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RESEARCH ARTICLE

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Translation of Earth observation data into sustainable development indicators: An analytical framework

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Abstract

In 2015, member countries of the United Nations adopted the 17 Sustainable Development Goals at the Sustainable Development Summit in New York. These global goals have 169 targets and 232 indicators that 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 often limited resources available. 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 develop a novel analytical framework for assessing the potential of EO approaches to populate the SDG indicators. We present a Maturity Matrix Framework and apply it to all of the 232 SDG indicators. The results demonstrate that although the applicability of EO-derived data do vary between the Sustainable Development Goal indicators, overall, EO has an important contribution to make towards populating a wide diversity of the Sustainable Development Goals indicators.

KEYWORDS

Earth observation (EO), indicators, socio-economic, Sustainable Development Goals (SDGs)

1 | INTRODUCTION

The 17 Sustainable Development Goals (SDGs) of the United Nations were ratified by the United Nations 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 United Nations created a conceptual framework of 169 targets and 232 indicators associated with the SDGs that 193 United Nations 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, 2015, p. 1).

The Inter-Agency Expert Group for the SDGs has developed the Global Indicator Framework of 232 indicators that were officially adopted by the United Nations Statistical Commission at the 48th session in March 2017, but indicators require a supply of good quality data. Data collection methods have been improved for monitoring aspects such as poverty, nutrition, child and maternal health, and access to water and sanitation (Brown & Beattie, 2015). However, there is scope for further improvement to data availability to facilitate 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).

Furthermore, some aspects of the SDG framework have been found to be weaker than others, for example, the monitoring and evaluation of progress under each goal. For instance, Blanc (2015) mapped the interconnections among SDGs targets using network analysis techniques and found that some targets are well connected with each other but there are concerns in other parts of the network. Hence, when agencies and institutions focus on a given goal and its targets, they should also take into account not only the concerned goal but also the potentially interconnected targets of other goals that may also be impacted. Spangenberg (2016) has also criticised the coherence of the SDGs and therefore their impact on implementation. He has classified the SDG targets using the well-established Driving Force-Pressure-State-Impact-Response framework (European Environment Agency, 1999; Organisation for Economic Co-operation and Development, 1993) and found a substantial imbalance in the nature of the targets in the SDG framework. In particular, pressure targets are recognised in his work as "… 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, "...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, 2016). He concludes, given this imbalance in the nature of the SDG targets, that achieving SDG would address to the symptoms of the issues being addressed but not to cure the causes (Spangenberg, 2016).

Earth observation (EO) provides a potential approach that may help with providing data to populate the SDG indicators. Indeed, EO-sourced data have been advocated by several international researchers and organisations to reduce the costs of traditional monitoring of various environmental and other parameters (e.g., forested areas and water bodies) over relevant times, scales, geographical locations, and spatial resolutions. EO spans many approaches, including the use of drones and aircraft, but in this paper, we focus on satellite-based systems. 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 (Parliamentary Office of Science and Technology, 2017). These operate mostly in the microwave spectral region (radar), although more recently, lidar systems, using pulsed light to measure distance, have also been developed. EO satellite-based 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, and buildings). Spatial resolution is a measure of the observable detail in an image. The highest resolution modern sensors can give resolutions of significantly less than 1 m although most of the freely available 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, that is, the width of observation across the ground. Generally, the higher the spatial resolution, the lower is the swath width.

The Group on Earth Observations (GEOs) and its space-agency arm Committee on Earth Observation satellites (CEOS) have presented an initial view as to how EO can support the population of SDG indicators and the GEO EO4SDG programme supported the potential of EO to advance the United Nations 2030 Agenda. CEOS has created an ad hoc team on the SDGs to better coordinate the activities of the CEOS agencies around the SDGs. GEO is working closely with the United Nations Statistics Division, the United Nations Committee of Experts on Global Geospatial Information Management, and the United Nations Sustainable Development Solutions Network (Anderson, Ryan, Sonntag, Kavvada, & Friedl, 2017). A recent report by GEO lists several SDG targets (Table 1) that they conclude that could be most readily supported by EO (GEO, 2017).

Although the GEO study summarised in Table 1 focused mostly on the environmental indicators within the SDGs, EO could potentially also contribute towards populating socio-economic indicators, through direct or proxy measures. For instance, recent studies have shown that night-time light images, obtained from suitable visible sensors, provide an almost direct measurement for estimating global population (Sutton, Roberts, Elvidge, & Baugh, 2001) and indirectly, can also provide data relevant to indicators of economic growth (Henderson, Storeygard, & Weil, 2011), socio-economic activities (Chen & Nordhaus, 2011), poverty (Ghosh, Anderson, Elvidge, & Sutton, 2013; Jean et al., 2016), electricity consumption (Doll & Pachauri, 2010), urbanisation impacts on the environment (Ma, Zhou, Pei, Haynie, & Fan, 2012), and fishing activities (Waluda, Yamashiro, Elvidge, Hobson, & Rodhouse, 2004). Night-time light imaging can even be used to contribute and to analyse the human rights (Li, Li, Xu, & Wu, 2017), corruption (Hodler & Raschky, 2014), and the incidence of breast cancer (Rybnikova & Portnov, 2017). The increasing availability and range of EO data presents a growing opportunity to complement or even replace traditional ground-based methods of collecting environmental and socio-economic data. Indeed, EO can provide data that are spatially and/or temporally richer than ground surveys and/or can be less expensive to acquire.

In this paper, we present the first version of an analytical framework, the Maturity Matrix Framework (MMF), for assessing the potential of EO to populate all 232 of the SDG indicators and provide examples as to how it can be used. The research is, we believe, the first to systematically review the scope for using EO especially for the full breadth of the SDG indicators and to assess its potential for providing data, either directly or indirectly, and wholly or partially, for their population. The paper sets out the MMF and its assumptions and presents results for two example indicators to illustrate the rationale involved and a summary of results for all 232 indicators.

2 | METHODOLOGY

2.1 | Maturity Matrix Framework

The authors reviewed systematically more than 80 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

TABLE 1 Group on Earth Observation's perspective on Sustainable Development Goals targets and indicators supportable via Earth observations. (after: GEO, 2017)

SDG	Title	Target	Indicator
1	No poverty	1.5	—
2	Zero hunger	2.3, 2.4, 2.c	2.4.1
3	Good health and well-being	3.3, 3.4, 3.9, 3.d	3.9.1
4	Quality education	—	—
5	Gender equality	—	5.9.1
6	Clean water and sanitation	6.3, 6.4, 6.5, 6.6, 6.a, 6.b	6.3.2, 6.4.2, 6.5.1, 6.6.1
7	Affordable and clean energy	7.2, 7.3, 7.a, 7.b	7.1.1
8	Decent work and economic growth	8.4	—
9	Industry, innovation and infrastructure	9.1, 9.4, 9.5, 9.a	9.1.1
10	Reduced inequalities	—	—
11	Sustainable cities and communities	11.3, 11.4, 11.5, 11.6, 11.7 11.b, 11.c	11.3.1, 11.6.2, 11.7.1
12	Responsible consumption and production	12.2, 12.a, 12.b	—
13	Climate action	13.1, 13.3, 13.b	
14	Life below water	14.1, 14.2, 14.3, 14.4, 14.6, 14.7, 14.a	14.3.1
15	Life on land	15.1, 15.2, 15.3, 15.4, 15.5, 15.7, 15.8, 15.9	15.1.1, 15.2.1, 15.3.1 15.4.1, 15.4.2
16	Peace, justice and strong institutions	—	—
17	Partnerships for the goals	17.6, 17.7, 17.9, 17.16, 17.17	—

Note. SDG: Sustainable Development Goals. The table shows the SDGs with most opportunities for the use of Copernicus data and services. The authors of the report conclude that Earth observation has potential to especially contribute towards SDGs 2, 6, 11, 13, 14, and 15 (shaded in the table).

included several SDG indicators in a single report). The review and the development of the MMF and its premises evolved iteratively, using an early set of papers and reports, to design an initial version of the MMF (shown in Table 2). Subsequently, the full MMF was applied for the all the papers, reports and SDG indicators reviewed. A Maturity Matrix Score (MMS) ranging from 0 (no evidence of potential) to 10 (strong evidence of potential) was derived for the potential role of EO to populate each SDG indicator using the assumptions and equations outlined below.

MMF is based upon two "premises." 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 two 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

TABLE 2 Maturity Matrix for the potential contribution of Earth observation to meeting the data needs for a Sustainable Development Goals indicator

	First premise			Second premise
Score		**Methods of processing EO data (Premise 1.1)**	**Requirement for non-EO information (Premise 1.2)**	**Level of completeness offered by EO data for the DR to fully satisfy the indicator (Premise 2). Please note the percentage is only given for guidance.**
0		Indicator cannot be measured by EO data	Indicator measured by non-EO data	Not applicable
1	Applications of algorithms to EO satellite data	Empirical or semi-empirical modelling	EO data supplements primary analysis based on non-EO data	Very low (1–25% of DR)
2		Pixel-based technique (unsupervised classification)	EO data used in approx. equal combination with non-EO data	Low (26% - 50% of DR)
3		Pixel-based and subpixel-based techniques	EO data used directly; non-EO DR, eg, as training set for artificial intelligence	Moderate (51–75% of DR)
4		Image Segmentation - Object-based classification	EO data used directly; limited non-EO data requirement, for example, for validation	High (76–90% of DR)
5	Preprocessed EO data	Visual interpretation	EO data used directly; non-EO derived data are not required	Very high (>91% of DR)
MMS = X (+/− x)				

Note. EO: Earth observation; DR: data required.

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, whereas in other cases, EO derived data may be enough to entirely populate the indicator. An 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 where there was no evidence in the literature for EO providing data were scored as 0.

We first use a mean formula for calculating the score from the two elements of Premise 1:

Premise 1.1: The range of methods for processing EO data

Premise 1.2: The requirement for non-EO information

Therefore:

$$\text{Premise 1 mean score (P1)} = \frac{\text{Premise 1.1} + \text{Premise 1.2}}{2}.$$

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 have multiple components that may vary in terms of their "addressability" via EO derived data. For example, they may have a numerator and denominator. Some components may be more amenable to being addressed via EO derived data than others. Therefore, under Premise 2, it is necessary to allow for multiple answers for one indicator, hence:

$$\text{Premise 2 mean score (P2)} = \textstyle\sum_{S=1}^{S=5}\frac{S}{n},$$

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:

$$\text{Maturity Matrix Score (MMS)for indicator} = \text{P1} + \text{P2}.$$

For example, with an indicator having the following scores (Table 2):

Premise 1.1: score 2 (pixel-based technique)

Premise 1.2: score 3 (EO data used directly but non-EO data are required)

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

$$\text{P1} = \frac{2+3}{2} = 2.5.$$

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:

$$\text{P2} = \frac{4+5}{2} = 4.5.$$

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

It should be noted that the scores allocated in the two premises are semi-quantitative, expert representations based on the published literature, although it does include a significant element of subjective judgement. Hence, although the MMS is a total of the average of Premises 1.1 and 1.2 plus the score for Premise 2, we have included an indication (the +/− element) for cases where a single score in Premise 2 is not assigned but a range is considered more appropriate.

2.2 | MMF assumptions

2.2.1 | 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 methods for processing EO data presented by the United Nations (2017) and Li, Zang, Zhang, Li, and Wu (2014), which are used to match against the approaches outlined in the literature. This is included in Table 2 for Premise 1 and distinguishes between data that were processed through the use of algorithms (Scores 1 to 4) and visual interpretation of preprocessed EO data (Score 5). 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, Gober, Brazel, Grossman-Clarke, and Weng (2011) and Weih and Riggan (2010) have shown how object-based classification out-performed "in terms of classification accuracy" both unsupervised and supervised pixel-based classification methods. Hence, our classification of Premise 1.1 is based on an assumed preference hierarchy of Object-based > Pixel-based > Empirical-based methods in terms of the quality of data that can be derived as support for an SDG indicator. It is acknowledged that this assumption of hierarchy can be challenged, but it does provide a first step towards a more comprehensive uncertainty analysis. The rationale for the scores under Premise 1.1 are set out in Table 3.

2.2.2 | Non-EO information (Premise 1.2)

The need for non-EO information (from surveys etc.) to complement EO data were evaluated in the second part of Premise 1, and a score between 1 and 5 was assigned. In much of the reviewed material, especially those relating 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 the papers a score from 1 to 5 depending on the non-EO data used, its importance, and implications. A low score implies that EO data are used only to supplement non-EO data. For intermediate scores, non-EO data are used to provide a "training set" for EO algorithms and for high scores, EO data are used directly with, perhaps, some non-EO data for validation purposes only.

TABLE 3 Rationale for scoring via the methods of processing EO data employed within Premise 1.1

Score	Method	Rationale
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. It 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	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 night-time luminosity dataset. The raw data are first transformed on an empirical basis to correct for various distortions (Chen & 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 (extracted from corrected NPP-VIIRS data and DMSP-OLS data) and the variable measured (GDP growth, electricity consumption, etc.).
2	*Pixel-based Technique Unsupervised classification (e.g. K-means, Iterative Self-Organizing Data Analysis (ISODATA), Self-Organizing Maps (SOM), hierarchical clustering)*	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 the attributing score 2 to this method, we have taken into account the level of accuracy presented in Weih and Riggan (2010).
3	*Pixel-based techniques and Sub-pixel based 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 night-time 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 five 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 and Fuzzy-spectral mixture analysis.
4	*Image Segmentation Object-based classification (OBIA)*	This performs a classification based on objects rather than pixels through image segmentation followed by the image objects being 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 high accuracy with object-based approaches (Myint et al., 2011; Wang, Sousa, & Gong, 2004; Weih & Riggan, 2010).
5	*Visual interpretation* methods	These are used directly on the pre-processed satellite data. A first step is to minimize distortions and/or errors that can affect the subsequent visual classification process. Once an image is generated and received from a satellite instrument (and before it is moved to the next stage), it can receive a number of pre-processing correction methods such as geometric, atmospheric, radiometric, band combinations and data fusion (Khorram, Koch, Van der Wiele, & Nelson, 2012). Most pre-processing algorithms will be adapted to deal with the specific application for which the data is being used. The visual interpretation is then performed by direct operator (human) examination of features from the imagery 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).

2.2.3 | Level of completeness (Premise 2)

This represents the level of completeness offered by EO data for the data required 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 requirements 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 multiaspect indicator.

3 | RESULTS

As an illustration of the results achieved to date using the MMF, we provide detailed examples below, which assess the potential of EO to calibrate two of the SDG indicators: illegal and unregulated fishing and corruption and bribery. 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 (SDG indicator 14.6.1)

Indicator 14.6.1 is applied to measure progress towards SDG Target 14.6 and is defined as:

> *"Progress by countries in the degree of implementation of international instruments aiming to combat illegal, unreported and unregulated fishing."*

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 survey questionnaire, circulated by FAO every 2 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. The essential features for the indicator regarding EO are set out in Table 4, and the results of applying the MMF are provided in Table 5.

Several papers referring to detecting and tracking of fishing vessels are available in the literature. A particularly relevant example is Straka et al. (2015) who used Suomi National Polar-Orbiting Partnership Visible Infrared Imaging Radiometer Suite to identify and track ship lights of fishery activities. A unique component of VIIRS is the day–night band. 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, Japan, and the Republic of Korea. There, the parties ratified the Sino-Japanese Fishery Agreement in 1997, establishing a Provisional Measures Zone with clear delimitations and laws. The study, including individual EO data collections and composites for several months,

TABLE 4 Essential questions in assessing the feasibility of Earth observation applicability to Indicator 14.6.1(illegal and unregulated fishing)

Essential questions to assess the feasibility of EO applications for SDGs indicators	Answer
What characteristic(s) is/are measured?	Illegal, unreported, and unregulated (IUU) fishing
What data are used?	Suomi National Polar-Orbiting Partnership (S-NPP) Visible Infrared Imaging Radiometer Suite
How is the EO data processed?	Visual interpretation of pre-processed EO data
What type of approach (direct/indirect) is used in the paper(s)/report(s) in relation to the SDG indicator?	Direct

Note. EO: Earth observation; SDG: Sustainable Development Goal.

TABLE 5 Completed Maturity Matrix for potential contribution of Earth observation data to Sustainable Development Goal Indicator 14.6.1 (illegal and unregulated fishing)

	First premise			Second premise
Score		Methods of processing EO data (Premise 1.1)	Requirement for non-EO information (Premise 1.2)	Level of completeness offered by EO data for the data required (DR) to fully satisfy the indicator (Premise 2). Please note the percentage is only given for guidance.
0		Indicator cannot be measured by EO data	Indicator measured by non-EO data	Not applicable
1	Applications of algorithms to EO satellite data	Empirical or semiempirical modelling	EO data supplements primary analysis based on non-EO data	Very low (1–25% of DR)
2		Pixel-based technique (unsupervised classification)	EO data used in approx. equal combination with non-EO data	Low (26–50% of DR)
3		Pixel-based and subpixel based techniques	EO data used directly; non-EO DR, for example, as training set for artificial intelligence	Moderate (51–75% of DR)
4		Image segmentation -object-based classification (OBIA)	EO data used directly; limited non-EO data requirement, for example, for validation	High (76–90% of DR)
5	Preprocessed EO data	Visual interpretation	EO data used directly; non-EO derived data are not required	Very high (>91% of DR)
MMS = 9 (+/− 1)				

Note. Shaded cells are the criteria that were selected to yield the Maturity Matrix Score (MMS) on the approach presented by Straka et al. (2015) who used Suomi National Polar-Orbiting Partnership Visible Infrared Imaging Radiometer Suite (S-NPP VIIRS) to identify and track ship lights of fishery activities.

provides clear evidence of the locations of fishing vessels with respect to the boundaries of these agreements. Such information can help FAO to determine which regions may be at risk of overfishing worldwide and thus which countries do not conform to the CCRF. Therefore, we assigned a score of 5 to both parts of Premise 1 of the maturity matrix for this use of preprocessed EO data because it could be interpreted visually and the EO data could be used directly without non-EO data in order 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. 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 (SDG indicator 16.5.1 and 16.5.2)

These indicators are defined as follows:

> 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"*
>
> 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."*

Both 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. The essential features for these indicators regarding EO are set out in Table 6 and the results of applying the MMF are provided in Table 7.

TABLE 6 Essential questions in assessing the feasibility of Earth observation applicability to indicators 16.5.1 and 16.5.2 (corruption and bribery)

Essential questions to assess the feasibility of EO applications for SDGs indicators	Answer
What characteristic(s) is/are measured?	Corruption and bribery
What data are used?	Satellite data on night-time light intensity and information about the birthplaces of the countries' political leaders.
How are EO data processed?	Pre-processing methods (corrections), Value classification and dependent variable
What type of approach (direct/indirect) is used in the paper reviewed in relation to SDG indicator?	Indirect

Note. EO: Earth observation; DR: data required.

TABLE 7 Completed Maturity Matrix for potential contribution of Earth observation data to Sustainable Development Goal indicators 16.5.1 and 16.5.2 (corruption and bribery)

	First Premise			Second Premise
Score		Methods of processing EO data (Premise 1.1)	Requirement for non-EO information (Premise 1.2)	Level of completeness offered by EO data for the data required (DR) to fully satisfy the indicator (Premise 2). Please note the percentage is only given for guidance.
0		Indicator cannot be measured by EO data	Indicator measured by non-EO data	Not applicable
1	Applications of algorithms to EO satellite data	Empirical or semiempirical modelling	EO data supplements primary analysis based on non-EO data	Very low (1–25% of DR)
2		Pixel-based technique (unsupervised classification)	EO data used in approx. equal combination with non-EO data	Low (26–50% of DR)
3		Pixel-based and subpixel based techniques	EO data used directly; non-EO DR, for example, as training set for artificial intelligence	Moderate (51–75% of DR)
4		Image segmentation - object-based classification (OBIA)	EO data used directly; limited non-EO data requirement, for example, for validation	High (76–90% of DR)
5	Preprocessed EO data	Visual interpretation	EO data used directly; non-EO derived data are not required	Very high (>91% of DR)
MMS = 4.5 (+/− 0)				

Note. Shaded cells are the criteria that were selected to yield the Maturity Matrix Score (MMS) on the empirical approach to measuring bribery and corruption using Defence Meteorological Satellite Program satellite night-time imagery demonstrated by Hodler and Raschky (2014). EO: Earth observation.

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 night-time imagery and non-EO information about the birthplaces of a country's political leaders from over 38,000 subnational regions of 126 countries between 1992 and 2009. Night-time light intensity is valuable as a proxy for economic activity (e.g., consumption and production; Ghosh, Anderson, Powell, Sutton, & Elvidge, 2009; Li, Xu, Chen, & Li, 2013; Shi et al., 2014). Therefore, Hodler and Raschky's (2014) EO data were able to serve as proxy evidence for regional favouritism in some 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 night-time 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 disproportionally in a leader's birthplace.

In Premise 1.1 of the matrix, we assigned a score of 1 due to corrections of the raw night-time 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 night-time light); thus, the obtained data sets are DN proportional to radiance. Therefore, the empirical model shows generally higher economic activity in the more night light-intense areas. In order to validate their assumptions, the DN data have been modelled through a variety of regression models, such as dummy variables in semi logarithmic regressions. The EO data were given a score of 2 for Premise 1.2 because complementary non-EO data for the political leaders' birthplace and the relationship of night-time light intensity with economic activity have been used in approximately equal proportions with the EO data for the night-time light intensity. Hodler and Raschky (2014) 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 night-time light intensity measurements. We scored a 3 for 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

TABLE 8 Earth observation potential to monitor Sustainable Development Goal indicator, final version, July 2018

1. NO POVERTY													2. ZERO HUNGER												
1.1	1.2		1.3	1.4		1.5			1.a			1.b	2.1		2.2		2.3		2.4	2.5		2.a		2.b	2.c
1.1.1	1.2.2	1.2.2	1.3.1	1.4.1	1.4.2	1.5.1	1.5.2	1.5.3	1.a.1	1.a.2	1.a.3	1.b	2.1.1	2.1.2	2.2.1	2.2.2	2.3.1	2.3.2	2.4.1	2.5.1	2.5.2	2.a.1	2.a.2	2.b.1	2.c.1

3. GOOD HEALTH AND WELL-BEING																									
3.1		3.2		3.3					3.4		3.5		3.6	3.7		3.8		3.9			3.a	3.b		3.c	3.d
3.1.1	3.1.2	3.2.1	3.2.2	3.3.1	3.3.2	3.3.3	3.3.4	3.3.5	3.4.1	3.4.2	3.5.1	3.5.2	3.6.1	3.7.1	3.7.2	3.8.1	3.8.2	3.9.1	3.9.2	3.9.3	3.a.1	3.b.1	3.b.2	3.c.1	3.d.1

4. QUALITY EDUCATION											5. GENDER EQUALITY													
4.1	4.2		4.3	4.4	4.5	4.6	4.7	4.a	4.b	4.c	5.1	5.2		5.3		5.4	5.5		5.6		5.a		5.b	5.c
4.1.1	4.2.1	4.2.2	4.3.1	4.4.1	4.5.1	4.6.1	4.7.1	4.a.1	4.b.1	4.c.1	5.1.1	5.2.1	5.2.2	5.3.1	5.3.2	5.4.1	5.5.1	5.5.2	5.6.1	5.6.2	5.a.1	5.a.2	5.b.1	5.c.1

6. CLEAN WATER & SANITATION											7. AFFORTABLE & CLEAN ENERGY						8. DECENT WORK & ECONOMIC GROWTH								
6.1	6.2	6.3		6.4		6.5		6.6	6.a	6.b	7.1		7.2	7.3	7.a	7.b	8.1	8.2	8.3	8.4		8.5		8.6	8.7
6.1.1	6.2.1	6.3.1	6.3.2	6.4.1	6.4.2	6.5.1	6.5.2	6.6.1	6.a.1	6.b.1	7.1.1	7.1.2	7.2.1	7.3.1	7.a.1	7.b.1	8.1.1	8.2.1	8.3.1	8.4.1	8.4.2	8.5.1	8.5.2	8.6.1	8.7.1

8. DECENT WORK & ECONOMIC GROWTH (contd.)								9. INDUSTRY, INNOVATION & INFRASTRUCTURE												10. REDUCED INEQUALITIES					
8.8		8.9		8.10		8.a	8.b	9.1		9.2		9.3		9.4	9.5		9.a	9.b	9.c	10.1	10.2	10.3	10.4	10.5	10.6
8.8.1	8.8.2	8.9.1	8.9.2	8.10.1	8.10.2	8.a.1	8.b.1	9.1.1	9.1.2.	9.2.1	9.2.2	9.3.1	9.3.2	9.4.1	9.5.1	9.5.2	9.a.1	9.b.1	9.c.1	10.1.1	10.2.1	10.3.1	10.4.1	10.5.1	10.6.1

10. REDUCED INEQUALITIES (contd.)					11. SUSTAINABLE CITIES & COMMUNITIES															12. RESPONSIBLE CONSUMTION & PROD[N]					
10.7		10.a	10.b	10.c	11.1	11.2	11.3		11.4	11.5		11.6		11.7		11.a	11.b		11.c	12.1	12.2		12.3	12.4	
10.7.1	10.7.2	10.a.1	10.b.1	10.c.1	11.1.1	11.2.1	11.3.1	11.3.2	11.4.1	11.5.1	11.5.2	11.6.1	11.6.2	11.7.1	11.7.2	11.a.1	11.b.1	11.b.2	11.c.1	12.1.1	12.2.1	12.2.2	12.3.1	12.4.1	12.4.2

12. RESPONSIBLE CONSUMTION & PROD[N] (contd.)							13. CLIMATE ACTION							14. LIFE BELOW WATER											
12.5	12.6	12.7	12.8	12.a	12.b	12.c	13.1		13.2	13.3		13.a	13.b	14.1		14.2	14.3	14.4	14.5	14.6	14.7	14.a	14.b	14.c
12.5.1	12.6.1	12.7.1	12.8.1	12.a.1	12.b.1	12.c.1	13.1.1	13.1.2	13.2.1	13.3.1	13.3.2	13.a.1	13.b.1	14.1.1 (a)	14.1.1 (b)	14.2.1	14.3.1	14.4.1	14.5.1	14.6.1	14.7.1	14.a.1	14.b.1	14.c.1

15.LIFE ON LAND														16. PEACE, JUSTICE & STRONG INSTITUTIONS											
15.1		15.2	15.3	15.4		15.5	15.6	15.7	15.8	15.9	15.a	15.b.	15.c	16.1				16.2			16.3		16.4	
15.1.1	15.1.2	15.2.1	15.3.1	15.4.1	15.4.2	15.5.1	15.6.1	15.7.1	15.8.1	15.9.1	15.a.1	15.b.1	15.c.1	16.1.1	16.1.2	16.1.3	16.1.4	16.2.1	16.2.2	16.2.3	16.3.1	16.3.2	16.4.1	16.4.2

16. PEACE, JUSTICE & STRONG INSTITUTIONS (contd.)												17. PARTENERSHIPS FOR THE GOALS													
16.5		16.6		16.7		16.8	16.9	16.10		16.a	16.b	17.1		17.2	17.3		17.4	17.5	17.6		17.7	17.8	17.9	17.10	17.11
16.5.1	16.5.2	16.6.1	16.6.2	16.7.1	16.7.2	16.8.1	16.9.1	16.10.1	16.10.2	16.a.1	16.b.1	17.1.1	17.1.2	17.2.1	17.3.1	17.3.2	17.4.1	17.5.1	17.6.1	17.6.2	17.7.1	17.8.1	17.9.1	17.10.1	17.11.1

17. PARTENERSHIPS FOR THE GOALS (contd.)										
17.12	17.13	17.14	17.15	17.16	17.17	17.18			17.19	
17.12.1	17.13.1	17.14.1	17.15.1	17.16.1	17.17.1	17.18.1	17.18.2	17.18.3	17.19.1	17.19.2

MMS dashboard of SDG Indicators

No evidence in the literature	4-7- Medium support from EO
1-4- Weak support from EO	7-10- Strong support from EO

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 data set or to establish a fully validated, local correlation of the EO data for local corruption, and bribery aspects.

3.3 | MMS dashboard

The MMF has been applied to all 232 indicators within the SDGs, and the results are presented as a “dashboard” in Table 8. The shading summarises the ranges of MMS values assigned to each indicator, with darker shading representing higher MMS and no shading indicating a MMS of zero. There were 84 indicators with sufficient evidence from the literature to generate a MMS above 0, and this represents 36% of the total number of SDG indicators.

MMS values between 1 and 4 represent a weak support from EO to SDG indicators. In this case, the indicator is mostly populated through an indirect approach, relying mostly on non-EO data; thus, EO is playing only a minor role. Where the MMS is between 4 and 7, the SDG indicator might be directly or indirectly populated by EO data; both type of data have equally implications and importance. MMS values between 7 and 10 denote a high potential of EO data directly to populate the SDG indicator, and non- EO data might be used only for validation. MMS 0 represents indicators with no present evidence in the literature of support for population via EO data.

4 | DISCUSSION

It first has to be noted that we recognise the MMF presented here for the applicability of EO-derived data for the SDG indicators has limitations even though the literature is used wherever possible to support the decisions made. Limitations exist for example in the various assumptions that underpin the MMS and in the degree of subjectivity in the evaluation of the EO potential. There is, of course, potential also for bias in our scoring system because there are two scores for Premise 1 and one for Premise 2 and also aspects of possible skew, overlap/double counting between Premise 2 and the second part of Premise 1, etc. Approaches exist for adjusting for such potential biases, for example, weighting, which can also be used deliberately to place greater weight on some attributes of the system than others when developing such aggregate scores. Nonetheless, it is necessary to unpack the key decisions within the MMF as much as possible to minimise such limitations. However, it still provides the first published example we are aware of that sets out to assess all of the SDG indicators in terms of their potential population via EO derived data, and although the findings need to be treated with some caution, they do provide clues.The results suggest that there is considerable potential to use EO-derived data for populating the SDG indicators but that this does vary across the spectrum of indicators and is not an “all or nothing” proposition (Table 8). Some of the findings are already well-known. For example, there is an abundance of literature showing how EO derived data are applied within deforestation, agriculture, water resource management, and land use change (see, for example, Singh, Semwal, Rai, & Chhikara, 2002; Zhang et al., 2003; Sawaya, Olmanson, Heinert, Brezonik, & Bauer, 2003; Kuemmerle et al., 2009; Margono et al., 2012; Lynch, Maslin, Balzter, & Sweeting, 2013). Lynch et al. (2013) argue that improving the spatial resolution and the revisit time would substantially 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.

Interestingly, the findings of the MMF suggest that many socio-economic indicators may also be amenable to population via EO and this is an area that has received much less attention in the literature. There are published examples of utilising EO derived data for socio-economic dimensions of sustainable development such as poverty (Ghosh et al., 2013; Jean et al., 2016), electricity consumption (Doll & Pachauri, 2010), human rights (Li et al., 2017), child labour and slavery (Boyd et al., 2018), corruption (Hodler & Raschky, 2014), and the incidence of breast cancer (Rybnikova & Portnov, 2017), but EO needs to achieve greater prominence with regard to its potential for supporting the SDGs that span both natural, social, and economic dimensions of sustainable development. Moreover, terrestrial applications of EO satellite data can respond in near real-time to humanitarian and peace-keeping operations (Corbane, Kemper, Pesaresi, Louvrier, & Freire, 2016) and natural disasters (e.g., flood hazard; Kerle & Oppenheimer, 2002). This allows for continuous monitoring and verification of on-the-ground reports with the aim of decreasing or preventing the humanitarian disaster and human rights crimes in politically unstable and chronic conflict areas. The potential of EO to help is certainly there and needs to be embraced more widely.

The results we have obtained 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. This could be applied to indicators not presently listed in the formal SDG system but which could have applicability to help address sustainable development targets. We readily acknowledge that the set of indicators defined by the UN for the SDGs will have a strong degree of “acceptability” amongst policy makers and others, and suggestions for alternative indicators, even if they are geared towards the same SDG target, may be regarded as being of lesser relevance. The SDG indicators may be seen as key performance reporting tools and attempts to replace or even supplement them with other indicators may be regarded with suspicion. However, we would argue for flexibility here, and it is the SDG targets that matter and care that does need to be taken that the indicators specified within the SDG system do not become overrigid, with no further consideration of alternatives.

As noted above, the MMF does need further development and with that goal in mind, research is continuing to develop a more detailed MMS framework that further increases the transparency and amenability to testing under “what if?” scenarios for the various assumptions we have made. We will also be seeking the views of experts in the EO and indicator communities on the further refinement and evolution of the MMS framework.

5 | CONCLUSIONS

The following conclusions can be drawn from this research:

- A novel MMF was developed and applied for systematic investigation of the potential of EO data to monitor/support (directly or indirectly) each of the 232 SDG indicators and to provide a "big picture" of the potential of satellite imagery data to address individual SDG indicators. This approach can help further development and opportunities to enhance the role of EO in offering rich support for the SDGs via robust, timely, readily updated, independent, transparent, and relevant data at economically sustainable cost.
- EO derived data can make a substantial contribution in supporting progress towards many of the SDGs, including those that are more socio-economic in nature.
- There is potential to develop indicators outside the established set of SDG indicators that may be more amenable to the use of EO-derived data.
- Future work with the MMF approach will integrate additional input and perspectives from the wider community of EO and indicator experts.

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