

Chapter 13

Digital Earth for Sustainable Development Goals



Graciela Metternicht, Norman Mueller and Richard Lucas

Abstract Sustainable development is nothing new, but it has proven notoriously difficult to implement in practice. The 2030 Agenda for Sustainable Development, with 17 goals, 169 targets and 232 associated indicators, was approved at the 2015 UN General Assembly and addresses the economic, social and environmental pillars of development, aspiring to attain by 2030 a sustainable future that balances equitable prosperity within planetary boundaries. While the goals are universal (i.e., applicable to both developing and developed countries), it is left to individual countries to establish national Sustainable Development Goal (SDG) targets according to their own priorities and level of ambition in terms of the scale and pace of transformation aspired to.

Keywords Sustainable development goals · Digital Earth · Earth Observation · Big Earth data · Indicators · Land cover classification

13.1 Fundamentals of Digital Earth for the Sustainable Development Goals

The Digital Earth (DE) exists in parallel to the physical Earth along with some translating elements between them (Sudmanns et al. 2019). Chapter 1 describes the origin, evolution and main elements of Digital Earth, and the links between Digital Earth, Big Data (Chap. 9) and big Earth data. Guo (2017) argues that, from the perspective of big data, big Earth data inherits big data's 'Vs' (volume, velocity and

G. Metternicht (✉)

School of Biological, Earth and Environmental Sciences, The University of New South Wales, High Street, Kensington, NSW 2052, Australia
e-mail: g.metternicht@unsw.edu.au

N. Mueller

Geoscience Australia/Digital Earth Australia (DEA), GPO Box 378, Canberra, ACT 2601, Australia

R. Lucas

Department of Geography and Earth Sciences, Aberystwyth University, Aberystwyth, Ceredigion, Wales SY233DB, UK

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variety) and, in this context, DE can be considered to be big Earth data. Furthermore, as big Earth data research focuses on synthesis of systematic observations of the Earth, as well as data-intensive methods for studying Earth system models, based on the premise of increased knowledge discovery (Chap. 1), Digital Earth can support countries in their implementation of the 2030 Agenda for Sustainable Development.

Through analysis of recent literature and a case study, this chapter collects and presents evidence of the potential and limitations of Digital Earth for systematic generation of information and knowledge for use in measuring progress towards the Sustainable Development Goals (SDGs). We frame the analysis and discussion around priorities for implementation (ICSU, ISSU 2015), including:

- (a) the design of SDG indicator metrics at national levels and how Digital Earth, through the Analysis Ready Data (ARD) concept, can contribute to that end
- (b) harmonized national metrics for SDG implementation, including for baseline determination and target setting
- (c) setting up monitoring platforms for tracking progress towards the SDGs
- (d) knowledge needs for assessing implementation of actions and strategies towards achieving set SDG targets
- (e) governance and institutional arrangements, including multi-stakeholder participation.

The remainder of the chapter is structured as follows. Section 13.2 identifies the information needs of countries for the implementation of the SDGs, including for the SDG Global Indicator Framework (GIF). Section 13.3 summarizes the findings of recent research and practice on the use of Digital Earth (including Earth Observation¹ and social sensing) in support of the SDGs. Section 13.4 presents a national case study of multi-stakeholder engagement in the operationalization of the Indicator Framework of the Sustainable Development Goals with Earth Observations. The chapter closes (Sect. 13.5) with an outlook on the prospects of Digital Earth and big Earth Data in relation to the SDGs.

13.2 Information and Knowledge Relevant to National Implementation of the SDGs

The SDGs provide a coherent, evidence-based framework for development planning and programming at a national level (Allen et al. 2017a). The goals and targets essentially set the desired destination for development through to 2030 and provide a framework for monitoring progress. This section introduces the metrics agreed for monitoring and reporting of the SDGs, and broadly identifies data and information requirements for their implementation.

¹The Earth Observation data in this chapter refers to the definition provided by Nativi et al. (2019).

13.2.1 How the SDGs Are Monitored and Reported

The Global Indicator Framework (GIF) was established in March 2016 to monitor progress towards achieving the SDGs (UN Statistical Commission 2016). The SDG indicators have been grouped into three different tiers according to the level of data availability and methodological development. Of the 232 SDG indicators that make up the GIF, as of March 2019, 101 are classified as being Tier I. This means that the indicator is conceptually clear, has an internationally established methodology and standards, and the data are regularly compiled for at least 50% of participating countries. The remaining indicators are Tier II (94 indicators), which are conceptually clear but for which the data are not regularly produced by participating countries, or Tier III (34 indicators), for which no internationally established methodology or standards are yet available. Six indicators are determined as having several tiers (Inter-Agency and Expert Group on Sustainable Development Goals 2019). Hence, three years after the adoption of the GIF, less than half (44%) of the SDG indicators can be confidently populated.

It is worth noting that the SDG indicators are essentially **performance metrics** and, as such, are reported regularly at *national levels* through National Voluntary Reports (NVRs) (UNGA 2015, paras. 79 and 84), and annually at the *global level*. The latter is undertaken by the UN Secretary General to inform the High-Level Political Forum based on a selection of indicators from the GIF for which data are available, as mandated by the General Assembly (UNGA 2015, para. 83). For Tier I and II indicators, the availability of data at national levels may not necessarily align with the global tier classification, and countries can create their own tier classification for implementation.

13.2.2 Information Needs for Implementation of the SDGs

Recent research (Allen et al. 2018, 2019) has identified challenges for implementing the SDGs that, in turn, influence information and knowledge needs.

- (a) The comprehensiveness of scope makes prioritization essential.
- (b) The goals are integrated, with very complex feedback and dynamics. This is a significant change from prior narrow, linear approaches to development.
- (c) The SDG targets have complex trade-offs and synergies, and conflict can emerge from the interactions between targets and goals (Lusseau and Mancini 2019; Nilsson et al. 2016; Le Blanc 2015; Allen et al. 2019).
- (d) Currently, there is a weak conceptual understanding of these interlinkages, which limits the ability to respond with coherent policy and management across sectors (Allen et al. 2018; Spangenberg 2017).

Challenges related to aspects of target-setting are that the system of SDGs is not coherent, but rather a network of interlinked targets and a reflection of the political

mapping of development priorities rather than a reflection of how the Earth System works (Le Blanc 2015). Furthermore, the SDGs do not reflect the cause–effect relationships that are needed to understand how the achievement of one target could impact on the other targets. Hence, national implementation of the SDGs requires more than information on performance metrics. For example, timely data in support of policy formulation and targeted interventions may be of much greater importance for countries aiming to advance the implementation of the SDGs according to their national circumstances than simply providing a metric around an agreed global indicator. Furthermore, implementation of the SDGs at national levels also requires determining a baseline for 2015, deciding on targets for 2030, as well as a system for tracking the progress towards the set targets, monitoring the performance of decisions (actions, policies and strategies) and reporting advances using the GIF.

Building an evidence-based framework for national implementation, monitoring and reporting of the SDGs requires government agencies (including National Statistics Offices) to address the what, why and how of data and information provision (Fig. 13.1).

- (a) What is happening requires baseline assessment of indicators related to SDG targets, identifying priorities (e.g., what SDG targets or goals a country is lagging behind) and the identification of data and information gaps needed for such assessment, as summarized in Allen et al. (2017b).
- (b) Why it is happening (e.g. drivers of and pressures leading to (un)sustainable development) relates to the need for systems analysis of interlinkages between SDG targets, understanding of cause–effect relationships, feedbacks and dynamics, and the identification of leverage points for actions and strategies to accomplish the transformational changes that the SDGs aim for.
- (c) How to accomplish changes, demands that countries answering the above questions also understand how data and information are to be obtained and integrated.



Fig. 13.1 National implementation of the SDGs requires evidence-based approaches for monitoring and reporting. As implementation will largely rely upon national action, government actions, through their policy, planning, regulatory and expenditure functions—i.e. the ‘plan, do, check, act’ planning cycle are central to the delivery

13.3 State of the Art for the SDGs in DE

Whether 3Vs, 5Vs (including volatility and veracity, as suggested by Hammer et al. 2017) or 6Vs (including volatility, veracity and value: Fig. 13.2), big data may offer new cost-effective or efficient ways of compiling indicators, improving timeliness, and compiling linkable datasets, and also open the way for cross-cutting analyses that may help with better understanding of the causation and identification of relevant and coherent policy interventions (see Fig. 13.1).

When adopting the SDGs, the United Nations (UN) Assembly recognized the contribution that could be made by Earth Observation (EO) and geospatial information (i.e., big Earth data) in supporting and tracking progress towards the SDGs (UNGA 2015, para. 76). Analysis and interpretation of big Earth data, including Earth Observation, have much to offer the SDGs and other multi-lateral environmental agreements (Sudmanns et al. 2019). However, MacFeely (2019) makes a case for the challenges that big data face (legal, technical and ethical) concerning their use in compiling SDG indicators. National statistical offices, government agencies and UN agencies, which are the custodians of specific SDGs tasked with implementing the



Fig. 13.2 The 6Vs of big data for official statistics. Modified from Hammer et al. (2017)









GIF, face concerns about whether big data are representative and stable enough to be used consistently for compiling the SDG indicators and also their operationalization. For example, in the Big Data Project Inventory compiled by the UN Global Working Group on Big Data, 34 national statistical offices from around the world registered 109 separate big data projects and their potential contribution to the SDG implementation. Most data projects focus on goals 3, 8, 11 and, with a lesser emphasis, goals 2, 15 and 16. Though promising, most projects have not yet moved beyond the planning stage, and others are dealing with legal issues related to data protection (MacFeely 2019). Specific to the EO community are challenges for consistently and systematically turning satellite and other remote sensing data into valuable global information layers in support of effective implementation of the SDGs.

In late 2018, the Committee on Earth Observation Satellites (CEOS) compiled a report on the potential of satellite EO for the SDGs (Paganini et al. 2018), and their findings suggest that EO data has a role to play in quantifying around 40 of the 169 Targets, and around 30 of the 232 Indicators. The CEOS argues that there is an unrealized potential for EO data to contribute to the Indicator Framework, with only a third of its data being routinely exploited today. This is based on the premise that only 12 out of the 30 indicators identified are listed as Tier I.

Moreover, the report points to the importance of EO in relation to Goal 6 (Clean water and sanitation), Goal 11 (Sustainable cities), Goal 14 (Life below water), and Goal 15 (Life on land). Most of the perceived contribution of EO towards these goals has been around the provision of information in relation to the mapping of land cover, land productivity, above ground biomass, soil moisture content, and water extent or quality characteristics, as well as air quality and pollution parameters (Table 13.1). A 2016 compilation of the Group on Earth Observation (GEO) appraised the potential of EO and geospatial information for informing all SDGs, although the document was vague in terms of specific contributions to SDG targets and indicators. A subsequent joint GEO-CEOS report (CEOS-GEO EO4SDG 2017) further investigated the potential of big Earth Data (EO and geo-information) for supporting countries in the implementation of the 2030 Agenda for Sustainable Development, arguing that it could contribute to the implementation of 29 indicators (through direct measurement or indirect support) and 71 targets of 16 goals (but not all indicators of these targets). By referencing national-scale satellite datasets (e.g. Terra/Aqua MODIS, Landsat, and Sentinel), Metternicht et al. (2018) concluded that EO satellite-derived information tends to have a more indirect contribution to the SDG targets and indicators (i.e. use as proxies). Using data available from the Australian Terrestrial Ecosystem Research Network platform (TERN), the study ascertained that EO-derived information was most relevant to Goal targets 15, 14, 13, 11, 6, 3, 2 and 1, and, to a lesser extent, Goal 9 (Fig. 13.3).










The potential of EO to support the SDG indicator framework appears in the biosphere cluster (Fig. 13.4) and to a lesser the SDG indicators related to society and the economy. This concurs with the argument of Plag and Jules-Plag (2019) that very few indicators can currently be quantified based on information extracted from EO alone because of the strong focus of the SDGs on human needs and the bias toward social and economic information and the built environment. Traditional

Table 13.1 Summary of research that shows the contribution of big Earth Data towards the SDGs

SDG	Supported targets						Supported indicators								
	1.4	1.5										1.4.2			
	2.3	2.4	2.c									2.4.1			
	3.3	3.4	3.9	3.d								3.9.1			
															
	5.a											5.a.1			
	6.1	6.3	6.4	6.5	6.6	6.a	6.b					6.3.1	6.3.2	6.4.2	6.5.1
	7.2	7.3	7.a	7.b								7.1.1			
	8.4														

(continued)

Table 13.1 (continued)

SDG	Supported targets										Supported indicators				
	9.1	9.2	9.3	9.4	9.5	9.a	11.b	11.c	11.3.1	11.6.2	11.7.1	9.1.1	9.4.1		
															
	10.6	10.7	10.a												
	11.1	11.3	11.4	11.5	11.6	11.7	11.b	11.c	11.3.1	11.6.2	11.7.1				
	12.2	12.4	12.8	12.a	12.b				12.1.1						
	13.1	13.2	13.3	13.b					13.1.1						
	14.1	14.2	14.3	14.4	14.6	14.7	14.1		14.3.1	14.4.1	14.5.1				
	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		
	16.8														
	17.2	17.3	17.6	17.7	17.8	17.9	17.16	17.17	17.6.1	17.18.1					

From Paganini et al. (2018)

Product	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Forest Cover						T6.6								T14.1	T16.1, T16.3, T16.2		
Woody extent *						T6.6								T14.1	T16.1, T16.4, T16.8		
Fractional cover	T1.5/1.5.4		T3.9 / 3.d			T6.6				T11.3, T11.7		T13.1, T13.3		T14.1	T16.3, T16.1, T16.2		
Persistent Green Vegetation Fraction						T6.6								T14.1	T16.3, T16.1, T16.2		
Foliage Projective Cover						T6.6								T14.1	T16.2		
Seasonal Fractional Cover			T3.9 / 3.d											T14.1	T16.1, T16.3, T16.2		
Seasonal Ground Cover														T14.1	T16.1, T16.2, T16.3, T16.4		
Seasonal Persistent Green Cover			T3.9 / 3.d											T14.1	T16.2		
Biomass			T2.3, T2.4 T3d			T6.6								T14.1	T16.1, T16.4, T16.8		
Vegetation height and structure Phenology			T2.4, T2a T3d											T14.1	T16.1, T16.4, T16.9		
Leaf Area Index			T3d			T6.6				T11.3, T11.7		T13.1, T13.3		T14.1	T16.1, T16.2, T16.3, T16.5		
Gross Primary Productivity	T1.5/1.5.4 T2.3, T2.4 T3d											T13.3			T16.3, T16.1, T16.2		
PAR			T3d			T6.6									T16.1, T16.2, T16.3, T16.5		
Active Crop Mapping* Grassland curing		T2.3, T2.4, T2a											T13.1, T13.3		T16.1		
Water Prevalence	T1.5/1.5.4					T6.4, T6.6								T13.1, T13.3			
Land surface temperature	T1.5/1.5.4									T11.7				T14.1			
Thermal Anomalies	T1.5/1.5.4												T13.1, T13.3				
Burnt area & day of burn	T1.5/1.5.4												T13.1, T13.3				
NRT Burnt Area	T1.5/1.5.4												T13.1, T13.3				
Fire patchiness (sub-pixel)	T1.5/1.5.4												T13.1, T13.3				
Annual Fire Scars	T1.5/1.5.4												T13.1, T13.3				
Total Land Cover (Land Condition Index)			T3.9 / 3.d										T13.1, T13.3	T14.1, T14.2	T16.1, T16.3		
Dynamic Land Cover Map		T2.3, T2.4, T2a	T3d			T6.6		T9.1		T11.3, T11.7				T14.1, T14.2	T16.1, T16.3, T16.2		
Ecosystem Disturbance Index	T6.6		T3d			T6.6								T14.1	T16.1, T16.4, T16.5, T16.8, T16.9		
Surface Reflectance			T3d			T6.6								T14.1	T16.3, T16.1		
NDVI			T3d			T6.6				T11.3, T11.7		T13.1, T13.3			T16.1, T16.2, T16.3, T16.5		
EVI			T3d			T6.6				T11.3, T11.7		T13.1, T13.3			T16.1, T16.2, T16.3, T16.5		

TERN Landscape governance as good practice of 'means of implementation'

Fig. 13.3 SDG targets that TERN Auscover products contribute to are listed in the table; the table cells are color-coded according to whether the contribution is more direct (green) or more indirect (yellow) (Metternicht et al. 2018)

EO techniques are designed for extracting information on environmental variables, with only a few being related to the built environment and associated infrastructure (e.g., built-up areas and roads). Hence, there are limitations on the possibility of EO *alone* producing reliable metrics for SDG indicators (see Table 13.1); however, approaches underpinned by big Earth data do have some potential, as evidenced in recent research by Kussul et al. (2019), Foody et al. (2019), Freire et al. (2018), and Corbane et al. (2017). Specifically:

- meta-optimization of EO with external data-intensive infrastructure has led to improved mapping of built-up areas in support of the global human settlement layer (Corbane et al. 2017)
- national mapping of SDG indicators 15.1.1, 15.3.1 and 2.4.1 has been achieved through synergy of in situ and multi-resolution satellite data (Kussul et al. 2019)
- big Earth Data (global census data and satellite-derived built-up area maps) has enabled enhanced mapping of population distribution along coastlines (Freire et al. 2018)
- EO and machine learning have enabled mapping of sites associated with slavery, in support of SDG target 8.7 (“take immediate and effective measures to eradicate forced labour; end modern slavery and human trafficking and secure the prohibition and elimination of the worst forms of child labour”) (Foody et al. 2019).

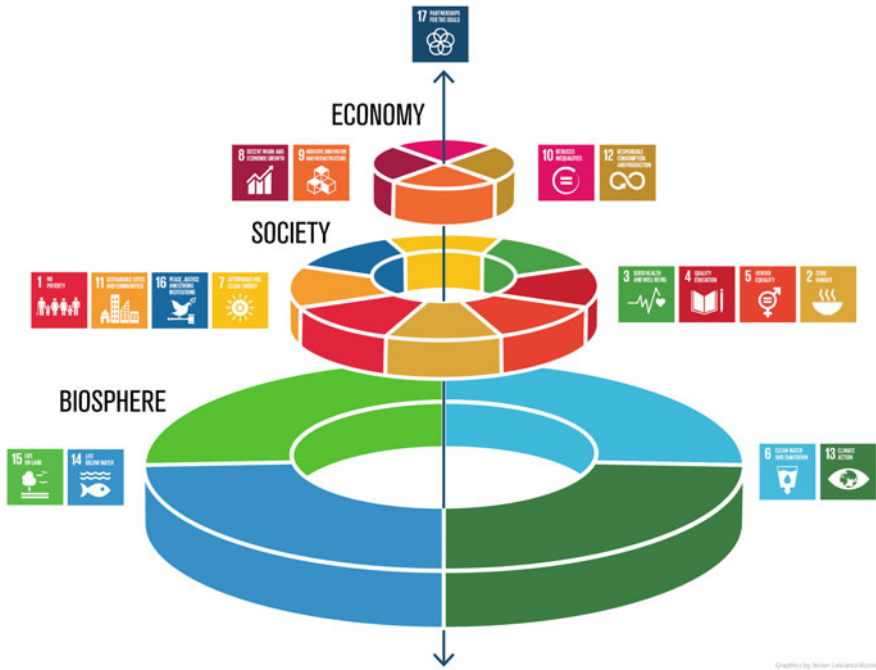


Fig. 13.4 Clustering of the SDGs that relate to the biosphere (earth life supporting system), society and economy. *Illustration* Azote for Stockholm Resilience Centre, Stockholm University

In summary, EO data does not directly deliver the SDG indicators agreed by the Inter-Agency and Expert Group (IAEG) on SDGs; rather, it provides a diversity of spatio-temporal information that can then be related to the indicator framework. For example, directly observed indicators can be specific biophysical aspects of entities (e.g., land cover status and type) that provide evidence for monitoring advances towards SDG targets. As an example, changes in land-cover states can be an indication of land improvement or land degradation in SDG target 15.3. Indirect cues derived from EO data can provide evidence for SDG domains related to human health, cities and infrastructure, ecosystem health and so on (Paganini et al. 2018; Sudmanns et al. 2019). Few studies, however, refer to specific SDG indicator metrics; many papers and reports highlight the potential of Earth Observation for targets and goals but fall short of being specific regarding the operationalization of Digital Earth for the SDG target or indicator.

For the full information potential of big EO data in support of the SDGs to be realized, approaches are needed that broaden the use of EO beyond specialized scientific communities and that support decision makers with the knowledge required by systematically analyzing all available observations by converting them into meaningful geophysical variables. Data Cubes (see Chap. 21) apply the concept of satellite ARD and are facilitating access to large spatio-temporal data (Giuliani et al. 2017). This

enables the coupling of EO with other big data such as demographic, economic, climatic, or administrative data, which are needed to make indicators and analysis more relevant and targeted to the SDGs. Furthermore, some of the proposed SDG targets relate to the so-called ‘means of implementation’, namely technology transfer and capacity building (i.e. SDG17; SDG targets 13.1, 1.3.3 and 16.8). In this regard, Digital Earth and EO infrastructure, as currently offered by Australia’s TERN Landscape initiative (TERN 2017) and other major international and national systems for big Earth data (e.g. Google Earth Engine, Amazon Web Services, Earth Server, Earth Observation Data Centre, Copernicus Data and Exploitation Platform-Deutschland, United States Geological Survey Earth Explorer, Swiss Data Cube, Digital Earth Australia, Chinese Academy of Sciences Earth, and *GEOEssential* of the Group on Earth Observations), could serve as ‘methodological frameworks’ and examples of good practice for cross-institutional governance models, thus indirectly contributing to progress towards these targets.

The case study presented hereafter is an example of how EO can be a promising complement to traditional national statistics. Digital Earth Australia (DEA) aligns with the current trends in EO of having open data policies and using cloud computing and data cubes for improving big Earth data integration and analysis, thereby strengthening environmental data and indicators (Dhu et al. 2017). In particular, this case shows how the analysis capabilities of DEA (see Chap. 21 for infrastructure) can be used to draw together and effectively link data from multiple domains in support of the implementation of the 2030 Agenda for Sustainable Development in Australia.

13.4 Case Study of Australia: Operationalizing the Indicator Framework of the SDGs Through DE and a Participatory Process

In July 2018, Australia produced its first Voluntary National Review (VNR) of the SDGs (Australian Government 2018). Australia’s consideration of the SDG Indicators has been a whole-government exercise. The Australian Bureau of Statistics (ABS) undertook a data-mapping exercise for the SDGs, in conjunction with lead agencies, exploring both ABS and other government-held data sources to identify those germane to supporting monitoring and reporting on the SDGs. A Reporting Platform² was created to: (a) house identified Australian government datasets relevant to the development of the country’s SDG indicator framework; (b) assist in identifying new datasets; and (c) refine the SDG indicators, particularly as the move from a Tier III to a Tier I or II occurs and where additional datasets may be needed. An inter-agency governance agreement assigned the responsibility for following up and completing additional data sets to individual agencies (particularly those that hold datasets relevant to the SDG indicator framework).

²<https://www.sdgdata.gov.au/>.

For the first VNR, a total of 118 indicators were reported online using data drawn from a national indicator dataset. For 57 indicators, potential data sources were identified. However, further analysis is needed to ensure the data are suitable for reporting and are comparable to the globally agreed methodology for each UN SDG indicator. 12 indicators were not reported either because the indicator was not relevant to Australia or because no suitable Australian government data source exists for the indicator. Another 57 were not considered because, at the time of reporting, a globally agreed methodology for these UN SDG indicators is lacking (i.e., Tier III). Therefore, Australia did not investigate potential data sources. In summary, the first Australian VNR took a narrative approach, addressing each of the SDGs, though no baseline was created. Targets were not specified and Australia had complete and relevant datasets for only half of the SDG indicators. The Australian government has acknowledged that EO technology can help progress towards the completion of datasets and, in tandem, inform decision-makers about performance against SDG targets and indicators (Australia Government 2018).

In this regard, EO-derived information could help in setting baselines against which SDG targets could be set and, in turn, measure progress against agreed goals— aspects that the first VNR did not tackle. Germane to this point is the DEA initiative led by Geoscience Australia, which has enabled the compilation, analysis and interpretation of decades of satellite sensor (largely Landsat) data into information and insights about Australia's terrestrial and marine ecosystems using ARD standards (Dhu et al. 2017; Lewis et al. 2016). Building on the DEA infrastructure (see Chap. 21), Geoscience Australia is leading an inter-institutional initiative to produce reliable, standardized, continental-scale maps of land cover and land-cover dynamics across Australia at 25 m spatial resolution using multi-scale time series of Landsat and Copernicus Sentinel datasets. This approach builds on the Earth Observation Data for Ecosystem Monitoring (EODESM; Lucas and Mitchell 2017), which is fully described in Lucas et al. (2019a) and which provides multi-scale and temporal land-cover and evidence-based change maps by integrating environmental variables retrieved from EO data and utilizing the framework of the Food and Agriculture Organisation (FAO) Land Cover Classification System (LCCS; Version 2, Di Gregorio 2016). The approach is based on the requirement for information about land cover and its change over time, as both are essential input metrics to several SDG targets (Fig. 13.3) and indicators (e.g. 6.6, 11.3.1, 15.2.1, 15.3.1). This information is also useful to other national and international reporting requirements on the state of the environment (e.g. United Nations Convention to Combat Desertification, Aichi Targets, and the Paris Agreement).

13.4.1 DEA to Map Land Cover and Dynamics Over Time

The DEA land cover product has been optimized for high-performance computing within the Open Data Cube (ODC) framework and is generating continental maps of land-cover datasets from environmental variables (thematic and continuous), with a

focus on those that are generated at a national level within DEA’s ODC environment (Lucas et al. 2019a) and for multiple points in time. These include the vegetation cover fraction of the Joint Remote Sensing Research Program (Gill et al. 2017), Water Observations from Space (WOfS) (Mueller et al. 2016), surface reflectance Median Absolute Deviation (MAD) (Roberts et al. 2018), and national mangrove distribution (Lymburner et al. 2019) (Fig. 13.5). Additional layers generated through DEA are also used (e.g., the InterTidal Elevation Model (ITEM) of Sagar et al. (2017). The mapping is undertaken at 25 m resolution and the initial focus has been on generating land-cover classifications according to the LCCS Level 3 taxonomy, which differentiates 8 classes relating to aquatic and terrestrial (semi) natural vegetation, cultivated and managed terrestrial and aquatic vegetation, artificial and natural (bare) surfaces, and natural and artificial water bodies (Fig. 13.5 and Table 13.2). More detailed classifications are being generated at what is termed Level 4 (e.g., vegetation canopy cover and height, and water hydroperiod), which are further described using

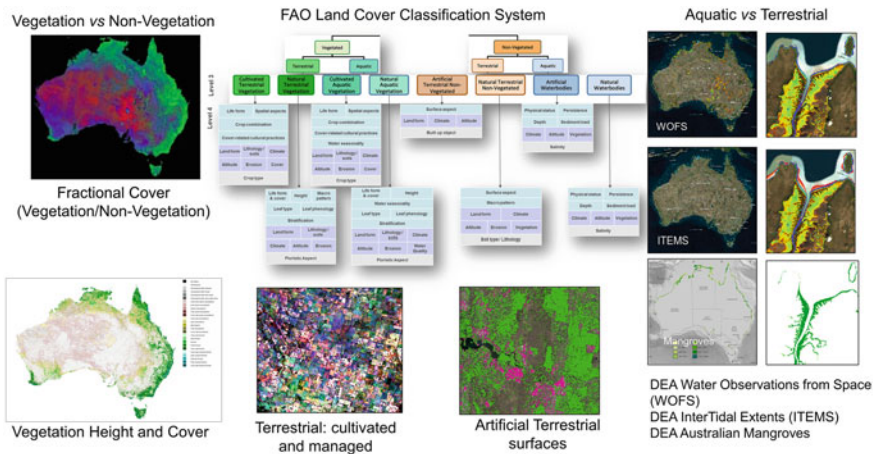


Fig. 13.5 Examples of data inputs for the application of the FAO LCCS level 3 within Digital Earth Australia used to produce standardized land cover maps at 25 m resolution

Table 13.2 Level 3 FAO land-cover classification (FAO LCCS) classes

Class name	Acronym
Cultivated terrestrial vegetation	CTV
Natural terrestrial vegetation	NTV
Cultivated aquatic vegetation	CAV
Natural aquatic vegetation	NAV
Artificial terrestrial non-vegetated	AS
Natural terrestrial non-vegetated	BS
Artificial waterbodies	AW
Natural waterbodies	NW

environmental variables that are external to the LCCS taxonomy (e.g., soil moisture and crop type), examples of which are given in Fig. 13.6.

The availability of multi-temporal land-cover layers enables change matrices (e.g. $T_1 - T_{baseline}$) to be generated between land covers obtained for any two time-separated periods. When only the LCCS Level 3 is considered, the temporal comparison between two land-cover maps results in 64 different change categories (Fig. 13.7a).

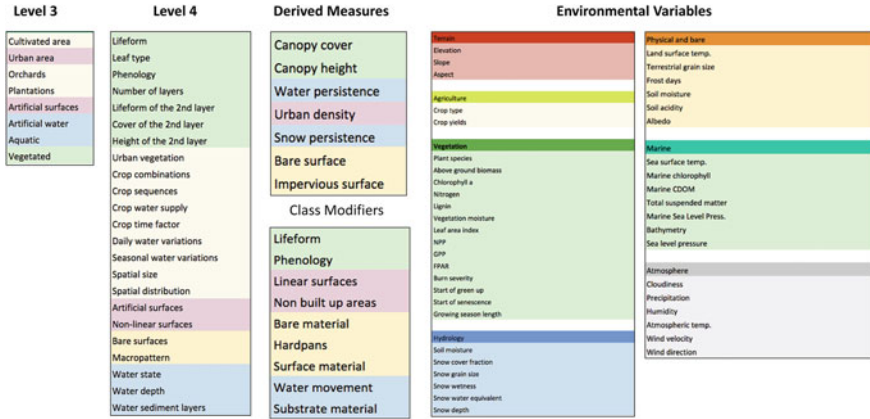


Fig. 13.6 Examples of environmental variables, class modifiers and derived measures required to implement the LCCS at level 3 and level 4 in Australia

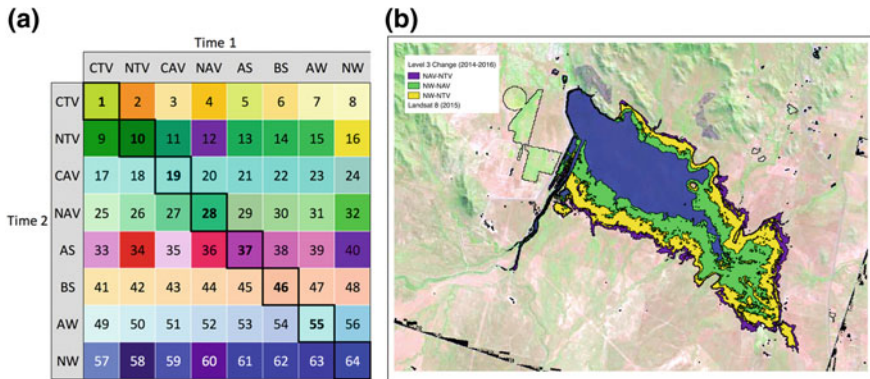


Fig. 13.7 **a** The 64 change categories generated through comparison of 2 LCCS Level 3 classifications (each with 8 classes) in the vicinity of Lake Ross (area of Townsville, Queensland) based on multi-temporal classification of Landsat images using LCCS level 3. The key changes are NAV-NTV: denoting changes from Natural Aquatic Vegetation (2014) to Natural Terrestrial Vegetation (2016); NW-NAV: Natural Waterbodies to Natural Aquatic Vegetation; and NW-NTV: Natural Waterbodies to Natural Terrestrial Vegetation. **b** The corresponding change map indicating a progressive loss of open water area, the retreat of aquatic (wet) vegetation and a transition to drier vegetation on the outer margins of the lake basin (Lucas et al. 2019a)

Diagonal cells represent areas where the land cover (e.g. natural/semi-natural terrestrial vegetation, natural water, artificial water, etc.) remains stable between the two time periods and unique codes can be assigned for the *From* → *To* changes in land cover. Figure 13.7b provides an example of a land-cover change matrix and map that result from applying FAO LCCS level 3 on an inland water ecosystem in the State of Queensland between two time periods.

One aspiration of DEA’s land cover product is to better inform management and interventions in order to advance assessment and monitoring of progress towards the SDGs at national levels. In this regard, research is being undertaken to concurrently develop a change alert system (historically and when new data and data products become available) that can associate changes in states (i.e., environmental variables) with the causative mechanisms (i.e., human activities and climatic variability) and the impacts that such changes produce (e.g. defoliation, land clearing, and increases in built-up area). Such changes are based on evidence, and exploit a newly developed change taxonomy (Lucas et al. 2019b). Geoscience Australia is extending the idea to integrate, within DEA’s land cover product, EODESM with the Drivers-Pressure-State-Impact-Response (DPSIR) framework (Lucas et al. 2019b; Metternicht et al. 2019). In doing so, links are—between economic and climate drivers and pressures of change and detailed information on states, state changes and environmental impacts (based on the change taxonomy). The drivers-pressure-state links can subsequently inform impacts on management and policy (from local to international I-levels). The ultimate ambition is to generate options for context-based policy and management responses related to the SDGs (Fig. 13.8). Through this approach, responsible

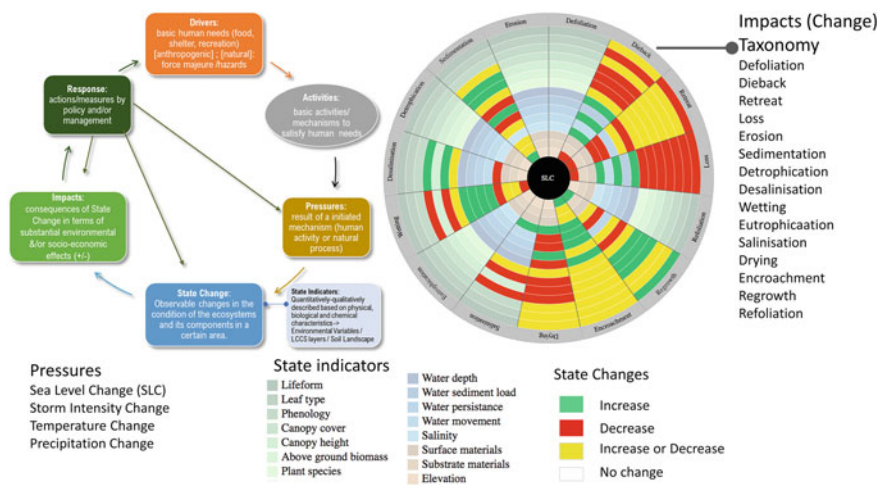


Fig. 13.8 Conceptual framework that links the DPSIR framework with the LCCS-derived land-cover maps within the DEA environment. Pressures (center of the wheel) are identified and state indicators derived from the LCCS comparison between T_0 – T_1 provide an estimation of state change. Cumulative information on state change builds evidence on impacts (outer part of the wheel)

authorities can make informed and timely decisions on interventions (e.g. management decisions, new regulations).

As an illustration of the application of the integrated EODESM-DPSIR framework, Fig. 13.9a shows the impact of rising sea levels (between 1991 and 2011) on water and vegetation variables in Kakadu National Park, located in Australia's Northern Territory. An increase in water depth, salinity and hydroperiod and a corresponding rise in vegetation biomass, height and cover, along with an associated transition from shrubs to trees (i.e., lifeform state change) was observed during this period. Such changes might lead to an increase or a decrease in mangrove species. In 2015, a substantive drop in sea level in the Gulf of Carpentaria (Duke et al. 2017) was also noted in the Northern Territory (Lucas et al. 2018), which led to changes in water conditions and a substantive dieback of mangroves. A loss of canopy cover (%) and above-ground biomass (Mg ha^{-1}) were the EO-derived state-change indicators of short-term change; they were mapped through multi-temporal comparison (2014–2016) of vegetation indices (primarily a Normalized Difference Vegetation Index (NDVI) and a Plant Senescence Reflectance Index (PSRI)) derived from Rapid-Eye satellite imagery. Dieback-affected mangroves were not removed and their height (m) did not change (at least in the short term). A reduction in moisture content (%) of woody vegetation was the proxy applied to differentiate dieback from defoliation (Fig. 13.9b). Information on this proxy indicator can be discerned from, for example, time series of Advanced Land Observing Satellite (ALOS) Phased Arrayed L-band Synthetic Aperture Radar (SAR) data. Figure 13.9 shows further aerial images of sea-water encroachment along creeks and the associated colonization by mangroves (9e), as well as mangrove dieback along the eastern and western shores of the West Alligator River (9f).

The combination of the EODESM and DPSIR frameworks enables mapping of where and how much change has occurred (extent and magnitude), the root causes (sea-level change), and impacts (e.g., regrowth and dieback). Furthermore, likely impacts on policy (e.g., the United Nations Framework Convention on Climate Change or the Convention on Biological Diversity) and land management (e.g., associated with Kakadu National Park) can be indicated and future interventions suggested. In the case of SDG 6.6 (“By 2020, *protect and restore water-related ecosystems, including mountains, forests, wetlands, rivers, aquifers and lakes*”), main policy actions to advance this target should address drivers of climate change (Metternicht et al. 2018; Asbridge et al. 2018), including also environmental monitoring through Digital Earth platforms (Lymburner et al. 2019).

Ongoing research is focusing on the use of DEA's land cover product to derive Australia-wide indicators for SDGs 6.6.1 (change in the extent of water-related ecosystems over time), 11.3.1 (ratio of land consumption rate to population growth rate), 15.1.1 (forest area as a proportion of total land area) and 15.3.1 (proportion of land that is degraded compared to total land area). For example, the 2018 Australia VNR mentions that the country is ‘exploring data sources’ for the implementation of Indicator 15.3.1.

The following are examples of how multi-temporal land cover maps produced within DEA using ARD satellite imagery (Landsat or Sentinel) and the combined

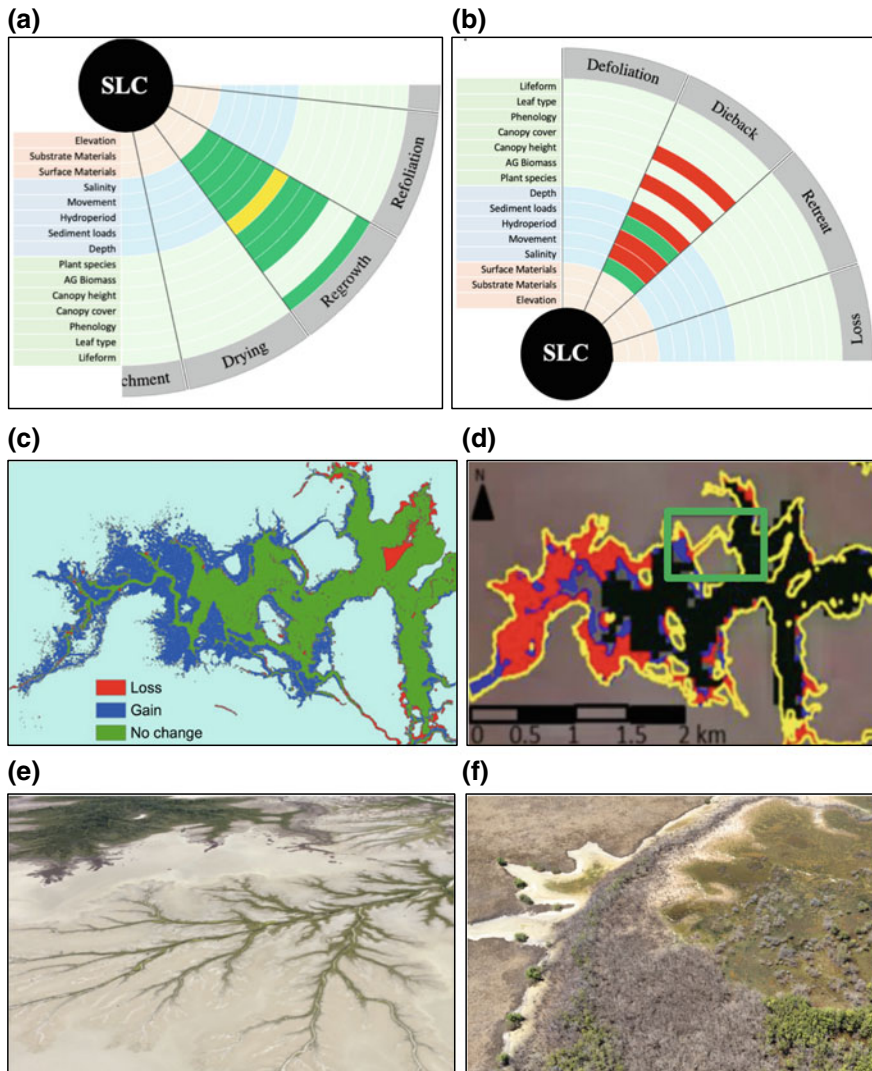


Fig. 13.9 Example of the application of the combined EODESM-DPSIR framework within DEA for Kakadu National Park, NT, Australia, where the impacts of sea-level change (SLC; center) result in **a** regrowth and colonization when rises occur and **b** dieback when drops in sea level follow. These impacts are illustrated by **c** high-resolution maps of change from time-series comparison of aerial photography from 1991 and LiDAR from 2011 (Asbridge et al. 2016), and **d** comparison of RapidEye data from 2014 and 2016. Aerial images of mangrove change taken in September 2016 show **e** landward colonization along small creeks and **f** dieback (see green box in **d**)

EODESMDPSIR framework could be used to derive metrics needed for baseline setting, target setting and/or monitoring and reporting of SDG Target 15.3, which aims ‘to combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world by 2030’.

13.4.2 DEA in Support of SDG Indicator 15.3.1

In the SDG Global Indicator Framework, indicator 15.3.1 “Proportion of land that is degraded over total land area” is based on the analysis of available data for three sub-indicators: land cover, land productivity and carbon stocks; this indicator takes a binary form (degraded/not degraded). Computing SDG Indicator 15.3.1 for the baseline (i.e., $T_{baseline}$) and subsequent monitoring years (T_1 – T_n) requires adding up all those areas where any changes in the sub-indicators (i.e. land cover, land productivity and soil organic carbon) are considered negative (or stable if the baseline or previous monitoring year labeled the area ‘degraded’) by national authorities. In turn this involves:

- i. assessing the land cover and changes in land cover (i.e., trends)
- ii. analyzing the status of and trends in land productivity based on net primary production
- iii. determining carbon stock values and changes, with an initial assessment of soil organic carbon as the proxy (Sims et al. 2017).

As a proxy for measuring progress towards SDG Target 15.3, indicator 15.3.1 presupposes that changes in land cover may point to land degradation if such change implies a loss of ecosystem services considered desirable in a local or national context. Hence, land cover information at the national level derived from a classification system such as the FAO LCCS can be used to assess and quantify land cover and trends in land-cover change (Step *i* from above) by disaggregating the landscape into ‘degraded/negative/declining’, ‘stable/unchanging’ or ‘improving/positive’.

Based on the example presented in Fig. 13.10, the change matrix (containing 64 possible types of land change), obtained by comparing two satellite images from two different periods classified using LCCS Level 3, can be translated into descriptors relevant to SDG indicator 15.3.1. Changes indicative of land degradation can be decided by individual countries, according to their national circumstances. In Fig. 13.10, changes highlighted in orange (e.g., agricultural and urban expansion, wetland drainage and vegetation loss) are considered examples of land degradation. Diagonal cells in blue denote areas of no change (i.e., the land cover remained stable between periods 1 and 2).³ Cells in green denote changes that the country would

³It is worth noting that land degradation can still occur within classes considered stable at LCCS Level 3. For example, a landscape may remain classified as terrestrial semi-natural vegetation at both T_1 – T_2 even though a loss of canopy cover may have occurred. This is described at Level 4 of the LCCS (as illustrated in Fig. 13.9).

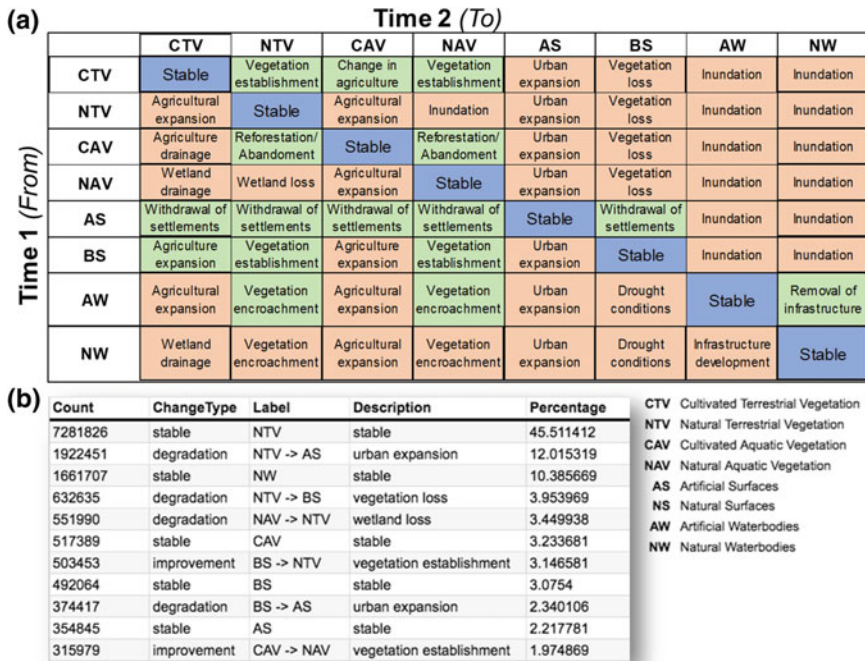


Fig. 13.10 Example of deriving the sub-indicator ‘trend in land cover’ through a change matrix that compares land-cover changes from time 1 to time 2. The land-cover layers are produced using the FAO LCCS level 3 and EO ARD available within the DEA. Expert knowledge input is needed to decide whether a change *From To* expresses an improvement (green cells), stability (blue cells), or degradation (orange cells)

consider to correspond to a decrease in degraded areas (i.e., an improvement) as a consequence of, for instance, sustainable land-management interventions that were made during the time period T_1-T_2 . Figure 13.10b shows the output of this EO-based mapping process, summarizing the number of hectares of land that remained stable, were improved or have been degraded further between T_1 and T_2 . This output can then be overlain and integrated with national information on land productivity status and trends, as well as soil organic carbon stocks, as suggested by the GIF metadata and good practice guidance for Indicator 15.3.1 (Sims et al. 2017).

Although it is still at the proof-of-concept stage, these applications show the potential of Digital Earth to assist countries in meeting several of the SDGs (particularly 6.6, 13, 14, and 15) where land cover and its change dynamics are relevant to reporting on the approved indicator (metric), tracking progress towards their attainment by 2030, helping to set targets according to national circumstances, and importantly, setting baselines. The baseline year for the SDG indicators is 2015 and for those related to land, its value (t_0) should be derived from time-series data for the period

2000–2015. The retrospective capacity of data provision by EO provides a unique comparative advantage to the achievement of this ambition.

13.4.3 Digital Earth in Support of SDG 17: Strengthen Means of Implementation

DEA is an example of big Earth data contributing to SDG 17 in aspects such as multi-stakeholder partnership, and production of data and systems for monitoring and accountability, and is also enhancing capacity-building support to developing and least-developed countries. The capabilities of the ODC to provide EO ARD and for scaling out across the world are significant contributions to Goal 17 in terms of strengthening means of implementation through technology transfer, capacity building and data, and monitoring and accountability.

The technology that lies beneath DEA, which was pioneered by Geoscience Australia, The Commonwealth Scientific and Industrial Research Organisation, and Australia's National Computational Infrastructure, underpins ODC initiatives being rolled out in developed (e.g. Switzerland) as well as developing countries (e.g. Vietnam) and regions (e.g. Digital Earth Africa: DEAfrica). DEAfrica is an example of Australia fulfilling Goal 17's aim of strengthening the means of implementation, as it builds technical and policy expertise as well as data analysis capability in-country with technical and operational guidance from DEA. A public–private investment partnership will provide continuing investment for DEAfrica, and it is envisaged that analysis, products and tools produced by DEAfrica will be accessible across the continent to inform decisions about land and water.

13.4.4 The Way Forward: Partnerships to Strengthen DEA in Support of the SDGs

The Australian Bureau of Statistics and other lead agencies (e.g. Department of Environment and Energy) that have contributed to the development of the Australian Reporting Platform (Fig. 13.11) recognize the importance of partnerships and collaboration with data providers for collecting datasets relevant to the SDG indicator framework. Big Earth data is needed to track the progress of Australia's performance on the goals and set targets, in addition to reporting to the United Nations High-Level Political Forum on the SDG Indicators Framework. Multi-source, multi-temporal data covering the socio-economic and environmental pillars of sustainable development can also assist in identifying interlinkages, overlaps and interactions between the SDGs, a key issue in the development of coherent policies and interventions, as discussed in Sect. 13.1.



Fig. 13.11 The Australian Government’s Reporting Platform for the SDGs adopts a participatory, whole-government approach

As progress is made on identifying datasets and on refining the SDG Indicators, particularly as they move from Tier III to Tier I or II, additional datasets will be uploaded to the platform, offering new data for indicator metrics and enabling the development of time-series of datasets. The government plans that the platform can assist in streamlining reporting for other nationally and internationally agreed goals (e.g. Aichi Targets, Sendai Framework, and implementation of the System of Environmental Economic Accounts (SEEA) framework). In keeping with the intention of the SDG indicator framework, the official GIF may be complemented by SDG indicators that are relevant at the regional and national levels (Australian Government 2018).

13.5 Big Earth Data for the SDG: Prospects

Measuring progress for the SDG targets through the Global Indicator Framework requires metrics that rely on biophysical, social, and economic data and information. This chapter has reviewed the current role of Digital Earth (EO as a sub-set of big Earth data) in the SDGs. It can be seen that progress has been made on identifying EO data and information for the SDG GIF (Sect. 13.3), and that participatory, cross-institutional approaches developed under a “Digital Earth” umbrella can deliver operational, standardized information that contributes to baseline and target setting, and to tracking progress towards the SDGs (4). Opportunities, and associated challenges, exist in relation to the realization of the full potential of DE for the SDG. This final section identifies and discusses these in terms of three main aspects: research and development (R&D) and technology; governance, institutional and normative aspects; and the science-policy interface.

13.5.1 R&D and Technology

Social sensing and other big data integrated within DE have the potential to meet current information and knowledge gaps for SDG indicators focused on socio-economic information (e.g. zero hunger, good health and well-being, and gender equality). Plag and Jules-Plag (2019) and Dong et al. (2019) conclude that new geospatial information for sustainability (e.g. on the built environment, land use and management), could be derived from the integration of traditional EO approaches to data gathering with citizen science, crowd-sourcing, social sensing, big data analytics and the Internet of Things. Hence, further research is needed to better establish how countries can profit from these new technologies for data gathering and analysis, embedded in a DE framework, and advance the development of indicators complementary to the core of the SDG GIF. This can support country-based interpretation and better, more coherent, narratives of national progress towards the 2030 Agenda for Sustainable Development (Metternicht et al. 2019).

Information on the *use and management* of land rather than land *cover* is needed for many SDGs (see Sect. 13.3 and Wunder et al. 2018); hence, it is relevant and pertinent to develop ‘Essential Land Variables’ or ‘Essential Land Use Variables’ to better support the information needs of the SDG targets and indicators. Digital Earth data, technology and analytics can underpin primary observations of the changes in state of land-related variables (Dong et al. 2019), with the potential to be linked to state-change indicators or to the pressures driving changes in state (see Sect. 13.4 and Lucas et al. 2019b), thus contributing to tracking progress on SDG implementation. Recent research (Plag and Jules-Plag 2019; Masó et al. 2019) has put forward ways of improving the current SDG indicator framework through considering Essential Variables. The Group on Earth Observation (GEO) and major international networks such as the Biodiversity Observation Network (GEO-BON) and the Global Ocean

Observing System (GOOS) have developed essential variables on climate (ECVs), oceans (EOVs), the water cycle (EWVs), and biodiversity (EBVs). However, standardized essential variables related to land (ELV) (or land use: ELUVs) are lacking. Global programs (e.g., Future Earth's GLP⁴) and EU-funded initiatives (e.g., the GEOEssential, ERA-PLANET⁵ and ConnectinGEO projects) have started discussions on the design and development of essential land variables; the research of Reyes et al. (2017), Masó et al. (2019), Lehmann et al. (2019), Nativi et al. (2019), and Plag and Jules-Plag (2019) provide the conceptual principles and the information needs that these variables should fulfil in order to address current SDG policy and the knowledge needs of indicators. A constellation of Essential Variables on land cover/use, agriculture, biodiversity, water, and climate could better support implementation of the SDGs and the associated GIF, and also underpin systematic generation of sustainability-related knowledge from big Earth data. This would benefit Agenda 2030's global-change policy, as well as other major international agreements and conventions (e.g. the Sendai Framework for Disaster Risk Reduction, and the Paris Agreement on Climate Change).

13.5.2 Normativity, Governance and Institutional Arrangements

Google Earth Engine and Amazon Cloud-based Web Services are among cutting edge initiatives providing efficient solutions that lower the barriers to ARD products. These allow users to concentrate on data analysis and interpretation for better use of the growing volume of EO data (Giuliani et al. 2017), and expand the ecosystem of 'next users' beyond specialized scientific communities. While this is a key requirement for unlocking the informational power of big EO data and expanding the number of potential EO data users, it presents normative and governance challenges concerning big data veracity (Dong et al. 2019). Lowering access barriers for data analytics by users beyond the scientific community could potentially deliver low-quality information products. In this regard, the DE community needs to expand and build upon existing norms, standards and guidelines that have been advanced in the context of EO data storage and processing (see Sudmanns et al. 2019) to include data validation and quality assurance for information products. For example, Hernandez (2017) postulates that Digital Earth will need to consider how to store the proper metadata so that any user can easily understand how accurate data are, and how the quality of the data has been evaluated or validated. More to the point, he argues for adequate e-infrastructure and standards.

⁴An 'Essential Land Use Variables world café' session was held at the 4th Open Science Meeting of the GLP, Bern, Switzerland, April 2019. https://www.conftool.com/osm2019/index.php?page=browseSessions&cols=3&form_session=112&mode=table.

⁵ERA PLANET: The European network for observing our changing planet.

Normative challenges also remain regarding how best to determine the quality and veracity of big data from a statistical perspective (e.g., ethical questions regarding ownership of data and products). What is legally, ethically and culturally acceptable for accessing and using big data? What should the governance of digital repositories, particularly those hosting globalized or multi-national big data sets, look like? MacFeely (2019) rightly reflects that “*open cloud, centralised statistical production rather than replicating many times in countries is tempting, though it faces challenges of data and information sovereignty, as it places data owners and the data themselves beyond the reach of national level systems*”.

Institutional adaptation for transformative data and information acquisition is needed as well. National Statistical Offices (NSOs) are tasked with assembling relevant data for national voluntary reports on the SDGs. The big Earth data community needs to understand how best to engage with this community to develop metrics derived from EO data that can be used for reporting. Soulard and Grenier (2018) summarize the challenges of using EO data for official statistics. Among the most salient are that datasets created from EO were not designed for use as official statistics. For integration of the EO datasets, and to better exploit the potential of big Earth data, Soulard and Grenier argue that NSOs need to develop methodologies to properly interpret existing datasets to provide estimates required by official statistics; evaluate the pertinence of global datasets that are often designed without regional considerations; keep up with the ever-increasing number of EO-generated datasets; adjust the national or regional data where local data of better quality highlight important shortcomings in the national or regional dataset; evaluate the complementarity of using EO data where other data often does not exist; and influence EO producers to integrate official statistical objectives into the EO processing workflow from the beginning. It is a two-way communication process.

13.5.3 Science-Policy Interface

Operationalization of big Earth Data proof-of-concepts is relevant to the scientific support for sustainable development policy strategies that are coordinated and coherent across goals. Reflecting on the status of operationalization of big data for SDGs from the perspective of NSOs, MacFeely (2019) argues that “*Advances, such as, the Internet of Things and biometrics will all surely present opportunities to compile new and useful statistics. The implications of this ‘big (data) bang’ for statistics in general, and the SDGs in particular, is not immediately clear, but one can envisage a whole host of new ways to measure and understand the human condition and the progress of development*”. The UN Economic Commission for Europe (2016) reflecting on their experiences, noted ‘High initial expectations about the opportunities of Big Data had to face the complexity of reality. The fact that data are produced in large amounts does not mean they are immediately and easily available for producing statistics’. Simply put, the interface between science and policy needs enhancement for context-based interpretation and communication as discussed below.

The implementation of ‘transformational’ policies and strategies for achieving the goals of the 2030 Agenda for Sustainable Development requires tracking the progress of set targets to ensure that responses to interventions (e.g., land restoration or sustainable cities) are as expected. In this regard, a major challenge of Digital Earth is the linking of scientific results concerning knowledge derived from EO to the policy decision space. On the one hand, multi-stake, whole-government, participatory processes, as implemented by the Government of Australia in setting its National Reporting Platform (see 4.1 and 4.4), contribute to bridging the gap between science and policy. On the other hand, DE frameworks more focused on the ‘knowledge’ element of the Data-Information-Knowledge-Wisdom (DIKW) paradigm are needed. SDG indicators should provide policy makers with the knowledge necessary for wise decisions, drawn from information gathered from observed data, whether through EO, social sensing, or other means. (Nativi et al. 2019). Most DE initiatives currently focus on ‘Data’ (i.e., ARD) as shown in the review by Sudmanns et al. (2019) of popular systems and portals for accessing or processing EO. This review makes clear that many portals facilitate data access—although in the end users struggle to produce information and ‘frame’ it according to context. This is an essential aspect of the policy and political decision-making processes related to the implementation of the SDGs, given that countries are to take into account their own national circumstances and priorities (UNGA 2015) in defining SDG targets and, hence, one-size-fits-all interventions do not exist.

13.6 Conclusion

The Sustainable Development Goals are highly ambitious and were adopted to stimulate action over the next 15 years in areas of critical importance for humanity and the planet (UNGA 2015). Digital Earth has untapped potential to improve the means of implementing the SDGs at both national and global scales. Through an extensive review of the recent literature and a case study of the operationalization of the SDG Indicator Framework in Australia, this chapter discussed information needs and promising operational initiatives underpinned by big Earth data and analytics, and, as importantly, multi-stakeholder partnerships. Digital Earth Australia is an example of the potential of Digital Earth to be an agent of ‘partnerships for the goals’, which can increase the availability of high-quality, timely and reliable data that is relevant in national contexts (SDG 17.18), and enhance regional and international cooperation on, and access to, science, technology and innovation (SDG17.6).

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Graciela Metternicht is a Professor in Environmental Geography at the University of New South Wales Sydney. Her research focuses on applications of geospatial technologies for environmental management and sustainability. Past appointments include Regional Coordinator of Early Warning and Assessment at UN Environment.

Norman Mueller is a Director of Product Development for Digital Earth Australia where he leads a team building time series tools and products for the monitoring and management of the environment from Earth observation data.

Richard Lucas holds a Sêr Cymru Research Chair at Aberystwyth University where his research focuses on the use of Earth observation data to better support monitoring, conservation, sustainable use and restoration of global environments.

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