classification used in the present study. This means that, even though some elements of this approach are applicable to the Cyprus agricultural sector disaggregation, the full use of this approach is not a possibility.

**Method 4 - Extension matrix idea and hybrid EIO-LCA**

This last disaggregation approach is not a disaggregation method *per se*, but it does achieve a similar purpose in that it aims to address the problem of using IOTs with a high sectoral aggregation. This is achieved by integrating detailed product-level (LCA) data into the analysis and matching these to the appropriate economic sectors without the need for a disaggregation of the actual IOT. Hybrid EIO-LCA techniques (Hendrickson, 1998; Joshi,
1999; Suh & Nakamura, 2007) have been around for quite some time, and there exist various ways to effectively combine physical process-based and monetary IOT data to improve the resolution of a model (see Suh & Huppes, 2005 for detailed review). Recent studies (Ewing et al., 2012; Steen-Olsen et al., 2012; Weinzettel et al., 2011) have developed a new variant or hybrid of process-based and EIO data specifically aimed at MRIO studies where one of the key priorities is to trace the flows and footprints of traded primary products.

According to Steen-Olsen et al. (2012), the extension matrix method is essentially a compromise between a full-blown disaggregation, which requires extensive new data, and making use of an existing international I-O classification – which is unable to distinguish different products within broader sectors\(^{46}\). Known footprints for individual primary products are introduced as an extension and are kept in physical as opposed to monetary units (see Figure 5.1). The model, MRIO-Footprint (MRIO-F), is described in detail in the supporting information of the Ewing et al. (2012) paper. The authors provide a numerical example which demonstrates how the extension matrix is created using FAOSTAT data which allocates primary products (such as crops) to consuming sectors and final consumers in the MRIO system. A set of conversion factors is finally used in the calculations to convert the physical quantities of primary products into footprints (Weinzettel et al., 2011).

The main advantage of the approach is that it provides the possibility to make use of available information on trade and consumption of primary crops – including fodder crops (Ewing et al., 2012). This is of direct importance to the agricultural sector disaggregation and water use, as the main embedded water use in livestock sectors comes from animal feed (Gerbens-Leenes et al., 2013; Hoekstra, 2012). Furthermore, the MRIO-F model is ideal for estimating impacts of consumption occurring outside the domestic realm (imported water from different sources is very well accounted for). The fact that this is achieved without the need to disaggregate numerous country IOTs into a harmonised classification is a strong selling point for this approach, especially in cases where studies intend to perform inter-country comparisons or investigate environmental footprints embedded in traded products, as in Steen-Olsen et al. (2012).

\(^{46}\) In most cases agriculture appears as a single sector in IOTs, even though some databases such as GTAP and EXIOPOL already use more disaggregated agricultural sectors. However, their sectoral resolution is still fairly low for the purposes of studies which need a comprehensively disaggregated agricultural sector.
Despite its apparent appeal, the aforementioned approach is not suitable for the present study. The main reason for this is that the construction of the extension matrices requires data on primary product utilisation by industrial sectors, and a complex series of assumptions with respect to commodity prices as well as additional measures to avoid double counting. Lenzen et al. (2013) have recently criticised this method for making use of databases which do not contain sufficient information with respect to the link between physical product-level data and the consuming sector, thereby requiring a pro-rating procedure that could lead to serious allocation errors. According to Lenzen et al. (2013), the only way to correct this is through manual manipulation of misallocated entries, which risks rendering the method almost as labour-intensive as performing a more conventional disaggregation (as with methods 1-3 above).

Final note on disaggregation methods and the chosen approach

This sub-section has critically reviewed the main disaggregation methods available in the literature in the context of the present study. The choice of disaggregation method is ultimately linked to the objectives of the study and the availability of data. In light of the data demands of the last method, method 4, in addition to the critique in Lenzen et al. (2013), it can be argued that a conventional disaggregation obtained through disaggregating the
original IOT is more appropriate, especially since the focus of the present study is on the volume of water used within the Cypriot economy and the way tourism demand impacts other economic sectors. This automatically excludes method 4. Method 3 is also not possible due to a lack of available data along with not having SUTs in basic prices for Cyprus.

The availability of agricultural statistics (CYSTAT, 2010) which allow a basic understanding of transactions taking place within the intra-matrix (between agricultural sub-sectors) as well as additional data and statistics allowing estimation of the value of inputs, value added, and outputs of agricultural sub-sectors, suggests that a combination of methods 1 and 2 offers the best compromise. This realises the main objective of disaggregation that is to produce a more detailed agricultural classification capable of assessing the economic and water use impacts of different tourist diets. As the disaggregation process results in an unbalanced matrix, the choice of the technique used to rebalance the matrix is also inherently a vital part of the disaggregation process. This is discussed in the following sub-section.

5.2.5 Matrix balancing techniques

Biproportional scaling and constrained optimisation techniques

It is to be expected that any attempts to disaggregate or update an IOT result in the table becoming unbalanced. The example in Appendix D demonstrates how more detailed information can create a numerical problem whereby certain cell values, even if correctly based on available data, still need to be readjusted to cater for the fact that total output must equal total inputs. The matrix therefore needs to be subjected to a rebalancing procedure in order to preserve the overall I-O balance. According to Liu et al. (2012), monetary data in grand total rows are constrained to match with monetary data in grand total columns as well as other available data on totals of the original aggregated sectors. Ideally, significant change requires a full industry survey to create a new IOT. However, such surveys are generally impractical and expensive (Oosterhaven et al., 1986). For this reason, IOTs are generally only published once every five years (Dietzenbacher & Miller, 2009). Furthermore, surveys may be incomplete or may be characterised by the suppression of confidential information (Lenzen et al., 2009).

47 Updating an IOT normally refers to creating a more recent table using new sectoral outputs on the basis of a previous interindustry transaction or coefficient matrix (Miller & Blair 2009).
There are various techniques proposed in the literature for updating matrix coefficients. These are divided into biproportional scaling techniques and constrained optimisation techniques (Lenzen et al., 2009). Biproportional scaling techniques, also known as RAS variants, generate a new coefficient matrix using a prior year table through an iterative procedure of scaling coefficients to target year intermediate inputs (column sums) and intermediate outputs (row sums) in addition to total industry outputs (R. Jackson & Murray, 2004). Constrained optimisation techniques involve general constrained matrix problems that cannot be solved using simpler scaling techniques (as they often involve non-linear programming), which aim to minimise some geometric measure of distance between elements of the prior and estimated matrix (Lahr & De Mesnard, 2004).

Jackson & Murray (2004) compare the results from 10 different methods and find that, in most cases, traditional RAS outperforms more complex techniques (including constrained optimisation approaches) when all values in the matrix are positive. The RAS procedure has several other desirable qualities. Firstly, the resulting matrix is the one with the least amount of deviation from the base-year matrix. Secondly, RAS has a sound economic basis, as the changes to the coefficients reflect necessary substitution and fabrication effects (Jackson & Murray, 2004; Miller & Blair, 2009). Thirdly, the RAS procedure preserves the signs of the original matrix elements, producing an iterative solution which is intuitive and straightforward to compute (Jackson & Murray, 2004), using linear programming. According to Lenzen et al. (2009), the ease of programming associated with traditional RAS is one of the main factors for its enduring popularity despite the emergence of various alternatives. Another invaluable quality of RAS, which also makes it unique in relation to other updating procedures, is the fact that it may be carried out both on the transactions (Z) and the coefficients (A) matrix, yielding identical results (Dietzenbacher & Miller, 2009).

For these reasons, the present review concentrates solely on RAS techniques, in order to select an appropriate methodology for rebalancing the disaggregated Cyprus matrix. More

48 RAS in not an abbreviation. The origin of the name is explained by equation 5.13.
49 The comparison is carried out by updating the coefficients of the 1967 23-sector US IOT from Miller & Blair (1985) to 1972 and then to 1977, with each of the ten methods. The relative performance of the alternative updating methods is subsequently assessed using four primary matrix comparison methods.
50 RAS, in fact, ensures that no negative values can be achieved (Lahr and de Mesnard 2004), provided all elements in the original matrix are positive (which is usually the case).
extensive reviews which include constrained optimisation approaches are offered by Jackson & Murray (2004) and Lahr & de Mesnard (2004). Despite certain weaknesses that are discussed later on, RAS techniques offer an established approach that is adequate for the purposes of the present study.

**Traditional RAS and hybrid models**

Based on an initial coefficients \((A)\) or transactions \((Z)\) matrix, the RAS algorithm estimates a new matrix with known row and column totals as well as total outputs (most of which have changed compared to the original matrix) by a biproportional scaling of the elements in the initial matrix (Gilchrist & St.Louis, 1999). The RAS approach was first developed and introduced by Stone (1961) and Stone & Brown (1962) in an attempt to update a given IOT without the need for a new set of inter-industry data (Jackson & Murray, 2004). The RAS technique is explained below using the notation in Miller & Blair (2009) and Jackson & Murray (2004). Following usual practice, this is presented here for updating coefficients (the \(A\) matrix), but the same approach can also be applied to the transactions matrix (the \(Z\) matrix).

Starting with \(A\) (0), where 0 represents a given year in the past for which the latest IOT is available, the aim is to calculate \(A\) (1), the target year coefficients matrix. The data required for the target year are total gross outputs, total inter-industry sales (total output minus final demand, \(x - y\)) and total inter-industry purchases per sector (total output minus value added minus imports, \(x - VA - m\)). The vector of total gross outputs is designated by \(x\) (1). The vector of total sectoral inter-industry sales, which represents the row totals of \(A\) (1), is designated by \(u\) (1). The vector of total sectoral inter-industry purchases, which represents the column totals of \(A\) (1), is designated by \(v\) (1). According to Miller & Blair (2009), assuming an \(n \times n\) matrix, the problem which RAS addresses is to use 3\(n\) pieces of information (\(n + n + n\)) to estimate the \(n^2\) coefficients of \(A\) (1).

The first step in RAS is to compute the \(u\) values that would have been valid if there had been no change in \(A\). The assumption in this case is that \(A\) (0) = \(A\) (1). Using known total outputs for the destination year:

---

\(\text{51 This refers to the total output, total sectoral inter-industry sales and total sectoral inter-industry purchases each of which are vectors of length } n.\)
This gives the set of inter-industry transactions assuming there had been no changes in \( A \). The row sums of \( Z(0) \) then become the \( u^0 \) vector and the column sums the \( v^0 \) vector. Dividing \( u \) (1) by \( u \) (0) gives a vector \( r^1 \) that gives the ratios of the differences between the target \( u \) and the one estimated using the older \( A \) matrix. This becomes a scaling factor that needs to be multiplied to the rows in order to scale them up (or down) to make them equal to \( u \) (1). This is carried out through:

\[
A^1 = r^1 A(0)
\]  

(5.10)

where \( r^1 \) is the diagonal matrix\(^{52} \) of \( r^1 \). Whereas post-multiplying a matrix by a diagonal vector as in (5.9) multiplies each element of each column by the same value, pre-multiplying a matrix by a diagonal matrix multiplies each element of each row by the appropriate scaling factor. This gives a first estimate of a target-year intermediate I-O structure, \( A^1 \), where row sums (total sectoral inter-industry sales) are equal to \( u \) (1).

Since the first step only corrects elements in order to adhere to the known row sums, the second step in RAS is to carry out a similar procedure to ensure that the column sums are scaled up or down to the values given by \( v \) (1). \( A^1 \) is used to estimate a new set of inter-industry transactions based on the updated matrix:

\[
Z^1 = A^1 \hat{x}(1)
\]  

(5.11)

This time, using the column sums vector of \( Z^1 \), denoted by \( v^1 \), along with known column sums of the target matrix, \( v \) (1), it is possible to estimate appropriate scaling factors for column elements\(^{53} \).

Dividing \( v \) (1) by \( v^1 \) gives a vector, \( s^1 \), that gives the ratios of the differences between the target \( v \) and the one estimated using the updated \( A^1 \) matrix. As in step 1, this becomes the scaling factor used to correct column sums:

\(^{52} \) A diagonalised matrix of a vector of length \( n \) is simply an \( n \times n \) square matrix with the vector values in its diagonal and zeros as all non-diagonal elements.

\(^{53} \) Note that, as in the previous step, the updated \( Z \) matrix also has a new set of row sums, \( v^1 \), which is not used as this step focuses on correcting column sums. In the previous step it was \( v^0 \) that remained unused.
where \( S^1 \) is the diagonal matrix of \( s^1 \). Using (5.10), (5.12) can be rewritten as:

\[
A^2 = \hat{r}^1 A(0) S^1
\]  

(5.13)

Ignoring any superscripts, “hats”, lower case letters or numbers, the right-hand side reads “RAS”, where \( R \) is a diagonal matrix row modifier, \( A \) is the coefficient matrix being modified, and \( S \) is a diagonal matrix of column modifiers. This is where the RAS technique gets its name from (R. E. Miller & Blair, 2009). The method is iterative, in the sense that \( A^2 \) is only the second of possibly several estimates of \( A \), before arriving at the final target year coefficients matrix \( A(1) \). With every row adjustment (as in step 1), column sums are disturbed and with each column adjustment (as in step 2), row sums are disturbed. Nevertheless, the estimates progressively improve. According to Jackson & Murray (2004), the procedure, in most cases, quickly converges to a stable estimate\(^{54}\). The number of adjustments required also depends on the desired level of accuracy, with respect to the closeness of the row and column sums of the adjusted matrix and known target-year values. Miller & Blair (2009) denote this level of accuracy as \( \varepsilon \), where \( \varepsilon \) is a small positive number, such as 0.001 or 0.005 which refers to differences in corresponding row and column elements\(^{55}\). This can be expressed as two inequalities:

\[
| u(1) - u^k \mid < \varepsilon \\
| v(1) - v^k \mid < \varepsilon
\]  

(5.14) \hspace{1cm} (5.15)

In Miller and Blair’s (2009) 3 x 3 matrix example, the target-year matrix is already known. This allows them to compare the estimated (adjusted) matrix to the actual matrix in order to ascertain the error in the estimate. Their results reveal that, even though the mean absolute percentage error (MAPE)\(^{56}\) is 63.8% on average, the estimated \( A \) matrix performs relatively well in practice. When converted into a Leontief inverse and used to estimate sectoral gross outputs for a given final demand vector, the errors (known as ‘holistic accuracy’) drop to

\(^{54}\) In a mathematical sense, the RAS solution is shown to minimise the sum of the weighted logarithms of the relative differences between elements in the base-year table and the updated table (Ooesterhaven et al. 1986).

\(^{55}\) This is the \( \varepsilon \) number set by Miller and Blair (2009, p.320-323) in their numerical example.

\(^{56}\) MAPE is the average percentage by which each coefficient differs from its true value.
below 5% per sector in relation to estimates using survey-based coefficients. This suggests that the level of accuracy of the RAS technique is adequate for the majority of studies focusing on sectoral and total economy outputs, including the present study.

The traditional approach has, over the years, been modified to take into account partial (such as missing values in the original $A$ matrix and/or missing row or column sums) or additional information (known cell values for the target matrix or known cell aggregates). This has given rise to several modifications or variants of the original RAS method, all based on biproportional scaling. Most variants of RAS concentrate on adding different restrictions to the new unknown matrix, such as known individual cell values or known combinations of individual cell values (Mínguez et al., 2009). These are grouped under the name ‘hybrid models’ (Miller & Blair, 2009) or ‘modified RAS’ (Lenzen et al., 2009) approaches. Examples of prominent RAS variants are the ‘three-stage RAS’ (TRAS) (Gilchrist & St.Louis, 1999; 2004) which includes an additional stage at each iteration to incorporate additional information, ‘generalised RAS’ (GRAS) (Junius & Oosterhaven, 2003) which deals with matrices which include negative numbers, and, finally, ‘extended RAS’ (ERAS), developed by Israilevich in his 1986 PhD dissertation entitled ‘Biproportional Forecasting of Input-Output Tables’, in order to fix interior cells to known values (Lahr & De Mesnard, 2004). A more recent variant is the Konfliktfreies (conflict-free) RAS (KRAS), developed by Lenzen et al. (2009) to improve the way RAS handles conflicting external data and inconsistent constraints.

**Choosing and developing a suitable RAS approach**

According to Lenzen et al. (2009), an aggregated table may also be considered as an additional piece of information information where the desired end-product is a more disaggregated national table. This argument is highly relevant to the present study, especially with respect to the intra-matrix, where the sum of the cells in the disaggregated matrix should not exceed that of the single aggregated cell in the original table. The required approach should therefore combine known information regarding the disaggregated sectors such as total inputs and outputs, along with estimates of final demand and value added for the disaggregated sectors (which allow estimates of $u$ and $v$), and remain consistent with constraints imposed by information in the original table (5.1-5.7).
Until recently, there has been a significant amount of debate on whether using additional information actually benefits the RAS technique. Despite the vast majority of published results showing improvements due to supplementary data, there were a few examples where additional exogenous information seemed to produce inferior results (compared to the traditional RAS). However, de Mesnard & Miller (2006) conclude that, in the overwhelming majority of cases, the introduction of additional information into RAS improves the resulting estimates\(^57\). For this reason, Gilchrist & St. Louis (1999, 2004) had earlier argued that, in the absence of a failsafe way to predict with any certainty that the performance of the method could be worsened by introducing additional information, the most sensible option would be to utilise all available data. In conclusion, as a general rule, accurate exogenous (additional) information improves the resulting estimates and this is precisely what RAS variants are meant to take advantage of in order to improve the performance of the balancing procedure (Miller & Blair, 2009). In the present case, the disaggregation is likely to be more valid if all available information is used, based on the simple idea that an aggregated matrix of the final disaggregated matrix must be as close as possible to the original (aggregate) matrix.

**TRAS – a suitable RAS variant**

Out of the available RAS variants, TRAS appears to offer all necessary qualities and the flexibility required for present purposes. TRAS is seen as an extension of the traditional RAS algorithm which can function through generalised information (not restricted to row and column sums) on various subaggregates of the cells in a target matrix (Gilchrist & St.Louis, 1999), and is based on earlier work by Oosterhaven et al. (1986). Using the example of Canadian provincial tables, Gilchrist & St. Louis (1999) show that certain matrix elements are often censored in the more disaggregated versions, but are kept in the more aggregated level of sectoring. In this sense, TRAS is an attempt to estimate the censored data based on its more aggregated but uncensored equivalent (Lahr & De Mesnard, 2004). Mathematically, this is carried out by incorporating this information as supplementary to that of the row and column total (Gilchrist & St.Louis, 2004), through an additional operation following the row

\(^57\) Nevertheless, this does not imply that the introduction of additional information will guarantee error reduction. It is also acknowledged by de Mesnard & Miller (2006), that the choice of distance measure used to compare the results between the traditional RAS approach and the RAS which makes use of additional information, has a significant influence on the outcome. This produces incomparable results between studies.
and column scaling modifications. This additional operation becomes the third step of the algorithm at each stage (iteration).

The explanation of the third step of TRAS necessitates the introduction of some new nomenclature and additional matrices. Following Gilchrist & St. Louis (2004), the procedure is performed on the transactions matrix \( Z \) as opposed to the coefficients matrix \( A \) as previously seen for RAS. Before initiating the conventional RAS algorithm using row and column sums, TRAS requires the prior definition of a new \( h \times k \) matrix, \( Z \), containing known information within the matrix. This can have any number of dimensions depending on how much information is known but will always be smaller than the \( Z \) matrix. An appropriate row aggregator matrix\(^{58} \) \( P \) with dimensions \( h \times m \), and an appropriate column aggregator matrix \( Q \) with dimensions \( n \times k \), are required to aggregate the target \( Z \) matrix (or any intermediate target matrix with the same dimensions) to \( Z \):

\[
P Z Q = \tilde{Z} \quad (5.16)
\]

Having defined \( Z \), the algorithm proceeds with the regular RAS steps (Gilchrist & St.Louis, 2004). By the end of the first two steps the result is the same as that reached in (5.13), with the only exception of \( Z \) in place of \( A \):

\[
Z^2 = \hat{r}^1 Z(0)^{\xi^1} \quad (5.9)
\]

The resulting matrix, \( Z^2 \), is then used along with \( Z \) to define a new matrix, \( G^1 \):

\[
G^1 = \tilde{Z} \div [P(Z^2)Q] \quad (5.18)
\]

where \( \div \) implies a Hadamard (element by element) division as opposed to a matrix division. \( G^1 \) is essentially a matrix whose elements are scaling ratios\(^{59} \) which ensure that any aggregation constraints will be fully satisfied in the target \( Z \) matrix. In order to apply these

---

\(^{58}\) Aggregator matrices are simple matrices which consist of values of 0 and 1, reviewed in Miller & Blair (2009, p. 161).

\(^{59}\) ‘Scaling ratios’ appear to be identical to ‘block scaling factors’ used in McDougall (2008) to rebalance disaggregated agricultural IOTs in the GTAP 7 database.
constraints to the $Z^2$ matrix, however, $G^n$ needs to be scaled up to match the dimensions of $Z^2$. This is achieved through:

$$T^1 = P'G^1Q'$$  \hspace{1cm} (5.19)

where $P'$ and $Q'$ are the transposes of the aggregation matrices in (5.17). $T^1$ is therefore a matrix with the same dimensions as $Z$, in which every cell in any aggregation block will contain the same $g$ value (where each $g$ value is an element of the matrix $G$). To complete the step, there is one last operation given by:

$$Z^3 = T^1.Z^2$$  \hspace{1cm} (5.20)

where, as above, this is a Hadamard product. The algorithm proceeds iteratively until a predefined convergence criterion (such as that defined by 5.14-5.15) is achieved, $|Z^n - Z^{n-1}|$ converges to zero, or until the three ratio matrices ($R$, $S$, and $T$) converge to unity (Gilchrist & St.Louis, 2004). The convergence is ‘business as usual’ in the sense that it is similar to the RAS procedure, with the only difference being the extra step at each iteration which adds a degree of rigour to the result. It also potentially slightly unbalances the row and column sums at each iteration, meaning that usually a higher number of iterations are required in order to reach convergence compared to conventional RAS.

It follows from the above description that the TRAS approach provides a balancing technique which is ideally suited to the requirements of the present study. There are three main reasons for which TRAS is preferred to the traditional RAS approach or other RAS variants:

1. The disaggregation case is one where supplementary data other than row and column sums are available for certain submatrices of the matrix (Gilchrist & St.Louis, 2004). Since aggregate sums of cell blocks are known from the original matrix and, by using these as constraints, the balanced disaggregated matrix solution remains tightly fitted to the ‘parent’ aggregate matrix. The TRAS numerical example in Appendix D demonstrates that aggregating the disaggregated inter-industry transactions matrix results in a matrix that is identical to the original aggregated transactions matrix.
2. In traditional RAS, common practice for dealing with known elements is to subtract
them from their corresponding column and row sums, replace them with zeros
during the balancing process, and then finally add them back in place of the zeros in
the balanced matrix (Miller & Blair, 2009). This ensures that these elements containing
superior quality information are not subject to any modifications during the RAS
iterations. Any zero values also remain zero, which is useful when it comes to
balancing the intra-matrix, where some agricultural sub-sectors are certain to have no
trade with others (an example is the pork sector with the olive sector or the dairy
sector). This approach may be quick and straightforward but it has a major
drawback. Where too many zero values are present in the matrix, RAS fails to
converge at specific coefficient or transaction values (Miller & Blair, 2009). This occurs
because too many zero cells block the capacity of the RAS algorithm to distribute
excess value from one sector to another (Lahr & De Mesnard, 2004). TRAS thus offers
an alternative to adding unnecessary zero values which can potentially affect the
ability of the procedure to converge to a solution by scaling known cells to ensure
they have the correct value at the end of each iteration.

3. Gilchrist & St. Louis (1999, 2004) compare the results from RAS and TRAS. Their
results show that TRAS outperforms RAS in all SUT matrices considered by the
authors, including situations where a complete aggregate matrix was not available
(Gilchrist & St.Louis, 1999). In their more recent paper, Gilchrist & St. Louis (2004)
use a marginal gain test to identify the incremental gain achieved by using TRAS as
opposed to RAS. This test is performed on an attempt to estimate a 1984 provincial
table for Alberta using national coefficients for Canada as a starting base. As in their
previous paper, the conclusion is that the ability of TRAS to make use of additional
aggregate information provides a statistically significant improvement over the
conventional RAS algorithm. On the basis of these results, Lahr & de Mesnard (2004,
p.126), argue that is ‘clear that timely, accurate input–output tables can be produced
with approaches like TRAS’.

Despite the considerable benefits of using TRAS, it still belongs to the family of RAS variants,
meaning that it suffers from some of the major drawbacks inherent in the RAS method. Over
the years, several authors in the literature have identified weaknesses in the traditional RAS
approach, some of which also apply to TRAS. Lenzen et al. (2009) identify four important ones:

(a) No consideration of the reliability of the initial estimate;
(b) No consideration of the reliability of external constraints;
(c) Inability to handle negative values and preserve the sign of matrix elements; and
(d) Inability to handle conflicting external data (such as in cases where two data sources prescribe different values for the same matrix entry).

TRAS does not explicitly rate the quality of prior information. The inability to handle negative values also applies to TRAS, unlike GRAS (Junius & Oosterhaven, 2003) which was designed to address this problem. According to Lahr & de Mesnard (Lahr & De Mesnard, 2004), who strongly argue that negative flows are difficult to interpret in economic terms, this should not be seen as an issue. Negative flows may often appear in stock inventories but have no place within the inter-industry matrix, which should, in principle, consist only of positive or zero values. This is certainly the case with the WIOT IOTs, where all inter-industry flows are positive.

The last weakness, (d), concerns the ability of the algorithm to handle conflicting information. Lenzen et al. (2009) developed KRAS mainly in an attempt to address this problem. Again, TRAS does not explicitly handle this issue. Nevertheless, where the algorithm is simply required to balance a disaggregated table, as is the case here, the original aggregate table is the only piece of information available, meaning that the algorithm need not be capable of handling conflicting information (d). Oosterhaven et al. (1986) argue that another negative theoretical aspect of RAS is the fact that zero cells cannot become non-zero. Even though this would make the algorithm more flexible, zero flows exist for a reason (in the sense that they have an economic significance as some sectors may not trade with others) and should thus be respected. Nevertheless, where the matrix contains too many zero values to the point where this severely diminishes the effectiveness of the algorithm to converge to an estimate, a suggested solution is to replace zeros with very small non-zero values (McDougall, 2008).
Final notes on TRAS

This section has allowed a decision to be taken with respect to an appropriate method to use for rebalancing the disaggregated matrix in a way as to ensure that the disaggregated matrix solution is consistent with the original IOT (previously used to generate the results in Chapter 4). The above review has shown that TRAS has numerous attractive features, making the technique an ideal choice for balancing the disaggregated Cyprus IOT. Appendix D contains a numerical example using a 3-by-3 matrix further demonstrating the ability of the technique to swiftly converge to an acceptable (with a very low degree of error) estimate of the target transactions matrix. The next section documents how the Cyprus WIOD 2007 IOT was disaggregated and rebalanced using the chosen methods.

5.3 WIOD 2007 matrix disaggregation in practice

5.3.1 Section introduction

The present section summarises the exact procedure followed in establishing a revised classification of the agricultural sector, detailing also how the table is subsequently rebalanced. The IOT used as the starting point of the disaggregation process is the 2007 WIOD IOT (identical to the IOT used in Part III). Following the guidelines for disaggregation and rebalancing established in previous sections of the current chapter, the original ‘mother’ 33-by-33 matrix is augmented to form a 52-by-52 ‘daughter’ matrix by disaggregating the agricultural sector into 20 sub-sectors.

5.3.2 Establishing a classification for the disaggregated agricultural sectors

Before deciding on the classification categories within the agricultural sector, available data was closely examined to ensure that any chosen classification would also be cross-compatible with international classifications to allow the harmonisation of imports and their water use coefficients. Classification harmonisation aids in linking trade between sectors and products in different countries and regions (Verhoog et al., 2008). The most straightforward solution would be to use native classifications such as those given in the Cyprus Agricultural Statistics (CYSTAT, 2010) or the Statistical Abstract (CYSTAT, 2011b), as these tend to match up well to water and land requirements per crop/area provided by the Cyprus WDD (WDD, 2011). However, this was not done so as to achieve a classification that can be matched to
those of other countries or databases, namely the FAOSTAT database (FAO, 2013) which represents a widely used source of agricultural trade data.

Since the Cyprus 2007 WIOD IOT is already in a classification largely based on the European NACE Rev.2 classification for economic activities (Eurostat, 2013), the most appropriate course of action is to use sub-categories (or some other variant of these which entails straightforward aggregation or other manipulation) of NACE Rev.2 to disaggregate the Cyprus agricultural sector. As Cyprus predominantly trades with other European countries, this classification ensures excellent compatibility with its EU trading partners. Furthermore, other non-EU trading partners are likely to use the International Standard Industrial Classification (ISIC) 3.1 classification which is also compatible with NACE, as NACE is derived from the ISIC system (see Figure 5.2).

5.3.3 Final choice of agricultural sub-sector classification

After considering FAO and CYSTAT data, a compromise between the amount of detail sought and the extent of harmonisation between the databases was achieved, giving rise to the classification shown in Table 5.3 below. Following the NACE agricultural structure, the agriculture sector is first disaggregated into agricultural crops and animal products, fishing and aquaculture, and ancillary products. In the case of Cyprus, the ancillary sector predominantly includes cheese production (which accounts for 97% of the sector’s output) along with a very modest amount of forestry, logging and hunting activities. A choice of sub-

![Figure 5.2 Associations across different classification systems in relation to geographical scale (global to national- vertically) and level of detail (activity to product – horizontally) (source: Eurostat 2002 in Verhoog et al. 2008).](image)
sectors is then finalised based on the main products of the Cyprus agricultural sector (CYSTAT, 2010) as well as trade data from the FAO (2013).

The final classification, shown below in Table 5.3 must be seen as a compromise rather than the best possible outcome between CYSTAT and FAO. For example, there are significant differences in terms of the water requirements of different cereals or legumes, yet these are grouped into the same category, thus forcing the assumption that their average water productivities are similar. Even though detailed water footprint estimates are available for different crops and varieties within the proposed sub-sectors (Zoumides & Bruggeman, 2010; Zoumides et al., 2013), the economic data (total output, value added and other matrix transactions) would be extremely difficult to estimate. The chosen distinction between different meat and crop groups already represents a substantial improvement over the more conventional use of a single aggregate agricultural sector and is detailed enough for considering differences in tourist diet preferences.

<table>
<thead>
<tr>
<th>Categories</th>
<th>Sub-sectors</th>
</tr>
</thead>
<tbody>
<tr>
<td>CROPS</td>
<td>Cereals, Leguminous plants, Fodder, Potatoes, Vegetables (all), Wine grapes, Table grapes, Citrus, Fruit (excluding citrus), Nuts, Olives</td>
</tr>
<tr>
<td>MEAT &amp; DAIRY</td>
<td>Beef (meat), Sheep and Goat (meat), Pork (meat), Poultry (meat), Milk (cow), Milk (sheep and goat), Eggs</td>
</tr>
<tr>
<td>FISH</td>
<td>Fishing &amp; aquaculture</td>
</tr>
<tr>
<td>OTHER</td>
<td>Ancillary production</td>
</tr>
</tbody>
</table>
5.3.4 Disaggregation operations – economic IOT

The main objective was to ensure that constraints with respect to value added, total output, inter-sectoral sales, exports and total inputs of sub-sectors and the agricultural sector as a whole, as given in the statistical abstract (CYSTAT, 2011b), the agricultural statistics data (CYSTAT, 2010) and the livestock feed data (Markou & Papadavid, 2007), were all satisfied, in addition to maintaining the initial properties of the WIOD 2007 IOT. The CYSTAT data and WIOD IOT were in some cases conflicting, a problem commonly encountered in disaggregation procedures (Lenzen et al., 2009), especially with respect to the domestic and imports intra-matrices. Assumptions based on the data as well as the successive use of RAS and TRAS ensured that the matrix satisfied all criteria at each stage of the disaggregation process. Figure 5.3 (p. 187) illustrates the steps followed in order to disaggregate the original agriculture sector into the 20 ‘new’ sectors.

![Diagram showing original IOT and disaggregated WIOD IOT](image)

**Figure 5.3** Overview of the disaggregation procedure for the agricultural sector, highlighting the order in which different parts of the matrix were estimated.
The following steps, the first four of which correspond to the numbers in Figure 5.3 above, detail the procedure followed in order to obtain a fully balanced disaggregated 2007 IOT for Cyprus:

1. **Disaggregating agricultural outputs [32-by-1 vector disaggregated to 32-by-20 matrix]**

   The total output of the agricultural sector was first pro-rated across agricultural sub-sectors using the national agricultural statistics (CYSTAT, 2010). The CYSTAT data also contained information on their total output separated into exports, intra-matrix inputs (sales to other agricultural sub-sectors), sales to industry, and final demand (all of these equalling total output, as is always the case in an IOT). Final demand was then further disaggregated into its component parts, in order to derive a final demand vector for households, further divided into domestic and imported final demand vectors using the 2009 household budget survey (CYSTAT, 2011a). Traditional RAS was then used to ensure consistency between row sums (CYSTAT data on agricultural sub-sector output) and column sums (IOT entries for total exports, intra-matrix sales, sales to industry and final demand for the whole agricultural sector), as shown in Table E1, Appendix E. As part of this step, a necessary operation to correct export and final demand allocation in the 2007 WIOD IOT was also performed in accordance with CYSTAT (2010; 2012). The balanced table (see Table E1, Appendix E) was subsequently used to pro-rate outputs of each of the newly-formed sectors with all the other common sectors, based on their relative share of industry sales, filling up the two yellow areas in Figure 5.3.

2. **Disaggregating inputs to agriculture [1-by-32 vector disaggregated to 20-by-32 matrix]**

   Inputs and value added were pro-rated in a similar way across agricultural sub-sectors to ensure that intra-matrix inputs (domestic) + other inputs + intra-matrix inputs (imported) + value added = total inputs. Statistical abstract data (CYSTAT, 2011b) on the ratio of value added to total output from each type of sub-sector (0.65 for crops, 0.24 for meat, 0.69 for fishing and aquaculture and 0.61 for ancillary production) ensured that value added components were accurate. The sum of value
added from all sub-sectors also needed to remain equal to the value added given in the agricultural statistics and the IOT table. Traditional RAS ensured that after several iterations all restrictions were satisfied as shown in Table E2, Appendix E. This step ensures that all purchases of the newly formed agricultural sectors from other sectors of the economy and abroad are consistent with the 2007 WIOD IOT. The relevant areas for this step are coloured in blue in Figure 5.3.

3. **Disaggregating sales between agricultural sectors [1 cell disaggregated to 20-by-20 matrix]**

The intra-matrix (refer back to Table 5.2, p. 163), tends to be the most challenging area of the table. Extensive data analysis and numerous assumptions are required in order to maintain the initial intra-matrix sum given in the original IOT, whilst simultaneously satisfying information with respect to transactions between agricultural sub-sectors. A consistent estimation of intra-matrix transactions is key to ensuring that the model reliably captures water flows within the agricultural sector and also those coming from imported agricultural products. Common knowledge tells us that most of the transactions taking place between agricultural sub-sectors involve crops being purchased as feed for animals by the meat sectors, crop sectors buying seed from home and abroad and also ancillary sectors such as cheese-making buying milk from the dairy sectors. The first stage of the intra-matrix disaggregation was to locate these kinds of transactions in the agricultural statistics (CYSTAT, 2010) and perform a pro-rata allocation based on their relative monetary values. Out of a total of 800 cells (400 in the domestic intra-matrix and 400 in the imported intra-matrix) most of them are expected to contain zeros because some transactions such as dairy to citrus or olives to beef and so on do not take place.

Once the initial monetary disaggregation was performed, a subsequent disaggregation is based on estimates of the quantities of feed required for different animals – based on data available in the agricultural statistics (Markou & Papadavid, 2007). The data used for inferring inputs and outputs between different agricultural activities and sub-sectors were the transactions within the agricultural sector as well as data on feed composition for different animals. For feed, the proportions of animals at different ages needed to be considered as this affects the respective food
composition. The vast majority of animals in Cyprus are not pasture-fed, but are rather given a combination of cereals, legumes (soya) and concentrate mixtures which consist of different ingredients depending on the age and intended use (milk/eggs or meat) of the animals. The combination of a monetary and quantitative (physical) disaggregation produces a table which traces flows of water or other resources more accurately compared to a disaggregation based solely on monetary parameters. Applying manual scaling to the domestic and imports intra-matrices ensured that their sums remained equal to the original sums of the single agriculture to agriculture cells. This is shown in red in Figure 5.3.

4. **Transactions between non-agricultural sectors [32-by-32 matrix remains unchanged]**

5. The final operation before applying the TRAS algorithm was to adjust the imports matrix in order to accommodate the changes made to the domestic matrix. Trade data (FAO, 2013) was used to pro-rate imports into their purchasing sectors and to manually correct some entries that looked erroneous in the original table.

6. Lastly, the disaggregated 52 x 52 domestic matrix was rebalanced using the TRAS algorithm (explained previously – also see Appendix D for numerical example). The TRAS step imposed the constraint that the disaggregated 52 x 52 table must be identical to the original IOT matrix when aggregated to a 33 x 33 classification. Table E3, Appendix E shows how the algorithm arrived at a satisfactory solution after 30 iterations. At the end of the 30th iteration, no single column or row sum was more than 0.5% off its target value, which should be satisfactory for most studies (R. E. Miller & Blair, 2009).

### 5.3.5 IOT disaggregation summary

The present section has outlined how the available data were used to successfully disaggregate and rebalance the Cyprus 2007 IOT. Several assumptions had to be made in order to reconcile data from various sources. The end product is an IOT with 20 agricultural sectors, thus offering a classification capable of tracing the impacts of different food groups. This is the first ever attempt to achieve such disaggregation in Cyprus. For this reason, there
are no previous estimates to allow any numerical comparison. Nevertheless, the availability of data from the CYSTAT agricultural statistics implies that, according to Lenzen (2011), the disaggregated IOT should be a more accurate representation of reality compared to the original aggregated IOT.

Making use of the disaggregated table in a way that would allow the relaxation of the linearity assumption and accounting for tourist dietary differences entails modifications to the conventional EIO model. This necessitates a reconsideration of how to estimate and utilise final demand vectors, previously discussed in Chapter 4. The next section (section 5.4) describes how an alternative EIO framework was established in order for this approach to fulfil its objectives.

5.4 Generating final demand vectors to represent tourism consumption

5.4.1 Section summary

Following the successful disaggregation of the IOT, the second challenge is developing a methodology to allow the use of disaggregated expenditure data, collected through surveys (to be reviewed in section 5.5), along with the disaggregated IOT. As previously elaborated in Chapter 3, EIO relies on the generation of a final demand vector \( y \) of suitable length which is then used to force the model to compute the economic and water use multipliers that cater for a given final consumption of goods and services. Ideally, the tourism final demand vector needs to be comparable to the vector of final household demand, in order to allow comparisons between different kinds of tourists against the local population and, additionally, to allow the use of household budget data to address any gaps or omissions in the primary tourist data. Following a short review of previous relevant EIO studies on food consumption and tourism consumption, this section develops a novel procedure for converting primary tourist expenditure from different groups into a series of suitable final demand vectors.
5.4.2 Final demand vectors – modelling consumption

Reviewing the EIO literature in search of an appropriate framework

Final demand by households, regularly included as a final demand column in IOTs, is frequently derived from household budget surveys (HBSs) through a process of sector matching originally described in Herendeen and Tanaka (1976). Studies linking energy use, household expenditure and I-O data for different family types and different lifestyles are prominent in the literature (Druckman & Jackson, 2008, 2009, 2010; Minx et al., 2009; Munksgaard et al., 2005; Weber & Matthews, 2008). Nevertheless, with the exception of Weber and Matthews (2008), who specifically focus on food miles, energy-related studies tend to use aggregated food-related expenditure since their focus is on overall energy use and associated carbon emissions. In contrast to water use where, as mentioned in previous chapters, agricultural activity is the major resource user, industry, services and households tend to be more important in energy-related studies, hence any disaggregation efforts are likely to concentrate on these sectors.

Recently published studies have used EIO analysis to model the effects of potential future shifts to healthier diets as well as the trade-offs between different diet types and their environmental impact on a household level (Cazcarro et al., 2012; Meier & Christen, 2012a; Tukker et al., 2011). As is pertinent to the present study, the aforementioned studies naturally make use of disaggregated food-related expenditure as well as disaggregated IOTs (with several agricultural sub-sectors and food and beverage sectors), in their attempt to capture the impacts of diverse diets. Following a careful evaluation of the frameworks employed by Tukker et al. (2011), Meier and Christen (2012a), and Cazcarro et al. (2012), it becomes evident that all three studies approach the issue from a ‘nutritional perspective’, in the sense that they rely on caloric estimates to generate their final demand vectors.

Tukker et al. (2011) assume that the original food balance sheet (FBS) dietary pattern corresponds to the status quo final demand for food products in monetary terms as recorded.

---

60 The authors convert familiar consumer activities such as food purchases into flows from the various industries that distribute food based on previous work by the US Bureau of Economic Analysis.

61 A food balance sheet (FBS) gives a comprehensive picture of the annual pattern of food supply for a given country or region. The FBS shows, for each food item, the total availability for human consumption along with the sources of supply and its utilisation (see http://faostat.fao.org/site/354/default.aspx).
in the EU25 E3IOT\textsuperscript{62} (Huppes et al., 2006; Tukker et al., 2006). They subsequently create different dietary scenarios based on calories and nutritional variables (to ensure that any proposed dietary changes meet medical recommendations) and finally use percentage changes relative to the status quo FBS to generate different final demand vectors. Cazcarro et al. (2012) follow a similar approach for households in Spain using a social accounting matrix (SAM), whereas Meier & Christen (2012a) use a hybrid EIO-LCA for Germany.

Whilst the ‘nutritional’ calorie-based approach provides a noteworthy methodological framework, it holds less promise with respect to tourism consumption. Health-related concerns are generally less relevant to tourism consumption, the nature of which is predominantly pleasure-oriented, in the sense that tourists often travel to sample local delicacies and to enjoy their meals. They are therefore less inclined to follow dietary guidelines while on holiday. Furthermore, tourists are more likely to differ in terms of how much they spend on food, the quantities they consume and the places where they dine, all of which contribute to different water use impacts which the present study seeks to compare. A constant calorie intake across different tourists, as assumed in the aforementioned studies (and also in Chapter 2 of the present thesis), does not take into account differences in the quantity of food consumed. A large degree of variability is also certainly true for households, as noted in Weber and Matthews (2008). Detailed studies of the eating habits of tourists that would allow their conversion to calories and other nutritional equivalents (such as fat, protein and carbohydrates) represents an intriguing future research avenue but falls outside the scope of the current study.

**Reviewing the tourism I-O literature in search of an appropriate framework**

Tourism-related EIO studies (Collins et al., 2012; Jones & Munday, 2007; Lundie et al., 2007; Munday et al., 2013) appear to make a series of assumptions to allow the creation of a final demand vector. This is mainly because tourists tend to spend most of their money on tourism-related activities, which may not correspond to commonly acknowledged sectors in the IOT classification (Fletcher, 1989; Jones et al., 2003). Generating a final demand vector for food-related tourism consumption presents a challenging proposition, not least because

\textsuperscript{62} The E3IOT is a highly disaggregated EIO model which represents the average EU economy for the year 2003. Its high level of product disaggregation covers about 50 food product groups (Tukker et al. 2011).
tourists, unlike households, do not make most of their food-related purchases directly from retailers or farmers but tend to eat at restaurants and hotels. The food which caters for tourism demand is thus procured in advance by others (restaurateurs, hotel owners, relatives or friends). This implies that spending on specific commodities and services is already a first round effect rather than a direct expenditure. Addressing this issue requires an assessment of available options and manipulations in order to produce the most reliable and comparable final demand vectors between tourist groups.

Despite the need for further disaggregation of important tourism consumption categories having been explicitly mentioned in the literature (Fletcher, 1989; Jones et al., 2003), food has not yet received any special attention in the tourism EIO literature. With the exception of Cazcarro et al. (2014), the above-mentioned studies all make use of broad aggregate spending categories such as ‘food and beverage’ or simply disaggregate spending on food into different hotel or restaurant categories. The level of disaggregation of tourism expenditure may also depend on TSA categories in places where TSAs are available (Jones & Munday, 2004, 2007; Jones et al., 2009), as was also the case in the approach outlined in the previous chapter. Older studies simulate the impacts of tourist spending on the economy through modifying the export component of the final demand vector to reflect the distribution of tourist spending in economic sectors that participate directly in tourism activities (this refers to sectors which are the initial recipients of tourist’s money) (Briassoulis, 1991).

As IOT sectors can often be too detailed in relation to reported tourism expenditure, more recent studies also make use of domestic household surveys in order to disaggregate tourism expenditure into the IOT classification (Lundie et al., 2007; Munday et al., 2013). Tourism expenditure is therefore refined by assuming that some of their expenditure patterns match those of local households. Surprisingly, none of the reviewed studies appears to detail the procedures followed to disaggregate or match tourism expenditure with IOT sectors, other than mentioning the step of ‘discounting’ gross tourism expenditure by applying relevant tax rates and re-allocating distribution margins where appropriate (Munday et al., 2013). This essentially corresponds to passing from purchasers’ to basic prices (see Box 2, Appendix B).
Jones et al. (2003, p. 2786) admit that the process of disaggregation and ‘discounting’ is ‘necessarily a complex procedure, which requires an element of estimation’. Lundie et al. (2007) also make a similarly vague remark that classifying certain items according to the IOT classification was a tricky undertaking. Following a review of the tourism I-O literature, it thus quickly becomes apparent that there is no standard procedure regarding the derivation of final demand vectors based on tourism consumption. It is therefore worth considering the practices found in non-tourism related household studies.

**Considering other options**

One of the most detailed explanations is found in a recent report by the Australian Bureau of Statistics (ABS). According to the ABS (2012, p.554):

‘HFCE\(^{63}\) data are compiled according to the Classification of Individual Consumption by Purpose (COICOP) and is disaggregated to IOPC\(^{64}\) level based on a balanced SUT and previous year’s I-O table. Any adjustments made through the SUT balancing process are applied to the appropriate IOPC based on the intelligence for the decision. If detailed information is not known, it is allocated based on previously balanced I-O tables.’

This suggests that primary data collected through household surveys are initially classified at COICOP level. In the case of Australia, the COICOP classification encompasses the following 12 major categories:

1. Food and non-alcoholic beverages
2. Alcoholic beverages, tobacco and narcotics
3. Clothing and footwear
4. Housing, water, electricity, gas and other fuels
5. Furnishings, household equipment and routine maintenance of the house
6. Health
7. Transport
8. Communications
9. Recreation and culture
10. Education

\(^{63}\) HFCE stands for Household Final Consumption Expenditure.
\(^{64}\) IOPC stands for Input-Output Product Classification
11. Hotels, cafes and restaurants

12. Miscellaneous goods and services

(ABS, 2012)

As seen in Druckman and Jackson (2009), the UK COICOP classification is very similar to the Australian one, with multiple subcategories detailing purchases. In the UK SUTs (ONS, 2011), there is a correspondence table between IOT sectors and COICOP categories. This table essentially provides the necessary information on how household expenditure in each COICOP category can be pro-rated across different IOT product sectors. The same table may also be employed to carry out the inverse operation (going from IOT sectors to COICOP categories and then functional uses), as detailed in Druckman and Jackson (2009).

This kind of detailed information does not exist for the Cyprus IOT. Nevertheless, the Cyprus TSA production accounts include a sub-table specifying the sectors from which tourist consumption makes its purchases. Unlike the main TSA sectors which appear to be based on COICOP categories, the sectors in the sub-table appear to be very similar to IOT sectors, allowing a realistic matching of tourist consumption to the IOT classification (as performed in Part III of the thesis). However, this sub-table cannot be employed when using an IOT with a disaggregated agricultural sector. This is because the TSA classification is unsuitable for working with primary tourism expenditure already disaggregated into different food choices, as it would naturally allocate all food-related expenses to the ‘food and beverage’ sector. The model would therefore run assuming an average diet (identical to that of residents) irrespective of the money being spent on different components of meals.

Another option is to bypass the TSA classification altogether, by ‘feeding’ the final demand data directly into the appropriate agricultural sub-sectors. However, this is also potentially problematic because some important transactions are likely to be omitted since tourists largely purchase their food from restaurants which, in turn, purchase their food supplies both from the ‘food and beverage’ sector as well as directly from the agriculture sectors. Completely bypassing the ‘food and beverage’ sector, which is responsible for the processing stages of many crops and meat products, means that important multipliers in the supply chain are not sufficiently captured.

---

65 This occurs because they correspond to sectors as given in the Cyprus National Accounts.
Ideally, the problem could be addressed by disaggregating the food and beverage sector so that it can handle different products, as performed in Cazcarro et al. (2012, 2014). The Cyprus Industrial Statistics (CYSTAT, 2012) offer disaggregated value added and output for 26 food and beverage subsectors. Nonetheless, disaggregating the ‘food and beverage’ sector in addition to the agricultural sector, and correctly distributing transactions between agricultural and ‘food and beverage’ sub-sectors based on minimal information, represents a huge undertaking, especially since the ‘food and beverage’ sub-sector classification in the Industrial Statistics does not match the agricultural sub-sector classification. This last option is therefore not explored any further, not least because it would require substantial additional data and time. In the absence of an existing procedure suitable for the present circumstances, the objective of the following sub-section is to formulate an original approach.

5.4.3 Developing a suitable EIO framework to account for dietary choices

Owing to limitations in the conventional EIO framework (see linearity problem in Chapter 4, 4.4.2), there is a need to apply some modification in order to develop an approach capable of providing effective comparisons of the impacts of different tourist food choices. The approach has to function with a single ‘food and beverage’ sector along with the already disaggregated agricultural sectors (see section 5.3.2, p. 184) in addition to the detailed dietary information obtained from tourist surveys (see section 5.5, p.208). The existence of a single ‘food and beverage’ sector in this case does pose an *a priori* problem because any impacts (economic or water use related) which occur during the processing stages of a specific food the tourist chooses to consume will be averaged out (based on how all agricultural sectors sell to the ‘food and beverage’ sector). This is, of course, assuming most of their spending on food would be allocated to the ‘food and beverage’ sector as is usually the case in the final demand vector for households66. As mentioned in the preceding discussion (section 5.4.2), tourists would be expected to buy most of their food from the restaurant/hotel sector which, in turn, purchases the majority of its inputs from the ‘food and beverage’ sector (both locally and from abroad). The problem of not capturing impacts associated with the processing of

---

66 According to the 2007 WIOD IOT final demand vector for Cyprus, households spent 619 million USD in the ‘food and beverage’ sector whereas they only spent 267 million USD directly in the agriculture sector.
different foods thus still remains, even if most of the tourist food-related expenditure is allocated to the restaurant/hotel sector.

The proposed solution to this problem is an adapted EIO approach that would treat water use and economic impacts separately in order to take full advantage of disaggregated food choices and a disaggregated agricultural sector. The idea would be that more of the supply chain could be captured in this way, bypassing the need to make the assumption that tourists eat the same diet (as dictated by transactions in the IOT) and to have to rely on the magnitude of the expenditure to determine the amount of water use impact, thus also giving rise to the linearity problem. Nevertheless, any attempt to independently estimate water use and economic impacts would require assumptions with respect to certain parts of the supply chain and their potential effect on the overall results. These must be set out and assessed in advance.

Two alternative ways to produce reliable final demand vectors using disaggregated tourism expenditure are initially proposed and subsequently discussed, weighing up their respective advantages and weaknesses, in order to select the one which has the potential to perform best in the present context. A quantitative comparison is finally performed upon completion of the theoretical explanation of the methods, using the Cyprus household final demand vector.

**Method 1**

The first suggested method involves the use of the power expansion method (Chapter 3, section 3.4.2), also referred to as the power series approximation of the Leontief inverse, shown here with an environmental extension:

\[
E = e (y_1 + Ay_1 + A^2y_1 + A^3y_1 + A^4y_1 + ...) 
\]

where \( E \) is total environmental impact, \( e \) is the vector of direct water resource coefficients (direct water use per sector divided by total output in USD), \( A \) is the coefficients matrix and \( y_1 \) is final demand. Note that for reasons of brevity and clarity, the above equation ignores

---

67 Using matrix algebra it is possible to reach an approximation of \((I-A)^{-1}\) by computing round-by-round effects instead of having to invert the matrix. According to Miller and Blair (2009), in most cases after round 7 or 8 of supply chain transactions the terms become insignificantly different from zero, meaning that they can be ignored with minimal difference to the overall result.
imports, although these should eventually be included in order to complete the supply chain. The power series approximation ‘opens up’ the Leontief inverse and allows visualising each and every round of transactions and allows separating out terms to provide a more customised framework. The present method proposes the use of two separate final demand vectors. This would allow capturing direct restaurant expenses and service-related expenses before subsequently replacing these with a revised final demand vector (that captures agricultural water use) in subsequent rounds. This is illustrated in the equation below:

\[ E = e (y_1 + Ay_1 + A^2y_2 + A^3y_2 + A^4y_2 + \ldots) \]  

(5.22)

where \( y_1 \) is an ordinary final demand vector in basic prices (same as in the equation above) composed of direct spending on IOT sectors in direct receipt of tourism expenditure (such as ‘hotels and restaurants’, ‘culture and recreation’, ‘transport’ etc.) with zeros for all other IOT sectors. \( y_1 \) is used for the direct impact as well as the first round of indirect impacts. Restaurants/hotels in Cyprus purchase the overwhelming majority (92.7%) of their food inputs from the food and beverage sector68 in the first round of purchases by that sector. As no disaggregation is required to capture this fact, \( y_1 \) is still used for the first round of inter-industry transactions (\( Ay_1 \) in 5.22). \( y_2 \) is a disaggregated final demand vector where, unlike in \( y_1 \), spending on food is disaggregated into the newly formed agricultural sectors (depending on the diet in a given tourist group as determined by primary data collection). The part of the final demand which is non-food related would stay the same as in \( y_1 \). Thus, from the second round of inter-industry transactions onwards (where the restaurants should be receiving most of their agricultural inputs via the food and beverage sector) the disaggregated final demand vector takes into account dietary preferences.

The food-related expenditure in \( y_2 \) would use commodity prices from the agricultural statistics (CYSTAT, 2010) for each product instead of the reported expenditure on food by tourists, as well as average quantities per portion as reported by restaurant owners (see Appendix G). This bypasses the problem posed by the fact that the reported price for a meal, even when converted into basic prices, includes all meal components, thus making it extremely difficult to value each one separately. Moreover, it allows taking into account

---

68 This is estimated using the transactions matrix of the IOT.
portion quantity, a key determinant of environmental impact not commonly considered in EIO when working with IOTs in monetary terms. This aspect of the approach is akin to the functional unit\(^{69}\) approach in LCA (Girod & de Haan, 2009, 2010; Hertwich, 2005). Mathematically this would imply that the elements of the \(y_2\) vector that are related to food expenditure will be calculated by multiplying the portion size by the basic commodity price (see Table G3, Appendix G, for portion size examples).

The justification for using the functional unit approach comes from Girod & de Haan (2010) who investigate whether higher-income Swiss households that spend significantly more on food are actually buying larger quantities of food compared to lower-income households. Based on results from 13 500 households, they firmly conclude that higher prices per physical unit do not correspond to a higher environmental impact per functional unit. In a similar way, by considering the quantity (weight) of a food portion and its associated basic price and water use impact in the model, the current approach attempts to correct for the linearity problem in conventional EIO which tends to overestimate the environmental impact of expensive products\(^{70}\). By creating two separate final demand vectors, the model is still capable of accounting for the fact that a higher initial expenditure would still generate more value added in the economy.

**Qualitative assessment:** The approach tries to capture direct and first-round indirect economic and environmental impact through the use of an aggregated demand vector, whilst the remaining indirect impacts are captured through the use of a demand vector where agricultural food-related purchases are disaggregated. The advantage of this approach over the conventional EIO is that the full environmental impact associated with dietary choice is estimated. It is therefore capable of differentiating between different foods and also different quantities of food consumed. During the disaggregation of the IOT, balancing algorithms were used to ensure that the total output of each agricultural sector, when divided by the basic price of the commodity in CYSTAT (2010), gives the total quantity of the commodity produced in 2007. This ensures that every portion should, in principle, cost

---

\(^{69}\) A functional unit describes the unit of use of a product (Girod & de Haan 2010). A functional unit for a meal, as in the present study, would measure a standard portion quantity in kilograms (of food).

\(^{70}\) This is due to the linear correlation between expenditure and environmental impact in the monetary IOT structure.
the same as it would in 2007. For the non-food purchases, necessary conversions can be made using the relative consumer price index (CPI) for different goods (CYSTAT, 2013).

The approach gives identical results to the conventional EIO model up to and including the term $Ay_1$. However, the terms which include $y_2$ will definitely yield different results because of the disaggregated agricultural purchases. The overall value of economic and environmental impact is likely to be lower than in conventional EIO because of using basic agricultural commodity prices\(^7\). Nonetheless, in relative terms, there should be more heterogeneity between different tourist groups because dietary preferences would be factored into $y_2$. The environmental impact is thus more representative of what people choose to eat. The lower impact is likely to be the significant drawback of this approach because the total sum of money used as input to the model is less. Assuming that the model captures direct economic impacts in restaurants and hotels (through $y_1$) and then first round economic impact through restaurant and hotel purchases from the ‘food and beverage’ sector (through $Ay_1$), it still misses out on the economic impact of purchases of agricultural commodities by the ‘food and beverage’ sector. This is because $y_2$ only considers that food purchases impact the agricultural sectors. The economic multipliers of that round are potentially substantial and there appears to be no way of capturing these when using the model described above.

**Method 2**

The power series approximation is not the only way to quantify the impact of different dietary choices. A second possibility is to estimate environmental and economic impacts using two separate equations. Unlike in the first method, this approach could then make use of the more commonly used Leontief inverse. The first equation would estimate economic impact using the basic IO model:

$$x = (I - A)^{-1} y_1$$

(5.23)

where $x$ is total direct and indirect economic contribution, $y_1$ stands for the final demand vector of expenditure in different spending categories in basic prices (this is identical to $y_1$ in 5.21 and 5.22). A second equation could then be used to estimate environmental (water use) impact using...
impacts by inputting food purchases into the relevant agricultural sectors depending on what exactly is purchased by the tourist, using the functional unit approach as in method 1:

\[ E = e (I - A)^{-1} y_2 \]  

(5.24)

where \( E \) stands for total direct and indirect water use and \( y_2 \) is a disaggregated vector of final demand, identical to \( y_2 \) in (5.21) and (5.22). In this case, food purchases are directly allocated to the appropriate disaggregated agricultural sectors, with the Cyprus household budget survey (CYSTAT, 2011a) used to fill in any gaps in the primary dataset and also to compare tourists with residents. Once again, in the case of \( y_2 \), food purchases are estimated using the functional unit approach described in method 1 and non-food purchases are subject to conversions using relative CPI for different goods from CYSTAT.

**Qualitative assessment:** The main advantage of this approach is that it captures the total chain of economic impacts as it uses the economic Leontief inverse. Equation (5.23) is also often extended to include value added, employment or other economic indicators. Furthermore, it calculates water use impact through the whole supply chain, with the exception of some of the water used directly in restaurants and the ‘food and beverage sector’, as this is bypassed in equation (5.24). This means that, unlike method 1 which misses some of the economic impact, this second method omits the first two stages of water use associated with food expenditure. Nevertheless, given the fact that the focus of the chapter is on the dietary aspect, the inability of the model to capture restaurant and industry water use involved in food production should not be seen as a significant drawback because water use in restaurants and the ‘food and beverage’ sectors is usually insignificant compared to agricultural water use. According to Hoekstra & Mekonnen (2012), 92% of total water use takes place in the agricultural stages of production. In Cyprus, if direct water use in household, hotels and restaurants (which is, in any case, added separately to avoid double counting as per equation 3.27) is excluded, agricultural use accounts for 95% of all supply chain water consumption (WDD, 2011) (see Table 5.5, p. 207). Method 2 also offers the invaluable advantage that non-food purchases may even be completely ignored in equation (5.24) where these are not of interest and/or do not contribute significantly to water use, thus giving more flexibility to the method.
Choosing the right approach - appraisal

Both methods offer advantages over conventional EIO analysis, mainly because of the mechanism allowing for the use of standard quantities or portion sizes instead of solely relying on expenditure in order to estimate water use. The essence of the methods is that they allow the use of primary data (obtained through surveys) on food preferences to be used in the EIO framework. Nevertheless, this can only be achieved at a cost, which is the loss of a certain part of the supply chain. Method 1 does not capture the full chain of economic and environmental impacts whereas method 2 does not capture the entire chain of water use impact. In principle, missing out on the economic impact of restaurant/hotel and ‘food and beverage’ sector activity is potentially more problematic than excluding the water use impacts of these sectors\(^2\), therefore method 2 theoretically offers the more attractive option.

A quantitative assessment of the methods in relation to conventional EIO analysis is also carried out to quantify the differences in results from the different methods, and should also allow the reader to understand how both model results differ from the conventional EIO. Comparing the proposed approaches to a conventional EIO analysis is difficult because there are many possibilities. It is possible to compare to a conventional EIO approach which uses an aggregated IOT and household final demand vector \((y)\) from Part III (dubbed ‘Aggregated EIO model 1’), or to use the same approach with a household final demand vector that would be more similar to tourist final demand in the sense that final demand for agricultural products would be allocated to the restaurant and ‘food and beverage’ sectors instead \((y_2\) - aggregated) (‘Aggregated EIO model 2’). A third possibility is to use the disaggregated EIO model with the same final demand vector \((y_2 \text{ – disaggregated})\) (Disaggregated EIO model). A comparison of the results from the three conventional EIO possibilities and the two methods introduced here (method 1 and method 2) for an average resident is shown in Table 5.4.

The results show that all models perform very similarly when it comes to the total output estimates. As expected, method 1 registers the lowest total output but this is still very close to the other models with respect to its economic impact estimate. Method 2 is identical to the

\(^2\) Direct water use in hotels would normally be added as an extra direct environmental impact and would be left out of the I-O model coefficients as per equation (3.27) in Chapter 3.
disaggregated EIO model proving that method 2, as expected, captures the entire supply chain. Nevertheless, there is a considerable range in results with respect to the water use impacts, which suggests that interactions in the model with respect to agricultural goods differ.

The difference between aggregated and disaggregated models is evident; this is consistent with previous studies that show large differences between disaggregated and aggregated CO₂ multipliers (Liu et al., 2012) and also in terms of the final results between different disaggregation methods (Wiedmann et al., 2011). The first aggregated model shows the highest amount of domestic water use with 849 l/cap/day. In addition to the aggregated IOT, the model also uses the WIOD final demand vector for households (y) which includes purchases in all sectors including the agricultural sector. It has been included here in order to provide a reference point but is the least relevant of the methods in the current context as it would not work with tourism final demand vectors where the allocation has to be made differently.

Table 5.4 Summary of results for the five different modelling possibilities. The results shown are estimates for an average resident of Cyprus in 2007.

<table>
<thead>
<tr>
<th></th>
<th>ECONOMIC IMPACT</th>
<th>ENVIRONMENTAL IMPACT</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total output</td>
<td>Equation</td>
<td>Domestic</td>
</tr>
<tr>
<td></td>
<td>(USD)</td>
<td></td>
<td>water use</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(l/cap/day)</td>
</tr>
<tr>
<td>Aggregated EIO model 1</td>
<td>83.18</td>
<td>( x = (I-A)\ y )</td>
<td>849*</td>
</tr>
<tr>
<td>IOT</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aggregated EIO model 2</td>
<td>83.18</td>
<td>( x = (I-A)\ y )</td>
<td>165</td>
</tr>
<tr>
<td>IOT</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disaggregated EIO model</td>
<td>83.22</td>
<td>( x = (I-A')\ y )</td>
<td>218</td>
</tr>
<tr>
<td>IOT</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proposed method 1**</td>
<td>82.85</td>
<td>( y_{1} + A'y_{1} + A''y_{2} + \ldots )</td>
<td>197</td>
</tr>
<tr>
<td>IOT</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proposed method 2</td>
<td>83.22</td>
<td>( x = (I-A')\ y )</td>
<td>479</td>
</tr>
<tr>
<td>IOT</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\( A' \) is used to denote the disaggregated (52-sector) A matrix.

* This result differs from Part III resident totals because there is no ‘domestic technology assumption’.

** Includes results up to the 7th round of indirect transactions, after which the figures are negligible.
The second aggregated model uses $y_1$ and this makes it more suitable for tourism purposes. It registers the lowest total water consumption (156 l/cap/day) of all the models as it relies on a single aggregated multiplier for the whole agricultural sector which is likely to underestimate the water use impact. The disaggregated EIO model with the same final demand vector (disaggregated from 33 to 52 sectors) has higher water consumption (218 l/cap/day). Nevertheless this is still likely to underestimate water use impact because $y_1$ does not include any purchases directly from the 20 agricultural sectors. Proposed method 1 has an even lower water use impact because of the use of $y_1$ in its two first terms. Method 2 registers a significantly higher water use (479 l/cap/day) which is more than double that of method 1 and the disaggregated EIO model. This demonstrates the impact of disaggregated food expenditure in $y_2$.

There is therefore a large difference in total water use impact between method 1 and method 2, despite their very similar economic impact results. This is related to the different model setups and final demand vectors. This highlights the importance of a final demand vector and the significant uncertainties inherent in any EIO framework (see section 5.4.2 on estimating final demand vectors in tourism). As already established in this section, both in tourism-related EIO and also in EIO studies in general, not enough attention or explanation is afforded to how the final demand vectors are generated. It is likely that there are often many possibilities all of which fall in the solution space. This means that the most pertinent question for present purposes is to consider which estimate is likely to be more reliable based on published figures for Cyprus.

The total water use figures in Table 5.4 are equivalent to a blue water footprint (consumptive water use) and do not include green or grey water for reasons discussed earlier. Blue water footprints for Cyprus or the wider geographical area are available from process-based (Mekonnen & Hoekstra, 2011; Vanham, Mekonnen et al., 2013) and EIO studies (Steen-Olsen et al., 2012). The estimates range from 605 l/cap/day to 821 l/cap/day, with the 618 l/cap/day estimate of Vanham et al. (Vanham et al., 2013). The range is consistent with the findings in Feng et al. (2011), who show that

---

73 This would explain why these figures are significantly lower than the total water footprint estimated in Part I of the thesis which include the green water component.
74 The authors estimate is 221 m³/cap/year which is equivalent to 605 l/cap/day.
75 The authors estimate is 300 m³/cap/year which is equivalent to 821 l/cap/day.
different approaches may lead to a substantial difference in terms of water footprints, even when based on the same database. The top estimate is closest to that of the aggregate EIO model (849 l/cap/day). It is likely that these results occur because of aggregation bias in IOTs. According to Feng et al. (2011), bottom-up (process-based) approaches use more detailed information on virtual water contents of agricultural products. It is therefore likely that the lower end of estimates is more correct (605 l/cap/day). This implies that method 2, with 479 l/cap/day, is the one that produces results which are most consistent with reasonable values for Cyprus. Owing to the high degree of disaggregation (of the agricultural sectors and final demand vectors) in addition the functional unit approach, the method behaves similarly to an EIO-LCA hybrid (Suh & Nakamura, 2007; Wiedmann et al., 2011).

5.4.4 Section conclusions

It can therefore be concluded that method 2 presents the method of choice for the purposes of the present study. Firstly, it captures the total chain of economic output; secondly, it is easier to run as it uses the conventional Leontief inverse; and, thirdly, the water use estimates it produces appear to be more consistent with per capita blue water footprints for Cyprus. It should still be reiterated that whilst the chosen approach (method 2) may be the most suitable for the purposes of the present study, it is still one of several options which give different results, as previously demonstrated in Table 5.4.

Following the disaggregation of the IOT (sections 5.2 & 5.3) and the establishment of a modelling framework (this section), the remaining task is to obtain primary data on tourist food consumption patterns and portions from tourist surveys. Primary data collection is the subject of the following section.
Table 5.5 Sectoral water use breakdown showing direct and indirect water use coefficients for 2007.

<table>
<thead>
<tr>
<th>#</th>
<th>Sector</th>
<th>Direct water (MCMs)</th>
<th>% total direct</th>
<th>Direct water use coefficient(m³/USD)</th>
<th>Total water use coefficient(m³/USD)</th>
<th>Intra-sector water use</th>
<th>% direct</th>
<th>% indirect</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Agriculture</td>
<td>143.0000</td>
<td>94.9208</td>
<td>0.1526</td>
<td>0.1671</td>
<td>91.37</td>
<td>8.63</td>
<td></td>
</tr>
<tr>
<td>2.</td>
<td>Mining and Quarrying</td>
<td>1.3917</td>
<td>0.9238</td>
<td>0.0108</td>
<td>0.0110</td>
<td>98.01</td>
<td>2.00</td>
<td></td>
</tr>
<tr>
<td>3.</td>
<td>Food, Beverages and Tobacco</td>
<td>2.6267</td>
<td>1.7436</td>
<td>0.0015</td>
<td>0.0196</td>
<td>7.70</td>
<td>92.30</td>
<td></td>
</tr>
<tr>
<td>4.</td>
<td>Textiles and Textile Products</td>
<td>0.0287</td>
<td>0.0190</td>
<td>0.0002</td>
<td>0.0024</td>
<td>8.24</td>
<td>91.76</td>
<td></td>
</tr>
<tr>
<td>5.</td>
<td>Leather, Leather and Footwear</td>
<td>0.0096</td>
<td>0.0064</td>
<td>0.0002</td>
<td>0.0011</td>
<td>16.07</td>
<td>83.93</td>
<td></td>
</tr>
<tr>
<td>6.</td>
<td>Wood and Cork</td>
<td>0.0887</td>
<td>0.0589</td>
<td>0.0002</td>
<td>0.0011</td>
<td>17.93</td>
<td>82.07</td>
<td></td>
</tr>
<tr>
<td>7.</td>
<td>Paper and Publishing</td>
<td>0.0938</td>
<td>0.0623</td>
<td>0.0002</td>
<td>0.0004</td>
<td>61.19</td>
<td>38.81</td>
<td></td>
</tr>
<tr>
<td>8.</td>
<td>Chemicals and Chemical Products</td>
<td>0.1391</td>
<td>0.0924</td>
<td>0.0006</td>
<td>0.0009</td>
<td>61.12</td>
<td>38.88</td>
<td></td>
</tr>
<tr>
<td>9.</td>
<td>Rubber and Plastics</td>
<td>0.0340</td>
<td>0.0225</td>
<td>0.0002</td>
<td>0.0004</td>
<td>38.04</td>
<td>61.96</td>
<td></td>
</tr>
<tr>
<td>10.</td>
<td>Other Non-Metallic Mineral</td>
<td>2.8576</td>
<td>1.8968</td>
<td>0.0037</td>
<td>0.0055</td>
<td>66.43</td>
<td>33.57</td>
<td></td>
</tr>
<tr>
<td>11.</td>
<td>Basic Metals and Fabricated Metal</td>
<td>0.2034</td>
<td>0.1350</td>
<td>0.0002</td>
<td>0.0004</td>
<td>61.12</td>
<td>38.88</td>
<td></td>
</tr>
<tr>
<td>12.</td>
<td>Machinery, Nec</td>
<td>0.0176</td>
<td>0.0117</td>
<td>0.0001</td>
<td>0.0002</td>
<td>45.44</td>
<td>54.56</td>
<td></td>
</tr>
<tr>
<td>13.</td>
<td>Electrical and Optical Equipment</td>
<td>0.0337</td>
<td>0.0224</td>
<td>0.0001</td>
<td>0.0003</td>
<td>54.69</td>
<td>45.31</td>
<td></td>
</tr>
<tr>
<td>14.</td>
<td>Transport Equipment</td>
<td>0.0094</td>
<td>0.0063</td>
<td>0.0002</td>
<td>0.0003</td>
<td>71.91</td>
<td>28.09</td>
<td></td>
</tr>
<tr>
<td>15.</td>
<td>Manufacturing, Nec; Recycling</td>
<td>0.0468</td>
<td>0.0311</td>
<td>0.0002</td>
<td>0.0007</td>
<td>36.34</td>
<td>63.66</td>
<td></td>
</tr>
<tr>
<td>16.</td>
<td>Electricity, Gas and Water Supply</td>
<td>0.0712</td>
<td>0.0472</td>
<td>0.0001</td>
<td>0.0002</td>
<td>56.27</td>
<td>43.73</td>
<td></td>
</tr>
<tr>
<td>17.</td>
<td>Construction</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0008</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>18.</td>
<td>Sale, Maintenance and Repair of Motor</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0001</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>19.</td>
<td>Wholesale Trade and Commission Trade</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0001</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>20.</td>
<td>Retail Trade</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0001</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>21.</td>
<td>Hotels and Restaurants</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0042</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>22.</td>
<td>Inland Transport</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0000</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>23.</td>
<td>Water Transport</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0001</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>24.</td>
<td>Air Transport</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0003</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>25.</td>
<td>Other Supporting Transport Services</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0002</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>26.</td>
<td>Post and Telecommunications</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0000</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>27.</td>
<td>Financial Intermediation</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0000</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>28.</td>
<td>Real Estate Activities</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0002</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>29.</td>
<td>Renting of M&amp;Eq and Other Business Activities</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0001</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>30.</td>
<td>Public Admin and Defence</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0001</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>31.</td>
<td>Education</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0007</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>32.</td>
<td>Health and Social Work</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0002</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td>33.</td>
<td>Other Community, Social and Personal Services</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.0002</td>
<td>0</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td><strong>Total direct water consumption</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>150.6519</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
5.5 Survey design and primary data collection

5.5.1 Section introduction

The model established in the previous section relies on having two final demand vectors, \( y_1 \) and \( y_2 \), one of which is based on expenditure data and the other is based on food preference and quantity consumed. Both kinds of data are highly quantitative and rely on obtaining accurate information from tourists whilst ensuring that questions will not be overwhelming. Ideally, tourism expenditure and food preferences must be as disaggregated as possible in order to ensure the highest degree of compatibility with the model. There is therefore a trade-off between the ideal level of desired information and the ease with which information may be collected.

This section focuses on the collection of primary data used to run the model established in the previous section. The first objective of the section is to review the relevant literature; in this case the focus is on expenditure- and food-related surveys in the tourism literature, in order to select suitable survey methods for collecting expenditure data (section 5.5.2) and food consumption data (section 5.5.3). The following sub-section (section 5.5.4) establishes a survey design and sampling strategy. The final sub-section (section 5.6) focuses on the practical aspects of the primary data collection.

5.5.2 Survey types for obtaining accurate expenditure data

Several methods have been used to estimate tourism expenditure in the literature. Frechtling (2006) offers a comprehensive review of available options. The options that are relevant to the current study are visitor surveys, tourism establishment surveys and direct observation. Visitor surveys are arguably the most popular method for gathering expenditure data. These can either take place at entry, on-site or at exit from the destination and are usually conducted through personal interviews and self-administered questionnaires (which includes asking the visitor to keep a diary of expenditures).

The secondary survey data, used in Part III, were collected by CYSTAT from exit surveys administered through questionnaires at airports (CYSTAT, 2011c). In this type of survey, tourists are either asked to provide an estimate of total expenditures during their entire visit, or, alternatively, an estimate of what they spent on their last day on the trip (Goldman et al.,
1994). However, as previously mentioned in Chapter 4, Section 4.4.1, one of the most significant sources of uncertainty in exit surveys is recall bias (Craggs & Schofield, 2009; Legohérel, 1998; Wilton & Nickerson, 2006). Due to the fact that tourists are usually asked to recall their expenses over a period of several days, they often underestimate or overestimate their expenditure. This is certainly the case with the CYSTAT data, where expenditure is reported for the total duration of the stay. Daily expenditure is then estimated by dividing total trip expenditure in each spending category by the length of stay. Minimising recall bias should be seen as one of the principal aims of the present survey design, since obtaining accurate information on both food and expenditure is essential for running the model established in previous sections.

One proposed solution for addressing the recall bias problem is to limit expenditure recall to the previous 24-hour period and then multiply this by the projected length of stay (Frechtling, 2006). However, this does assume that expenditure from the previous day is representative of the average daily expenditure, which is not necessarily the case. According to Goldman et al. (1994), this could be addressed by randomly interviewing people in order to ensure the sample contains spending for any day of the visit. This is, of course, not possible in exit surveys which often take place in airports on the day of departure. An on-site survey is required in this case, which would need to take place at commonly visited sites other than airports. Moreover, interviewing tourists at different times of the day would also ensure that spending taking place throughout the day is better represented than would, for example, be the case if interviews always took place at night or in the morning.

Another proposed solution to the problem of recall bias is the use of the diary method. As its name implies, the visitors are given a diary in which they are expected to fill in each day’s expenditure (Frechtling, 2006). The main advantage of the diary method is that, provided tourists note down their expenditure as they go, minimum recall is required, and this is especially useful if highly detailed information is sought (Goldman et al., 1994). In a study carried out at entry in eight Montana airports, Wilton & Nickerson (2006) firstly collected front-end data for intercepted travel groups in order to establish socio-demographic and trip-related characteristics, and then asked travel groups who had agreed to participate to complete a diary questionnaire which they later had to return by mail in a provided postage-paid envelope. In the diary questionnaire, visitors were supposed to record their spending
for one day of their trip. Depending on the number of days the visitors were planning to stay, the day for which expenditures was to be reported was either the current day, the next day, or two days from the intercept day thus ensuring representation of all possible days (Wilton & Nickerson, 2006). This is a considerable improvement compared to reporting averaged expenditure over the previous 24-hour period.

The diary method does, however, have some serious limitations. First and foremost, it relies on the visitors’ commitment to complete and send back their recorded expenditures. It also assumes visitors have understood and then remember to record exactly what they had been asked to record. It is likely that both of these assumptions are often violated, thus resulting in a smaller sample and introducing error and bias that may have been avoided had the interview method been employed. According to Goldman et al. (1994), other major shortcomings of this method are that the act of recording expenses may alter the tourist's spending habits, and that participation tends to be low as many vacationers view this as an additional chore. In general, the diary method is perceived to be one which places a lot of responsibility on the respondent (Robson, 2011).

In terms of the goals of the present study, another limitation of the diary method would be that expenditure types cannot be disaggregated even further without making the questionnaire extremely complicated and increasing the possibility of non-response or incomplete answers. The I-O sector classification lists products and economic sectors in a very unique way. In order to be able to match these to tourism expenditure, the expenditure type categories will need to be even more complex, but that could often require further elaboration and prompting in order to help the tourist recall what exactly was purchased. In a face-to-face situation, the interviewer has advantages in the form of prompting or probing in order to help the respondent. From the available methods reviewed here, real-time survey-based methods appear to be the most suited to the aims and scope of the present study. This conclusion is reinforced by the fact that self-administered questionnaires appear to be the method of choice in studies that have estimated the economic impacts of sporting and other events using I-O analysis (Collins et al., 2012; Jones & Munday, 2004; Lee & Taylor, 2005).
5.5.3 Obtaining food consumption information

As previously elaborated (see section 5.4), price is not necessarily a proxy for the quantity of food consumed. When it comes to water use considerations, the quantity of product consumed becomes the determining factor of impact. This kind of information is unlikely to be accurate if only obtained from the tourist. It therefore becomes necessary to supplement the data collected through tourist surveys by conducting some additional meal surveys with catering managers and owners of restaurants and hotels. Tourist surveys can be used to obtain both expenditure data (see previous sub-section) as well as to provide a sufficient indication of what most tourists prefer to eat and some of the establishments they are most likely to visit for their meals. This should then provide a sample of restaurants to be targeted for further information on portion sizes.

Meal surveys do not appear to be as abundant as expenditure surveys in tourism studies. Torres (2003) combines a hotel survey with a tourist survey in order to determine food consumption by nationality and guest type, with the purpose of investigating existing patterns of demand. The tourist survey was conducted on tourists awaiting flights in airports. However, there is no elaboration on what was actually asked and what the results were.

One recent study from China (Yang et al., 2011), has specifically conducted tourist meal surveys with the purpose of estimating water footprints. Yang et al. (2011) used a sample of tourist groups who were asked what they had consumed at each meal over a number of consecutive days. The unit of study was the whole group of tourists as opposed to the individual tourist, allowing an average to be then calculated. The type and quantities of food were then calibrated with the help of the chef and kitchen staff following each meal survey to ensure that the information provided by the tourists was accurate. As consumers, tourists can select only from the kinds of foods and drinks available at their destination (Sims, 2009). Often in à la carte meals the portion quantity tends to be standard. The chef and kitchen staff are the most suitable agents to interview with regards to the nature and quantity of food consumed. A small sample of restaurants, fast food restaurants and street vendors could then allow an estimate of the average quantity and price range of different foods consumed. Yang et al. (2011) finally use estimates from Chapagain & Hoekstra (2004) on the water footprint of different food products (in a similar way to the approach in Part II of this thesis).
For the purposes of gathering information on meals and expenses, both studies reviewed above use a combination of tourist surveys with staff surveys. This appears to be a suitable strategy for the present study in view of the need for compatible information on both price and quantity of food consumed. The study has therefore pursued selected chef, catering manager and restaurateur interviews in order to provide the necessary quality control and to establish standard dishes and associated portion sizes. The following section considers the type of tourist surveys required along with their design.

5.5.4 Designing the tourist survey – steps and considerations

Choice of survey design and method

Given the highly quantitative nature of the data required, a cross-sectional research design is chosen. This ‘entails the collection of data on more than one case and at a single point in time in order to collect a body of quantitative or quantifiable data in connection with two or more variables, which are then examined to detect patterns of association’ (Bryman, 2012, p.59). In terms of the method of data collection, a highly structured form is required as the expenditure and food consumption data required are highly specific. Nevertheless, there should still be room for flexibility in the research design for any tourists wishing to provide additional information on their meals and expenditure, or any personal views with respect to portion sizes and general satisfaction.

An appropriate data collection medium in this case is a questionnaire survey, which is a structured approach to data collection based on broad contours of what is needed, established in advance by the researcher (Bryman, 2012). Also known as an interview schedule, a questionnaire is essentially made up of a set of questions in a pre-determined order which guide the interview process. This is an established and commonly used method of quantitative research characterised by a fixed design, the collection of a limited amount of data in a standardised form from a large number of individuals and the selection of a representative sample from a known population (Robson, 2011). Two options of questionnaire administration have been considered in this study: interviewer-based (where an interviewer asks questions and completes the questionnaire) and self-completion (where respondents are expected to fill in the answers by themselves).
As already established in section 5.5.2, collecting data in situ, through interviewer-administered questionnaires, appears to represent the most suitable mode of primary data collection with respect to minimising recall bias. The potential advantages are considered here in more detail. Firstly, interviewer-administered questionnaires allow the interviewer to achieve good rapport and to provide assistance where necessary (Brace, 2008). This can be achieved through various kinds of probing and prompting using images, gestures or verbal means. Prompts are also a way to enhance the respondents’ memory of events they might have otherwise forgotten (Simmons, 2011). This is invaluable in a survey which asks the respondent to recall their detailed expenditure over the last day. However, maintaining consistency in the use of prompts in order to ensure everybody gets more or less the same amount of help is essential. Secondly, interviewer-administered questionnaires are associated with higher response rates compared to other questionnaire kinds such as electronic or paper-based self-completion questionnaires. Thirdly, the ability to offer additional clarification and explanations in person gives the interviewer the confidence of asking more intricate questions compared to those in a self-completion questionnaire (Robson, 2011).

In conclusion, it is evident that self-administered questionnaires are the most suitable method of investigation in the current context. Nevertheless, despite the numerous advantages of this type of survey, considerable effort is still necessary to ensure that any sources of error and bias are minimised, ethical requirements are met, and a relevant sampling method is chosen to ensure that the sample is as representative as possible of the population of interest. These issues are discussed below.

**Minimising bias**

One of the most important aims of surveys is to remove as much bias as possible from the research process, in order to ensure that the results are replicable, reliable, valid and representative (May, 2011). For the results to be replicable, the procedures followed must be clearly described in order to allow other researchers to repeat the study (Bryman, 2012). Reliability can only be achieved through standardisation of questions to ensure consistency in terms of measurement (Robson, 2011). Reliability can be improved through pilot surveys which allow an assessment of how questions are interpreted by respondents and whether or
not answers are consistent (either over time or between subjects). Validity refers to the issue of whether an indicator actually measures the concept it was meant to quantify (Bryman, 2012) and can also be improved through pre-testing and piloting the questionnaire. Finally, the results need to be representative, meaning that they can be generalised to beyond the sample used in the study. The concept of representativeness is closely tied to the use of a reliable sampling technique as well as having statistically significant findings (May, 2011).

Additionally, the respondent needs to appreciate that there is no incentive in misreporting any of their expenditure or food consumption. This is made clear in the preamble of the questionnaire (see Appendix F). Nonetheless, various hidden factors which may introduce some degree of social desirability response bias (such as a desire to appear healthier or less frivolous) need to be acknowledged. Another potential source of bias is the order in which foods and items are to be listed. Research has shown that items at the top or bottom of a list may be selected more frequently than the available alternatives, giving rise to primacy (where the first option is favoured) and recency (where the most recent option is favoured) effects (Lietz, 2010). A possible way to reduce this type of bias is to rearrange the items in the list in some of the interviews. This source of bias can be minimised by re-sorting the list of items purchased and foods consumed on different interview dates or time slots during the same day.

Another source of bias is related to communication issues between the interviewer and the respondent. Ideally, the respondent must be in a position to understand the question in the way the researcher intends to, be able to offer the requested information, be willing to provide an answer and, finally, actually give an answer in the necessary form (Robson, 2011). According to Lietz (2010), the request for information is initially encoded in the form of a stimulus (question). The respondent then needs to decode the stimulus and encode an answer in the standardised format set by the researcher. Particular care and effort need to be afforded, therefore, to the initial encoding of the question in order to facilitate the respondent’s decoding-encoding process. According to Simmons (2011), the success of a survey does not only depend on the questions being asked and the order in which they are presented, but also the way in which they have been phrased. Asking for complex information in an unstructured way is likely to contribute to what Brace (2008) refers to as respondent fatigue. This is potentially a source of bias and must be avoided at all costs.
As alluded to earlier (see introductory section 5.5.1, p. 208), there is, evidently, a trade-off between detail and clarity/practicality that must be assessed critically. The central task of the researcher is to produce a questionnaire that allows respondents to fully understand what is wanted from them but which also remains faithful to the research task (Robson, 2011). Even though it may have been highly desirable to obtain expenditure and food breakdown for each agricultural sector in the IOT, this is unlikely to prove a realistic target. On the other hand, enquiring about purchases and meals in an unstructured manner would not allow an appreciation of the possible variety of consumption. Consequently, using the disaggregated sector classification is the obvious starting point when it comes to structuring the interview schedule. Subsequent pre-testing and piloting ensures that any problems with the questionnaire are fully overcome before the actual interviews are carried out (Robson, 2011).

**Sampling strategy**

Before carrying out a survey, it is imperative that the kind of population suited to the investigation is established, along with a plan of how the population is to be sampled. In some cases it is possible to survey the whole population by means of a census. These circumstances are rare and certainly do not apply to most tourism studies where there is only sufficient time and resources to allow interviewing of a limited number of tourists. Sampling is a key component to any survey as it is important that the sample characteristics (collected at a specific place in a specific point in time) are the same as those of the population (May, 2011). Although it is impossible to eliminate all possible sources of error, a clearly defined sampling strategy is crucial in keeping sampling error\(^7\) to a minimum (Bryman, 2012). There are two main types of sampling strategies: probability (random) and non-probability (non-random). This section critically reviews the available options for the present study.

Researchers generally favour probability or random sampling methods over non-probability sampling because they are considered to be more accurate and rigorous (Trochim, 2006). Probability sampling uses a full list of the population (known as a sampling frame) to randomly generate a sample (Robson, 2011). This, in theory, creates a sample in which any member of the population has an equal chance of being selected, thus making the sample

\(^7\) Sampling error is the error in the findings which occurs due to the difference between the sample and the population it was drawn from (Bryman, 2012).
more representative. Completely random sampling, such as a simple random sample where random numbers between 1 and N (where N is the total population size) are drawn in order to meet the required sample size, is rarely used alone for drawing population samples (Sturgis, 2011). More complex random sample designs such as cluster sampling and stratified sampling are often employed to ensure that either the sample is confined within a certain geographical area (in the case of cluster sampling), or that different subgroups with different characteristics are equally represented (in the case of stratified sampling). One of the main advantages of probability sampling is that it allows statistical (quantitative) inferences about the whole population to be made based on the responses of the sample (Robson, 2011).

Where obtaining a probability sample is not feasible, such as in cases where there is no sampling frame, resources are unavailable or the size of the sample (n) is not known a priori, non-probability (or non-random) sampling is employed (Robson, 2011). Non-probability sampling methods may be divided into two broad types: accidental or purposive (Trochim, 2006). Accidental or convenience sampling is the simplest form of sampling, as it uses a sample that is readily available and accessible (Bryman, 2012). According to Robson (2011), this type of sampling should be regarded as the least satisfactory method as it is prone to largely unspecifiable biases and influences. The consequence of this is that findings cannot usually be generalised to the whole population. Purposive sampling, on the other hand, is a more sophisticated type of non-probability sampling based on the idea of sampling predefined groups. According to Trochim (2006), there are five main types of purposive sampling: modal instance (where sampling aims to capture the most frequent or typical case), expert sampling (targeting people who are known to have experience on the topic of interest), quota sampling (where respondents are selected according to a fixed quota), heterogeneity sampling (where the purpose is to sample for as much diversity as possible), and, lastly, snowball sampling (a special case often employed in qualitative research where respondents recommend other relevant people to be interviewed).

Bryman identifies three sources of sampling bias: when the sample is not random, when the sampling frame is inadequate and where there are sample members who refuse to

---

77 Bryman (2012, p.187) defines sampling bias as ‘a distortion in the representativeness of the sample that arises when some members of the population stand little or no chance of being selected for inclusion in the sample’.
participate (non-response problem). In the current study, all three sampling biases exist as the sample is not random, no sampling frame is available, and the response rate varies depending on the location and the time of day. As it is evident that purposive sampling is preferable to convenience sampling, an attempt was made to minimise bias as much as possible, through considering the use of heterogeneity sampling. The aim was thus to carry out questionnaires in different locations in Cyprus, in order to capture tourists of different ages, as well as a good mix of tourists staying in different kinds of accommodation in the package and non-package categories. Priority was given to British tourists due them being the largest country segment and also being easier to approach for language reasons.

Ethical considerations

Even though the present study is highly quantitative and does not pose any potentially contentious questions, there was still a need to ensure that all aspects of the study and the way it was to be executed, meet commonly accepted ethical standards. In any questionnaire, the researcher relies on the willingness of members of the public to give their time and cooperation to answer questions (Brace, 2008). This needs to be respected during both the preparation and execution stage of the interview. Following consultation of the University Ethics Committee website (University of Surrey Ethics Committee, 2012), it was concluded that the present questionnaire (see Appendix F) meets all of the main ethical principles. The tourists were also made aware of this fact in the pre-amble of the questionnaire.

5.5.5 Designing the restaurant/hotel survey – steps and considerations

In these surveys, the desired outcome is obtaining portion quantities for the most popular dishes from restaurants and hotels frequented by tourists. The sampling is thus dependent on tourist responses and convenience. There is no need for a set questionnaire as this can often act as a deterrent for restaurant and hotel managers who will understandably show suspicion to someone demanding such detailed information. Instead, an informal conversation with willing owners who gave information with respect to portion composition and portions was pursued. Further information was also obtained from food menus and pictures of the dishes available outside many tourist restaurants.
5.5.6 Survey outcomes and generating final demand vectors

Questionnaires

The tourist questionnaires (see sample in Appendix F) were carried out in a number of different locations in Cyprus in September 2012 (shown in Figure 5.4). A total sample of 179 completed tourist questionnaires (of which 141 were British) and 9 restaurant/hotel questionnaires was obtained in the space of 3 weeks. A detailed analysis of bias in the tourist sample and the issues encountered during data collection is available in Appendix I. The outcomes of the restaurant/hotel manager interviews are summarised in Table G2, Appendix G. A wealth of qualitative information, some of which is subsequently brought into the discussion in the next chapter, was also obtained through additional conversations with interested tourists and restaurant/hotel managers.

Figure 5.4 Map of Cyprus showing tourist sampling locations and numbers of tourists interviewed at each site (map source: Google Earth).

Generating final demand vectors and setting up the model

The last major step before setting up the modified EIO model (see Figure 5.5 below) was to pre-process and recode the questionnaire responses into appropriate portion sizes (see Appendix G) along with the use of agricultural statistics (CYSTAT, 2010) and the CYSTAT HBS (CYSTAT, 2011a) to determine basic prices of agricultural commodities and a typical
diet for Cypriot households (for means of comparison as well as to fill in data on meals where tourists reported eating at home with friends or family) \(^78\). These were then used to generate final demand vectors as shown in Figure 5.5. Direct water use coefficients for domestic and imported crops were available from previous studies specific to Cyprus (Zoumides & Bruggeman, 2010; Zoumides et al., 2013). Domestic livestock sector coefficients were taken from the Cyprus WDD (WDD, 2011) and imported livestock sector water footprints were estimated using FAOSTAT trade data for Cyprus and weighted global water footprints for animal products from Mekonnen and Hoekstra (2012) (See Table H1 in Appendix H).

---

\(^78\) See Appendix G for conversion tables and estimates of daily expenditure and basic commodity prices for Cyprus households.
5.6 Chapter conclusions

The chapter has demonstrated how a series of tasks - IOT disaggregation and rebalancing, the modification of the EIO model to account for food portions and, finally, primary data collection - have been employed to create a novel framework (shown in Figure 5.5 above) for estimating the water use associated with dietary choices and the economic impact arising from tourist total expenditure. The primary objectives (see section 5.1.2, p. 156) related to addressing the issues of linearity, the low agricultural sector disaggregation and the use of recent primary data, have all been met in this chapter. The last remaining objective is to demonstrate and evaluate the capabilities of the approach. This is tackled in the ensuing chapter (Chapter 6).
Chapter 6: Model results and discussion

6.1 Chapter summary

The purpose of the chapter is to demonstrate how the proposed framework can contribute more detailed information on the dietary component of the indirect water use of tourists, by performing comparisons between different tourist groups. The sample of 179 completed questionnaires (out of which 176 are fully usable for generating final demand vectors) does not lend itself to statistical segmentation in the same way as the secondary dataset (see previous chapter), because some of the sub-clusters would have small numbers of tourists leading to small sample sizes. The objective is therefore to compare different tourist groups emerging from the survey. Cross-tabulation of variables allows for the formation of numerous segment combinations, only some of which are explored here. Specifically, this chapter explores COO segmentation (British compared to others) and segmentation by accommodation type.

The chapter is structured as follows: the following section (section 6.2) presents the final demand vectors for each of the tourist segments considered in the analysis. The subsequent section presents the water use and water productivity estimates for the same tourist segments (section 6.3). Section 6.4 provides a discussion of the strengths and limitations of the approach developed in Part IV of the thesis, in addition to some of the implications with regards to food consumption in tourism. Finally, section 6.5 concludes the chapter.

6.2 Final demand vectors

6.2.1 Observations

Table 6.1 (p. 223) and Table 6.2 (p. 224) show the final demand vectors generated for a total of 10 segments. The values show considerable heterogeneity, with a range of 3.72 USD to 28.68 USD per day on food (all tourists) and 36.23 USD to 99.06 USD on total daily expenditure (non-package tourists only). This reflects the variety of choices in terms of meals and spending exhibited by the tourists in the sample. Even before running the EIO model to obtain multipliers in order to consider the supply chain water use and value added, it is evident that the different tourists groups have their own unique characteristics in terms of
the sectors of the economy they are more likely to have an impact on. British-born Cypriots (BBCs) were not initially a cluster that had been planned in advance, but it was decided to separate them out because the survey revealed that this group had very unique characteristics, as demonstrated by a low overall spend but a very high food-related expenditure, most of which is made up of halloumi cheese to take back home (as shown in the ancillary category in Table 6.1).

6.2.2 Appraisal

It must be acknowledged that some segments have small numbers mainly because of the overall small presence of these types of tourists (BBC and villa/luxury hotel) in the sample. Nevertheless, these numbers are sufficient to demonstrate the strength of this novel methodological framework. Having such a wealth of disaggregated information allows an in-depth understanding of different tourist types, which in turn provides a basis for developing appropriate water conservation and efficiency strategies in different establishments, in the same way as discussed in Becken et al. (2003) with respect to energy issues. It also reinforces the argument made in Lundie et al. (2007) that from a destination management perspective, each tourism market segment is potentially associated with a mixture of economic, environmental and social impacts that are generated as a result of the mix of services utilised during their stay. The more detailed and accurate this information is, the greater the potential to draw useful conclusions and put forward realistic recommendations and guidelines.
Table 6.1 Food expenditure (y2) breakdown for different tourist groups based on the primary data analysis.

<table>
<thead>
<tr>
<th>CROPS</th>
<th>TOTAL</th>
<th>NON-UK</th>
<th>UK</th>
<th>UK ACCOMMODATION SEGMENTS</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>BBCs*</td>
<td>Villas/luxury</td>
</tr>
<tr>
<td>Cereals</td>
<td>0.08</td>
<td>0.10</td>
<td>0.08</td>
<td>0.07</td>
<td>0.09</td>
</tr>
<tr>
<td>Leguminous</td>
<td>0.07</td>
<td>0.00</td>
<td>0.05</td>
<td>0.51</td>
<td>0.00</td>
</tr>
<tr>
<td>Fodder</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Potatoes</td>
<td>0.06</td>
<td>0.05</td>
<td>0.07</td>
<td>0.05</td>
<td>0.09</td>
</tr>
<tr>
<td>Vegetables (all)</td>
<td>0.30</td>
<td>0.29</td>
<td>0.32</td>
<td>0.34</td>
<td>0.36</td>
</tr>
<tr>
<td>Wine grapes</td>
<td>0.03</td>
<td>0.01</td>
<td>0.03</td>
<td>0.00</td>
<td>0.06</td>
</tr>
<tr>
<td>Table grapes</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Citrus</td>
<td>0.08</td>
<td>0.07</td>
<td>0.08</td>
<td>0.06</td>
<td>0.11</td>
</tr>
<tr>
<td>Fruit</td>
<td>0.08</td>
<td>0.10</td>
<td>0.08</td>
<td>0.12</td>
<td>0.08</td>
</tr>
<tr>
<td>Nuts</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Olives</td>
<td>0.84</td>
<td>0.50</td>
<td>0.85</td>
<td>0.61</td>
<td>0.77</td>
</tr>
<tr>
<td>Beef</td>
<td>0.26</td>
<td>0.17</td>
<td>0.24</td>
<td>0.19</td>
<td>0.30</td>
</tr>
<tr>
<td>Sheep and Goat</td>
<td>0.24</td>
<td>0.05</td>
<td>0.23</td>
<td>0.27</td>
<td>0.28</td>
</tr>
<tr>
<td>Pork</td>
<td>0.57</td>
<td>0.40</td>
<td>0.51</td>
<td>0.36</td>
<td>0.57</td>
</tr>
<tr>
<td>Poultry</td>
<td>0.42</td>
<td>0.34</td>
<td>0.43</td>
<td>0.47</td>
<td>0.52</td>
</tr>
<tr>
<td>Milk (cow)</td>
<td>0.13</td>
<td>0.16</td>
<td>0.12</td>
<td>0.12</td>
<td>0.14</td>
</tr>
<tr>
<td>Milk (sheep)</td>
<td>0.01</td>
<td>0.00</td>
<td>0.00</td>
<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td>Eggs</td>
<td>0.05</td>
<td>0.08</td>
<td>0.12</td>
<td>0.31</td>
<td>0.16</td>
</tr>
<tr>
<td>Fishing</td>
<td>1.00</td>
<td>0.68</td>
<td>0.97</td>
<td>0.14</td>
<td>1.82</td>
</tr>
<tr>
<td>Ancillary</td>
<td>2.62</td>
<td>0.72</td>
<td>3.09</td>
<td>25.04</td>
<td>1.22</td>
</tr>
<tr>
<td>TOTAL FOOD (USD B.P)</td>
<td>6.85</td>
<td>3.72</td>
<td>7.26</td>
<td>28.68</td>
<td>6.57</td>
</tr>
</tbody>
</table>

| Sample     | 176   | 38   | 138  | 12  | 14  | 19  | 31  | 16  | 19  | 34  |
| Length of stay | 19.7 | 17.5 | 20.3 | 15.6 | 10.6 | 27.9 | 16.7 | 10.75 | 21.2 | 15.7 |

*Note: BBC stands for British-born Cypriots.
Table 6.2 Expenses (y\$) breakdown for different tourist groups based on the primary data analysis.

<table>
<thead>
<tr>
<th>TOTAL SPENDING IN DIFFERENT CATEGORIES (USD CONSUMER PRICES)</th>
<th>Villas/luxury</th>
<th>Own house</th>
<th>Family/friends</th>
<th>2*/3*</th>
<th>4*</th>
<th>Hotel appts</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>UK ACCOMMODATION SEGMENTS</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Package per day</td>
<td>55.69</td>
<td>48.56</td>
<td>58.02</td>
<td>0.00</td>
<td></td>
<td>92.45</td>
</tr>
<tr>
<td>Food and beverages</td>
<td>1.38</td>
<td>0.86</td>
<td>1.52</td>
<td>4.88</td>
<td></td>
<td>0.29</td>
</tr>
<tr>
<td>Meal expenses</td>
<td>21.77</td>
<td>20.86</td>
<td>22.01</td>
<td>16.55</td>
<td></td>
<td>24.80</td>
</tr>
<tr>
<td>Other purchases</td>
<td>5.11</td>
<td>8.59</td>
<td>4.15</td>
<td>2.46</td>
<td></td>
<td>2.45</td>
</tr>
<tr>
<td>Culture and recreation</td>
<td>6.99</td>
<td>3.71</td>
<td>7.90</td>
<td>2.48</td>
<td></td>
<td>26.25</td>
</tr>
<tr>
<td>Transport</td>
<td>6.45</td>
<td>7.00</td>
<td>6.30</td>
<td>8.28</td>
<td></td>
<td>7.80</td>
</tr>
<tr>
<td>Accommodation</td>
<td>46.44</td>
<td>33.33</td>
<td>52.01</td>
<td>1.59</td>
<td></td>
<td>23.81</td>
</tr>
<tr>
<td>TOTAL non-package</td>
<td>88.14</td>
<td>74.36</td>
<td>93.90</td>
<td>36.23</td>
<td></td>
<td>85.40</td>
</tr>
<tr>
<td>TOTAL package**</td>
<td>97.39</td>
<td>89.59</td>
<td>99.90</td>
<td>-</td>
<td></td>
<td>154.03</td>
</tr>
</tbody>
</table>

| Sample number (N)                                           | 176           | 38        | 138            | 12    | 14 | 19           |
| Length of stay (LOS)                                         | 19.7          | 17.5      | 20.3           | 15.6  | 10.6| 27.9         |

* BBC stands for British-born Cypriots.

** This is a weighted average for different package deals. Packages vary in terms of what they include. Package tourists were specifically asked to respond to what deal they were on (e.g. B&B, half-board, full-board or all-inclusive) and what else their deals included. Where this included flight prices, an average price for flight plus airport taxes obtained from CYSTAT through personal communication was subtracted from the total price.
6.3 Water use and water use intensity estimates

6.3.1 Results analysis

The data presented in Table 6.1 was used to create a final demand vector of suitable length that was ‘fed’ into the disaggregated IOT EIO model, whereas the data shown in Table 6.2 was used in the aggregated IO economic model using the original WIOD 2007 IOT. Direct water use is not considered here as the focus is on the dietary component, but estimates are straightforward to include if necessary, using the approach followed in the previous chapter. Selected results are analysed and discussed.

Figure 6.1 shows the total aggregated embedded water use contained in the diet of each of the 10 tourist groups in addition to local residents (based on household budget survey data converted to daily consumption). The overall range is considerably less than in Part III. The results show that BBCs consume a significant amount of water (around 1000 l daily), 32% of which is imported. This is likely to include grains fed to animals to produce milk, which is then used to produce halloumi cheese. 4-star hotels also appear to use significant amounts of water (over 700 l daily), 80% of which is locally sourced. Most of this water appears to stem from the consumption of pork (see Table 6.1), which is eaten at breakfast buffets as well as being a commonly eaten meat used in kebabs and other local meat dishes.

Figure 6.2 shows the water use intensity (in l per USD value added) for all groups. The range of values is considerable, especially when compared to the aggregated EIO model results from Chapter 4 (see section 4.3). This is testament to the ability of the functional unit approach in the revised model as well as the ability of the model to consider the exact composition of the diet based on primary data. In terms of the results, the average water productivity of the whole sample is around 4.9 l for each USD of value added produced in the economy. This is less than half the amount required by a resident to produce the same amount of value added. This result is in close agreement with the results of the aggregated model and reflects the intensive nature of tourism consumption and its ability to generate a significant amount of value added in the local economy, often using less resources compared to other economic activities. Nevertheless, some groups such as the BBCs display almost six

---

79 See discussion in Chapter 3 (section 3.2.2) as to why the inverse of water productivity is appropriate in a tourism context.
times less water productivity in comparison to the average tourist, largely because of their significant food-related purchases in combination with their low total expenditure.

One of the most noteworthy findings is the fact that the most ‘efficient’ group in terms of indirect water use appears to be the 2/3 star hotel category, with a water productivity of 4.3. This segment represents what is commonly labelled as ‘cheap mass tourism’, a type of tourism that Cyprus has traditionally been associated with. Given the recent debate over and attempts to attract higher-spending tourists to the island (Boukas & Ziakas, 2012; Louca, 2011), this is an interesting finding, with thought-provoking sustainability implications. The results in Table 6.3 reinforce this argument, as they show that tourists from this segment generate 95 USD of value added per day, which is only 6.5% less than that of the average tourist in the sample. The very high end of the market also appears to perform well in terms of water productivity. Tourists who stay in villas do not appear to consume as much meat and dairy because they tend to prefer fish, which has a very low water footprint (mainly

---

**Figure 6.1** Water use associated with the production of agricultural commodities that cater for the demand of each of the groups, showing percentages of local and imported water.

---

<table>
<thead>
<tr>
<th>Group</th>
<th>Local water</th>
<th>Import water</th>
</tr>
</thead>
<tbody>
<tr>
<td>Local residents</td>
<td>74%</td>
<td>26%</td>
</tr>
<tr>
<td>Hotel apartments</td>
<td>77%</td>
<td>23%</td>
</tr>
<tr>
<td>4 star hotels</td>
<td>80%</td>
<td>20%</td>
</tr>
<tr>
<td>2/3 star hotels</td>
<td>76%</td>
<td>24%</td>
</tr>
<tr>
<td>Visiting friends/family</td>
<td>73%</td>
<td>27%</td>
</tr>
<tr>
<td>Home owners</td>
<td>74%</td>
<td>26%</td>
</tr>
<tr>
<td>Villas</td>
<td>79%</td>
<td>21%</td>
</tr>
<tr>
<td>BBCs</td>
<td>68%</td>
<td>32%</td>
</tr>
<tr>
<td>All UK</td>
<td>77%</td>
<td>23%</td>
</tr>
<tr>
<td>Non-UK</td>
<td>74%</td>
<td>26%</td>
</tr>
<tr>
<td>Total</td>
<td>73%</td>
<td>27%</td>
</tr>
</tbody>
</table>
relating to the feed components of farmed fish). Their value added is the highest of any group with 123 USD per day, which is 21% higher than the average.

![Figure 6.2 Water use intensity for all groups, showing a considerable range of values compared to the aggregated model.](image)

<table>
<thead>
<tr>
<th>Value added per tourist segment in USD per capita per day</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Value added</strong> (USD per capita per day)</td>
</tr>
<tr>
<td>Total</td>
</tr>
<tr>
<td>Non-UK</td>
</tr>
<tr>
<td>All UK</td>
</tr>
<tr>
<td>BBCs</td>
</tr>
<tr>
<td>Villas</td>
</tr>
<tr>
<td>Home owners</td>
</tr>
<tr>
<td>Visiting friends/family</td>
</tr>
<tr>
<td>2/3 star hotels</td>
</tr>
<tr>
<td>4 star hotels</td>
</tr>
<tr>
<td>Hotel apartments</td>
</tr>
<tr>
<td>Local residents</td>
</tr>
</tbody>
</table>
6.3.2 Results appraisal

The above results demonstrate the value of obtaining information with respect to tourist dietary preferences and their food habits. The possibilities for creating tourist segments are endless and it is possible to compare groups depending on their age, their purpose of visit, the time of year (temporal), the area of the island they are visiting (spatial), their total expenditure in specific spending categories, or even other more specific information such as whether they play golf or whether they visit the mountains or archaeological sites. A tourist questionnaire such as the one designed in the present work is capable of delivering extremely disaggregated information with respect to specific tourist needs and preferences, which can then be translated into economic returns or environmental impacts (water is only one of many possibilities). The results obtained highlight the importance of certain key products such as dairy (predominantly halloumi cheese) and pork, both of which are readily consumed by tourists on the island.

Locally-sourced food in tourism is commonly considered to be a way to increase economic multipliers (Sims, 2009; Torres, 2002, 2003) but is also usually thought of as a more environmentally sustainably option (Gössling et al., 2011; Sims, 2009). Nevertheless, the results presented here show that where certain resources (water in this case) are scarce, caution needs to be exercised, and an understanding of the dietary preferences and the supply chain of specific products is key to evaluating how environmentally sustainable locally-sourced food actually is. The results presented here are aggregated to give the total water use and economic impact for each tourist segment. However, the initial model output contains water use per sector for each final demand vector, which potentially provides the opportunity to assess water use and its implications for specific agricultural and other economic sectors.

6.4 Discussion of the framework and implications of the findings

6.4.1 Advantages of the proposed modelling approach

The proposed framework builds on previous more conventional methods of assessing the environmental impacts of tourist consumption (Cazcarro et al., 2014; Munday et al., 2013), in the sense that it uses highly disaggregated information (on an individual level) in addition to
detailed tourist characteristics that potentially allow stratification of the sample in numerous ways. This is much more useful than relying on a national average to produce a vector of tourist final consumption that assumes that tourists eat a diet similar to that of locals. Furthermore, in contrast to previous EIO studies on food consumption (Meier & Christen, 2012a; Tukker et al., 2011), it moves away from a consideration of calories and other nutritional components by proposing a more practical approach using portion sizes and real-time tourist data.

Another invaluable contribution of the proposed framework is its potential use for scenario planning. Most tourists reported that food portions in Cyprus are very generous, with some of them stating that they were rarely able to empty their plates. On the other hand, catering managers and restaurant owners took pride in their large portion sizes (see Appendix G for typical portion sizes), providing the justification that tourists find it attractive and are more likely to return to the restaurant if the food is plentiful. These findings suggest that there is potential to decrease portion sizes, especially the meat or dairy components of meals. The current approach could be used to simulate any water use impacts arising from hypothetical decreases in meat portion sizes. As an example, considering the high average portion size, a 15-20% reduction of meat portion size could be considered realistic in the future, whilst keeping price and all other parameters equal. However, there also needs to be a consideration of the resulting economic impacts (such as employment and value added).

The framework is also flexible in that it allows different scenarios to be tested, using economy-wide figures in a top-down methodological framework. A process-based (bottom-up) LCA can provide excellent figures for specific hotels or establishments but lacks the economy-wide components, as well as the ability to integrate economic impact effects such as value added, employment or other national or regional economic, social or environmental indicators. Becken and Patterson (2006) conclude that, in the absence of detailed data on energy use and/or tourist behaviour, the bottom-up approach entails extensive additional collection of primary data. In the present framework, additional data is still necessary in the form of detailed tourist surveys. Nonetheless, these could, in the future, be collected as part of broader tourist surveys routinely carried out by tourism organisations. The rest of the data required, such as IOTs, HBS data and water use data, are secondary and can be regularly updated using programming software or Excel spreadsheets to ensure that prices and food
portions remain up-to-date. Ideally, combinations of the bottom-up and the top-down approaches could yield very accurate data on the environmental impacts of tourism consumption.

6.4.2 Limitations and uncertainty

The approach corrects many of the inherent flaws of the EIO framework used in Part III, namely linearity between expenditure and environmental impact and the problem of a low agricultural disaggregation which did not allow a consideration of differences in dietary consumption. This has been accomplished at the cost of using several additional datasets such as agricultural statistics, HBS data and primary data on expenditure and food consumption. The outcomes of the approach thus become highly reliant on the quality of these datasets. The quality of the agricultural statistics and HBS data could not be controlled as these are secondary data collected by CYSTAT. The study thus sought to ensure that the choice of a disaggregation and balancing algorithm was the most appropriate, in order to ensure that any uncertainties are minimised. Furthermore, an attempt was made to collect as representative a sample as possible by travelling to different parts of the island.

With respect to the primary dataset, the approach places trust in the responses given by tourists and restaurant/hotel managers. An obvious way to enhance the study would be to engage in further data collection in order to acquire a larger sample. However, under the circumstances, the sample collected was deemed adequate for a demonstration of the model capabilities. The relative consistency between portion sizes across the small sample of establishments (See Table G2 in Appendix G) suggests that restaurants and hotels in Cyprus tend to have standard portions. The modified EIO model is highly reliant on accurate portion sizes as the linearity between expenditure and water use impact is essentially replaced with linearity between quantity consumed and water use impact. This is much closer to reality although it also implies that accurate portion sizes are a prerequisite for the approach to work. In this instance, average country-wide portion sizes were used in the analysis. A future refinement would be to obtain a large enough sample that would allow weighted averages for different areas of the island or types of establishment.

Performing a sensitivity analysis could allow a quantification of errors associated with the quality of different datasets. In the supplementary material of their article, Cazcarro et al.
(2014) offer an example of how final demand vectors could easily be modified in order to perform a simple sensitivity analysis. Such a sensitivity analysis could in the present case take into account uncertainty estimates for portion sizes, prices and secondary data. As previously mentioned in Chapter 4, Section 4.4.2, Monte Carlo techniques can also be used to estimate uncertainty in the EIO framework (Bullard & Sebald, 1988; Lenzen, Wood, & Wiedmann, 2010b).

6.4.3 Sustainable food supply in tourism

Food has been attracting considerable attention in the sustainable tourism literature in recent years, in terms of its potential impacts on both climate change (Gössling et al., 2011) and water use (Becken et al., 2013; Cazcarro et al., 2014; Gössling et al., 2012; Hadjikakou et al., 2012; Hadjikakou, Chenoweth, & Miller, 2013). The present discussion focuses on three aspects related to food, all of which can be studied using the framework developed in this chapter: the components of the tourist diet, the quantities consumed, and trade-offs between different environmental and economic impacts.

The choice of foods on offer can greatly affect the virtual water consumption component of the tourism industry (UNEP-UNWTO, 2012). According to Gossling (2012), tourists generally tend to consume a greater share of higher-order, protein-rich foods with a higher water footprint. This is certainly the case for tourism in Cyprus based on the findings shown previously (see Table 4.4). One of the main reasons for this appears to be the ‘full English breakfast’ commonly served at breakfast buffets, which, in addition to local lunch and dinner options that are also meat-based, creates a daily menu with a very high embedded water content. Gossling et al. (2011) offer a number of recommendations to promote ‘climatically sustainable’ food management for tourist establishments. Many of their recommendations such as buying less beef, offering more vegetarian options, and arranging buffets so that less carbon-intensive foods are at the centre are also valid from a water reduction perspective.

Quantity and portion size are closely related to the products being consumed. The previously mentioned study has also highlighted the need to regulate portion sizes in buffets to reduce the carbon footprint (Gössling et al., 2011); this is certainly compatible with water use reduction targets as well. Most of the tourists interviewed expressed their amazement at the quantities being served at buffets and restaurants, with standard meat portions
sometimes exceeding 300g per person. This suggests that there is certainly the potential to reduce at least the meat component in many of the meals and buffets with negligible impact on tourist satisfaction levels. Doing so will also limit the amount of food waste, which is a common problem in hotel buffets. The EIO approach developed here allows the testing of hypotheses and scenarios relating to reduced portion sizes as well as different tourist numbers and changes in dietary preferences.

The last aspect is the issue of trade-offs. Guidelines for water use may in fact clash with guidelines for energy or carbon reduction in certain cases. In general, water management is much more dependent on the local context. In climates where water is not scarce and there is plenty of abundant grass, beef may have a very low blue water footprint (Gerbens-Leenes et al., 2013; Ridoutt & Pfister, 2010a) and may not present a ‘worse’ choice than other meats in terms of its embedded water use\(^80\). Where water is scarce, on the other hand, importing certain products which require significant amounts of water could be a favourable option, even though this would almost always be contraindicated in carbon reduction guidelines. The recent report by UNEP-UNWTO (2012) concludes that, in order to comprehensively address water use aspects, water-stressed destinations need to employ water use inventories, detailing water uses and identifying options where potential savings can be prioritised. In addition, when pursuing potential water savings it is important to ensure that any decisions to shift to less environmentally-intensive products will not have significant economic side-effects. Local delicacies are often highly prized by tourists despite their potentially high water use, and the best compromise may be to regulate their supply chain better rather than limit their availability. The proposed solution needs to consider a complex array of factors, many of which can be handled in a framework such as the one developed here.

\(^{80}\) Even if this may not be the case with respect to other types of environmental footprints.
6.5 Chapter conclusions

The approach developed in this Part of the thesis allows for the exploration of the food component of tourist consumption in an unprecedented degree of detail. Its application to tourism across Cyprus in September 2012 demonstrates the ability of the approach to highlight important components of water use, along with the dietary choices associated with a higher supply-chain water use in the present context. The model is built for Cyprus in this case, but it can be replicated for other countries or tourism destinations provided that the secondary data are available and that the necessary primary data collection takes place.

Water issues are inherently local meaning that only general conclusions and implications pertinent to other localities can be drawn from the results. A detailed analysis using local data is necessary before pursuing specific recommendations. In the absence of IOTs or any other modelling framework, such as in a developing country context, detailed tourist surveys alone are still a valuable source of quantitative and qualitative information. The proposed framework can similarly be extended beyond the realm of tourism research. National and regional household budget surveys usually contain a wealth of information on food prices and quantities purchased by households, opening up a number of research avenues with potentially significant policy implications.

The next Part of the thesis (Part V) comprises the concluding chapter (Chapter 7), which brings together the contributions of all three approaches. Chapter 7 will also examine some of the implications of the findings, especially with respect to food consumption, expanding on some of the issues discussed in the present chapter.
Appendix D – Numerical disaggregation and balancing examples

2 sectors disaggregated to form 3 sectors

A hypothetical 2-sector economy (Table D1) taken from p.22 in Miller and Blair (2009) is used here to illustrate disaggregation when input and output shares from the new sectors are known precisely or may be estimated using industry accounts or appropriate national statistics. Note that, for purposes of simplification, the Payments sector stands for value added and imports, whereas final demand includes exports.

Table D1 Hypothetical 2-sector economy (R. E. Miller & Blair, 2009).

<table>
<thead>
<tr>
<th>Sector</th>
<th>Sector A</th>
<th>Sector B</th>
<th>Final demand</th>
<th>Total Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sector A</td>
<td>150</td>
<td>500</td>
<td>350</td>
<td>1000</td>
</tr>
<tr>
<td>Sector B</td>
<td>200</td>
<td>100</td>
<td>1700</td>
<td>2000</td>
</tr>
<tr>
<td>Payments sector</td>
<td>650</td>
<td>1400</td>
<td>1100</td>
<td>3150</td>
</tr>
<tr>
<td>Total inputs</td>
<td>1000</td>
<td>2000</td>
<td>3150</td>
<td>6150</td>
</tr>
</tbody>
</table>

Assume that sector A is to be disaggregated into two sectors, sectors A₁ and A₂. It is also known that each of these sectors produces 50% of the output share and 50% of value added (and imports) whereas sector A₁ uses 60% of the intermediate inputs of the aggregated sector A. Knowing the input/output shares allows a straightforward estimation of how sectors A₁ and A₂ interact with sector B. These ratios have been used to fill in the cells surrounded by dotted lines following the principles laid out in the previous sub-section. The cells surrounded by double lines are those which remain unchanged. The most challenging part of disaggregation is the knowledge of what goes on in the intra-matrix (see shaded rectangle Table D2). This is because the intra-matrix requires knowledge of how the two newly formed sectors interact with each other. In this case, a total flow of 150 needs to be disaggregated between 4 cells. Simply dividing the total aggregated flow by the number of corresponding cells in the disaggregated table will almost never provide an accurate representation of economic flows between the new sectors. Frequently, where one sector is disaggregated into several smaller sectors, the intra-matrix contains several 0 values, as illustrated in Liu et al. (2012) with respect to the electricity sector.

In the present example, the assumption is that sector A₁ does not make any purchases from A₂ but does purchase from itself. A₂ purchases from itself and from A₁ in equal proportions. This essentially means that the original 150 that was traded within sector A in Table D1 needs to be divided by three and distributed between the three appropriate cells as shown in Table D2.
Table D2 Hypothetical 3-sector economy where sector A has been disaggregated into 2 new sectors.

<table>
<thead>
<tr>
<th></th>
<th>Sector A₁</th>
<th>Sector A₂</th>
<th>Sector B</th>
<th>Final demand</th>
<th>Total Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sector A₁</td>
<td>50</td>
<td>50</td>
<td>250</td>
<td>175</td>
<td>500</td>
</tr>
<tr>
<td>Sector A₂</td>
<td>0</td>
<td>50</td>
<td>250</td>
<td>175</td>
<td>500</td>
</tr>
<tr>
<td>Sector B</td>
<td>120</td>
<td>80</td>
<td>100</td>
<td>1700</td>
<td>2000</td>
</tr>
<tr>
<td>Payments sector</td>
<td>325</td>
<td>325</td>
<td>1400</td>
<td>1100</td>
<td>3150</td>
</tr>
<tr>
<td>Total inputs</td>
<td>500</td>
<td>500</td>
<td>2000</td>
<td>3150</td>
<td>6150</td>
</tr>
</tbody>
</table>

Although the principles outlined in the previous section can produce a new table, Table D2 is not balanced in the sense that the sum of inputs (columns) or outputs (rows) for sectors A₁ and A₂ does not add up to 500 as it should. This implies that the inter-industry matrix is not correct with respect to value added, output and final demand and must be updated to correct for this. Some straightforward mathematical trial and error manipulations allow the estimation of a possible solution for a balanced table in this simple 3 x 3 example (shown in Table D3).

Table D3 Balanced version of Table A7.

<table>
<thead>
<tr>
<th></th>
<th>Sector A₁</th>
<th>Sector A₂</th>
<th>Sector B</th>
<th>Final demand</th>
<th>Total Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sector A₁</td>
<td>55</td>
<td>20</td>
<td>250</td>
<td>175</td>
<td>500</td>
</tr>
<tr>
<td>Sector A₂</td>
<td>0</td>
<td>75</td>
<td>250</td>
<td>175</td>
<td>500</td>
</tr>
<tr>
<td>Sector B</td>
<td>120</td>
<td>80</td>
<td>100</td>
<td>1700</td>
<td>2000</td>
</tr>
<tr>
<td>Payments sector</td>
<td>325</td>
<td>325</td>
<td>1400</td>
<td>1100</td>
<td>3150</td>
</tr>
<tr>
<td>Total inputs</td>
<td>500</td>
<td>500</td>
<td>2000</td>
<td>3150</td>
<td>6150</td>
</tr>
</tbody>
</table>

Note that the simplicity of the problem in this example allows the matrix to be balanced manually. This is not possible when working with larger matrices such as the one used in this Part of the thesis.

**TRAS example using a 3-by-3 matrix**

Starting from the matrix in Table 4B, the TRAS method outlined above is applied to balance the matrix. Estimated total output – final demand for each sector are used as row sums ($u$) and total inputs – payment sector for each sector, are used as column totals ($v$):

$$ u(1) = [325 \ 325 \ 300] \quad \text{(D1)} $$

$$ v(1) = [175 \ 175 \ 600] \quad \text{(D2)} $$

Following standard nomenclature, $Z$ is simply the aggregate inter-industry matrix with which the target matrix must be compatible:
The above serves as the third step at each iteration. The aim is to carry on until the errors are small and it is clearly apparent that the values are converging to a final target matrix. Following 6 iteration cycles (rounds), it became evident that the TRAS algorithm was performing well and that all constraints were being satisfied along with row sums and column sums remaining accurate, despite the additional step at each cycle. Table D4 shows how the row and column sums converge towards their target value. The results are those reported at the end of each iteration, which includes the TRAS step. This means that while the row and column sums have converged towards the target values, all restrictions (5.1-5.7, in Chapter 5) regarding all submatrices in the disaggregated matrix needing to match their parent cells are respected. This is indicated by the sums of row 3 and column 3 which are always equal to the target value at the end of every iteration, as a result of these values involving sector B which remained unchanged, as well as transactions between this sector and the other sector which were constrained to meet the aggregates in Table D1.

Table D4 Row and Column sums at the end of each TRAS iteration along with final error values.

<table>
<thead>
<tr>
<th>Round</th>
<th>Row 1</th>
<th>Row 2</th>
<th>Row 3</th>
<th>Col 1</th>
<th>Col 2</th>
<th>Col 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Round 1</td>
<td>326.9527</td>
<td>323.0473</td>
<td>300</td>
<td>173.9422943</td>
<td>176.0577057</td>
<td>600</td>
</tr>
<tr>
<td>Round 2</td>
<td>325.2993</td>
<td>324.7007</td>
<td>300</td>
<td>174.8594070</td>
<td>175.140593</td>
<td>600</td>
</tr>
<tr>
<td>Round 3</td>
<td>325.0417</td>
<td>324.9583</td>
<td>300</td>
<td>174.9800768</td>
<td>175.0199232</td>
<td>600</td>
</tr>
<tr>
<td>Round 4</td>
<td>325.0059</td>
<td>324.9941</td>
<td>300</td>
<td>174.9971945</td>
<td>175.0028055</td>
<td>600</td>
</tr>
<tr>
<td>Round 5</td>
<td>325.0008</td>
<td>324.9992</td>
<td>300</td>
<td>174.9996045</td>
<td>175.0003955</td>
<td>600</td>
</tr>
<tr>
<td>Round 6</td>
<td>325.0001</td>
<td>324.9999</td>
<td>300</td>
<td>174.9999443</td>
<td>175.0000557</td>
<td>600</td>
</tr>
</tbody>
</table>

Targets (u,v) 325 325 300 175 175 600

Final error (ε) 0.000117 0.000117 0 0.000055743 0.000055743 0

Final error 0.000255 0.000255 0 0.000225988 0.000225988 0

The final 3 X 3 target matrix is given by:

\[
\hat{Z} = \begin{pmatrix}
150 & 500 \\
200 & 100 \\
\end{pmatrix}
\]  

(D3)

The solution remains fairly fitted with the desired target conditions in the original unbalanced target matrix (Table D2) and also results in a balanced inter-industry matrix which allows its subsequent use to conduct analysis. Note also that if the two first sectors of \(Z^{18} \) are aggregated into one in order to match the original sector classification, the resulting matrix is identical to the original inter-industry matrix \(\hat{Z} \) in Table D1.

According to Oosterhaven et al. (1986), even though not commonly seen in popular practice, the RAS method can be used on both intermediate and final transactions. This opens up the
possibility for allowing value added and imports to be included in the matrix to be balanced. However, Oosterhaven et al. (1986) still appear to recommend externalising value added and imports from the balancing process where sufficient prior information is available. This essentially means estimating these values in advance and using the conventional $u$ and $v$ row and column sums as balancing criteria.
## Appendix E – WIOD 2007 IOT disaggregation procedures

Table E1 Disaggregated agricultural sector outputs pro-rated based on agricultural statistics (CYSTAT 2008) and the WIOD IOT, balanced using the RAS algorithm to the nearest 1000 euro (3 d.p) after a total of 7 iterations.

<table>
<thead>
<tr>
<th>Categories</th>
<th>Sub-sectors</th>
<th>Intra-matrix</th>
<th>Industry sales</th>
<th>Final demand</th>
<th>Exports</th>
<th>ROW SUMS</th>
<th>PRO-RATED OUTPUT</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CROPS</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Cereals</td>
<td>3.458</td>
<td>10.464</td>
<td>0.211</td>
<td>0.000</td>
<td>14.132</td>
<td>14.132</td>
</tr>
<tr>
<td></td>
<td>Leguminous plants</td>
<td>1.096</td>
<td>1.106</td>
<td>5.379</td>
<td>0.334</td>
<td>7.915</td>
<td>7.915</td>
</tr>
<tr>
<td></td>
<td>Fodder</td>
<td>23.438</td>
<td>0.941</td>
<td>0.115</td>
<td>0.000</td>
<td>24.493</td>
<td>24.493</td>
</tr>
<tr>
<td></td>
<td>Potatoes</td>
<td>5.765</td>
<td>2.747</td>
<td>7.798</td>
<td>56.175</td>
<td>72.485</td>
<td>72.485</td>
</tr>
<tr>
<td></td>
<td>Vegetables (all)</td>
<td>1.617</td>
<td>0.576</td>
<td>98.834</td>
<td>2.629</td>
<td>103.656</td>
<td>103.656</td>
</tr>
<tr>
<td></td>
<td>Wine grapes</td>
<td>0.000</td>
<td>7.746</td>
<td>1.498</td>
<td>0.000</td>
<td>9.244</td>
<td>9.244</td>
</tr>
<tr>
<td></td>
<td>Table grapes</td>
<td>0.175</td>
<td>0.429</td>
<td>2.020</td>
<td>0.090</td>
<td>2.714</td>
<td>2.714</td>
</tr>
<tr>
<td></td>
<td>Citrus</td>
<td>0.000</td>
<td>16.416</td>
<td>16.021</td>
<td>28.950</td>
<td>61.386</td>
<td>61.386</td>
</tr>
<tr>
<td></td>
<td>Fruit (except citrus)</td>
<td>0.000</td>
<td>0.060</td>
<td>72.642</td>
<td>0.167</td>
<td>72.869</td>
<td>72.869</td>
</tr>
<tr>
<td></td>
<td>Nuts</td>
<td>0.000</td>
<td>0.515</td>
<td>2.525</td>
<td>0.188</td>
<td>3.227</td>
<td>3.227</td>
</tr>
<tr>
<td></td>
<td>Olives</td>
<td>0.000</td>
<td>9.514</td>
<td>10.584</td>
<td>0.022</td>
<td>20.120</td>
<td>20.120</td>
</tr>
<tr>
<td></td>
<td>Beef</td>
<td>0.000</td>
<td>1.891</td>
<td>13.556</td>
<td>0.300</td>
<td>15.747</td>
<td>15.747</td>
</tr>
<tr>
<td></td>
<td>Sheep and Goat</td>
<td>0.000</td>
<td>0.000</td>
<td>39.694</td>
<td>0.000</td>
<td>39.694</td>
<td>39.694</td>
</tr>
<tr>
<td></td>
<td>Pork</td>
<td>0.000</td>
<td>24.471</td>
<td>82.012</td>
<td>7.020</td>
<td>113.503</td>
<td>113.503</td>
</tr>
<tr>
<td></td>
<td>Poultry</td>
<td>0.000</td>
<td>3.186</td>
<td>92.297</td>
<td>2.887</td>
<td>98.370</td>
<td>98.370</td>
</tr>
<tr>
<td></td>
<td>Milk (cow)</td>
<td>19.936</td>
<td>66.783</td>
<td>0.636</td>
<td>0.000</td>
<td>87.355</td>
<td>87.355</td>
</tr>
<tr>
<td></td>
<td>Milk (sheep and goat)</td>
<td>7.888</td>
<td>26.424</td>
<td>0.252</td>
<td>0.000</td>
<td>34.565</td>
<td>34.565</td>
</tr>
<tr>
<td></td>
<td>Eggs</td>
<td>6.784</td>
<td>0.000</td>
<td>10.989</td>
<td>0.101</td>
<td>17.875</td>
<td>17.875</td>
</tr>
<tr>
<td><strong>MEAT &amp; DAIRY</strong></td>
<td>Fishing &amp; aquaculture</td>
<td>0.000</td>
<td>0.000</td>
<td>62.744</td>
<td>0.000</td>
<td>62.744</td>
<td>62.744</td>
</tr>
<tr>
<td></td>
<td>Ancillary production</td>
<td>6.850</td>
<td>3.474</td>
<td>64.340</td>
<td>0.048</td>
<td>74.712</td>
<td>74.712</td>
</tr>
</tbody>
</table>

| COLUMN SUMS       | 77.008          | 176.742      | 584.146       | 98.911      |
| IOT SECTOR SUMS   | 77.008          | 176.742      | 584.146       | 98.911      |
Table E2 Disaggregated agricultural sector inputs pro-rated based on percentages of value added to total output from agricultural statistics (CYSTAT 2008) and the WIOD IOT, balanced using the RAS algorithm to the nearest 1000 euro (3 d.p) after a total of 29 iterations.

<table>
<thead>
<tr>
<th>Categories</th>
<th>Sub-sectors</th>
<th>Total inputs</th>
<th>Value added</th>
<th>ROW SUMS</th>
<th>PRO-RATED OUTPUT</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CROPS</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leguminous plants</td>
<td>2.750</td>
<td>5.165</td>
<td>7.915</td>
<td>7.915</td>
<td></td>
</tr>
<tr>
<td>Fodder</td>
<td>8.511</td>
<td>15.982</td>
<td>24.493</td>
<td>24.493</td>
<td></td>
</tr>
<tr>
<td>Potatoes</td>
<td>25.189</td>
<td>47.296</td>
<td>72.485</td>
<td>72.485</td>
<td></td>
</tr>
<tr>
<td>Vegetables (all)</td>
<td>36.020</td>
<td>67.635</td>
<td>103.656</td>
<td>103.656</td>
<td></td>
</tr>
<tr>
<td>Wine grapes</td>
<td>3.212</td>
<td>6.032</td>
<td>9.244</td>
<td>9.244</td>
<td></td>
</tr>
<tr>
<td>Table grapes</td>
<td>0.943</td>
<td>1.771</td>
<td>2.714</td>
<td>2.714</td>
<td></td>
</tr>
<tr>
<td>Citrus</td>
<td>21.332</td>
<td>40.055</td>
<td>61.386</td>
<td>61.386</td>
<td></td>
</tr>
<tr>
<td>Fruit (except citrus)</td>
<td>25.322</td>
<td>47.545</td>
<td>72.869</td>
<td>72.869</td>
<td></td>
</tr>
<tr>
<td>Nuts</td>
<td>1.121</td>
<td>2.106</td>
<td>3.227</td>
<td>3.227</td>
<td></td>
</tr>
<tr>
<td>Olives</td>
<td>6.992</td>
<td>13.128</td>
<td>20.120</td>
<td>20.120</td>
<td></td>
</tr>
<tr>
<td>Beef</td>
<td>11.913</td>
<td>3.834</td>
<td>15.747</td>
<td>15.747</td>
<td></td>
</tr>
<tr>
<td>Pork</td>
<td>85.865</td>
<td>27.638</td>
<td>113.503</td>
<td>113.503</td>
<td></td>
</tr>
<tr>
<td>Poultry</td>
<td>74.416</td>
<td>23.953</td>
<td>98.370</td>
<td>98.370</td>
<td></td>
</tr>
<tr>
<td>Milk (cow)</td>
<td>66.084</td>
<td>21.271</td>
<td>87.355</td>
<td>87.355</td>
<td></td>
</tr>
<tr>
<td>Milk (sheep and goat)</td>
<td>26.148</td>
<td>8.417</td>
<td>34.565</td>
<td>34.565</td>
<td></td>
</tr>
<tr>
<td>Eggs</td>
<td>13.522</td>
<td>4.353</td>
<td>17.875</td>
<td>17.875</td>
<td></td>
</tr>
<tr>
<td>Fishing &amp; aquaculture</td>
<td>19.529</td>
<td>43.216</td>
<td>62.744</td>
<td>62.744</td>
<td></td>
</tr>
<tr>
<td>Ancillary production</td>
<td>32.7450</td>
<td>41.962</td>
<td>74.712</td>
<td>74.712</td>
<td></td>
</tr>
<tr>
<td><strong>MEAT &amp; DAIRY</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beef</td>
<td>11.913</td>
<td>3.834</td>
<td>15.747</td>
<td>15.747</td>
<td></td>
</tr>
<tr>
<td>Pork</td>
<td>85.865</td>
<td>27.638</td>
<td>113.503</td>
<td>113.503</td>
<td></td>
</tr>
<tr>
<td>Poultry</td>
<td>74.416</td>
<td>23.953</td>
<td>98.370</td>
<td>98.370</td>
<td></td>
</tr>
<tr>
<td>Milk (cow)</td>
<td>66.084</td>
<td>21.271</td>
<td>87.355</td>
<td>87.355</td>
<td></td>
</tr>
<tr>
<td>Milk (sheep and goat)</td>
<td>26.148</td>
<td>8.417</td>
<td>34.565</td>
<td>34.565</td>
<td></td>
</tr>
<tr>
<td>Eggs</td>
<td>13.522</td>
<td>4.353</td>
<td>17.875</td>
<td>17.875</td>
<td></td>
</tr>
<tr>
<td>Fishing &amp; aquaculture</td>
<td>19.529</td>
<td>43.216</td>
<td>62.744</td>
<td>62.744</td>
<td></td>
</tr>
<tr>
<td>Ancillary production</td>
<td>32.7450</td>
<td>41.962</td>
<td>74.712</td>
<td>74.712</td>
<td></td>
</tr>
<tr>
<td><strong>COLUMN SUMS</strong></td>
<td></td>
<td>496.559</td>
<td>440.248</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>IOT SECTOR SUMS</strong></td>
<td></td>
<td>496.559</td>
<td>440.248</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table E3 TRAS minimum and maximum deviation of row and column sums from the desired outcome at the end of each iteration. The table shows the minimum and maximum values when all row and column sums are divided by their target sums at the end of each complete iteration.

<table>
<thead>
<tr>
<th>Iteration round</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.460</td>
<td>1.223</td>
</tr>
<tr>
<td>2</td>
<td>0.800</td>
<td>1.183</td>
</tr>
<tr>
<td>3</td>
<td>0.904</td>
<td>1.147</td>
</tr>
<tr>
<td>4</td>
<td>0.949</td>
<td>1.121</td>
</tr>
<tr>
<td>5</td>
<td>0.971</td>
<td>1.101</td>
</tr>
<tr>
<td>6</td>
<td>0.983</td>
<td>1.085</td>
</tr>
<tr>
<td>7</td>
<td>0.990</td>
<td>1.072</td>
</tr>
<tr>
<td>8</td>
<td>0.994</td>
<td>1.062</td>
</tr>
<tr>
<td>9</td>
<td>0.996</td>
<td>1.053</td>
</tr>
<tr>
<td>10</td>
<td>0.998</td>
<td>1.046</td>
</tr>
<tr>
<td>11</td>
<td>0.999</td>
<td>1.040</td>
</tr>
<tr>
<td>12</td>
<td>0.999</td>
<td>1.035</td>
</tr>
<tr>
<td>13</td>
<td>0.999</td>
<td>1.031</td>
</tr>
<tr>
<td>14</td>
<td>0.999</td>
<td>1.027</td>
</tr>
<tr>
<td>15</td>
<td>0.999</td>
<td>1.024</td>
</tr>
<tr>
<td>16</td>
<td>0.999</td>
<td>1.021</td>
</tr>
<tr>
<td>17</td>
<td>0.999</td>
<td>1.019</td>
</tr>
<tr>
<td>18</td>
<td>0.999</td>
<td>1.017</td>
</tr>
<tr>
<td>19</td>
<td>0.999</td>
<td>1.015</td>
</tr>
<tr>
<td>20</td>
<td>1.000</td>
<td>1.013</td>
</tr>
<tr>
<td>21</td>
<td>1.000</td>
<td>1.012</td>
</tr>
<tr>
<td>22</td>
<td>1.000</td>
<td>1.011</td>
</tr>
<tr>
<td>23</td>
<td>1.000</td>
<td>1.010</td>
</tr>
<tr>
<td>24</td>
<td>1.000</td>
<td>1.009</td>
</tr>
<tr>
<td>25</td>
<td>1.000</td>
<td>1.008</td>
</tr>
<tr>
<td>26</td>
<td>1.000</td>
<td>1.007</td>
</tr>
<tr>
<td>27</td>
<td>1.000</td>
<td>1.006</td>
</tr>
<tr>
<td>28</td>
<td>1.000</td>
<td>1.006</td>
</tr>
<tr>
<td>29</td>
<td>1.000</td>
<td>1.005</td>
</tr>
<tr>
<td>30</td>
<td>1.000</td>
<td>1.005</td>
</tr>
</tbody>
</table>
Appendix F – Tourist questionnaire template

Preamble

- I am assisting with some PhD research at the University of Surrey on sustainable tourism focusing on British tourists in Cyprus. Could you spare 10 minutes to answer a few questions about your stay in Cyprus? Participation in the study is voluntary and you can end your participation at any time.
- Let me just say that this is completely anonymous and confidential and has been approved by the University of Surrey Ethics Committee.
- The questions relate to your activities and purchases in the last 24 hours, including any meals or snacks. There are also some initial general questions on the characteristics of your trip.
- Are you happy to proceed? If at any time you are unsure or prefer not to give an answer to a question, please say so. I am also more than happy to explain why certain questions are being asked or what I intend to do with the data at the end.

Part I: general characteristics

Q1: Do you currently live in the UK? Yes / No

Q2: What is your primary travel purpose?
1. Leisure ☐
2. Business ☐
3. Other ☐ (please specify) _______________________

If you answered 1. Leisure, go to question 3, otherwise jump to question 4

Q3: Are you here on a package holiday? Yes / No

If yes, circle which elements are included in the package deal:
Flight / Hotel / Car rental

Q4: Is this your first time in Cyprus? Yes / No

Q5: Which area of the island are you spending the largest amount of your time in?
1. Pafos ☐
2. Ayia Napa ☐
3. Larnaca ☐
4. Lemesos ☐
5. Paralimni/Protaras ☐
6. Other ☐ (please specify) _______________________

Q6: Total number of days of your visit to Cyprus. _______

Q7: Which day are you on at the present moment? _______ (enter current day e.g. 5th day)

Q8: Are you travelling alone or with family/friends?
1. Alone □
2. With others □ If so, how many people in total including children? _____

Please also make note of sex ( M / F ) and age range (20 - 30, 30 - 40, 40 - 50, 50 - 60, over 60)

Part II: Accommodation

Q9: What kind of accommodation are you staying in?
   1. Hotel □ (please specify star rating) _____________________
   2. Apartment □ (please specify category/name) _____________________
   3. Private villa □
   4. With friends or relatives □
   5. Own residence □
   6. Other □ (please specify) ___________________

If answered 1. Hotel, go to question 10, otherwise jump to question 11

Q10: What are the terms of your accommodation?
   1. Accommodation only □
   2. Bed and breakfast □
   3. Half board □
   4. Full board □

Q11: How much do you pay per night for your accommodation? __________

Part III: Activities and getting around

Q12: In the last 24 hours, have you engaged in any leisure or sports activities (e.g going to the beach, playing golf or tennis, swimming in the hotel pool)?
   Yes / No

Q13: Have you visited any sites/museums/been to a concert/some kind of exhibition?
   Yes / No

If answered Yes to either Q12 or Q13, go to question 14, otherwise jump to question 15

Q14: Could you please specify the type of activity and the amount spent?

__________________________________________________________________
Q15: Have you used any form of public or private (including rented) transport?
Yes / No

If answered Yes, go to question 16, otherwise jump to the next section

Q16: Could you please specify the transport means along with the total amount spent?

Part IV: Meals and restaurant expenses

Q17: We are interested in your food and beverage consumption within the last 24 hours. Could you please give me a summary of what you have consumed in this period, along with an estimate of the cost?

[NB: take note of whether they are responding for only themselves, or for their family as a whole]

Breakfast: (when they are responding, make sure to get information on: where they had breakfast, e.g. at the hotel or elsewhere; whether it was a buffet or not; whether they had coffee/tea with it, etc)

Lunch: (get information on what type of restaurant they ate at, e.g. taverna, kebab shop/fast food, etc; make sure side dishes are included e.g. salad or chips served with a steak; was bread included, etc)

Dinner: (get information on what type of restaurant they ate at, e.g. taverna, kebab shop/fast food, etc; make sure side dishes are included e.g. salad or chips served with a steak; was bread included, etc)

Snacks: (e.g. ice-cream, coffee, soft drink, cake, fruit, corn on the cob, nuts, etc)
**Q18:** Have you purchased any food items as gifts? If yes, please specify including the approximate cost:

*examples: halloumi, Cypriot wines/spirits, biscuits, honey, traditional sweets, olives, olive oil, etc.*

**Part V: Other expenditure**

**Q19:** Have you made any other purchases in the last 24 hours? If yes, please describe the item or service, and the approximate cost.

*(Examples: souvenirs – brief description; tobacco products; textiles/clothes; books; medical services)*

*(If possible, note where they bought the item, i.e. what type of shop)*

Sir/madam, thank you for your time! I hope you enjoy the rest of your time in Cyprus and have a safe journey back home!

===============================================================================

**Part VI: Additional information**

*Insert any useful extra notes (e.g tourist characteristics such as eating preferences/habits, what to ask restaurant owners etc.)*

________________________________________________________________________________

________________________________________________________________________________

________________________________________________________________________________

________________________________________________________________________________

________________________________________________________________________________

________________________________________________________________________________

________________________________________________________________________________

________________________________________________________________________________

(End of document)
### Appendix G – Food portion sizes and expenditure

Table G1 Menu composition with appropriate portion sizes based on chef/restaurant owner interviews, menu observations and expert judgement.

#### Breakfast options

<table>
<thead>
<tr>
<th>Breakfast options</th>
<th>Portion 1</th>
<th>Portion 2</th>
<th>Portion 3</th>
<th>Portion 4</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>English breakfast</strong></td>
<td>2 portions</td>
<td>pork (bacon + sausage)</td>
<td>1 portion</td>
<td>eggs</td>
</tr>
<tr>
<td></td>
<td>0.5 portion</td>
<td>tomato (vegetable)</td>
<td>1 portion</td>
<td>bread (cereals)</td>
</tr>
<tr>
<td><strong>Continental breakfast</strong></td>
<td>2 portions</td>
<td>cereal (pastries, toast)</td>
<td>0.5 portion</td>
<td>fruit (jam)</td>
</tr>
<tr>
<td></td>
<td>1 portion</td>
<td>cow’s milk (coffee, butter)</td>
<td>1 portion</td>
<td></td>
</tr>
<tr>
<td><strong>Fried buffet breakfast</strong></td>
<td>1 portion</td>
<td>pork (bacon + sausage)</td>
<td>1 portion</td>
<td>eggs</td>
</tr>
<tr>
<td></td>
<td>0.5 portion</td>
<td>tomato (vegetable)</td>
<td>1 portion</td>
<td>bread (cereals)</td>
</tr>
<tr>
<td><strong>Breakfast cereal</strong></td>
<td>1 portion</td>
<td>cereal</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.5 portion</td>
<td>cow milk</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Croissant</strong></td>
<td>0.5 portion</td>
<td>cereal</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Eggs on toast</strong></td>
<td>1 portion</td>
<td>cereal</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1 portion</td>
<td>eggs</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Beans on toast</strong></td>
<td>1 portion</td>
<td>cereal</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1 portion</td>
<td>legumes</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Toast and jam</strong></td>
<td>1 portion</td>
<td>cereal</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.5 portion</td>
<td>fruit (jam)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Omelette</strong></td>
<td>1 portion</td>
<td>eggs</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1 portion</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Yoghurt</strong></td>
<td>1 portion</td>
<td>cow’s milk</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### Lunch/dinner options

<table>
<thead>
<tr>
<th>Lunch/dinner options</th>
<th>Portion 1</th>
<th>Portion 2</th>
<th>Portion 3</th>
<th>Portion 4</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Salad (main meal)</strong></td>
<td>2 portions</td>
<td>vegetables</td>
<td>0.5 portion</td>
<td>citrus (lemon)</td>
</tr>
<tr>
<td><strong>Salad (side dish)</strong></td>
<td>1 portion</td>
<td>vegetables</td>
<td>0.5 portion</td>
<td>citrus (lemon)</td>
</tr>
<tr>
<td><strong>Sandwich (no description)</strong></td>
<td>1 portion</td>
<td>cereal</td>
<td>1 portion</td>
<td>vegetables (salad)</td>
</tr>
<tr>
<td></td>
<td>1 portion</td>
<td>vegetables (salad)</td>
<td>1 portion</td>
<td>cow milk (cheese)</td>
</tr>
<tr>
<td><strong>Sandwich (ham)</strong></td>
<td>1 portion</td>
<td>cereal</td>
<td>1 portion</td>
<td>vegetables (salad)</td>
</tr>
<tr>
<td></td>
<td>0.5 portion</td>
<td>pork</td>
<td></td>
<td>poultry</td>
</tr>
<tr>
<td><strong>Sandwich (turkey)</strong></td>
<td>1 portion</td>
<td>cereal</td>
<td>1 portion</td>
<td>vegetables (salad)</td>
</tr>
<tr>
<td></td>
<td>0.5 portion</td>
<td>poultry</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Pita with halloumi</strong></td>
<td>1 portion</td>
<td>cereal</td>
<td>1 portion</td>
<td>vegetables (salad)</td>
</tr>
<tr>
<td>Table G1 (continued)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>----------------------------------------------------------</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Taverna mezze (meat)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion chicken</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion pork</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion vegetables (salad)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion potatoes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion ancillary (halloumi)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion citrus (lemon)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion olives</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Taverna mezze (mixed)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion chicken</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion pork</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion vegetables (salad)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion potatoes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion ancillary (halloumi)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion citrus (lemon)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion olives</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 portions fish</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Fish mezze</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 portions fish</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion potatoes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion vegetables (salad)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion citrus (lemon)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion olives</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Vegetarian mezze</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 portions vegetables</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion potatoes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion ancillary (halloumi)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion citrus (lemon)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion olives</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Steak + chips + wine</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.5 beef</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion potatoes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion wine grapes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Buffet</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.4 portion beef</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.4 portion sheep/goat</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.4 portion pork</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.4 portion poultry</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.4 portion fish</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion vegetables</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5 portion cereal</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5 portion potatoes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion lemon</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Burger + chips</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion beef</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion potatoes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5 portion cereal</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Pasta and cheese</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.5 portion cereal</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion milk</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Kleftiko</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 portions sheep/goat</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion potatoes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Pork/chicken souvlaki</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion pork/chicken</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion cereal (pita)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion vegetables (salad)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5 portion citrus (lemon)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### Table G1 (continued)

<table>
<thead>
<tr>
<th>Food Item</th>
<th>Portions</th>
<th>Ingredients</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Kebab, generic</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5 portion pork</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5 portion chicken</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion vegetables (salad)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5 portion citrus (lemon)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion cereal (pita)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Fish. chips. salad</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion fish</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion potatoes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion vegetables (salad)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion citrus (lemon)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Calamari and chips</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion fish</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion potatoes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5 portion citrus (lemon)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Mixed grill (for one)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5 portion pork</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5 portion beef</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5 portion sheep/goat</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5 portion poultry</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion citrus (lemon)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion vegetables (salad)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Pizza</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion cereal (flour)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion cow’s milk</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion vegetables (tomato)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Hot dog and chips</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion cereal (flour)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion potatoes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5 portion pork</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Sushi</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion cereal (rice)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 portions fish</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Jacket potato, cheese, salad</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion potatoes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion vegetables</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5 portion cow’s milk</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Hummus (where mentioned)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion legumes</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Pasta (generic)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion cereal</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5 portion cow’s milk (for cheese)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Dessert/Snack options</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Cake</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5 portion cereal</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Fruit snack</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion fruit</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Ice-cream/frozen yoghurt</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion cow’s milk</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Frappe (coffee)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion cow’s milk</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Coffee/tea</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5 portion cow’s milk</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Cheesecake</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5 portion cow’s milk</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Apple pie</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.5 portion cereal</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 portion fruit (other)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table G1 (continued)

<table>
<thead>
<tr>
<th>Koupes (kibbeh)</th>
<th>0.5</th>
<th>cereal</th>
<th>0.5</th>
<th>beef</th>
</tr>
</thead>
</table>

Alcoholic drinks with meal*

<table>
<thead>
<tr>
<th>Wine bottle</th>
<th>5 portions</th>
<th>wine grapes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beer (pint)</td>
<td>1 portion</td>
<td>beverage</td>
</tr>
</tbody>
</table>

*Alcoholic drinks were generally omitted from the analysis as people felt uncomfortable providing estimates for this. Nevertheless, wine or beer that was part of a meal was often stated by the respondents (even without prompting) and has therefore been included in the analysis. Note: if the food was reported for two people, it was assumed that for one person, the portions are half of each meal. If, for instance, the respondents listed "tuna salad and omelette", the amount recorded would be 0.5 vegetables and 0.5 fish (half a tuna salad), and 0.5 portion eggs (half an omelette).

Note on ‘olives’ and ‘wine grapes’: Listed one portion for a serving of olives in a taverna (as part of a mezze platter). Also listed one bottle of olive oil if bought as a gift etc. Olive oil and wine were converted into olives and grapes equivalents.

Table G2 Portion sizes for meat and other animal products
(source: interviews with restaurant and hotel managers).

<table>
<thead>
<tr>
<th>Animal protein portion sizes</th>
<th>Ayia Napa (2)</th>
<th>Larnaca (2)</th>
<th>Tochni Village (1)</th>
<th>Nicosia (2)</th>
<th>Pissouri (1)</th>
<th>Columbia Hotel (Pissouri) (1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meat kebabs (chicken, pork, lamb)</td>
<td>250g</td>
<td>225g</td>
<td>250g</td>
<td>300g</td>
<td>350g</td>
<td>350g</td>
</tr>
<tr>
<td>Omelette</td>
<td>2 eggs</td>
<td>2 eggs</td>
<td>2 eggs</td>
<td>3 eggs</td>
<td>3 eggs</td>
<td>-</td>
</tr>
<tr>
<td>Halloumi (cheese)</td>
<td>100g</td>
<td>100g</td>
<td>100g</td>
<td>100g</td>
<td>150g</td>
<td>100g</td>
</tr>
<tr>
<td>Beef steak</td>
<td>220g</td>
<td>250g</td>
<td>-</td>
<td>-</td>
<td>250g</td>
<td>340g</td>
</tr>
<tr>
<td>English breakfast</td>
<td>2 eggs, 1 sausage, 2 strips of bacon</td>
<td>2 eggs, 1 sausage, 2 strips of bacon</td>
<td>2 eggs, 1 sausage, 2 strips of bacon</td>
<td>-</td>
<td>-</td>
<td>3 eggs, 2 sausage, 3 strips of bacon</td>
</tr>
<tr>
<td>Meat mezze</td>
<td>450g</td>
<td>375g</td>
<td>500g</td>
<td>400g</td>
<td>500g</td>
<td>350g</td>
</tr>
<tr>
<td>Beef burger</td>
<td>150g</td>
<td>175g</td>
<td>200g</td>
<td>200g</td>
<td>200g</td>
<td>-</td>
</tr>
</tbody>
</table>
Table G3 Total production, output, basic price and default portion size used to estimate water use multipliers.
Source: author estimates based on CYSTAT (2010, 2011), interviews of chefs and restaurateurs, food menus and expert judgement.

<table>
<thead>
<tr>
<th>Food group</th>
<th>Quantity</th>
<th>Production value</th>
<th>Price per kg</th>
<th>Portion size</th>
<th>Portion description</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(metric tons)</td>
<td>(1000 euros)</td>
<td>(euros)</td>
<td>(kg)</td>
<td></td>
</tr>
<tr>
<td>Cereals</td>
<td>63533</td>
<td>9,984</td>
<td>€ 0.16</td>
<td>0.200</td>
<td>two (2) slices of bread or one (1) serving of pasta</td>
</tr>
<tr>
<td>Legumes</td>
<td>3318</td>
<td>4,331</td>
<td>€ 1.31</td>
<td>0.100</td>
<td>one (1) serving of beans or lentils</td>
</tr>
<tr>
<td>Potatoes</td>
<td>155500</td>
<td>51,210</td>
<td>€ 0.33</td>
<td>0.200</td>
<td>two (2) medium-sized potatoes</td>
</tr>
<tr>
<td>Vegetables</td>
<td>86358</td>
<td>73,231</td>
<td>€ 0.85</td>
<td>0.150</td>
<td>one (1) salad serving or grilled vegetables</td>
</tr>
<tr>
<td>Wine grapes</td>
<td>29433</td>
<td>6,531</td>
<td>€ 0.22</td>
<td>0.280</td>
<td>one (1) glass of wine</td>
</tr>
<tr>
<td>Table grapes</td>
<td>4459</td>
<td>1,917</td>
<td>€ 0.43</td>
<td>0.100</td>
<td>one (1) plate serving</td>
</tr>
<tr>
<td>Citrus</td>
<td>122911</td>
<td>43,369</td>
<td>€ 0.35</td>
<td>0.250</td>
<td>one (1) orange/grapefruit or two (2) mandarins</td>
</tr>
<tr>
<td>Fruit (other)</td>
<td>71876</td>
<td>51,481</td>
<td>€ 0.72</td>
<td>0.200</td>
<td>one (1) apple or one (1) portion other seasonal fruit</td>
</tr>
<tr>
<td>Olives</td>
<td>13705</td>
<td>14,214</td>
<td>€ 1.04</td>
<td>0.050</td>
<td>one (1) serving of olives or olive oil</td>
</tr>
<tr>
<td>Nuts</td>
<td>981</td>
<td>2,280</td>
<td>€ 2.32</td>
<td>0.100</td>
<td>one (1) packet</td>
</tr>
<tr>
<td>Beef</td>
<td>3920</td>
<td>11,125</td>
<td>€ 2.84</td>
<td>0.250</td>
<td>one (1) steak or two (2) burgers</td>
</tr>
<tr>
<td>Sheep/goat</td>
<td>7107</td>
<td>28,043</td>
<td>€ 3.95</td>
<td>0.250</td>
<td>three (3) lamb chops or one (1) serving of stew</td>
</tr>
<tr>
<td>Pork</td>
<td>54978</td>
<td>80,188</td>
<td>€ 1.46</td>
<td>0.250</td>
<td>two (2) skewers of pork kebab or one (1) pork chop</td>
</tr>
<tr>
<td>Poultry</td>
<td>29335</td>
<td>67,840</td>
<td>€ 2.31</td>
<td>0.250</td>
<td>1/4 chicken or breast fillet</td>
</tr>
<tr>
<td>Milk (cow)</td>
<td>144100</td>
<td>61,715</td>
<td>€ 0.43</td>
<td>0.200</td>
<td>one (1) glass</td>
</tr>
<tr>
<td>Milk (sheep/goat)</td>
<td>39380</td>
<td>24,419</td>
<td>€ 0.62</td>
<td>0.200</td>
<td>one (1) glass</td>
</tr>
<tr>
<td>Eggs</td>
<td>8577</td>
<td>12,628</td>
<td>€ 1.47</td>
<td>0.050</td>
<td>two (2) eggs</td>
</tr>
<tr>
<td>Cheese (ancillary)</td>
<td>2950</td>
<td>25,672</td>
<td>€ 8.70</td>
<td>0.100</td>
<td>half (1/2) a halloumi cheese</td>
</tr>
<tr>
<td>Fish (caught or farmed)</td>
<td>5537</td>
<td>44,328</td>
<td>€ 8.01</td>
<td>0.250</td>
<td>One (1) small fish</td>
</tr>
</tbody>
</table>
Table G4 Food-related expenditure per adult-equivalent. Source: author estimates based on 2009 HBS (CYSTAT 2011).

<table>
<thead>
<tr>
<th>Expenditure category</th>
<th>Expenditure per 10 000 euros (€)</th>
<th>Total annual expenditure 2009 consumer prices (€)</th>
<th>Daily Expenditure 2009 consumer prices (€)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Agricultural products</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cereals</td>
<td>225.00</td>
<td>471.80</td>
<td>1.29</td>
</tr>
<tr>
<td>Leguminous plants</td>
<td>13.00</td>
<td>27.26</td>
<td>0.07</td>
</tr>
<tr>
<td>Fodder</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Potatoes</td>
<td>16.00</td>
<td>33.55</td>
<td>0.09</td>
</tr>
<tr>
<td>Vegetables (all)</td>
<td>99.00</td>
<td>207.59</td>
<td>0.57</td>
</tr>
<tr>
<td>Wine grapes</td>
<td>9.00</td>
<td>18.87</td>
<td>0.05</td>
</tr>
<tr>
<td>Citrus</td>
<td>15.00</td>
<td>31.45</td>
<td>0.09</td>
</tr>
<tr>
<td>Fruit (not citrus)</td>
<td>76.00</td>
<td>159.36</td>
<td>0.44</td>
</tr>
<tr>
<td>Nuts</td>
<td>19.00</td>
<td>39.84</td>
<td>0.11</td>
</tr>
<tr>
<td>Olives</td>
<td>12.00</td>
<td>25.16</td>
<td>0.07</td>
</tr>
<tr>
<td>Beef</td>
<td>8.00</td>
<td>16.78</td>
<td>0.05</td>
</tr>
<tr>
<td>Sheep and Goat</td>
<td>40.00</td>
<td>83.88</td>
<td>0.23</td>
</tr>
<tr>
<td>Pork</td>
<td>57.00</td>
<td>119.52</td>
<td>0.33</td>
</tr>
<tr>
<td>Poultry</td>
<td>43.00</td>
<td>90.17</td>
<td>0.25</td>
</tr>
<tr>
<td>Milk (cow)</td>
<td>95.97</td>
<td>201.25</td>
<td>0.55</td>
</tr>
<tr>
<td>Milk (sheep/goat)</td>
<td>38.03</td>
<td>79.74</td>
<td>0.22</td>
</tr>
<tr>
<td>Eggs</td>
<td>11.00</td>
<td>23.07</td>
<td>0.06</td>
</tr>
<tr>
<td>Fish</td>
<td>38.00</td>
<td>79.68</td>
<td>0.22</td>
</tr>
<tr>
<td>Ancillary (cheese)</td>
<td>74.00</td>
<td>155.17</td>
<td>0.43</td>
</tr>
<tr>
<td><strong>Food and beverage (including processed)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Processed meat</td>
<td>41.00</td>
<td>85.97</td>
<td>0.24</td>
</tr>
<tr>
<td>Processed fish</td>
<td>17.00</td>
<td>35.65</td>
<td>0.10</td>
</tr>
<tr>
<td>Cooking oils</td>
<td>23.00</td>
<td>48.23</td>
<td>0.13</td>
</tr>
<tr>
<td>Processed vegetables</td>
<td>8.00</td>
<td>16.78</td>
<td>0.05</td>
</tr>
<tr>
<td>Chocolates and sweets</td>
<td>62.00</td>
<td>130.01</td>
<td>0.36</td>
</tr>
<tr>
<td>Spices, seasonings, coffee + tea etc</td>
<td>53.00</td>
<td>111.14</td>
<td>0.30</td>
</tr>
<tr>
<td>Non-alcoholic drinks</td>
<td>113.00</td>
<td>236.95</td>
<td>0.65</td>
</tr>
<tr>
<td>Wine</td>
<td>9.00</td>
<td>18.87</td>
<td>0.05</td>
</tr>
<tr>
<td>Beer</td>
<td>16.00</td>
<td>33.55</td>
<td>0.09</td>
</tr>
<tr>
<td><strong>Eating out at cafes, hotels and restaurants</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>853.16</td>
<td>1789.00</td>
<td>4.90</td>
</tr>
<tr>
<td><strong>TOTAL</strong></td>
<td><strong>2084.16</strong></td>
<td><strong>4370.29</strong></td>
<td><strong>7.07</strong></td>
</tr>
</tbody>
</table>
Table G5 Daily food consumption per adult-equivalent. Source: author estimates based on 2008 agricultural statistics (CYSTAT 2010).

<table>
<thead>
<tr>
<th>Expenditure category</th>
<th>Quantity kilos (kg)</th>
<th>Daily quantity kilos (kg)</th>
<th>Price per kg (2007) basic price 2007 - euro (€)</th>
<th>Total daily expenditure basic price 2007 - euro (€)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Agricultural products</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cereals</td>
<td>78.00</td>
<td>0.21</td>
<td>0.16</td>
<td>0.03</td>
</tr>
<tr>
<td>Leguminous plants</td>
<td>6.90</td>
<td>0.02</td>
<td>0.51</td>
<td>0.01</td>
</tr>
<tr>
<td>Fodder</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Potatoes</td>
<td>50.10</td>
<td>0.14</td>
<td>0.33</td>
<td>0.05</td>
</tr>
<tr>
<td>Vegetables (all)</td>
<td>115.10</td>
<td>0.32</td>
<td>0.63</td>
<td>0.20</td>
</tr>
<tr>
<td>Wine grapes</td>
<td>19.80</td>
<td>0.05</td>
<td>0.22</td>
<td>0.01</td>
</tr>
<tr>
<td>Table grapes</td>
<td>0.00</td>
<td>0.00</td>
<td>0.43</td>
<td>0.00</td>
</tr>
<tr>
<td>Citrus</td>
<td>44.20</td>
<td>0.12</td>
<td>0.35</td>
<td>0.04</td>
</tr>
<tr>
<td>Fruit (not citrus)</td>
<td>122.40</td>
<td>0.34</td>
<td>0.44</td>
<td>0.15</td>
</tr>
<tr>
<td>Nuts</td>
<td>0.00</td>
<td>0.00</td>
<td>2.32</td>
<td>0.00</td>
</tr>
<tr>
<td>Olives</td>
<td>7.50</td>
<td>0.02</td>
<td>1.04</td>
<td>0.02</td>
</tr>
<tr>
<td>Beef</td>
<td>7.00</td>
<td>0.02</td>
<td>2.84</td>
<td>0.05</td>
</tr>
<tr>
<td>Sheep and Goat</td>
<td>11.10</td>
<td>0.03</td>
<td>3.95</td>
<td>0.12</td>
</tr>
<tr>
<td>Pork</td>
<td>58.40</td>
<td>0.16</td>
<td>1.46</td>
<td>0.23</td>
</tr>
<tr>
<td>Poultry</td>
<td>38.90</td>
<td>0.11</td>
<td>2.31</td>
<td>0.25</td>
</tr>
<tr>
<td>Milk (cow)</td>
<td>68.47</td>
<td>0.19</td>
<td>0.43</td>
<td>0.08</td>
</tr>
<tr>
<td>Milk (sheep/goat)</td>
<td>27.13</td>
<td>0.07</td>
<td>0.62</td>
<td>0.05</td>
</tr>
<tr>
<td>Eggs</td>
<td>211.00</td>
<td>0.58</td>
<td>1.47</td>
<td>0.85</td>
</tr>
<tr>
<td>Fish</td>
<td>18.10</td>
<td>0.05</td>
<td>8.01</td>
<td>0.40</td>
</tr>
<tr>
<td>Ancillary</td>
<td>20.50</td>
<td>0.06</td>
<td>8.70</td>
<td>0.49</td>
</tr>
<tr>
<td><strong>Food and beverage (including processed food)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Processed meat</td>
<td>18.00</td>
<td>0.05</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Processed fish</td>
<td>4.70</td>
<td>0.01</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fruit products</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chocolates and sweets</td>
<td>27.90</td>
<td>0.08</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spices, seasonings, coffee + tea etc</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-alcoholic drinks</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wine</td>
<td>19.80</td>
<td>0.05</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beer</td>
<td>56.50</td>
<td>0.15</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Appendix H – Blue Water Footprints of imported animal products

Table H1 Source: author estimates based on FAOSTAT trade data for Cyprus and weighted global water footprints for animal products from Mekonnen and Hoekstra (2012).

<table>
<thead>
<tr>
<th>Product</th>
<th>BWF (m³/ton)</th>
<th>Total import value (1000$)</th>
<th>Total quantity (tons)</th>
<th>Total blue WF (m³)</th>
<th>Total BWF (litres)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beef</td>
<td>550</td>
<td>18434</td>
<td>2357</td>
<td>1296350</td>
<td>1296350000</td>
</tr>
<tr>
<td>Sheep/Goat</td>
<td>522</td>
<td>8892</td>
<td>1674</td>
<td>873828</td>
<td>873828000</td>
</tr>
<tr>
<td>Pork</td>
<td>459</td>
<td>15046</td>
<td>3529</td>
<td>1619811</td>
<td>1619811000</td>
</tr>
<tr>
<td>Chicken</td>
<td>313</td>
<td>22040</td>
<td>6354</td>
<td>1988802</td>
<td>1988802000</td>
</tr>
<tr>
<td>Eggs</td>
<td>244</td>
<td>3619</td>
<td>1554</td>
<td>379176</td>
<td>379176000</td>
</tr>
<tr>
<td>Milk</td>
<td>86</td>
<td>3838</td>
<td>1886</td>
<td>162196</td>
<td>162196000</td>
</tr>
<tr>
<td>Butter</td>
<td>465</td>
<td>6559</td>
<td>1348</td>
<td>626820</td>
<td>626820000</td>
</tr>
<tr>
<td>Milk powder</td>
<td>398</td>
<td>2016</td>
<td>387</td>
<td>154026</td>
<td>154026000</td>
</tr>
<tr>
<td>Cheese</td>
<td>439</td>
<td>44010</td>
<td>7750</td>
<td>3402250</td>
<td>340225000</td>
</tr>
</tbody>
</table>
Appendix I – Tourist sample analysis

This appendix provides a review of the data collection process along with a preliminary analysis of selected tourist characteristics in order to explore bias in the sample. The first section offers some observations made during data collection. The following section then compares means for characteristic variables in the sample to the 5-year average for the period 2007-2011 using data from CYSTAT. This comparison is performed in order to quantify bias in the sample compared to what would have been expected in a more extensive survey. It also allows an appreciation of the possibilities for cross-tabulation and segmentation which exist in the primary dataset.

Selected outcomes of pilots and data collection (report)

In order to make the questionnaire less cumbersome, many of the food-related questions had to be changed into open-ended questions, where the respondent was afforded the liberty to describe their meal as they wished. This has given rise to one of the problems mentioned in Simmons (2011), who pointed out that open questions may often yield answers that are ambiguous, wide-ranging and difficult to categorise. In order to address this problem, broader categories of meals and foods that match the I-O classification of the disaggregated agricultural sector were established.

One of the assumptions usually made in preparing for surveys, is that people asked will be willing to afford some of their time to answer questions. Extensive piloting of the questionnaire in several beaches around Cyprus revealed that a much lower percentage agreed to take part in the survey than had been anticipated. Even though the day-to-day response rate varied enormously depending on the site and the time of day, only around 1 in 5 people approached agreed to be interviewed during the piloting stage. The low response rate was due, mainly, to the fact that people were highly suspicious of the interviewers. This was often based on an a priori assumption that, in the absence of any visible sign to suggest otherwise, they were being approached for commercial purposes or some issue that was not of interest to them.

As a way to increase the overall response rate and ensure a less biased sample, it was decided that one of the key modifications required was to improve the initial approach. Adding the University of Surrey logo on the clipboard would immediately associate the interviewers with a university institution and put the interviewee’s mind at ease that they were not about to be harassed into buying something. Universities are associated with research and people are often sympathetic towards students carrying out surveys as part of their degrees. Furthermore, the University of Surrey is likely to represent a familiar institution as far as British tourists are concerned, thus further facilitating data collection. Another measure taken to improve the overall response rate was to open up the questionnaire to non-British tourists who showed a willingness to be interviewed during the initial approach. The above modifications may have, partly, accounted for an improved overall response rate in the actual survey compared to the pilot, from around 1 in 5 to 1 in 4.

It follows from the above paragraph that an important source of bias in the sample is likely to come from the fact that most of the tourists who agreed to be interviewed were people who appeared to be friendlier and less busy. Attempts were made to be as polite as possible when approaching tourists, with extra care afforded to cases where tourists appeared to be
busy doing something else. It was, however, decided not to interrupt people during meals or private moments for ethical reasons. The result of these decisions is that, according to Bryman (2012), the people interviewed are not necessarily typical. This is another uncontrolled source of bias which needs to be acknowledged.

Preliminary analysis of results

As the sample is non-random, it is not possible to assess how successful the sampling was using confidence intervals (margins of error). Instead, selected variables are chosen and compared to the mean from the previous 5 years in order to ascertain the extent of bias. It is also envisaged that the descriptive statistics can be used to characterise the final sample and provide some additional insight with regards to how data collected may be analysed.

Total number of completed questionnaires (cases): 179

Total number of tourists included in the sample: 367 (mean party size = 2.05)

Purpose of visit:

<table>
<thead>
<tr>
<th>Purpose of visit</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leisure</td>
<td>151</td>
<td>84.4</td>
</tr>
<tr>
<td>Visiting</td>
<td>9</td>
<td>5.0</td>
</tr>
<tr>
<td>Incentive</td>
<td>13</td>
<td>7.3</td>
</tr>
<tr>
<td>Business</td>
<td>1</td>
<td>.6</td>
</tr>
<tr>
<td>Work</td>
<td>3</td>
<td>1.7</td>
</tr>
<tr>
<td>Studying</td>
<td>2</td>
<td>1.1</td>
</tr>
<tr>
<td>Total</td>
<td>179</td>
<td>100.0</td>
</tr>
</tbody>
</table>

As expected, the overwhelming majority of tourists interviewed (84.4%) came to Cyprus for holidays. This is slightly higher (5.3%) than the average for the previous 5 years (2007-2011) which was 80.18% (CYSTAT 2012). The incentive category is composed mostly of tourists attending a wedding or coming for their own wedding. The numbers in categories other than leisure appear to be insufficient for segmentation analysis but an analysis of leisure (151) vs. other (28) is possible.
### Package:

**Table I2 Purpose of visit (frequency and percentage).**

<table>
<thead>
<tr>
<th></th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>YES</td>
<td>63</td>
<td>35.2</td>
</tr>
<tr>
<td>NO</td>
<td>116</td>
<td>64.8</td>
</tr>
<tr>
<td>Total</td>
<td>179</td>
<td>100.0</td>
</tr>
</tbody>
</table>

The majority of the tourists interviewed (64.8%) were not travelling on a package holiday. This percentage is 24.08% higher than the average for 2007-2011 which was 40.72%. This is possibly a result of carrying out the survey in September, which is a month likely to have less package tourists. Nevertheless, despite this significant deviation from the average, the numbers still allow a comparison between package and non-package.

### First time or Repeat:

**Table I3 First time or repeat (frequency and percentage).**

<table>
<thead>
<tr>
<th></th>
<th>Frequency</th>
<th>Percent</th>
<th>Cumulative Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>First Time</td>
<td>55</td>
<td>30.7</td>
<td>30.7</td>
</tr>
<tr>
<td>Repeat</td>
<td>124</td>
<td>69.3</td>
<td>100.0</td>
</tr>
<tr>
<td>Total</td>
<td>179</td>
<td>100.0</td>
<td></td>
</tr>
</tbody>
</table>

The majority of tourists interviewed (69.3%) were repeat tourists, most of which had been to Cyprus numerous times. This is 18% higher than the average for 2007-2011 which was 51.3%. This, again, is likely to be the result of carrying out the survey in September, as well as the fact that the majority of the sample are British, which tend to be more likely to have previously visited the island or have friends/own property on the island. The sample numbers are, however, large enough to allow for a comparison.
Area coverage:

Table I4 Area visited (frequency and percentage).

<table>
<thead>
<tr>
<th></th>
<th>Frequency</th>
<th>Percent</th>
<th>5-year (2007-2011) mean (percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Protaras</td>
<td>25</td>
<td>14.0</td>
<td>15.0</td>
</tr>
<tr>
<td>Ayia Napa</td>
<td>20</td>
<td>11.2</td>
<td>17.1</td>
</tr>
<tr>
<td>Larnaka</td>
<td>42</td>
<td>23.5</td>
<td>10.1</td>
</tr>
<tr>
<td>Lemesos</td>
<td>29</td>
<td>16.2</td>
<td>13.4</td>
</tr>
<tr>
<td>Pafos</td>
<td>51</td>
<td>28.5</td>
<td>33.6</td>
</tr>
<tr>
<td>Nicosia</td>
<td>4</td>
<td>2.2</td>
<td>5.7</td>
</tr>
<tr>
<td>Other</td>
<td>8</td>
<td>4.5</td>
<td>5.2</td>
</tr>
<tr>
<td>Total</td>
<td>179</td>
<td>100.0</td>
<td></td>
</tr>
</tbody>
</table>

The attempt to sample for heterogeneity meant that several areas of the island were visited. Comparing the percentage for each area from the sample to the 5-year mean shows that the sample captures heterogeneity in the five principal tourist destinations: Protaras (14%), Ayia Napa (11.2%), Larnaka (23.5%), Lemesos (16.3%) and Pafos (28.5%). These percentages, with the exception of Larnaka and Nicosia are within +/- 35% from the 5-year average. Larnaka is over-represented by 123% because it offered the most accessible location to sample. Nicosia is under-represented mainly because any attempts to interview tourists in Nicosia proved unsuccessful. It is also likely that tourists interviewed in Nicosia come from other cities just for the day, mostly to visit the old town or the archaeological museum. Nicosia, being an inland city, receives a very small amount of foreign tourists.

Age group:

Table I5 Age group (frequency and percentage).

<table>
<thead>
<tr>
<th></th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Valid</td>
<td>20-30</td>
<td>46</td>
</tr>
<tr>
<td></td>
<td>30-40</td>
<td>39</td>
</tr>
<tr>
<td></td>
<td>40-50</td>
<td>36</td>
</tr>
<tr>
<td></td>
<td>50-60</td>
<td>37</td>
</tr>
<tr>
<td></td>
<td>60+</td>
<td>21</td>
</tr>
<tr>
<td>Total</td>
<td>179</td>
<td>100.0</td>
</tr>
</tbody>
</table>
The partition of the sample between age groups reveals the intention to sample for heterogeneity. Direct comparison between the sample and the CYSTAT data is not straightforward because of the differences in groups thresholds employed. Nevertheless, the age groups of the sample reveal a slight bias towards younger tourists. 25.7% of the sample were aged 20-30 whereas the 5-year mean for tourists aged 20-31 was 19.3%. The rest of the groups cannot really be directly compared. The CYSTAT 5-year mean was 24.7% for people aged 32-44 and 33.3% for people between 45-64.

LOS:

<table>
<thead>
<tr>
<th></th>
<th>Mean (sample)</th>
<th>5-year mean (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; month</td>
<td>12.0</td>
<td>9.1</td>
</tr>
<tr>
<td>&lt; year</td>
<td>19.6</td>
<td>9.9</td>
</tr>
</tbody>
</table>

The average length of stay in the sample appears to be higher than the 5-year mean. It is 32% higher for tourists staying for less than a month and 98% higher for tourists staying for between a month and a year. This is mainly a result of the time of year which results in less short-term mass tourists and more home-owners or repeat tourists spending larger amounts of time on the island. As the sample is small, a few high values bring up the average significantly.

Accommodation type:

<table>
<thead>
<tr>
<th></th>
<th>Frequency</th>
<th>Percent</th>
<th>5-year (2007-2011) mean (percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HOTELS</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2-star Hotel</td>
<td>3</td>
<td>1.7</td>
<td>-</td>
</tr>
<tr>
<td>3-star Hotel</td>
<td>21</td>
<td>11.7</td>
<td>-</td>
</tr>
<tr>
<td>4-star Hotel</td>
<td>19</td>
<td>10.6</td>
<td>-</td>
</tr>
<tr>
<td>5-star Hotel</td>
<td>8</td>
<td>4.5</td>
<td>-</td>
</tr>
</tbody>
</table>
Table I7 (continued) Accommodation type (frequency and percentage).

<table>
<thead>
<tr>
<th>Accommodation type</th>
<th>Frequency</th>
<th>Percentage</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>APARTMENT</td>
<td>32.5</td>
<td>19.5</td>
<td>179</td>
</tr>
<tr>
<td>Deluxe</td>
<td>1</td>
<td>.6</td>
<td>No</td>
</tr>
<tr>
<td>Category A</td>
<td>8</td>
<td>4.5</td>
<td>-</td>
</tr>
<tr>
<td>Category B</td>
<td>31</td>
<td>17.3</td>
<td>-</td>
</tr>
<tr>
<td>Category C</td>
<td>13</td>
<td>7.3</td>
<td>-</td>
</tr>
<tr>
<td>Traditional</td>
<td>5</td>
<td>2.8</td>
<td>-</td>
</tr>
<tr>
<td>OTHER</td>
<td>39.2</td>
<td>32.1</td>
<td></td>
</tr>
<tr>
<td>Villas</td>
<td>13</td>
<td>7.3</td>
<td>-</td>
</tr>
<tr>
<td>Own residence</td>
<td>21</td>
<td>11.7</td>
<td>5.9</td>
</tr>
<tr>
<td>Friends/Relatives</td>
<td>36</td>
<td>20.2</td>
<td>14.7</td>
</tr>
<tr>
<td>Total</td>
<td>179</td>
<td>100.0</td>
<td></td>
</tr>
</tbody>
</table>

Sampling for heterogeneity was difficult with regards to accommodation type because several attempts to obtain access to hotel facilities of different classes proved unsuccessful. The aim was, therefore, to hope that sampling in different places would also capture some of the heterogeneity in terms of accommodation type. Comparing the questionnaire results to the 5-year mean, it becomes evident that the sample is biased towards people who stayed in apartments. The percentage of tourists staying in apartments (32.5%) is 67% higher in the sample than in reality. On the other hand, the percentage of tourists staying in hotels (28.5%) is 41% lower than it has been in the last five years. As the majority of the sampling was carried out in public beaches, it is more likely that people staying in hotels were not sampled because they either spent their time at the hotel pool or in the private beach of the hotel. The significantly higher percentage of tourists staying in their own residence (98% higher in the sample) or with friends or relatives (37% higher in the sample) are possibly due to the time of year that the data collection was carried out as September has a lower proportion of package tourists.
Table I8 COO (frequency and percentage).

<table>
<thead>
<tr>
<th></th>
<th>Frequency</th>
<th>Percent</th>
<th>5-year mean (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>UK</td>
<td>141</td>
<td>78.8</td>
<td>48.6</td>
</tr>
<tr>
<td>Germany</td>
<td>8</td>
<td>4.5</td>
<td>6.1</td>
</tr>
<tr>
<td>Sweden</td>
<td>7</td>
<td>3.9</td>
<td>5.0</td>
</tr>
<tr>
<td>Russia</td>
<td>1</td>
<td>0.6</td>
<td>9.0</td>
</tr>
<tr>
<td>Greece</td>
<td>0</td>
<td>0</td>
<td>5.8</td>
</tr>
<tr>
<td>Other</td>
<td>23</td>
<td>16.3</td>
<td>40.3</td>
</tr>
<tr>
<td>Total</td>
<td>179</td>
<td>100</td>
<td></td>
</tr>
</tbody>
</table>

The sample is biased towards UK tourists. This was done intentionally as the UK, being by far the largest COO market segment as well as a segment that was approachable in terms of language, forms the basic focus of the study. Within the UK segment, 13 (9.2%) are British-born Cypriots. Even though they are officially counted as UK tourists and do not form a distinct segment, the survey has revealed that they have unique characteristics and spending behaviour. As a result of the low overall response rate it was decided that other English-speaking tourists willing to give an interview would be targeted as well. Germany and Sweden, being two of the other large segments, are only slightly underrepresented in the sample, by 26% and 22% respectively. This is in contrast to Russia and Greece which are heavily underrepresented. This is because most of the Russian tourists approached were not comfortable enough to give an interview in English.

With regards to Greece, no Greek tourists were encountered during data collection. This could be due to the fact that most of the visitors from Greece tend to come during festive periods to visit relatives and would be unlikely to spend a lot of their time on the beach or near hotels. The other segment is composed of: Dutch (5), Irish (3), Russian (1), Czech (1), Finland (3), Romania (1), Canada (1), Ukraine (1), Belgium (2), Switzerland (2), Australia (1), Norway (1) and Poland (1). These segments, including Germany and Sweden are too small to form distinct segments in an analysis but could be used to form a sizable (38) non-UK segment which could be compared to establish a difference between UK and non-UK tourists.
Conclusion of preliminary dataset analysis

The preliminary analysis reveals biases (>50%) in terms of package/non-package, area, accommodation, COO and LOS. Apart from the bias in COO, which was intentional, the rest have largely occurred because of the time of year in which the survey was carried out, as well as the fact that most of the questionnaires were carried out on public beaches. Nevertheless, the sample should still be adequate for demonstrating the capability of the model, using a functional approach based on highly disaggregated primary data.
PART V

Water and Tourism: method appraisal and looking ahead
Chapter 7: Conclusions

7.1 Chapter introduction

7.1.1 Overall contribution of the thesis

The thesis set out to develop approaches towards comprehensively quantifying the water use and water productivity of tourism, concentrating on the previously understudied issue of indirect water use arising from the tourism supply chain. Given the economic importance of the tourism sector worldwide (WTTC, 2013b), in addition to its continuing growth (UNWTO, 2013c), it is imperative that water use efficiency along its supply chain is maximised – not only to ensure that the sector’s impact on the environment is minimised, but also to ensure its own survival. As stated by Gössling et al. (2012), looking beyond direct water use in hotels, swimming pools and other onsite activities should be seen as an immediate commitment by the tourism industry.

Two major challenges lie ahead in terms of managing and maximising water productivity from different tourism products in different destinations. Firstly, dedicated approaches capable of estimating total (direct and indirect) tourism water use are necessary. Existing research suggests that direct water use varies widely with the type of tourism and the specific services sought (De Stefano, 2004; Hof & Schmitt, 2011; Mangion, 2013; Rico-Amoros et al., 2009; Tortella & Tirado, 2011). There is a need to complement this existing body of research through frameworks which explicitly quantify indirect water use, whilst factoring in the influence of specific choices, behaviours and preferences (diets, accommodation type and activities pursued). The second and, ultimately critical, challenge is to devise sustainable management solutions that are customised to specific tourism products in different destinations.

The present research has made a contribution primarily towards addressing the first challenge. A more complete understanding and quantification of water use is a prerequisite for subsequently devising informed and sustainable solutions. Using the island of Cyprus as its central case study of a water scarce tourism destination, the thesis has delivered three complementary frameworks for estimating water use arising from a diverse selection of tourist types. Each of the methods was designed to have its own strengths and, consequently, its own use. A secondary output of the thesis are the findings with respect to
the performance of different tourist segments, which, in turn, have yielded some noteworthy theoretical and policy implications relevant to Cyprus and beyond.

7.1.2 Chapter outline

The remaining sections of the chapter are structured as follows: the following section (section 7.2) individually reviews each of the approaches corresponding to Parts II, III and IV of the thesis, assessing their respective contributions to the literature and their possible applications, against the principal objectives of the thesis. The subsequent section (section 7.3) singles out the most important theoretical and policy implications emerging from the study, previously alluded to in Chapters 2, 4 and 6. The penultimate section (section 7.4) explores directions for future research, beginning with potential improvements and modifications that could enhance the present work and closing with interesting and worthwhile ways to expand the scope of the research. The final section (section 7.5) briefly reiterates the contribution of the thesis.

7.2 Appraisal and usefulness of the frameworks

7.2.1 First approach

The approach presented in Part II (Chapter 2) of the thesis relates to objective 1:

> Consider how freely available data could be employed to estimate direct and indirect water use for different kinds of tourism in different destinations as part of a simple, intuitive framework.

The emergence of the virtual water (Allan, 1996, 1998) and water footprint (Hoekstra, 2003) concepts has highlighted that, in addition to the water used directly for showering, cleaning and cooking, vast quantities of water are consumed indirectly, embedded in products we require on a daily basis. A staggering 86% of the water footprint of humanity is linked to the consumption of agricultural products (Hoekstra & Chapagain, 2008). The relevance of the water footprint concept with respect to tourism has already been considered (Gössling et al., 2012; Llamas et al., 2010; Yang et al., 2011), but there have been no previous attempts to integrate direct and indirect water use components of tourism water use and to perform comparisons between different tourist types in different destinations.
The proposed framework, published in Hadjikakou et al. (2013), creates four distinct hypothetical tourist holiday scenarios in different water scarce Mediterranean destinations (two in Cyprus, one in Greece and one in Turkey). It then estimates the total (direct and indirect) water footprint of each holiday scenario using a component-based approach where the total water footprint is made up of water used directly in accommodation and activities (such as swimming pools or golf courses) and indirectly through diet (each scenarios assumes a certain diet) and fuel (depending on the flights and other local travel). In order to perform the calculations, the study relied on previously published data on water use in hotels (Eurostat, 2009; Rico-Amoros et al., 2009) and tourist activities (Gössling et al., 2012; Hof & Schmitt, 2011), in addition to readily available data from the Water Footprint Network (Mekonnen & Hoekstra, 2010a, 2010b, 2011) and the FAO (2010, 2011b) with respect to the water footprints and origin of foodstuffs in different countries. This type of scenario- and component-based approach builds on a body of previous work by Gössling et al. (2002b), WWF (2002) and Hunter & Shaw (2007) on the ecological footprint of tourism and Chenoweth (2009) on the carbon footprint of tourism.

The resulting range of daily per capita tourist water footprints (5790 – 8880 l) is consistent with previous estimates (Gössling et al., 2012), and also shows that tourist water footprints are higher than those of local residents in the four destinations, based on figures in Mekonnen & Hoekstra (2011). The results highlight the importance of the diet component of the water footprint, which accounts for 75-91% of the total water footprint across all scenarios. The accommodation component accounts for 1-14% (depending on the class of accommodation), the fuel component 7-10% (depending on the distance of the flight), and the activity component less than 2%.

A disaggregation of the dietary components serves to better understand the water use impact of different food groups, in addition to differentiating between national water (embedded in local produce) and external water (in imported produce). This aspect of the framework highlights the fact that the diet component of the water footprint results from a complex interplay of climate, local produce availability, trade decisions (especially the origin of fodder crops) and tourist preferences. It also challenges the simplistic view that sourcing local food must always be promoted in order to foster economic linkages between tourism and agriculture (Mak et al., 2012; Telfer & Wall, 1996; Torres, 2002, 2003) and to make...
tourism more sustainable (Everett & Aitchison, 2008; Sims, 2009). For water scarce destinations, the option of boosting local agricultural production must be scrutinised before a final decision is taken.

The framework necessitates significant simplifying assumptions with respect to dietary choice, and is also heavily reliant on the water footprint concept which has received some criticism in recent years (Chenoweth et al., 2013; Gawel & Bernsen, 2011b; Wichelns, 2010b, 2011; Witmer & Cleij, 2012; Yang et al., 2013). Given that the approach also does not take into account economic impact, which is a key factor in tourism management, it is not intended for directly devising strategies to manage water use. Nonetheless, the outcome of Part II is an uncomplicated approach, previously lacking with respect to water use in tourism, which only requires secondary data and is thus likely to appeal to the policy and consultancy domains where there is a need for quicker and more intuitive methodologies or scoping exercises. It also serves as the foundation for the more elaborate approaches in the thesis.

7.2.2 Second approach

The approach presented in Part III (Chapters 3 and 4) of the thesis relates to objectives 2 and 3:

*Perform market segmentation to create diverse tourist groups in order to improve understanding of consumption patterns and their associated impacts on water use and productivity (objective 2).*

*Develop an integrated approach that can estimate total water use and productivity for inbound tourism in Cyprus based on the market segments established in the previous objective, with the intention of performing comparisons between segments (objective 3).*

This composite approach recognises the need to estimate total (direct and indirect) water use impact alongside total (direct and indirect) economic impact for different market segments. Inspired by the concept of eco-efficiency (Becken & Patterson, 2006; Gössling et al., 2005; Peeters & Schouten, 2006) and the notion of a sustainable tourism yield (Becken & Simmons, 2008; Dwyer et al., 2006; Lundie et al., 2007; Northcote & Macbeth, 2006), the intention is to
deliver an original framework which is specialised on water use as opposed to other environmental impacts which have already attracted substantial research interest. The approach is also innovative since it considers the process of creating distinct tourist types (objective 2) and the subsequent step of estimating their water use and economic impact trade-offs (objective 3) as part of an integrated modelling framework. This combination lends itself not only to making comparisons between tourist types with controlled variances, but also has the potential to inform the development of bespoke management interventions to align economic impact and water productivity objectives for each tourist segment.

The approach combines the widely used statistical technique of market segmentation (Dolnicar, 2008; UNWTO, 2007) with Environmental Input-Output (EIO) modelling (Leontief, 1970; Miller & Blair, 2009), which has been used to capture direct and indirect environmental and economic impacts for diverse consumption patterns (Lenzen & Foran, 2001; Munday et al., 2013; Munksgaard et al., 2005). The segmentation procedure, recently published in Hadjikakou et al. (in press), employs expenditure-based segmentation (Mok & Iverson, 2000; Spotts & Mahoney, 1991) and Two Step cluster analysis (SPSS, 2001) in order to enhance the existing country of origin (COO) segmentation for Cyprus.

EIO modelling is subsequently employed using the outputs of the segmentation, reclassified into the Input-Output (I-O) classification using Tourism Satellite Accounts (TSAs) as in Lundie et al. (2007) and Jones & Munday (2007), in order to estimate total water use and economic impact for each segment. The approach uses a selection of indicators: direct and indirect water use, water productivity, total value added, and total employment contribution, in order to appreciate the performance of each of the segments with respect to different criteria. Matrix graphs (Dwyer & Forsyth, 2008; Dwyer et al., 2010; Lundie et al., 2007) allow a visualisation of how segments fare across different indicators in addition to providing a means to perform comparisons between them.

The segmentation procedure successfully establishes new segments within the large British country market which accounted for 37 to 55% of inbound tourism to Cyprus in the last decade (CYSTAT, 2012). Breaking up a large COO segment is of direct relevance to mature tourism destinations reliant on large country markets because it produces segments with distinct characteristics. As specified in objective 2, segmentation results in the formation of
tourist groups with distinct features, characterised by different expenditure patterns and other demographic and trip-related characteristics. Segment characteristics with respect to area and type of accommodation also facilitate estimates of direct water use, thus further highlighting the usefulness of combining segmentation with water use and economic impact estimates.

The EIO results show that there are significant variations in total water use (from around 900 to 2150 l per capita daily) as well as in the relative ratios of direct and indirect water use between segments, owing mainly to their diverse spending patterns. Although higher-spending segments appear to have the highest water productivity because their overall spending compensates for their water use, several low-spending segments appear to offer high value added and employment contribution with respect to their expenditure and water use. These findings caution against seeing diversification as a panacea in tourism management, at a time when Cyprus, like other mature destinations, is aspiring to move towards the luxury end of the market. This is consistent with recommendations made by previous researchers (Ayres, 2000; Farsari et al., 2007; Ioannides & Holcomb, 2003; Sharpley, 2003).

The approach contributes significantly towards meeting the overall aim of the study in that it defines different tourist groups and then compares their total water use and economic impact, thus providing a more complete set of results compared to the first approach. Nonetheless, whilst capturing the importance of indirect water use, most of which is related to food consumption, the approach does not allow detailed considerations of the dietary aspect, mainly as a result of inherent limitations in the conventional EIO framework. The main issues are a high degree of sector aggregation in both the I-O classification and the secondary expenditure dataset (a common issue in EIO, see Briassoulis, 1991; Jones & Munday, 2004; Lundie et al., 2007), and the linearity between total expenditure and environmental impact (previously discussed in Hendrickson, 1998; Lenzen & Foran, 2001; Murray et al., 2010; Wiedmann, 2009). Despite the aforementioned weaknesses, which the third approach attempts to address, the framework shows potential in evaluating the trade-offs across multiple indicators (water use and economic impact) likely to arise from potential management decisions such as attracting a higher percentage of luxury tourists, as intended
in objective 3. The data required to carry out the approach are freely available for many developed countries.

### 7.2.3 Third approach

The approach presented in Part IV of the thesis relates to objectives 4 and 5:

*Design a novel modelling framework for quantifying the water use and economic impact of diverse dietary preferences (objective 4).*

*Test the model developed as part of the preceding objective, using primary data collected in different parts of Cyprus, for a selection of tourist types (objective 5).*

Given that water use embedded in food accounts for at least 70% of total water use in all scenarios and segments previously considered, Part IV of the thesis set out to investigate how highly disaggregated data on tourist dietary choices could be used to obtain more exact estimates of water use and economic impact. This entails considering the type and quantity of food consumed and not solely relying on food expenditure as being indicative of impact. These features are normally characteristics of studies which estimate water in food consumption through process-based life cycle assessment (LCA) (Hoekstra & Mekonnen, 2012; Vanham et al., 2013). A handful of EIO water studies capture the impact of different foods (Cazcarro et al., 2012, 2013, 2014; Meier & Christen, 2012a, 2012b), only two of which explicitly consider the quantity of food consumed (Meier & Christen, 2012a, 2012b). However, the aforementioned studies rely on secondary expenditure and nutrition data for households, which are not applicable to tourists. Designing a novel approach is thus a requirement to meeting objective 4. Additionally, testing the model in order to realise objective 5 necessitates highly disaggregated statistics on expenditure and food consumption which, in the complete absence of such data for tourists, must be obtained through primary data collection.

In order to ‘build’ the modelling framework, there is firstly a need to disaggregate the existing Input-Output table (IOT). A single agricultural sector is disaggregated into 20 sectors, each of which represents a different group of crops or animal products. This is accomplished using agricultural statistics (CYSTAT, 2010; Markou & Papadavid, 2007), and
the resultant IOT matrix is subsequently balanced with the ‘three-stage RAS’ (TRAS) technique (Gilchrist & St.Louis, 1999, 2004). A functional unit approach (Girod & De Haan, 2010; Hertwich, 2005), based on average portion sizes established through hotel and restaurant surveys, serves as the basis for estimating water use impacts associated with diet. Finally, surveys focusing on British tourists in different locations of Cyprus are used to collect data on food consumption and expenditure. Combining the primary data with the disaggregated classification is where the most innovative aspect of the approach lies, as water use is estimated using the functional unit approach, whereas the economic impact is estimated using expenditure and a conventional EIO model. Objective 4 is thus met, delivering a novel approach capable of estimating the impacts of dietary choice.

The results demonstrate how disaggregated information with respect to dietary preferences and food habits of tourists can be used to pinpoint key products in the supply chain that are consumed abundantly and tend to have a high water use impact. In the case of Cyprus, these products are local cheese and pork. Improved knowledge of the economic and water use impacts taking place in the food supply chains of different kinds of tourists, areas, or types of establishment is an invaluable tool in making decisions with respect to which ingredients to source and in what amounts. The framework is also flexible enough to allow for the examination of scenarios such as a decrease in the size of meat portions or a reduction in waste and their potential impacts on water use and economic impact. This could potentially be used to control any adverse impact on the economy as a result of attempts to make tourist meals more sustainable. The findings appear to suggest that cheaper forms of tourism may offer the best economic return in relation to their indirect water consumption, once again challenging the notion of pursuing luxury forms of tourism at all costs.

This framework is the most complex in a technical sense and also requires specialised data, some of which (primary data on tourist food consumption) are not commonly collected. As such, this framework is perhaps more restricted to the academic domain compared to the previous two approaches. However, it does make a strong case for pursuing disaggregated data collection on a regular basis. As diet is arguably the most significant yet most understudied component of indirect water consumption from tourism, disaggregated data and similar approaches are critical to overcoming the two major challenges defined in section 7.1.1. Limitations of the framework include using only a single ‘food and beverage’
sector, its reliance on averaged portion sizes, and the trust it places in tourists sharing their food consumption habits. Notwithstanding the aforementioned limitations, the third approach, with its ability to produce highly detailed dietary water use estimates, addresses the important limitations in the previous two approaches, thus helping to achieve the principal aim of the thesis.

7.2.4 Synthesis of approach contributions

All three approaches individually make a contribution to the literature in the sense that there were previously no methods capable of capturing the heterogeneity of tourist choices and their respective impacts on indirect water consumption. Nonetheless, the approaches should not be seen as mutually exclusive. They should ideally be considered as parts of a spectrum, from the first approach being the simplest and least data-intensive, to the third approach which is highly specialised and data-demanding. Each approach also builds on the previous approach, in an attempt to address limitations and offer a more complete understanding of the indirect water use component, which is the overall aim of the thesis. Combining elements of the three approaches is certainly a possibility which will depend on data availability and the study objectives. The next section focuses on the key implications emerging from the findings of the thesis.

7.3 Wider implications of key findings

A prominent issue throughout the thesis is that of tourism food consumption and its water use and economic impacts at the destination. Current trends in food consumption driven by western diets and their associated environmental (and health) impacts have become a major point of concern in recent years (Duchin, 2005; Fresco, 2009; Godfray et al., 2010; Gössling & Hall, 2013; Kearney, 2010; Meier & Christen, 2012a; Tukker et al., 2011). Tourism food consumption in its conventional form epitomises western food consumption patterns in terms of the quantities and the nature of foods consumed. With respect to quantity, research suggests that people consume more food when on holiday (Cohen & Avieli, 2004). This is exemplified by the fact that tourists spend around one-third of their total expenditure on meals (Gössling et al., 2011; Telfer & Wall, 2000; Torres, 2003), compared to an average of only 10-15% of household income in OECD countries going towards satisfying daily food needs (Fresco, 2009). Disregarding the fact that income differs from expenditure and that
households tend to have significantly more varied expenses compared to tourists, these numbers arguably suggest that people spend considerably more on food when on holiday.

According to Gossling (2012), there is also evidence to suggest that tourists tend to consume higher amounts of animal products compared to what they consume at home. The primary dataset in this study provides further substantiation for both claims since, on average, 26% of daily expenditure was food-related and the pork and dairy consumption of many of the tourists was particularly high compared to local residents. Meat and dairy foods have a significantly higher water use impact per calorie compared to plant-based foods (Hoekstra, 2012; Mekonnen & Hoekstra, 2012; Vanham, Mekonnen et al., 2013; Vanham et al., 2013). This is likewise the case with respect to carbon footprints (Gössling et al., 2011; Weber & Matthews, 2008) and most other environmental impacts such as land requirements (Low Carbon Oxford, 2013; Steen-Olsen et al., 2012). Given the fact that food is often seen as an important element of the leisure aspect of a holiday (Cohen & Avieli, 2004; Gössling & Hall, 2013; Okumus et al., 2007; Pratt, 2013; Sims, 2009), with protein-rich foods often featuring as culinary highlights, it would appear that the tourism sector faces the challenge of promoting sustainable food consumption without compromising guest satisfaction.

In previous chapters of the thesis, the discussion on managing food consumption focused entirely on interventions from the tourism service provider perspective. Measures such as controlling the kinds and quantities of foods available in buffets in addition to looking to achieve synergistic water, energy and waste savings through appropriate procurement have all been suggested. However, this discussion somewhat ignores the role of the tourists themselves. During the interviews conducted for this study, many tourists commented on the huge portion sizes in most restaurants and hotel buffets in Cyprus and some expressed concerns over the amount of food being wasted. This suggests that smaller food portions could, contrary to what restaurant and hotel owners would expect, increase satisfaction levels for some tourists, whilst also reducing water use and other environmental impacts. This ideal situation is essentially what Jackson (2005) refers to as the ‘double dividend’ of sustainable consumption and what Kallbekken & Sælen (2013), who recently published positive results using smaller plate sizes in a Scandinavian hotel, present as a win-win environmental measure. Restaurants and hotels could even potentially increase their own profits through such measures, in addition to being able to market themselves as ‘green’ or
sustainable, thus giving rise to a ‘triple dividend’. Future research on sustainable food consumption in tourism must therefore include a better understanding of tourist behaviour and psychology (see section 7.4.2).

The other major issue emerging from the present research is that the findings appear to support the notion that cheaper forms of tourism can be more environmentally and economically sustainable than up-market tourism (depending on the indicator used). Moving away from mass tourism by pursuing diversification and rejuvenation of the tourist product is often seen as being synonymous with sustainability (Dodds & Butler, 2010; Farsari et al., 2007). However, despite the apparent profitability of up-market tourism in pure economic sustainability terms, research appears to indicate that in mature destinations where resources such as sunshine and beaches exist in abundance, there appears to be a persistence of the mass tourism product (Aguiló et al., 2005; Farsari et al., 2007; Sharpley, 2003).

Frequently cited advantages of mass tourism over up-market tourism include higher visitor numbers characterised by repeat visitation and loyalty (Alegre & Cladera, 2006; Claver-Cortés & Pereira-Moliner, 2007), and less need for imports of specialised products and associated leakage (Ioannides & Holcomb, 2003). As shown in the current work for Cyprus in Hadjikakou et al. (in press), lower-spending tourists with mass tourism characteristics tend to spend a higher percentage of their money in higher impact (in terms of value added and employment) expenditure categories.

When environmental impacts are also added to the equation, the lower end of the market offers an even more attractive option. Research on direct water use has concluded that mass tourism uses significantly less on a per visitor basis (Hof & Schmitt, 2011; Rico-Amoros et al., 2009; Rico-Amoros et al., 2013; Tortella & Tirado, 2011). The present thesis supports these findings, having shown that supply chain water use tends to be significantly lower for the mass tourism market. Previous research has also questioned the more general environmental impacts (not restricted to water) of luxury tourism development such as golf courses and private resorts with lush gardens and other facilities (Ayres, 2000; Farsari et al., 2007). The tentative conclusion from the present work is that the lower end of the tourism market has some attractive attributes which result in a good economic-environmental yield.
Nonetheless, tourism is highly diverse, and so is the higher-end of the market. Research elsewhere shows that some consumers willingly pay higher prices for lower environmental impact and that higher quality products could (and should) be made to have a lower environmental impact than cheaper alternatives (Girod & De Haan, 2010). This is also likely to apply to tourism, where some sustainably run higher-end resorts, could, in theory, outperform cheaper establishments in terms of direct and indirect water, energy and other resource uses. For this reason, before drawing any final conclusions with respect to the overall performance of different types of tourism, further research using a wider selection of impact indicators (environmental, economic and social) and alternative segmentation procedures is required to compare the full spectrum of tourism in Cyprus and in other destinations (see section 7.4.1). Ultimately, it is perhaps preferable to accept that it is difficult to define an optimal tourist type (Becken & Simmons, 2008). Tourists will always come in an assortment of different market segments and there is no ‘one-size-fits-all’ management approach for reducing water use (and other environmental) impacts. Thorough quantification, offered by approaches such as the ones developed in this thesis, could help understand and minimise economic-environmental trade-offs across the tourism spectrum.

The topics of sustainable food consumption and the comparison between different kinds of products and consumption patterns are not only inter-related but are both also concerns that transcend the boundaries of tourism research. In this respect, the present research has offered some place- and context-specific findings which add to an evolving body of literature on sustainable consumption.

### 7.4 Further research avenues

#### 7.4.1 Building on the proposed approaches

The approaches developed in the thesis could be used as a basis for improving existing methodologies as well as to pursue further analysis with potential policy implications. Some ideas are as follows:

- The seasonal and spatial resolution of the models could be improved in order to account for the different impacts arising from tourists visiting different parts of the island at different times of the year. This could include a consideration of the sources
of water (groundwater, surface water, desalination) used in different resorts at different times of year and their relative opportunity costs.

- Using actual and projected trends in numbers for different tourist types, the EIO model could be used to test the water use and economic impacts assuming certain percentages of different tourist segments. For example, this could include increases in arrivals from certain countries or increased numbers of golf tourists.

- An invaluable line of research to pursue using the existing models would be to establish baskets of commonly consumed products (including food and non-food items) and to subsequently assess their origin and estimate detailed impacts occurring along their supply chain. This could also include key imported products catering for tourists in Cyprus (or in other destinations). This could make use of techniques published elsewhere for highlighting water use ‘hotspots’ in the supply chain (Lenzen, Moran, Bhaduri et al., 2013; Ridoutt & Pfister, 2010b).

- Detailed audits in hotels and restaurants across the island could be used to provide bottom-up data in order to supplement the present top-down analysis. This could then provide more accurate data with respect to the products and quantities used in different kinds of establishment and would provide more hands-on information on how to minimise water use in the tourism supply chain.

- Water use is only one of several key environmental impacts of tourism. The use of additional environmental indicators such as carbon emissions, waste, or land use associated with different consumption patterns would provide a more complete picture of environmental-economic trade-offs and synergies, allowing for an alignment of several environmental objectives. EIO frameworks have previously been used for multi-indicator analysis (Ewing et al., 2012; Fang et al., 2014; Lundie et al., 2007; Steen-Olsen et al., 2012; Tukker et al., 2011). However, a greater emphasis on tourism, food products and water is certainly required.

- The integrated segmentation-yield framework should also be considered as iterative. Pursuing alternative methods of segmentation could be especially beneficial. Assuming sufficient data (such as the data collected in Part IV) are available, initial segmentation could take place using any variable, including water use or other environmental impact indicators (see previous point), or even culinary interests (Ignatov & Smith, 2006). This would then allow for the profiling of tourists who use
the most or least water according to the model, to see where they are likely to stay, what they tend to eat and what their other characteristics are.

7.4.2 Expanding the scope of the research

The largely quantitative nature of the present study and aforementioned future research investigations (section 7.4.1) should be supplemented with qualitative data on tourist behaviour, attitudes and psychology in order to ascertain opportunities to promote more environmentally sustainable tourist consumption. This could be achieved in the following ways:

- Through additional in-depth surveys (including open-ended questions) of tourists and hotel and restaurant managers, research could explore why different tourist types have different preferences, in an attempt to better understand consumption patterns associated with higher water use intensity. Inversely, such studies could be employed to gauge the possible effect of different water-saving and other environmentally friendly measures on tourist satisfaction.

- In the context of tourism, it would be highly relevant to investigate how, where and when it is possible to reap the benefits from a ‘double dividend’ or win-win situation, whilst ensuring that revenues remain unaffected or, preferably, increased to provide an incentive for hotel and restaurant owners. Previous research warns of a gap between favourable attitudes and actual behavioural patterns (Vermeir & Verbeke, 2006) therefore surveys will also need to be coupled with empirical research to test the effectiveness of any proposed measures based solely on attitudes.

- Finally, the thesis has demonstrated the advantages of obtaining and using detailed information with respect to tourist consumption patterns. Nevertheless, data typically collected by statistical authorities tends to be aggregated and lacks the detail required to make subtle distinctions between different tourist kinds. The reasons for this are related to costs, lack of trained personnel, and a lack of understanding of how data may be used beyond crude economic impact assessments. Ultimately, further research is required to ascertain what kinds of additional data can realistically be collected on a regular basis by statistical authorities with respect to tourist
consumption, either by tweaking the original passenger surveys or through supplemental studies in hotels and restaurants.

7.5 Closing remarks

The primary aim of the thesis was to make a methodological addition to the literature by developing three cumulative approaches to cater for different research objectives and data requirements. The approaches make an important contribution towards achieving sustainable water use through improved quantification and, consequently, an appreciation and better understanding of the heterogeneity in water use across different tourism products. It is envisaged that the approaches presented will be applicable to any tourism destination where the necessary data are available, allowing place-specific findings to be generated. The thesis also sought to assess water use in the tourism sector relative to the economic benefits for the destination. To this end, the secondary aim was to use the approaches to generate results that are of significance to tourism management in Cyprus and other water scarce destinations. Comparisons between different types of tourism in Cyprus show that cheaper forms of tourism tend to have a significantly lower total water use and, in many cases, higher water productivity compared to other forms associated with higher expenditures. With several water scarce destinations currently investing in the diversification of their tourist products in an attempt to attract higher-spending visitors, this finding is of immediate relevance to their future sustainability. The findings also highlight the value of acquiring detailed information with respect to tourist dietary habits as a means to promote sustainable consumption patterns in the tourism sector.

As one of the world’s largest and fastest-growing industries, and in light of a future of increasingly scarce water resources, the tourism sector has an immediate obligation to improve its sustainability – consideration of its supply chain water use and its water productivity, facilitated by the approaches outlined in this thesis, is essential.
Thesis references


_Proceedings of the National Academy of Sciences, 107_(12), 5687-5692._

De Mesnard, L., & Miller, R. E. (2006). A note on added information in the RAS procedure: 
reexamination of some evidence. _Journal of Regional Science, 46_(3), 517-528._

medpotourismreportfinal_ofnc.pdf.

within a social accounting matrix framework. _The Economic Journal, 94_(373), 111-136._

Deng, S. (2003). Energy and water uses and their performance explanatory indicators in 
hotels in Hong Kong. _Energy and Buildings, 35_(8), 775-784._

Deng, S., & Burnett, J. (2002). Water use in hotels in Hong Kong. _International Journal of 
Hospitality Management, 21_(1), 57-66._

World Input–Output Tables in the WIOD Project. _Economic Systems Research, 25_(1), 71-98._

Dietzenbacher, E., & Miller, R. E. (2009). Ras-ing the transactions or the coefficients:it makes 
no difference. _Journal of Regional Science, 49_(3), 555-566._

segmentation of sport tourists. _Journal of Sport & Tourism, 17_(1), 5-21._

Dodds, R., & Butler, R. (2010). Barriers to implementing sustainable tourism policy in mass 
tourism destinations. _TOURISMOS, 5_(1), 35-53._

& Tourism Marketing, 12_(1), 1-22._

established methodological weaknesses and some recommendations for 
 improvement.11(2), 5-12.

approaches in tourism. _Journal of Travel Research, 42_(3), 244-250._

(pp. 129-150). Cambridge: CABI.

towards carbon reduction in the UK. _Ecological Economics, 66_(4), 594-604._


PART V – References


287


296


