Translation of Remote Sensing data into Sustainable Development Indicators


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Abstract

In 2015, member countries of the United Nations adopted the 17 Sustainable Development Goals (SDGs) at the Sustainable Development Summit in New York. These global goals have 169 targets and 232 indicators which are based on the three pillars of sustainable development: economic, social and environmental. Substantial challenges remain in obtaining data of the required quality, especially in developing countries, given the limited resources involved. One promising and innovative way of addressing this issue of data availability is to use Earth Observation (EO). This paper presents the results of research to analyse and optimise the potential of EO approaches to populate the SDG indicators and targets. We present a matrix of EO technologies with respect to the full set of current SDG indicators which shows the potential for direct or proxy calibrations across the span of the social, economic and environmental SDG indicators. We have focussed particularly on those SDG indicators covering the social and economic dimensions of sustainable development as these are relatively unexplored from an EO context. Results suggest that EO can make an important contribution towards populating the SDG indicators, but there is a spectrum from at one end the sole use of EO to the other end where the EO derived data have to be used in concert with data collected via non-EO means (surveys etc.). Complicating factors also include the lack of driving force and pressure indicators in the SDG framework and the use of ‘proxy’ indicators not part of the SDG framework but more amenable to EO-derived assessment. The next phase of the research will involve the presenting of these ideas to experts in the EO and indicator arenas for their assessment.

Keywords: Earth Observation (EO), indicators, DPSIR Framework, Sustainable Development Goal (SDG)

1. Introduction

The 17 Sustainable Development Goals (SDGs) of the United Nations were ratified by the UN General Assembly at the Sustainable Development Summit in New York on 25th September 2015. They span the main components of global sustainable development: economic growth, social inclusion and environmental sustainability to 2030. In order to monitor the progress of all nation states towards these global goals, the UN created a conceptual framework of 169 targets and 232 indicators associated with the SDGs that 193 UN member states will use and develop to frame their agendas and policies out to 2030. The intention is to monitor, measure and report progress or regress in all signatory countries, whether developed or developing, following the principle of “no one will be left behind” (United Nations, 2015b,p.1).

The United Nations Statistics Division (UNSD) and the United Nations Economic and Social Council (ECOSOC) have agreed upon the initial Global Indicator Framework for SDGs. The UNSD created the Inter-Agency Expert Group for the SDGs (IAEG-SDGs), which interacts with National Statistical Offices (NSOs) and provides strategies for countries for the implementation of the SDGs and for reporting on progress towards the targets (United Nations, 2015b).

IAEG-SDGs has developed the Global Indicator Framework of 232 indicators that were officially adopted by the UN Statistical Commission at the 48th session in March 2017. The IAEG-SDGs has classified the indicators into three different tiers based on the methodology and level of data availability to allow the population of the indicator as follows:

- TIER I: established methodology and data are widely available to populate the indicator.
- TIER II: established methodology but data are not collected regularly by the countries
- TIER III: no established methodology to collect the required data.

IAEG-SDGs regularly reviews the Global Indicator Framework to add more indicators if needed or to update the status of the TIER categorisation of the indicator.

In recent years, data collection methods have been improved for monitoring aspects such as poverty, nutrition, child and maternal health and access to water and sanitation (United Nations, 2015a). Despite this, there still remains considerable
scope for further improvement to data availability for a more up-to-date and complete population of SDG indicators, especially in the least developed countries. In many remote areas, high-quality data are lacking and it can be argued that a data crisis exists: “too many countries still have poor data, data arrives too late and too many issues are still barely covered by existing data” (Independent Expert Advisory Group on a Data Revolution for Sustainable Development, 2014, p.11).

1.1 Earth Observation

EO spans many approaches, including the use of drones and aircraft, but in this paper, we focus on satellite-based systems. The Explorer 7 satellite, launched in October 1959, initiated an era of satellite-based Earth Observation (EO) that continues to this day. Nowadays, several hundred active Earth Observation satellites are operated by both national Space Agencies and commercial operators (https://eoportal.org). EO satellite imagery can be divided into two types depending on how the sensors capture imagery: passive and active. Passive EO sensors detect radiation emitted by (thermal infrared/microwave) or reflected from (visible, shortwave infrared) the Earth’s surface (and atmosphere). Most instruments of this type are optical and are not able to penetrate cloud cover. Active EO satellites emit radiation and receive the echoes that are backscattered from the Earth surface (POST, 2017). These operate mostly in the microwave spectral region (radar), though more recently, lidar systems have also been developed. As well as the split between ‘active’ and ‘passive’ sensors, the main distinction for satellites is between those in ‘geostationary’ orbit that continuously observe the same point on Earth and those in ‘low Earth orbit’ which track across the Earth’s surface as they orbit.

EO satellite sensors provide data at various spectral, spatial and temporal resolutions. The spectral resolution refers to the wavelengths of radiation that can be detected. In the visible and shortwave infrared regions, the information in different spectral bands provides a spectral ‘signature’ for different land cover types (e.g. vegetation, soil, water, buildings). Spatial resolution is a measure of the observable detail in an image. The highest resolution modern sensors, usually only available commercially, can give resolutions of significantly less than 1 m e.g. down to 0.5 m. High-resolution imagery from public space agencies typically has a resolution of tens of metres. Temporal resolution relates to the revisit time: the frequency with which a sensor crosses any point on Earth. This depends on the orbit and on the swath width, i.e. the width of observation across the ground. Generally, the higher the spatial resolution, the lower is the swath width. For instance, Lynch et al. (2013) argue that improving the spatial resolution and the revisit time (e.g. satellite DMC constellation) would benefit the monitoring of forest degradation as part of the REDD+ programme and act as an early warning system assisting authorities in tackling illegal logging.

1.2 EO for the SDGs

An innovative way to seek accurate and reliable data by which to address the SDG indicators and targets is to harness the new technologies within the broad sphere of EO. EO-sourced data has been advocated by several international researchers and organisations as a means to reduce the costs of traditional monitoring of various environmental and other parameters (e.g. forested areas, water bodies etc.) over relevant times, scales, geographical locations and spatial resolutions. It is apparent that EO can support a number of the indicators in the UN SDG framework by providing accurate and reliable data on the state of atmosphere, oceans, crops, forests, weather, natural disasters (immediate, independent response in real time), natural resources, ice, urbanisation, biodiversity. This view is supported by the UN Global Working Group on Big Data: “Satellite imagery has significant potential to provide more timely statistical output, to reduce the frequency of surveys, to reduce respondent burden and other costs and to provide data at a more disaggregated level for informed decision making.” (https://unstats.un.org/unsd/bigdata/taskteams/si-gsd/default.asp).

The EO community, through GEO and its space-agency arm CEOS, has presented an initial view on how EO can support the population of SDG indicators. The GEO EO4SDG programme supports the potential of EO to advance the UN 2030 Agenda. CEOS has created an ad hoc team on the SDGs (http://ceos.org/ourwork/ad-hoc teams/sustainable-development-goals/) to better coordinate the activities of the CEOS Agencies around the SDGs. GEO is working closely with the UN
1.3 Beyond the existing framework and experience

While the GEO study referred to above has focussed mostly on the environmental indicators within the SDGs, EO can potentially also contribute towards populating socio-economic indicators, through direct or proxy measures. For instance, recent studies have shown that nighttime light images, obtained from suitable visible sensors, provide an almost direct measurement for estimating global population (Sutton et al., 2001) and, indirectly, can also provide data relevant to indicators of economic growth (Henderson, et al., 2011), socio-economic activities (Chen and Nordhaus, 2011), poverty (Ghosh et al, 2013; Jean et al, 2016), electricity consumption (Doll and Pachauri, 2010), urbanisation impacts on the environment (Ma et al., 2012) and fishing activities (Waluda, et al., 2004). With care, nighttime light imaging can even be used to contribute to estimations of human rights (Li, et al., 2016), corruption (Hodler and Raschky, 2014) and the incidence of breast cancer (Rybnikova and Portnov, 2017).

While the preceding discussion shows interesting potential for applying EO to the indicators and targets of the SDGs, these prospects are highly dependent on the specific nature of the targets and the underlying indicators that have been chosen to date. For example, Spangenberg (2017) has classified the SDG targets using the well-established Driving Force-Pressure-State-Impact-Response (DPSIR) framework (EEA, 1999; OCDE, 1993). He found a substantial imbalance in the nature of the targets in the SDG framework; in particular targets for pressure are “…missing…” and targets for Driving Forces “… are mentioned … but … not a reversal of the past direction is advocated, but more of the same, …”. Furthermore, he notes that “…in the approach used here there are no targets referring to responses.” which he defines as “…responses are policy actions to turn targets into reality…” (Spangenberg, 2017). Given this imbalance in the nature of the SDG targets, similar imbalance in the nature of the SDG indicators (the subject of this paper) can be expected which, in turn, will have some bearing on the extent to which EO data can contribute to the broad suite of SDG indicators. This raises many ancillary questions. For example, to what extent can EO be used to populate indicators classified via DPSIR? Can it be assumed that EO is better suited to populate Pressure, State and Impact indicators rather than Response or perhaps Driving Force, or can EO contribute to them all? In theory, it may be possible to create ‘proxy’ indicators that are not listed with the SDG framework but which may allow the target to be assessed via EO.
The increasing availability and range of EO data is a growing opportunity to complement or even replace traditional ground-based methods of collecting environmental and socio-economic data. EO approaches are expected to be especially valuable where traditional data is sparse or absent. Furthermore, in a number of cases, EO can provide data that is spatially and/or temporally richer than ground surveys and/or can be less expensive to acquire. While EO technology has progressed rapidly, and institutions such as GEO are facilitating the use of EO-sourced data for several of the SDGs, the use of EO data particularly for the socio-economic indicators remains rare and unclear. We consider, however, that EO data may have a much more substantial role to play in helping to calibrate the more socio-economic SDG indicators that has been widely appreciated to date.

1.4 Objectives of this paper

In the research described here we had three main objectives:

1. To review the SDG indicators with regard to their potential for assessment using EO-derived data.
2. To explore how the analysis under (1) meshes with the DPSIR classification of the SDG indicators. Is there evidence that EO-derived data are best suited for particular components of the DPSIR?
3. What potential is there to use indicators more amenable to population via EO-derived data, to address the SDG targets?

The research in this paper is, we believe, the first to systematically review the scope for using EO especially for the socio-economic SDG indicators and to assess its potential for providing data, either directly or indirectly, and wholly or partially, for such SDG indicators.

2. Methods

2.1 Method overview

We have reviewed systematically about eighty papers and reports that explore the use of EO satellite data to deliver results that support the monitoring of indicators of sustainable development. Of these, fewer than five referred specifically to the SDG indicators (some of these included several SDG indicators in a single report). The review was designed to:

- Assess the state-of-the-art in the range of sustainable development indicators that have had EO data and EO approaches applied to their calibration
- Provide a basis for a meaningful classification of the varying types of the contribution of EO data specifically for the SDG indicators and of the overall potential of EO for the SDG indicators – this was developed into a ‘maturity matrix’ described below

Emphasis was placed on the socio-economic indicators of sustainable development in the selection of the material reviewed.

A systematic classification representing two overall ‘premises’ within the maturity matrix (see Table 2) was evolved through the process of assimilating the review information. In the First Premise (Premise 1), the technical methods of processing EO satellite data and combining it with data derived from non-EO based methods, such as surveys, were assigned a 1 to 5 score in each of 2 categories (Premises 1.1 and 1.2). In the Second Premise (Premise 2), an equivalent score from 1 to 5 was assigned to a single category representing the level of contribution that the EO data assessed in the First Premise was able to make to fully satisfy the data needs for a given indicator. In Table 2 we imagine a gradient of contribution from EO data to the indicator. It is assumed here, for example, that for some indicators EO derived data may only be able to supplement data collected from other sources such as via surveys, while in other cases the EO derived data may be enough to populate the indicator without other data being required. A simple unweighted average of these scores is used to provide an overall assessment of the potential role for EO in providing the data needed for that SDG indicator. The equal weighting of these scores is contestable, of course, and may well be refined in future research. SDG indicators with no evidence in the literature that EO can provide useful data support were scored as 0.
An aggregate score is derived for the potential role of EO in calibration of the indicator from the equations below. We refer to this as the Maturity Matrix Score (MMS). We first use a mean formula for calculating the score from the two elements of Premise 1, where:

Premise 1.1: The range of methods for processing EO data
Premise 1.2: The requirement for non-EO information

Therefore:

\[
Premise\ 1\ mean\ score\ (P1) = \frac{Premise\ 1.1 + Premise\ 1.2}{2}
\]

The Premise 1 mean score is applied to the indicator irrespective of the number of components it contains. For example, some indicators will have a numerator and denominator, but with Premises 1.1 and 1.2, the scores are allocated to the indicator as a whole.

However, under Premise 2 – the level of completeness offered by EO data for the data required to fully satisfy the indicator – there is a complication in that some of the SDG indicators (e.g. a numerator and denominator) have multiple components that may vary in terms of their ‘addressability’ via EO derived data. Some elements of the indicator may be more amenable to being addressed via EO derived data than others. We provide an example of this later in the paper (Table 4) but under Premise 2 it is necessary to allow for multiple answers for one indicator, hence:

\[
Premise\ 2\ mean\ score\ (P2) = \sum_{S=1}^{n} \frac{S}{n}
\]

Where

\( S \) = scores for the various components of the indicator under Premise 2
\( n \) = number of indicator components scored under Premise 2

The two premises are combined as follows:

\[
Maturity\ Matrix\ Score\ (MMS)\ for\ indicator = P1 + P2
\]

It should be noted that the scores allocated in the two premises are semi-quantitative, expert representations. They are derived from the framework (described below) applied consistently to each review but does include a significant element of subjective judgement.

For example, with an indicator having the following scores (please see Table 2 for details):

Premise 1.1: score 2 (pixel-based technique)
Premise 1.2: score 3 (EO data used directly but non-EO data are required)

Then the mean value for Premise 1 (P1) is given by:

\[
P1 = \frac{2 + 3}{2} = 2.5
\]

For Premise 2, we assume that the indicator has two components – a numerator and denominator – with scores (S) of 4 (high level of completeness offered by EO data) and 5 (very high level of completeness offered by EO data) respectively. This yields an average score (P2) as follows:

\[
P2 = \frac{4+5}{2} = 4.5
\]

The MMS (Premise 1 and Premise 2) for the indicator is then given by 2.5 + 4.5 = 7.

Please note that the MMS is a total of the average of Premises 1.1 and 1.2 plus the score for Premise 2 and includes an indication (the +/- element) for cases where a single score in Premise 2 is not assigned but, rather, a score range is appropriate (see Table 4 in Results).
2.2 Maturity Matrix System

2.2.1 First Premise

Methods of processing EO data (Premise 1.1)

The methods of processing EO data are explained in many papers and reports. We have used a classification of EO processing data presented by United Nations (2017) and Li, et al. (2014) which are compiled and matched with the approaches of the papers/reports reviewed. This distinguishes between data that was processed through the use of algorithms (scores 1 to 4) and interpretive raw EO data (score 5) - this distinction is included in Table 2 for Premise 1. In addition, the scoring methods with 2, 3 and 4 have been chosen based on the level of accuracy for Supervised, Unsupervised and Object-Based classification presented in Weih and Riggan, (2010). Myint, et al. (2011) and Weih and Riggan (2010) have shown how object-based classification (OBIA) out-performed both unsupervised and supervised pixel-based classification methods, thus it has improved overall classification accuracy.

Each reviewed paper/report was evaluated according to the classifications outlined below (Table 2) in which a score of 5 represents a high direct use of EO data and a score of 1 represents a low direct usage of EO data. Notably, scores 2, 3 and 4 refer to satellite image classification methods and their level of accuracy.

Table 2. Maturity Matrix for the potential contribution of EO to meeting the data needs for a SDG indicator.

<table>
<thead>
<tr>
<th>Score</th>
<th>First Premise</th>
<th>Second Premise</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Indicator cannot be measured by EO data</td>
<td>Indicator measured by non-EO data</td>
</tr>
<tr>
<td>1</td>
<td>Empirical or semi-empirical modelling</td>
<td>EO data supplements primary analysis based on non-EO data</td>
</tr>
<tr>
<td>2</td>
<td>Pixel-based technique (unsupervised classification)</td>
<td>EO data used in approx. equal combination with non-EO data</td>
</tr>
<tr>
<td>3</td>
<td>Pixel-based and sub-pixel based techniques</td>
<td>EO data used directly; non-EO data required e.g. as training set for artificial intelligence</td>
</tr>
<tr>
<td>4</td>
<td>Image Segmentation - Object-based classification (OBIA)</td>
<td>EO data used directly; limited non-EO data requirement e.g. for validation</td>
</tr>
<tr>
<td>5</td>
<td>Visual interpretation</td>
<td>EO data used directly; non-EO derived data are not required</td>
</tr>
</tbody>
</table>

MMS = X (+/- x)

Score 1 Empirical and Semi-empirical modelling involves the use of statistical data established between the EO measured data and the variable measured (ground-based), without there being a well-understood causal relationship. This approach requires the collection of in-situ data to establish the empirical relationship between what is measured through EO and the
measure of interest. These methods may not be reliable when used outside the conditions under which the relationship was established and, without a strong theoretical basis, it is difficult to assess where such conditions do not apply.

**Semi-empirical modelling** is used when the relationship between the EO measurement and the indicator quantity can be partially described through a theoretical relationship, the parameters of which are determined statistically using ground observations. This method combines knowledge about the process with statistical models. For example, Tripathy et al., 2013 used a semi-empirical method which incorporates physiological measures, spectral measures and spatial features to estimate wheat yield.

An illustrative example would be the creation of a nighttime luminosity dataset. The raw data are first transformed on an empirical basis to correct for various distortions (Chen and Nordhaus, 2011) and then secondly through regression models. For instance, the most common statistical model is linear regression used to fit the correlation between the total night light intensity (which is extracted from corrected NPP-VIIRS data and DMSP-OLS data) and the variable measured (GDP growth, electricity consumption, etc.)

**Score 2 Pixel-Based Technique Unsupervised classification** (e.g. K-means, Iterative Self-Organizing Data Analysis (ISODATA), Self-Organizing Maps (SOM), hierarchical clustering) is a pixel-based technique using clustering mechanisms to group image pixels into unlabelled classes, without the help of training data or prior knowledge of the study area (Li et al., 2014). In terms of attributing score 2 to this method, we have taken into account the level of accuracy presented in Weih and Riggan’s (2010) paper.

**Score 3 Pixel-Based techniques and Sub-pixel based techniques** Li et al. (2014) have presented a review of the major remote sensing image classification techniques.

**Pixel-Based techniques** include the following methods: *Supervised Classification* (SC) (e.g. Maximum likelihood, Minimum distance-to-means, Mahalanobis distance, Parallelepiped, k-nearest Neighbours), *Machine learning* (ML) (e.g. artificial neural network, classification tree, random forests, support vector machine, genetic algorithms). SC requires input from the analyst through a training set. This plays an important role as the accuracy of the methods depends on the samples taken for training. The algorithm then segregates all the pixels in the image into classes. ML is an extension of empirical modelling, where formal ‘machine learning’ algorithms such as neural networks are used to generate the relationship between the indicator quantity and the EO measurements. The ML method is useful if there are appropriate data available from *in situ* observations to train the models and evaluate their fit and are increasingly considered as part of the “Big Data” toolkit. They can be successfully applied to a variety of fields that deal with socioeconomic data. For instance, Jean et al. (2016) demonstrated how novel machine learning approaches using high-resolution daytime and nighttime satellite imageries pre-trained with socioeconomic data and using statistical models (e.g. convolutional neural networks), could estimate with reasonable accuracy the consumption expenditure and wealth in 5 less developed African countries.

In **Sub-pixel-Based techniques**, each pixel is considered amalgamated and the proportion of each class is estimated through a different approach such as Fuzzy classification, Neural networks, Regression modelling, Regression tree analysis, Spectral mixture analysis, Fuzzy spectral mixture analysis, Fuzzy-spectral mixture analysis.

**Score 4 Image Segmentation Object-based classification (OBIA)** performs a classification based on objects rather than pixels through image segmentation then image objects classified using spectral and other relevant criteria. Object-based approaches are considered more suitable for very high resolution (VHR) remote sensing images. Many studies have proven that high accuracy has been achieved with object-based approaches (Myint et al., 2011; Wang et al., 2004; Weih and Riggan, 2010)

**Score 5 Visual interpretation methods** performed by direct operator (human) examination of features from raw satellite imagery when combined in different channels or bands. These methods are used to extract visual elements such as tone, shape, size, pattern, texture, and shadow from the imagery when a target is measured (e.g. urbanisation patterns, deforestation, fishery activities).
Non-EO information (Premise 1.2)

The need for non-EO information to complement the EO data was evaluated in this second part of Premise 1. Similarly to the first part, a Score between 1 and 5 was assigned. Non-EO data can be collected from a wide range of sources such as census, household or agricultural surveys, administrative data, environmental and meteorological data and can complement EO data. In much of the reviewed material, especially those referring to socio-economic indicators of sustainable development, the results were not exclusively based on EO data and non-EO data played a crucial role. We assigned a score 1 to 5 depending on the non-EO data used, its importance and implications (see Table 2). A low score implies that EO data is used only to supplement non-EO data. For intermediate scores, non-EO data is used to provide a “training set” for EO algorithms and for high scores, EO data is used directly with, perhaps, some non-EO data for validation purposes only.

2.2.2 Level of completeness of EO data (Premise 2)

Level of completeness offered by EO data for the data required (DR) to fully calibrate the indicator (Score 1 to 5). In Premise 2 we assessed the ability of the type of measure(s) used in the reviewed material to provide the necessary data to fully satisfy the data needs of the SDG Indicator. In several cases, a range of scores was assigned because EO data may have been able to fully calibrate one element of an indicator but were less able to calibrate other aspects of a multi-aspect indicator (such a case is described in detail in the Results).

3. Results and Discussion

The methods defined above are being applied on an on-going basis to papers and reports concerning the use of EO to address the SDG indicators. We provide detailed examples below of the outcomes from using our MMS system to assess the potential of EO to calibrate two of the SDG indicators. The essential features of the EO approaches reported for the example indicators are summarised at the beginning of each example, the purpose(s) of each indicator explained and a justification for the MMS is presented for each.

3.1 Example 1: Illegal and unregulated fishing

Example 1 - SDG indicator 14.6.1 ‘Progress by countries in the degree of implementation of international instruments aiming to combat illegal, unreported and unregulated fishing’

Indicator 14.6.1 is applied to measure progress towards SDG Target 14.6. It is based on efforts made by FAO member countries to implement key international instruments aiming to combat overfishing and also country responses to the Code of Conduct for Responsible Fisheries (CCRF) survey questionnaire, circulated by FAO every two years (https://unstats.un.org/sdgs/metadata). FAO is currently working on a worldwide programme called Global Fishing Watch, which combines satellite data with cloud computing technology to track fishing and identify suspicious vessel activity. Monitoring systems housed on fishing vessels and based on satellite data are being proposed for tracking fishing activities and could significantly contribute to FAO’s efforts to tackle (IUU) fishing, increase detection of illegal activities, and also offer cost saving by reducing the need for in-situ inspection.

Table 3. Essential questions in assessing the feasibility of EO applicability to Indicator 14.6.1.

<table>
<thead>
<tr>
<th>SDG Indicator 14.6.1</th>
<th>Essential questions to assess the feasibility of EO applications for SDGs Indicators</th>
<th>Answer</th>
</tr>
</thead>
<tbody>
<tr>
<td>What characteristic(s) is/are measured?</td>
<td>Illegal, unreported and unregulated (IUU) fishing</td>
<td></td>
</tr>
<tr>
<td>What data are used?</td>
<td>Suomi National Polar-Orbiting Partnership (S-NPP) Visible Infrared Imaging Radiometer Suite</td>
<td></td>
</tr>
<tr>
<td>How is the EO data processed?</td>
<td>N/A</td>
<td></td>
</tr>
<tr>
<td>What type of approach (direct/indirect) is used in the paper(s)/report(s) in relation to the SDG indicator?</td>
<td>Direct</td>
<td></td>
</tr>
</tbody>
</table>
Several papers referring to detecting and tracking of fishing vessels are available in the literature. A particularly relevant example is Straka et al., (2015) (see Table 3) who used Suomi National Polar-Orbiting Partnership Visible Infrared Imaging Radiometer Suite (S-NPP VIIRS) to identify and track ship lights of fishery activities. A unique component of VIIRS is the day-night band (DNB). This is a high-sensitivity visible sensor designed to obtain images both day and night. It is very sensitive to low levels of light and is therefore capable of detecting the light from individual streetlamps (despite the 750 m spatial resolution). Straka et al. (2015) present a notable example of ship tracking from ship lighting in the East China Sea, an area shared by People’s Republic of China (PRC), Japan and the Republic of Korea (ROK). There the parties ratified the Sino-Japanese Fishery Agreement in 1997, establishing a Provisional Measures Zone (PMZ) with clear delimitations and laws. The study, including individual EO data collections and composites for several months, provide clear evidence of the locations of fishing vessels with respect to the boundaries of these agreements.

Table 4. Completed Maturity Matrix for potential contribution of EO data to SDG Indicator 14.6.1.

<table>
<thead>
<tr>
<th>Score</th>
<th>First Premise</th>
<th>Second Premise</th>
</tr>
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<tbody>
<tr>
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<td>Requirement for non-EO information (Premise 1.2)</td>
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<td>5</td>
<td>Raw EO data</td>
<td>Visual interpretation</td>
</tr>
</tbody>
</table>

MMS= 9 (+/- 1)

Such information can help FAO to determine which regions may be at risk for over-fishing worldwide and thus which countries do not conform to the CCRF. Therefore, we assigned a score of 5 both parts of Premise 1 of the maturity matrix (Table 4) for this use of EO data because raw satellite data was interpreted visually and requirement EO data were capable of being used directly without non-EO data to monitor the presence of fishing vessels relevant to indicator 14.6.1.

However, in terms of how completely EO data alone can provide the data to fully satisfy the indicator (Premise 2) we assigned a score range of 3 to 5 (Table 4). The use of a range is due to the indicator covering multiple aspects of fishery activities. For instance, Straka et al., (2015) only monitored certain areas at a specific date and time. In order to monitor the progress made by a country to tackle IUU fishing, we need more dynamic data representing a time series of EO data. Furthermore, the S-NPP VIIRS data does not provide the country of origin of vessels nor other aspects such as detailed
fishing gear features and operational aspects, vessel permitting/licensing information etc. (possibly very high resolution and time series imagery can address some of these attributes).

3.2 Example 2: Corruption and bribery

Example 2 - SDG Indicators 16.5.1 ‘Proportion of persons who had at least one contact with a public official and who paid a bribe to a public official, or were asked for a bribe by those public officials, during the previous 12 months’ and 16.5.2 ‘Proportion of businesses that had at least one contact with a public official and that paid a bribe to a public official, or were asked for a bribe by those public officials during the previous 12 months’.

These indicators are focused on information about experiences of bribery, typically but not exclusively between business and institutions. The data collection to measure these two indicators are usually undertaken by household surveys (https://unstats.un.org/sdgs/metadata) and, at first sight, it is difficult to conceive of a contribution that EO might make to fully or even largely satisfy the data needs for these indicators.

Table 5. Essential questions in assessing the feasibility of EO applicability to Indicators 16.5.1 and 16.5.2

<table>
<thead>
<tr>
<th>SDG Indicators 16.5.1 and 16.5.2</th>
<th>Essential questions to assess the feasibility of Earth observation applications for SDGs Indicators</th>
<th>Answer</th>
</tr>
</thead>
<tbody>
<tr>
<td>What characteristic(s) is/are measured?</td>
<td>Corruption and bribery</td>
<td></td>
</tr>
<tr>
<td>What data are used?</td>
<td>Satellite data on nighttime light intensity and information about the birthplaces of the countries’ political leaders.</td>
<td></td>
</tr>
<tr>
<td>How are EO data processed?</td>
<td>Value classification and dependent variable</td>
<td></td>
</tr>
<tr>
<td>What type of approach (direct/indirect) is used in the paper reviewed in relation to SDG indicator?</td>
<td>Indirect</td>
<td></td>
</tr>
</tbody>
</table>

A direct EO measurement of bribery is almost impossible. However, Hodler and Raschky (2014) have demonstrated an empirical approach to measuring bribery and corruption using DMSP satellite nighttime imagery and non-E0 information about the birthplaces of a country’s political leaders from over 38,000 subnational regions of 126 countries between 1992 and 2009 (see Table 5). Nighttime light intensity is valuable as a proxy for economic activity (e.g. consumption, production) (Shi et al., 2014; Li, et al., 2013; Ghosh, et al., 2009). Therefore, Hodler and Raschky’s EO data was able to serve as proxy evidence for regional favouritism in a number of less developed countries with weak political institutions. They identified that some leaders choose policies that mainly benefited their preferred regions (usually birthplace and the area with the most votes received) and this was reflected in increased nighttime light intensity when measured before and after elections. The EO data in this paper are proposed as a measure of regional favouritism, this being associated with inference of a series of bribery and corruption acts. Equal access to public services and a correctly functioning, inclusive economy is not synonymous with governments’ budgets that are invested disproportionately in a leader’s birthplace.

In Premise 1.1 of the matrix, we assigned a score of 1 (see Table 6) due to corrections of the raw nighttime satellite imagery. After the corrections are performed (due to the cloud coverage, fires reflectance, or other ephemeral), the annual stable lights data are presented as digital numbers (DN) on a scale from 0 (none) to 63 (high nighttime light), thus the obtained datasets are DN proportional to radiance. Therefore, the empirical model shows generally higher economic activity in the more night light-intensive areas. In order to validate their assumptions, the DN data has been modelled through a variety of regression models, such as dummy variables in semi-logarithmic regressions.

The EO data was given a score of 2 (see Table 6) for Premise 1.2 because complementary non-E0 data for the political leaders’ birthplace and the relationship of nighttime light intensity with economic activity has been used in approx. equal proportions with the EO data for the nighttime light intensity. Hodler and Raschky (2015) combined these data to infer the
presence of bribery and corruption behaviour by public officials and politicians associated with favouritism in economic development, as observed through nighttime light intensity measurements.

*Table 6. Completed Maturity Matrix for potential contribution of EO data to SDG Indicators 16.5.1 and 16.5.2.*

<table>
<thead>
<tr>
<th>Score</th>
<th>Methods of processing EO data (Premise 1.1)</th>
<th>Requirement for non-EO information (Premise 1.2)</th>
<th>Level of completeness offered by EO data for the data required (DR) to fully satisfy the indicator (Premise 2) (% given only for guidance)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Empirical or semi-empirical modelling</td>
<td>EO data supplements primary analysis from non-EO data</td>
<td>Very low (1-25% of DR)</td>
</tr>
<tr>
<td>2</td>
<td>Pixel-based technique (unsupervised classification)</td>
<td>EO data in approx. equal combination with non-EO data</td>
<td>Low (26% - 50% of DR)</td>
</tr>
<tr>
<td>3</td>
<td>Pattern-based and sub-pixel based techniques</td>
<td>EO data used directly; non-EO data required e.g. as training set for artificial intelligence</td>
<td>Moderate (51% - 75% of DR)</td>
</tr>
<tr>
<td>4</td>
<td>Image Segmentation-Object-based classification (OBIA)</td>
<td>EO data used directly; limited non-EO data requirement e.g. for validation</td>
<td>High (76% – 90% of DR)</td>
</tr>
<tr>
<td>5</td>
<td>Raw EO data Visual interpretation</td>
<td>EO data used directly; non-EO data is not required</td>
<td>Very high (&gt; 91% of DR)</td>
</tr>
</tbody>
</table>

\[MMS = 4.5 (+/- 0)\]

We scored as a 3 the completeness of EO data (Premise 2) in representing regional favouritism relevant to the indicators 16.5.1 and 16.5.2. Thus, we consider that the approach in this paper offers valuable EO data support to address these indicators (especially where other data are sparse or absent) but that a full calibration of the indicators will need either ground-truthed census-type data as a core component of the dataset or to establish a fully validated, local correlation of the EO data for local corruption and bribery aspects.

3.3 DPSIR framework analysis

In order to gain a fuller perspective on the potential for EO to support the SDG indicators, we assessed the indicators with regard to the well-established DPSIR Framework (Figure 1). This recognises how the structure and mechanisms of a balanced set of indicators can support sustainable development in general and, from previous experience, which groups of indicators within the DPSIR framework have been shown to have been readily amenable to support by EO. We note that the DPSIR model was not a specific basis for the creation of the SDG targets and indicators and so we did not anticipate or envisage *a priori* any specific alignment between these 2 frameworks.
We evaluated SDG indicators according to the DPSIR Framework model based on its components described in the introduction. The classification was based on our judgement along with views expressed in the literature (where available) and we recognise that classifying indicators into the DPSIR categories is not a precise science. We found (seeFig.2) that the indicators are indeed unevenly distributed, which may place an unwanted limitation on the opportunity for EO support across the widest possible range of indicators. An analysis/critique of the array of SDG indicators and targets is outside the scope of this paper.

Only 3 % and 6 % of the SDG indicators fell into the Pressure or Driving Force DPSIR categories respectively. The States indicators were the most strongly represented at 41 % and were found in most of the SDGs. EO could contribute strongly to many of these indicators e.g. 1.1.1, 1.2.1, 1.4.1, 7.1.1, 7.1.2, 7.2.1, 7.3.1, 10.3.1, 11.3.1, 16.b.1. Impact indicators represented 18 % or the total spread, and were mostly related to human health (3.3.3, 3.6.1, 3.9.1, 11.5.1, 11.5.2, 13.1.1) several of which can be indirectly supported by EO. Most SDGs include at least one Response indicator, with 32 % of indicators being of this type. These, however, are typically hard to measure directly by EO. As discussed herein, we consider that there is scope for the use of supportive monitoring by EO data of the progress/regress made by a country in accordance with legislation and national and international agreements and norms relating to the SDGs.

We believe that the unevenness in distribution of the types of SDG indicators, as seen here in the context of the DPSIR framework, places some restriction on the potential role that EO could play in providing data to support the SDGs. As shown in Figure 2 we assess that more than 90 % of the SDG indicators fall into the Response, Impact and State categories of the DPSIR framework. Pressure indicators such as forest fires, over-fishing, emissions to air, water and land, infrastructure, land-use, light pollution, urbanization, are all quite readily tractable to EO but they are not mentioned in the SDG global framework. Indeed, only 3 % of the SDG indicators are Pressure indicators in our interpretation of the DPSIR framework (these being 9.1.2, 9.4.1, 11.1.1., 12.3.1, 14.1.1 (only the part referring to “floating plastic debris density”)), which appear to have a potential for EO data contribution. However, Pressure indicators are important because they are causal in the issue (European Commission, 2001). For instance, pressures on the environment from over-exploitation of resources or the emission of pollution lead to environmental change (Maxim, et al., 2009; European Commission, 2001). In the DPSIR framework, it is common for a target to have a Pressure indicator(s) associated with the appropriate State indicator(s) in order to address problems in a manner linked to cause and effect chains (Spangenberg, 2016). From this brief exploration of the nature of the SDG indicators, we find that considerable unevenness exists between the various DPSIR framework categories and the nature of indicators present currently in the SDG framework. This concurs with Spangenberg’s (2016) finding for the SDG targets. We suggest that when revising the SDG indicators it would be beneficial to consider the effect

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**Figure 1. DPSIR Framework model.** (source: EEA, 1999)
of this imbalance on two main outcomes, 1) the fundamental support of the indicators for the achievement of the SDGs themselves, and 2) maximising the opportunity to harness EO in support of the SGDs.

Figure 2. The proportion of SDG indicators within each of the 5 groups of the DPSIR Framework.

3.4 Discussion

The results presented here suggest that there is potential to use EO-derived data for populating the SDG indicators, but potential does vary across the spectrum of indicators and is not an ‘all or nothing’ proposition. For example, it is important to consider the contribution of EO to indicators that will also require data collected ‘on the ground’, perhaps via surveys. There is also potential to use EO-derived data to triangulate other data and check for accuracy. Proxy indicators have a role here and it is important to consider how EO-derived data applied to the indicators may allow for contributions towards assessing progress towards SDG targets.

Interestingly, the analysis of the SDG indicators suggests that the vast majority fit into the Response, Impact and State components of DPSIR, with few within the Driving Force or Pressure components. But EO can help a great deal with Pressure indicators, as the indicators can be assessed regularly, perhaps daily. Therefore, maybe there should be some reconsideration of the SDG indicators to include more Driving Force and Pressure components, particularly if technology is now available to help with their assessment. We realise that this may be a contentious call and some may argue that availability of data should not be the prime consideration when selecting SDG indicators, but the lack of Driving Force and Pressure indicators in the framework should be a concern in any case whether they are amenable to EO-derived data or not. The results we have presented in the paper relate to example indicators from the SDG framework but there is also potential
to apply the framework to prospectively test hypothetical or as yet untried opportunities for applying EO to SDGs, using indicators not listed in the formal system but which could have applicability to help address targets. We would argue that it is the SDG targets that matter and care does need to be taken that the indicators specified within the SDG system do not become set in stone with no further consideration of alternatives.

Table 7 summarises in ‘dashboard’ form our emerging assessment from the maturity matrix systematic scoring system (MMS) of where the EO ‘opportunities’, particularly those in the socio-economic domain, exist across the full spectrum of the SDGs and their indicators. This ‘dashboard’ type presentation is based on the reviewed papers/reports and the GEO case studies with the colour banding summarising ranges of MMS values assigned to each indicator based on the Premises presented at methods section. A green rating in Table 7 denotes a high potential of EO data directly to measure the SDG indicator, assigned when the MMS is 7 or more. Yellow indicates the SDG indicator might be directly or indirectly measured by EO data, MMS between 4 and 7. Red indicates that the indicator is mostly measured through an indirect approach with EO data playing a minor role, MMS between 1 and 4. In the ultimate version of the dashboard, scores of 0 will be included representing those indicators where no support at all from EO data has been found.

**Table 7. EO potential to monitor SDG Indicator (MMS: red 1-4; yellow 4-7; green 7-10; grey - in progress)**

The dashboard green and yellow colours reflect the greatest potential for satellite data to monitor, support, or contribute, directly or indirectly, to SDG indicators. As can be seen, this is on-going work and a comprehensive assessment of the full set of indicators is under development. The maturity matrix is in an incipient form at present and we expect further evolution based on continuing review of emerging papers/reports.
We recognise a number of limitations in this assessment system for the applicability of EO-derived data for the SDG indicators. First, it should be noted that there is a degree of subjectivity in the assessment of the EO potential, although the literature is used wherever possible to support the decisions that were made. Nonetheless, there is potential for bias in our scoring system because there are two scores for Premise 1 and one for Premise 2. There are also aspects of skew, overlap/double counting between Premise 2 and the second part of Premise 1 etc. There are approaches to adjust for such potential biases e.g. weighting, which can also be used deliberately to place greater weight on some attributes of the system than others when developing such aggregate scores. In the next phase of the research, we will be extending and developing the framework described here, primarily through consultation and opinion-gathering with experts in EO and indicators.

4. Conclusions

We have drawn the following conclusions from this research:

- EO data has a substantial contribution to make in supporting progress towards many of the SDGs. We have found potential for EO data to populate (entirely or in part as valuable, complementary data) several of the socio-economic SDG indicators.
- We have developed a maturity matrix in order to systematically investigate the potential of EO data to monitor/support (directly or indirectly) each SDG indicator and to provide a ‘big picture’ of the potential of satellite imagery data to address individual SDG indicators. This can help further development and bring opportunities to enhance the role that EO can play in offering rich support for the SDGs via the provision of robust, timely, readily updated, independent, transparent and relevant data at economically sustainable cost.
- We have examined the SDG indicators with regard to the DPSIR framework and found an imbalance in the number of indicators attributed to each DPSIR component. This affects and narrows the benefits of EO data which can give full support to Pressure and Driving forces indicators.
- We suggest that some flexibility is required with the SDG indicator set, and there is potential to develop indicators outside of the existing set but which may help with assessing progress towards the SDG targets and also be more amenable to the use of EO-derived data.
- Future work will seek to develop the assessment framework using input from EO and indicator experts.

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