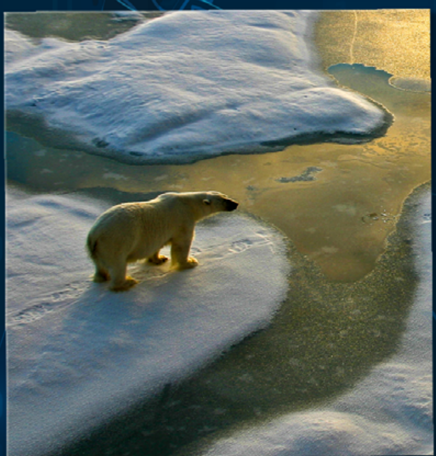
EARTH OBSERVATION FOR SDG

Compendium of Earth Observation contributions to the SDG Targets and Indicators

May 2020



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Preface

The 2030 Agenda for Sustainable Development and its 17 Sustainable Development Goals (SDG) adopted by world leaders at the United Nations Sustainable Development Summit on 25 September 2015, provide a global framework for action on sustainable development for the next two decades. In support of the measurement and monitoring of progress towards the 17 SDGs and the 169 associated targets, the UN has established a Global Indicator Framework, designed around 232 SDG Indicators. In order to progress towards the achievement of the SDG goals and targets, this framework needs to be assessed using evidence, drawn from accurate and robust data, on a continuous basis.

In July 2015, this need was already recognised by the UN's Third International Conference for Financing for Development which produced a comprehensive framework—the Addis Ababa Action Agenda (AAAA). The agenda highlighted more than 100 actions to be taken to finance the sustainable development agenda and explicitly recognizes the need to fund "science, technology, innovation and capacity building," as well as "data, monitoring and follow-up" *[RD-1]*. Therefore, monitoring and evaluation, based on accurate and robust data, must not only be at the centre of the Global Indicator Framework, but of the Agenda 2030 for Sustainable Development in its entirety. Indeed, data and evidence are the foundation of development policies and effective program implementation, as recognised by the Independent Expert Advisory Group on a Data Revolution for Sustainable Development (IEAG) *[RD-2]* in 2014. National Statistical Offices (NSOs) should generate a sustainable flow of high quality, timely, authoritative and accessible data for on-going monitoring of progress towards Agenda 2030. In response, the Global Partnership for Sustainable Development Data (GPSDD) was launched in 2015 in Addis Ababa and New York. It is an open, independent, multi-stakeholder network harnessing the data revolution for sustainable development. This message was further promulgated when the Cape Town Global Action Plan for Sustainable Development Data was launched in early 2017 and subsequently adopted by the United Nations Statistical Commission at its 48th Session *[RD-3]*. The Plan identified key actions in six strategic areas that could strengthen national statistical systems to respond to statistical needs to achieve the 2030 Agenda and beyond. The strategic areas were coordination and strategic leadership, innovation and modernization, strengthening of basic statistical activities, dissemination and use of sustainable development data, multi-stakeholder partnerships and statistical capacity building.

Although this compendium recognises the contribution of all types of accurate and timely data to further sustainable development, it focuses particularly on location-based or geospatial data, obtained by satellite-based Earth Observation (EO). However, integrated geospatial economic, social and environmental datasets are scarce for many countries, presenting an unrealised opportunity for space technology to play a key role in the global indicator framework. The compendium shows how to take advantage of this opportunity and highlights how geospatial information and EO, the collection of satellite and in-situ information about Earth's physical, chemical and biological systems, by tracking and assessing their evolution through time, has the potential to complement traditional sources of socio-economic data for both indicators and targets. Although EO is an all-encompassing term for a range of EO instruments, both on the ground and in the air, this compendium focusses on geospatial information obtained by EO satellites. Satellite-based EO has the advantage of coverage of the most remote areas of the world, across political boundaries and oceans, with regular and repeat observations, and continuously over decades for most of free and open data. EO can improve and complement conventional statistical data collection, as well as provide new types of environmental information. For example, censuses and household surveys are costly to administer over large territories and therefore have limitations such as sparse sampling regimes and poor coverage in remote areas. EO can remotely map land cover over time from local to regional scales, from which economic use of the land can be inferred, supporting census and household surveys and filling information gaps.

This report shows how EO technologies can and should fit into national statistical systems for monitoring the progress indicators as well as setting the targets of the SDG framework. In addition, earth observation has the potential to demonstrate how new and relevant indicators for the SDG framework could be developed. It illustrates how observations can directly or indirectly support indicators, and how countries can set and plan their SDG targets using EO-based support tools. Importantly it shows how earth observation can support evidence-based decision making in support of sustainable development policies. There is clearly huge potential for involving the wide range of current and emerging Earth Observation products in target setting and indicator monitoring. For instance, consistent, comparable and readily available time series of relevant earth observations will go a long way to supporting countries in meeting their monitoring and reporting commitments. Access to earth observations in a ready-to-use format would enable countries to build capacity in developing methodologies where EO is a sustainable source of primary observation. If this need were met it would greatly enhance our ability to keep global sustainable development under proper review and take well informed policy decisions to achieve some goals.

Key Recommendations

This compendium underlines the important contribution that satellite-based EO can make to the indicator framework of Agenda 2030. It shows that up to 34 indicators can be either directly (17 indicators) or indirectly (17 indicators) informed with EO data across 29 targets and 11 goals. Not only are there potential technical improvements afforded by EO in the indicator methodologies but there are also multiple benefits of EO for supporting the indicator framework in the long term. Data continuity has improved greatly with the advent of the Sentinel satellite constellations from the European Copernicus Programme, with Sentinel-1A launched in 2014, and the USGS/NASA Landsat 8 continuity mission launched in 2013. These are publicly funded EO missions which are supported by open and free data policies, democratising access to EO data for all. The technical infrastructure needed to process and extract meaningful information from EO data has matured with the advent of advanced cloud computing and parallel processing systems. Inter-agency coordination has also improved thanks to the efforts of the Group on Earth Observations (GEO) and the Committee on Earth Observation Satellites (CEOS) to listen to the needs of countries, coupled with capacity building efforts specifically targeting developing countries. However, ongoing efforts are needed to build on this momentum and to ensure continual progress in developing the potential of EO to inform Agenda 2030, in particular that we adhere to the principle of the SDGs "that no one be left behind".

Below are some key recommendations, drawn from evidence presented throughout this compendium, which outline how the global EO and SDG community should proceed in bringing the full potential of EO to Agenda 2030.

1. Communicate and demonstrate the potential of satellite Earth Observation so that it can be fully exploited in indicator methodologies

EO brings new and exciting possibilities for the methodologies of 34 of the SDG indicators, as well as in national target setting for a least 29 SDG targets. Yet this potential has not been clearly communicated to date, in particular to countries and statisticians who need the data the most. There is an ever increasing number of civilian space agency funded and commercial EO satellites in operation which has raised the expectation that many environmental, economic and social change can be measured from space. This expectation should now be fulfilled with concrete action. A first step is to communicate the success stories and the barriers which have been overcome and no longer restrict EO data use worldwide. Previous limitations in satellite sensor performance in certain geographical settings, e.g. in areas prone to cloud cover, have been overcome by launching satellites in constellation, increasing the probability of clear observations. The time scales of EO data availability have also increased, e.g. for indicators requiring historical baselines there are now continual, multi-decadal EO data records, with Landsat time series spanning from the late 1970s to the present. Moreover, since then systematic global coverage by multiple missions has expanded to reach almost all locations on Earth, as is the case today. The main limitation now is not if EO data exists but where it can be stored, accessed and in a format ready to be used. Finally, accuracy of EO data is improving, both at the point of image acquisition, and in derived products such as land cover, atmospheric constituents and ocean colour – just like statistical data, the accuracies of these derived datasets need to be clearly documented by both communities (EO and statistics) to meet the demands of statistical rigour, demanded by the SDG indicators.

2. Information flows need to be improved to inform SDG related decision making

The flow of environmental information from EO to geospatial datasets to indicators and into the hands of policy makers in decision making fora should be streamlined within countries. Custodian agencies are UN bodies (and sometimes other international organisations), who are responsible for compiling and verifying country data. Although custodians have issued methodological guidelines at the country level, information must flow seamlessly if EO (as well as other forms of geospatial data) is to be integrated into national systems and processes. Potential bottlenecks, e.g. where information is exchanged between government ministries or from private to public sectors within countries, should be identified and appropriate strategies designed to improve data flow, e.g. using spatial data infrastructures. Furthermore, the Inter-Agency and Expert Group on SDG Indicators (IAEG-SDGs) members and Inter Governmental Organisations such as the UN should explore the demand side of requests for EO, e.g. as stated by policy makers, rather than the current emphasis on the supply side. It is important therefore to improve the cooperation between governments and agencies within countries, and to increase their awareness of EO. This could be achieved by focusing efforts on providing policy makers with the relevant information needed for them to become "EO literate," so that they can see how gaps in the knowledge landscape can potentially be filled with EO data.

3. Partnerships between National Statistical Offices (NSOs) and geospatial experts need to be strengthened

There should be stronger collaboration between NSOs and EO experts, to enable the potential of EO to be fully realised within the national statistical systems. In particular, if EO data are to be merged with traditional sources of statistical data such as census and other big statistical data collection exercises. New and old ways of thinking need to be combined for a more complete integration of EO with statistics, as part of the end-to-end information flow to decision makers. In many countries the statistical agencies, geospatial and remote sensing experts are to be found in different parts of government. Creating partnerships amongst the different agencies and departments is a first step to building an effective collaboration. When working together, identifying and managing technical language differences (accuracy, validity, variables can refer to different things) should also be properly addressed. Finally, strong partnerships are especially beneficial to the communities when they are bolstered with training plans and capacity building efforts.

4. Commercial image providers should be encouraged to work with countries on the provision of very high resolution earth observations

Commercial satellite operators generally provide access to the very high resolution satellite imagery needed for certain applications in SDG reporting. Some of the SDG indicators, especially those related to small scale environmental phenomena such as urban greening, waste water pollution and treatment, climate-smart agriculture in small-holder farming or disaster risk mapping necessitate measurements at very high spatial resolutions (VHR). Therefore, low to middle income countries in particular should be financially supported to access VHR imagery for SDG monitoring and reporting where costs for national or even sub-national coverage might be prohibitive. The Small Island Developing States (SIDS) are also one of the most impacted by environmental changes and would definitely benefit of accessing VHR imagery to help monitor their coastlines evolution, water quality or impacts of disasters. Data access agreements should be brokered between the commercial sector and companies in countries with the ministries responsible for SDG reporting. This could be a potential solution to greater access to such data. Ultimately the demand for VHR imagery should be passed onto space agencies or their third party providers if low to middle income countries are to be supported in the long term in meeting their SDG reporting needs.

GeoVille DHI GRAS UN environment programme WCMC

UNEP-DHI PARTNERSHIP
Centre on Water and Environment
UNEP DHI


COMPENDIUM OF EO CONTRIBUTIONS TO THE SDG TARGETS AND INDICATORS









Introduction

Target audience

This report is intended as a resource for four communities: first and foremost are countries, consisting of multi-disciplinary actors involved in indicator reporting at the national level and monitoring progress towards the SDGs; second are the custodian agencies responsible for indicator methodological development who can realise the opportunities for Earth Observation (EO) in indicator methodologies; third are policy makers interested in evidence that supports progressive, data-driven policy goals; fourth are EO specialists in order to identify how their work can contribute to the realisation of Agenda 2030. We hope that the compendium will encourage an ongoing commitment from all stakeholders to realize the full potential of the invaluable set of EO tools, techniques and examples presented in this report. As a result, we hope indicator custodians and countries will take every available opportunity and creative step to enhance monitoring of sustainable development at the national, regional and global level.

The 2030 Agenda for Sustainable Development

The United Nations (UN) system has a long history of seeking to promote and address sustainable development across society and to establish governance frameworks to achieve it:

- 1972: UN Conference on the Human Environment (Stockholm), the first major conference on environmental sustainability marking a political turning point;
- 1992: UN Conference on Environment and Development (The Earth Summit, Rio de Janeiro) that included Agenda 21 calling for global action in all areas of sustainable development spanning social, economic and environmental issues, and the initiation of the three Rio Conventions on sustainable development (UNFCCC – the UN Framework Convention on Climate Change; CBD – Convention on Biological Diversity; and UNCCD – the UN Convention to Combat Desertification);
- 2000: The Millennium Declaration that sought to reduce poverty and set out targets for the year 2015 – known ultimately as the eight Millennium Development Goals (MDGs);
- 2002: The World Summit on Sustainable Development (WSSD) also known as 'Rio+10' (Johannesburg);
- 2012: The UN Conference on Sustainable Development ('Rio+20', Rio de Janeiro) that resulted in 'The Future We Want' political outcome document, containing practical measures for implementation of sustainable development principles and a path to development of Sustainable Development Goals (SDGs).

Out of the consensus achieved at the UN Conference on Sustainable Development in Rio 2012 arose the 2030 Agenda for Sustainable Development *[RD-4]*. The Agenda was agreed and adopted by the United Nations General Assembly in September 2015 where Heads of States and Governments recognised 17 Sustainable Development Goals and their 169 targets, as a framework for the 2030 Agenda. Although the eight MDGs were realistic and easy to communicate, their scope was limited to issues that mostly concerned developing countries - child mortality, extreme poverty and universal access to education. Building on the MDGs, the SDGs embraced the three dimensions of sustainable development (environmental/ biosphere, social/society and economy, as illustrated in Figure 1), made them applicable to both developing and developed nations and identified concrete actions for people, planet, prosperity, peace and partnership. They also emphasise integration, coherence, indivisibility– and an underpinning philosophy of "we will leave no one behind". Overall the Implementation of the 2030 Agenda requires a more holistic, coherent and integrated approach at national, regional and global levels. It is the responsibility of governments to set and meet national targets that collectively will achieve the global ambition. National policies to implement the 2030 Agenda need to address inter-linkages within the social, economic and environmental dimensions of sustainable development. This presents unprecedented challenges as well as opportunities for joined-up, cross-sectorial thinking.

An overview of the 17 Goals is provided below (Box 1). The UN System has established a range of formal processes for achieving the sustainable development goals and monitoring progress towards the SDG Targets, with a particular focus on supporting the least developed countries. Further details on the individual SDGs and the 169 targets can be found at the SDG knowledge platform *[URL-1]*.

Each government is also requested to define their own targets, guided by the global level of ambition, but taking into account their national circumstances and specificities. The SDG process is supposed to be country-owned and country-led, which implies that countries are leading both on the delivery and the follow-up of the SDGs; in addition countries are encouraged to use the framework of globally agreed indicators to report on national progress. Currently there are 231 agreed global indicators covering the targets. This represents a huge monitoring burden on countries and will require a significant

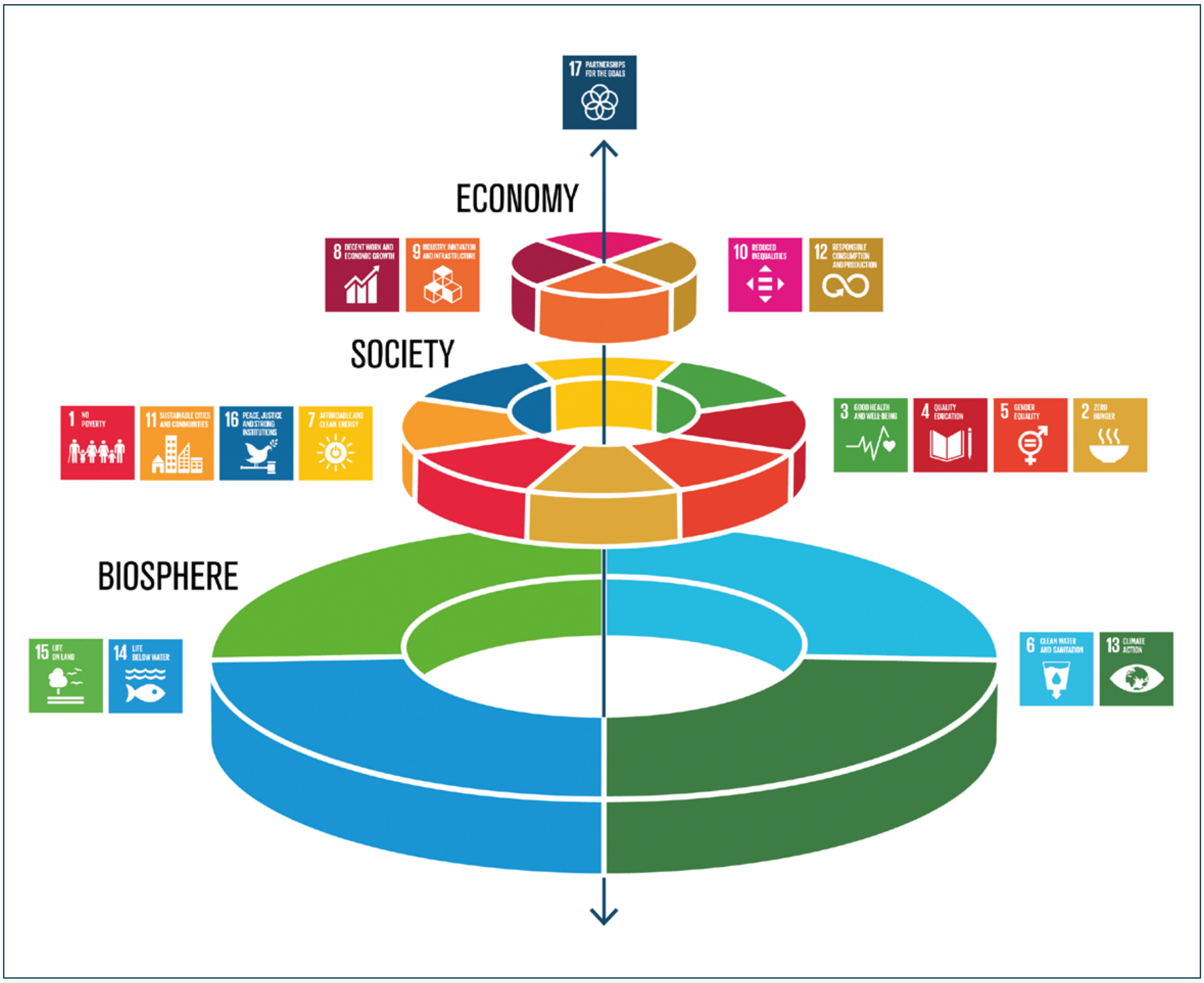


Figure 1: Illustration of the 17 Sustainable Development Goals across the three spheres of sustainable development: biosphere, society and economy. *Source: (Azote Images for Stockholm Resilience Centre)*

level of capacity and resources, especially since not all indicators yet have fully established methodologies or available data at the global level. However, countries are free to choose which indicators to report on, and should use existing national statistics where possible, in order to compile indicators which measure the progress against the goals and targets. The SDG framework is a data-driven global agenda, and data is at the core of the SDGs. This indicates a transformative change in the way countries deal with development policies. Primarily, it sees a step change in how data are used to inform sustainable development polices and that data are recognised as of central importance in tracking progress through indicators. In addition to statistical data already in use by countries for national use, new and complementary sources of data are needed. Geospatial, or location-based information, is one of these data sources as recognised by the United Nations Agenda 2030 *[RD-4]*. Satellite-based Earth Observation, as a tool to acquire this geospatial information, is therefore a key technology which must be taken full advantage of. Countries are also encouraged to align SDG reporting with the demands of other Multilateral Environmental Agreements (MEAs), especially those of the three Rio Conventions and frameworks such as the Sendai Framework for Disaster Risk Reduction *[URL-2]* and the New Urban Agenda *[URL-3]*. In theory, this alignment should allow countries to focus resources and increase reporting efficiency.

The ability to disaggregate SDG indicators where relevant, into thematic areas related to age, gender, economic status, and income is a key tenet of the "leave no one behind" philosophy so as to better understand the circumstances of multiple groups within society including women, the elderly, children, those on low incomes and so on. Indicators should also be disaggregated spatially at the sub-national level, e.g. by administrative or functional units such as urban and rural areas. This concept of spatial disaggregation is an important consideration for the suitability of EO-based approaches in indicator methodologies.

Goal 1. End poverty in all its forms everywhere.

Goal 2. End hunger, achieve food security and improved nutrition and promote sustainable agriculture.

Goal 3. Ensure healthy lives and promote well-being for all at all ages.

Goal 4. Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all.

Goal 5. Achieve gender equality and empower all women and girls.

Goal 6. Ensure availability and sustainable management of water and sanitation for all.

Goal 7. Ensure access to affordable, reliable, sustainable and modern energy for all.

Goal 8. Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all.

Goal 9. Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation.

Goal 10. Reduce inequality within and among countries.

Goal 11. Make cities and human settlements inclusive, safe, resilient and sustainable.

Goal 12. Ensure sustainable consumption and production patterns.

Goal 13. Take urgent action to combat climate change and its impacts.

Goal 14. Conserve and sustainably use the oceans, seas and marine resources for sustainable development.

Goal 15. Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss.

Goal 16. Promote peaceful and inclusive societies for sustainable development, provide access to justice for all and build effective, accountable and inclusive institutions at all levels.

Goal 17. Strengthen the means of implementation and revitalize the global partnership for sustainable development.

Box 1: The 17 Sustainable Development Goals (SDGs) of the 2030 Agenda

Scope and purpose of the compendium

The UN 2030 Agenda and its Sustainable Development Goals (SDGs) has stated its commitment to "leave no one behind". Countries will need to align their national policies with the SDGs to be able to achieve the goals, as well as setup mechanisms to measure progress and report on the SDG indicators against the Targets.

In this spirit, this compendium is intended as a resource for all countries (National Statistical Offices and line ministries, which are national focal points for SDG monitoring and reporting) to realise the potential of Earth Observation (EO) technology to meet the informational needs of SDG targets and indicators and to gain an appreciation for how EO can be used to produce high quality, repeatable indicators to assess progress towards targets. The technical detail and broad treatment of the indicator framework within this compendium will also be valuable to the UN Custodian Agencies, the UN Statistical Commission and its Inter-Agency and Expert Group on SDG Indicators (IAEG-SDGs), the UN Global Working Group on Big Data including a team on Geo-spatial information and satellite imagery *[URL-4]*, and the UN Committee of Experts on Global Geospatial Information Management (UN-GGIM, established in July 2011) so that efforts can be aligned and duplication avoided between these various initiatives. The EO community should also find it useful, especially those who are unaware of the opportunities for EO in the SDGs.

The success of the SDGs themselves relies on access to knowledge and technological development. The SDG targets 9.5 ("Enhance scientific research, upgrade the technological capabilities of industrial sectors in all countries…", 9.B ("Support domestic technology development, research and innovation in developing countries…" and 9.C ("Significantly increase access to information and communications technology…in least developed countries by 2020") all mention innovation in support of sustainable development, especially SDG 9.C. This compendium therefore also makes a major contribution to Goal 17 which seeks to strengthen global partnerships and capacity building activities in support of the SDGs.

Finally, the compendium is seen as a catalyst to stimulate dialogue among national governments, the UN system, the EO community, civil society, the private sector and other actors in order to mainstream EO in the SDG monitoring framework.

The compendium is complementary to the collaborative efforts of the Group on Earth Observations (GEO) and the Committee on Earth Observation Satellites (CEOS) to promote the use of EO for the SDGs. It can also be a useful resource to support other SDG stakeholders, e.g. the GEO Earth Observation for Sustainable Development Goals (EO4SDG) initiatives, the Inter Agency and Expert Group on SDG indicators (IAEG-SDGs) and its Working Group on Geospatial Information (WGGI), the Global Partnership for Sustainable Development Data (GPSDD), National Line Ministries, National Mapping and Cadastral Authorities (NMCAs) and others beyond the science-policy sphere (researchers and NGOs).

The Global SDG Indicator Framework

To keep track of progress towards the 17 Sustainable Development Goals and their associated 169 targets, a Global Indicator Framework of 232 SDG indicators[1] , was officially adopted by the UN Statistical Commission at its 48th session in March 2017 following an open and transparent process involving stakeholders at all levels, and is reviewed annually. The framework collectively provides a management tool for countries to implement development strategies and report on progress toward the SDG Targets.

The UN Statistical Commission (UNSC), the highest authority of the UN statistical system and a functional commission of the UN Economic and Social Council (UN ECOSOC), has the mandate of overlooking the development and implementation of the Global Indicator Framework for the SDGs. The other major actors in the organisation of the global SDG indicator framework are shown in figure 2.

The High Level Political Forum (HLPF)

Progress towards the Sustainable Development Goals is discussed by the UN's High Level Political Forum which meets annually under the auspices of the UN Economic and Social Council (ECOSOC), and every four years under the auspices of United Nations General Assembly (UNGA). The Forum has a leadership and review function for the 2030 Agenda, inviting countries to present Voluntary National Reviews (VNR) of progress towards implementation and presenting thematic reviews of specific goals and cross cutting themes. An annual review of progress is published as the Sustainable Development Goals Report *[RD-5]*.

The 2018 meeting of the HLPF took place 9-18 July 2018, at UN Headquarters in New York *[RD-6]*. At this occasion, a side-event on EO ("From up there to down here - big space data and the SDGs") was organised by Australia and showcased country examples to raise the awareness and promote the potential in using EO satellite-data in the process. The 2020 session of the HLPF, under the auspices of UN General Assembly, looked retrospectively and prospectively at the totality of the agenda for the ensuing four-year cycle, informed by the Global Sustainable Development Report. Head of States and governments called for a decade of actions to deliver the SDGs by 2030 and announced actions to advance the agenda. The SDG Summit resulted in the adoption of a political declaration: *"Gearing up for a decade of action and delivery for sustainable development"*.

The Inter-agency and Expert Group on SDG Indicators (IAEG-SDGs)

In March 2015 at its 46th session, UNSC created an Inter-Agency and Expert Group on SDG Indicators (IAEG-SDGs), made up of representatives of National Statistical Offices (NSOs), to develop and implement the Global Indicator Framework for the monitoring of the Goals and Targets of the 2030 Agenda.

Indicators have been classified by the IAEG-SDGs into three tiers based on globally accepted methodologies and availability of data, as described in table 1 *[URL-5]*. The classifications are reviewed annually based on changes in methodologies, data availability and progress in the development of indicators (as documented in work plans) *[URL-6]*. The classification in Table 1 reflects the decision made during the 51st session of the UN Statistical Commission in March 2020, following the 2020 comprehensive review of the Global Indicator Framework.

The updated tier classification contains 115 Tier I indicators, 95 Tier II indicators and 19 indicators with a tier level between I and II, pending a data availability report. As of the 51st meeting of the UN Statistical Commission (UNSC) in March 2020, the global indicator framework does not contain any Tier III indicators anymore. In addition to these, there are 2 indicators that have multiple tiers (different components of the indicator are classified into different tiers).

1 This number of indicators will change as new indicators are added and others removed during annual reviews by the IAEG-SDGs and based on ad hoc requests by indicator custodians. Following the 2020 comprehensive review, the number of indicators of the Global Indicator Framework has been reduced to 231 indicators.

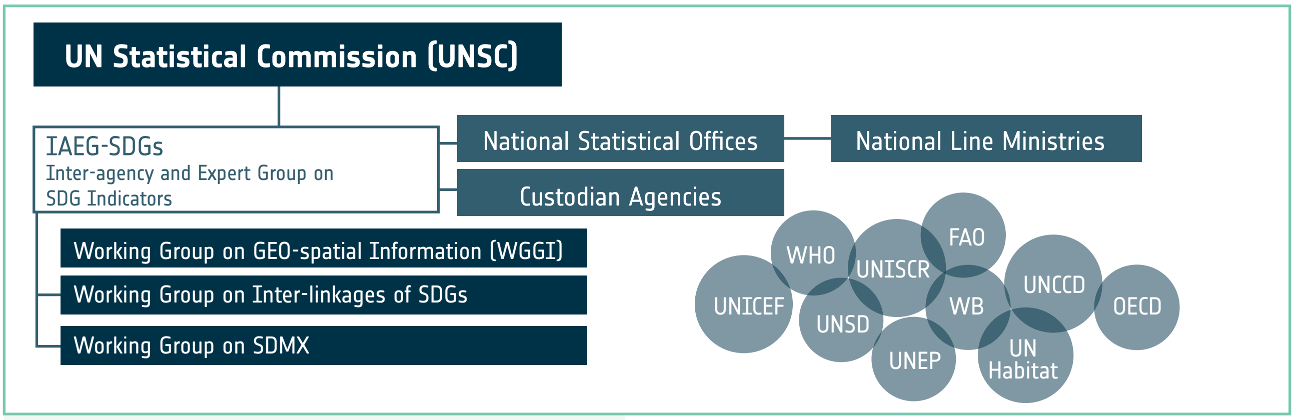


Figure 2: Organisation of the Global SDG Indicator Framework

Tier Level	Tier classification	No. of indicators
I	Conceptually clear, have established methodologies, standards are available and data are regularly produced by countries (at least 50 per cent of countries and of the population in every region where the Indicator is relevant).	115
II	Conceptually clear, have established methodologies, standards are available but data are not regularly produced by countries	95 19 indicators with a tiering (between I and II) pending a data availability review. 2 indicators will multiple tiers (different components of the indicator classified in tier levels I or II)
III	There are no established methodologies and standards or methodology/standards are being developed/tested	0[2]

Table 1: Updated Tier classification based on the 2020 comprehensive review of the Global Indicator Framework and approved at the 51st session of the UN Statistical Commission (March 2020).

The tier classification of many indicators is still expected to change as methodologies are developed and data availability increases. Two comprehensive reviews of the Global Indicator Framework are planned by the IAEG-SDGs to support the global monitoring of the 2030 Agenda without increasing the number of indicators. These reviews include the replacement, deletion, refinement or adjustment of indicators, and in a few selected cases, additional indicators. Additional indicators may be considered only in exceptional cases when a crucial aspect of a target is not being monitored or to address a critical or emerging new issue that is not monitored by the existing indicators. A deletion will be considered when the methodological development of a tier III indicator has stalled or not produced the expected results. The 2020 comprehensive review was conducted by the IAEG-SDGs and resulted in a revision of the Global Indicator Framework into 231 indicators classified either in Tier I or in Tier II.

The implementation of the global indicator framework presents a considerable challenge even for the most advanced countries. As acknowledged by the UN General Assembly, existing statistical systems must be employed where possible while also leveraging new sources of information and observations, where needed, to supplement existing ones. At its 3rd meeting in Mexico (30 March-1 April 2016), the IAEG-SDGs established three working groups to give guidance to countries on how to implement the monitoring framework by examining different data sources. The expert groups were on (i) Statistical Data and Metadata Exchange (SDMX), (ii) Geo-spatial information (WGGI), and (iii) Interlinkages of SDG Statistics, to allow for more closely integrated analyses in monitoring. The work of the WGGI is the most relevant for this compendium and will be examined.

IAEG-SDGs Working Group on Geospatial Information (WGGI)

Although the development of the Global Indicator Framework has primarily been based on statistical data, it is recognized that geospatial information (including EO) provides new and consistent data sources that can support and inform official statistics and consequently the indicators for the SDGs. The mandate of the WGGI is to review the Global Indicator Framework through a "geographic location" lens, to identify existing geospatial data gaps and methodological issues, and to assess how geospatial information and EO can contribute to the Global Indicator Framework. The UN Committee of Experts on Global Geospatial Information Management (UN GGIM). which leads the global agenda for the management of geospatial information to address key global challenges, provides the secretariat for the WGGI through the Global Geospatial Information Management (GGIM) Section of the UN Statistics Division (UNSD).

The WGGI is therefore building on progress made by the UN-GGIM, the UN GGIM Expert Group on the Integration of Statistical and Geospatial Information (EG-ISGI), the Group on Earth Observations (GEO), the UN Global Working Group on Big Data (an outcome of the 45th Meeting of the UN Statistical Commission) and other various related groups, in the development of geospatial information and EO data inputs into the global indicator framework.

The WGGI - currently led by NSO representatives from Mexico and Ireland - has recently updated its terms of reference and membership to strengthen the coordination between the statistical and the geospatial information

2 As of the 51st UNSC (March 2020), the global indicator framework does not contain any Tier III indicators communities. This includes a stronger connection to related activities, especially the work of custodian agencies, and a wide consultation on the status of geospatial data collection by countries. The WGGI workplan for the years 2020 and 2021, includes the development of a SDG geospatial roadmap with a story-telling mechanism to better communicate the value of geospatial information and Earth Observations for the SDG indicators, the interlinkages with expert groups such as the EO4SDG initiative of the Group on Earth Observations (GEO), the showcase of best practice examples that will support Member States to improve their application of geospatial information and Earth observations, and the development of guidance and recommendation regarding the use of proven toolkits, including SDG EO toolkits. The Compendium represents an input to the work of the WGGI, through the contribution of GEO EO4SDG.

Custodian Agencies

Recognising the scale of the challenge in ensuring appropriate methodologies, in data availability and in consistent and comparable reporting by countries, the UN has appointed specialised Agencies to play a coordinating role as Custodians of SDG Indicators relevant to their area of expertise. Custodian agencies are the United Nations bodies (and in some cases, other international organizations) that are responsible for compiling international data series, metadata on SDG indicators, and for providing the data, along with regional and global aggregates, to the United Nations Statistics Division (UNSD). These agencies have also the mandate to compile monitoring guidelines for measuring and reporting on the indicators, to support countries on their implementation and strengthening national statistical capacities, and to collect national data for the global reporting mechanism. To do so, custodians are expected to coordinate closely with countries and their national statistical systems, regional bodies and international stakeholders on indicators' development.

Each SDG indicator has one nominated custodian, or co-custodians as the case of the UN Environment Programme (UNEP) for the indicator 6.6.1 on waterrelated ecosystems and further partner agencies. Custodian agencies provided information on their data collection processes and also nominated a focal point for each of the indicator which can be useful when questions or issues arise about definitions, methods or data.

These agencies may publish the country data in their own databases and use it for thematic reporting. The country data need to be internationally comparable. Therefore, the custodians advocate for strict standards for countries to follow in the indicator methodologies. According to the 2030 Agenda, SDG reporting is the responsibility of countries and conducted in compliance with the UN's Fundamental Principles of Official Statistics. These principles are considered a basic framework that national statistical offices and other statistical organizations must follow in recognizing official statistics as a public good.

To this end, the agencies are also responsible for developing international standards and recommending methodologies for monitoring. Noting that if they can "recommend" methodologies for standardization purpose, it is up to countries in the end to follow those methods or use others if more relevant to their national specificities. Measurement of some of the indicators is entirely achievable for many countries today, whilst tracking other indicators will require further improvements in underlying data and statistics, as well as corresponding availability of robust methodologies for National Statistical Offices (NSOs) and the relevant ministries to follow.

Another central responsibility of the custodian agencies is to strengthen national monitoring and reporting capacity. When country data are missing, or collected using a different methodology or inconsistently reported by different sources, custodian agencies need to do estimates or adjust the data together with the specific countries. All final data submitted to UNSD for the global reporting on SDG indicators need to be validated and approved by countries.

National Statistical Offices and line ministries

The responsibility for the collection of national data is country-specific and typically consists of an oversight authority – the National Statistical Offices (NSOs) – and line ministries responsible for their respective SDG Indicators.

In order to assist NSOs with this effort, especially in countries low on capacity, the Cape Town Global Action Plan for Sustainable Development Data was conceived by the UNSC to recognise that the implementation of the SDGs requires coordinated action and considerable resources to process vast and disparate data sources *[RD-4]*. The action plan calls for enhanced capacity building in countries facing high data challenges, modernized national statistical systems, and encourages NSOs to embrace open data initiatives while integrating new data sources (including EO data) into statistical production programmes. The Global Action Plan proposes to leverage the efforts of the NSOs to modernize their national statistical systems, and also the efforts of international organizations and partnerships such as those of the EO community to promote EO in support of SDG monitoring.

The importance of Earth Observation in the indicator framework

Advantages and opportunities of Earth Observation

Of the various forms of earth observations, including those from space-borne, airborne and in-situ platforms, satellite-based EO is the primary source of additional and complementary observations for national statistics at the appropriate scale for SDG reporting. Other forms of EO are also important at the national and subnational levels, especially for indicator disaggregation at finer spatial scales.

There is huge potential for satellite EO to support the aim of the 2030 Agenda in "leaving no one behind" as, by nature, space-borne observations are borderless, impartial and inclusive of all. It is also a crucial data source for many of the indicators describing the environmental aspects of the planet and as a spatial disaggregation method of other geospatial statistics. Designed for planetary-scale coverage, satellite EO has some key characteristics which make it an indispensable source of data for a select few SDG indicators and a supporting source of data for many others. Satellite EO provides:

1. **A synoptic view of the Earth's surface**: polar-orbiting, sun synchronous EO sensors observe wide swathes of the Earth in one pass, acquiring and storing large amounts of Earth surface imagery under constant conditions of solar illumination. Geostationary satellites observe hemispherical-scale patterns and can produce imagery up to every 15 minutes.
2. **Regular and repeatable observations**: polar-orbiting EO satellites orbit the Earth several times per day allowing consistent and systematic surface observations of the entire Earth surface. The continuity of observations in the long term is now guaranteed through dedicated, operational missions such as those of the Copernicus programme.
3. **Multi-annual time series of observations**: since the 1970s the average operational lifetime of an EO mission has almost tripled to today's average mission lifetime of 8.6 years *[RD-7]*, enabling more stable and continuous observations from the same sensor over several years or more.
4. **Cost-effectiveness for monitoring remote and inaccessible areas**: EO satellites are designed to observe any location on the Earth's surface at some time in their orbit, albeit with some constraints around polar regions, permitting observation of areas otherwise inaccessible for ground based surveys.

In addition to these technical benefits, access to EO data is increasingly democratised and open with free and open data policies proliferating as well as the processing infrastructure to process them. The Copernicus programme of the European Commission has made data from its Sentinel satellite programme free for all – data continuity is an essential element of the Copernicus program. The United States Geological Survey (USGS) also liberated the vast archive of Landsat data in 2012, dating from 1978 onwards, making it free for all to use. These progressive initiatives set a precedent for future EO programmes. Other geospatial data and statistics are increasingly free and open, in line with the GEO principles of sharing of data, information, knowledge, products and services. One of the main outcomes of GEO since its inception (2005) is actually to have stimulated the open data policy as it has gone from the exception to the global norm.

Earth Observation processing infrastructure

Coupled with this Big Data revolution, the EO data processing and analytics infrastructures has also advanced considerably. The widespread use of data architectures and servers on the internet, enabling "cloud computing", has been a key element of this revolution. High Performance Computing (HPC) is another. HPC allows advanced processing infrastructure to run efficiently, reliably and quickly meaning that larger, more complex datasets, especially from new data sources, i.e. Big Data, can be processed more efficiently than before. The advent of cloud computing and HPC has led to several advances in EO data processing. Some of the main enabling infrastructures are described below – the Earth Observations Data Cubes (e.g. the Open Data Cube promoted by CEOS or the Euro Data Cube supported by ESA), the European Commission's Data and Information Access Services (DIAS) and the ESA Thematic Exploitation Platforms (TEPs). In addition, Trends.Earth, a customised platform for SDG monitoring reporting with EO data, is briefly presented.

Data cubes organise satellite imagery into stacks of consistent, calibrated, geographic 'tiles', underpinned by a relational database ready for rapid manipulation in a high powered, computing environment. Data cubes can serve the EO data and information needs (in terms of data discovery, access, processing and analysis) of the large community of SDG stakeholders, addressing both global and national data processing needs. Some of the most widespread data cubes for processing and analysing large spatiotemporal geospatial datasets are listed here:

- CEOS Data Cube *[URL-8]*
- Earth System Data Cube (ESDC) *[URL-9]*
- Digital Earth Australia Open Data Cube (ODC) *[URL-10]*
- Euro Data Cube *[URL-11]*
- Google Earth Engine *[URL-12]*
- Open Data Cube *[URL-13]*

The European Copernicus Programme has deployed five cloud-based platforms known as the DIAS which are funded by the European Commission *[URL-14]*. The DIAS facilitate access to Copernicus data and services, including the Sentinel data, as well as to on-line EO data processing and analytic tools. The Amazon Web Services (AWS) are also providing access to Sentinel-2 imagery, through the Sentinel Hub *[URL-15]*, thereby significantly reducing the user burden of downloading, archiving and processing petabytes of data.

The Thematic Exploitation Platforms (TEPs) were created by ESA to help users access an interconnected, virtual work environment, providing access to EO data and the tools, processors, and processing infrastructure required to work with them, through one coherent interface. Instead of the user downloading and working locally on EO and non-EO data, the TEP allows the user to access these data on the cloud. Currently there are TEPs addressing the following applications:

- Coastal *[URL-16]*
- Forestry *[URL-17]*
- Hydrology *[URL-18]*
- Geohazards *[URL-19]*
- Polar *[URL-20]*
- Urban *[URL-21]*
- Food security *[URL-22]*

Trends.Earth *[URL-23]*, an EO-based tool, developed by Conservation International in corporation with NASA and Lund University, under funding of the Global Environment Facility, is a customised platform for SDG monitoring reporting with EO data, currently equipped with tools for reporting on SDG 15.3.1 on land degradation. It integrates national level data with globally available EO datasets to calculate the proportion of degraded land. It is based on standardised methods that have been compiled in a Good Practice Guidance by the UNCCD and partners including CSIRO *[RD-8]*, while also providing the flexibility for customisation to local conditions. The tool uses data from three sub-indicators –land cover, vegetation productivity and soil organic carbon - to estimate the degraded land area and is able to produce spatially explicit outputs as well as tabular results.

Challenges and limitations of Earth Observation

It is all too easy to view EO data and processing tools as solutions with endless possibility, that will solve many of the SDG data challenges but there are limitations to EO data and the human and technical capacity to process them. Here the main technical and capacity limitations are discussed in relation to optical and radar-based methods of data acquisition.

Optical satellites, i.e. those that passively record reflected solar radiation from the Earth's surface, are affected by cloud coverage as reflected light cannot pass through cloud. Equally they cannot operate at night. Therefore, optimal viewing conditions for optical satellite are cloud-free days – infrequent in moist and humid climates such as those in the Tropics. The availability of dense time series, combined with the capacity for pixel-based processing, due to high geometrical accuracies (within pixel), allows extraction of useful information, especially in cloudy regions such as in the tropics. Optical satellites are also subject to trade-offs between spatial and temporal resolution, between revisit time and geographical coverage. This necessitates, for example, that optical satellites which achieve very high resolutions, e.g. <1m, cover less area and acquire imagery of smaller dimension than a medium resolution satellite which could image larger areas in one pass. The emergence of satellite constellations (including constellation of micro satellites) allows high revisiting even at high spatial resolutions. Trade-off also applies to revisit time as satellites that acquire imagery in lower detail can generally revisit the same point on the Earth's surface more regularly, even once or twice per day for some satellite systems.

Satellites carrying radar, i.e. those that actively emit a high frequency signal, can operate at night and through cloud cover as they are not dependent on sunlight as a source of illumination to image the Earth's surface. The ability to image the same area repeatedly regardless of cloud cover or time of day gives radar a significant advantage over optical imagery. The limitation in this is that, being an active instrument with power limitations, radar cannot remotely sense the whole surface of the globe as done by the optical instruments. All radar systems have a duty cycle (a fraction of the time when the radar is transmitting). Although radar is a powerful tool for remote sensing in tropical and ice-covered regions, it is also subject to the same trade-offs in temporal and spatial resolution as described above. In addition it has the unique and undesirable property of producing speckle in imagery which results from the nature of the radar signal interacting with surface objects, and is therefore not as intuitive as optical imagery. Earth surfaces do not appear as the human eye might see them. Radar imagery needs extra pre-processing and expert interpretation to be used effectively. Some big progresses have also been made by radar. For example the Sentinel 1 mission allows imaging of the whole land surface of the globe every 12 days, and every observation is a 'good' observation, since it is not affected by clouds and by sun illumination.

In addition to the technical characteristics of EO data acquisition, there are limitations associated with integration of EO into national statistics. The challenge of synthesising multiple data sources will be a key one for custodians and NSOs alike as will the design of methodologies which can harmonise EO with statistical data according to the rigorous standards demanded by official national statistics. As EO data is a highly specialised field, the technical capacity and financial resources to stock, process and manipulate EO data can be an issue for countries. Space agencies, with specialists in these realms, are increasingly launching initiatives to make EO data less complex and accessible for users. At an international level these efforts are being coordinated by the Committee on Earth Observation Satellites (CEOS) which includes promotion of Analysis Ready Data (ARD) standards and exploration of open data platforms such as the Open Data Cube.

Other limitations include the difficulties for some countries to access and process the large amount of EO data available on their countries and the need to have some large computing infrastructures to process and analyse the data. Cloud-based solutions can be used to overcome this problem, as these allow remote access to the data and the processing capacities. However due to sovereignty reasons some governments are reluctant to use cloud-based platform and lose control of their national data, and hence prefer using their local computing platforms which are confronted to big data challenges. Another obstacle is the lack of technical expertise in some countries, hence the need for capacity building. Many EO Massive Open Online courses (MOOCs) have been developed to build these capacities, and some organisations (CEOS or national scientific organisations) are also dedicated to provide technical training and technology transfer to help countries use EO data and run these platforms.

GEO initiatives related to the SDGs

There is more open access to EO data and cloud computing power than ever before, such that EO products and the computational tools to process them, can now readily help countries to monitor change in many land, freshwater and ocean surface processes. However, with a plethora of satellite sensors and downstream products, it is challenging for users to identify those which meet their reporting needs. The Group on Earth Observations (GEO) is a key player to ensure that such observations are easily accessible and fit for purpose.

The Group on Earth Observations (GEO) is an intergovernmental partnership that aims to improve the availability, access and use of Earth observations for a sustainable planet. GEO promotes open, coordinated and sustained data sharing and infrastructure for better research, policy making, decisions and action across many disciplines. Formed in 2004 at the third Earth Observation Summit by a resolution from almost 60 countries, GEO now consists of 105 governments, 126 Participating Organizations, and vast EO resources in the Global Earth Observation System of Systems (GEOSS) Platform. GEOSS is a central part of GEO's Mission, consisting of coordinated, independent EO data, information and processing systems that serve free data to a myriad of public and private sector users, underpinned by open data sharing policies and practices. In addition to building observation systems, GEO supports policy making through its strategic engagements with the 2030 Agenda on Sustainable Development, the Paris Agreement for Climate, and the Sendai Framework for Disaster Risk Reduction. Very recently, the NextGEOSS Platform has recently been published to address more specifically the SDG process *[URL-24]*. GEO plays an instrumental role in promoting and showcasing the value of EO in support of the SDGs and launched the EO4SDG initiative in 2016 *[URL-25]*. The **GEO EO4SDG initiative** is run in close partnership with the UN agencies and the NSOs and has four primary lines of actions: (i) national pilot projects integrating EO with national statistical data; (ii) capacity building around the methodologies needed to apply EO data; (iii) identification and development of data and information products to advance understanding and access to suitable EO resources and (iv) outreach and engagement.

In addition to the GEO EO4SDG initiative, a number of GEO flagships, initiatives, foundational tasks and community activities are designed to bring scientific observations to users who need them in different sectors such as biodiversity, forestry, agriculture or urban. A number of GEO activities and how they support the SDG indicator framework are briefly introduced below:

GEO Biodiversity Observation Network (GEO BON) *[URL-26]* is aimed at users in the biodiversity community. GEO BON initiates and coordinates efforts to design and implement interoperable national and regional biodiversity monitoring networks and is spearheading the emerging Essential Biodiversity Variables – a set of variables required to report on and monitor biodiversity change. These observation networks support indicators that concern life on land (15.1.1, 15.1.2), in freshwater (6.6.1) and oceans (14.4.1).

AquaWatch *[URL-27]*, the GEO Water Quality Initiative, aims to develop and build the global capacity and utility of Earth Observation-derived water quality data, products and information to support water resources management and decision making. AquaWatch is aiming to produce a global monitoring system for water quality by 2025 called the Water Quality Information Service which will be a direct contribution to indicator 6.3.2 (water quality), 6.1.1 and 6.1.12 (sanitation).

GEO Global Agricultural Monitoring (GEOGLAM) *[URL-28]* is an initiative that supports the Agricultural Market Information System (AMIS) and provides monthly crop monitoring and early price warnings, food supply stress (2.4.1,2c.1) and sustainable use of resources such as water (6.4.2, 6.5.1). In addition the GEOGLAM initiative has supported the development of the world's first Rangelands and Pasture Productivity (RAPP) Map *[URL-29]*. The RAPP Map is the spatial data platform for GEOGLAM's RAPP activities.

GEO Blue Planet *[URL-30]* plays a coordinating role in ocean and coastal observations. It is an umbrella initiative for many other programmes responsible for gathering observations in ocean and coastal waters. It improves engagement with users across a variety of disciplines to improve the quality of services delivered to them and to ensure inter-operability of marine observational data. Through its activities, the Blue Planet initiative raises awareness of the societal benefits of ocean observation for both the public and policy sectors. The activities of Blue Planet are of particular relevance to the SDG indicators on coastal marine pollution (14.1.1) and ocean acidification (14.3.1).

Global Forest Observation Initiative (GFOI) *[URL-31]* was a concept that arose from the Forest Carbon Tracking Project undertaken as part of the 2009-2011 GEO Work Plan whose start-up phase commenced in 2012. The GFOI is primarily tasked with ensuring a sustained supply of observations for national forest monitoring systems and assisting countries in making best use of them. In addition, it helps countries in starting up national forest observation systems according to GEO principles of openness and common standards. The GFOI interfaces with the major international forest assessments and assist countries to report to the Global Forest Resource Assessments of the Food and Agricultural Organisation (FAO) and the national Green House Gas (GHG) inventories reported to the UNFCCC using IPCC methods. For the SDGs, the GFOI is mainly concerned with indicator 15.1.1 (Forest areas).

The **GEO-Wetlands** *[URL-32]* initiative aims to realise the possibility of a Global Wetlands Observation System (GWOS) on behalf of the Ramsar Convention. Being a GEO Initiative it follows the same basic principles of openness and data sharing. This will be achieved through a wetland community geo-portal. GEO-Wetlands is already building a community of wetland observation practitioners, spanning a range of actors and has pilot projects, e.g. Global Mangrove Watch, with a view to building the GWOS. GEO Wetlands will play a major role in coordinating data collection for indicator 6.6.1(water-related ecosystems).

The **GEO Human Planet** *[URL-33]* initiative is focused on developing a global baseline map of human settlement and population density, as well as testing methods for regular updates of the baseline for post-2015 indicators such as those of the SDGs, the UNFCCC and the Sendai Framework. The core partnership consists of several universities and agencies with expertise in human settlement mapping. EO plays a key role in the Human Planet mapping approach, both for baseline studies and mapped updates, as it captures the physical infrastructures of human settlements. For SDGs, the Human Planet initiative is a key partnership for indicator 11.3.1 (land consumption).

The **GEO Global Network for Observation and Information in Mountain Environments (GEO-GNOME)** *[URL-34]* initiative addresses the paucity of observations and information on mountains. It specifically aims to halt and manage the drivers of change in mountain ecosystems that result in negative consequences for the health of these ecosystems such as land use and climate change by bring the best available data for decision making impacting mountain communities. Some of its data-oriented tasks involve more precise delineation of mountain ecosystems and harnessing the best available spatial data to characterise mountain ecosystems, including EO-derived land cover change data. Therefore, it is of particular relevance for 15.4.1 (mountain green cover) and 15.4.2 (mountain biodiversity).

The **GEO Land Degradation Neutrality (GEO LDN)** Initiative *[URL-35]* was launched in 2018 to enhance national capacities to map and measure the extent of degraded lands and report on SDG Indicator 15.3.1 ("proportion of land that is degraded over total land area") and ultimately to achieve Land Degradation Neutrality (LDN; SDG Target 15.3) under the auspices of the UNCCD. GEO is well-placed to assist the UNCCD (the custodian agency for Target 15.3 and Indicator 15.3.1) and its contracting parties with the rapid provision and deployment of EO datasets, in-country capacity building and training, along with guidance on the use and development of EO tools and platforms.

Previous assessments of EO contribution to the SDGs

Recognising the fundamental role for satellite EO in the realisation of the Global Indicator Framework, CEOS has identified the SDGs as a top priority and established in October 2016 the CEOS Ad-Hoc Team on SDGs (AHT SDG) *[URL-36]* dedicated to better coordination of the world's space agencies in support of the provision of satellite data for the 2030 Agenda. The AHT SDG team aligns with the SDG agenda through GEO, UN agencies and at national level through NSOs and ministries. The team is also dedicated to fulfil its unique role in providing information about satellite data to the SDG community, and informing space agencies about specific data requirements to help measure some indicators.

There have been many studies and reports made available on the contribution of EO to the SDG indicator framework and to the Agenda 2030 more broadly. Here, three of the most relevant assessments are briefly described – that of the IAEG-SDGs WGGI; GEO with the support of Japanese Space Agency (JAXA); CEOS with the support of the European Space Agency (ESA).

In 2016-2017, the IAEG-SDGs WGGI convened two meetings, one in Mexico City *[RD-9]* and one in Kunming, China *[RD-10]*, and identified a short-list of 24 SDG indicators which could benefit from geospatial data, categorized into two types (direct contribution or indirect but significant support). They suggested that there are 15 indicators where geospatial information together, with statistical data, can contribute directly to the production of indicators and 9 indicators where geospatial data can significantly support the production of indicators.

In 2017, GEO, in collaboration with JAXA and CEOS, produced a booklet entitled “Earth Observations in support of the 2030 Agenda for Sustainable Development” on the potential role that EO data can play in relation to the 17 SDGs *[RD-11]*. This booklet mainly featured case studies showcasing EO for specific indicators as well as a very brief assessment of SDG Targets and Indicators that can be supported by EO. Their conclusion was that almost a half (71) of the targets could be supported and about one eighth (29) of the indicators.

In 2018 CEOS, supported by ESA, produced a handbook on “Satellite Earth Observations in Support of the Sustainable Development Goals” *[RD-12]*. CEOS analysed which targets and indicators could be supported by EO, the distribution of the custodian agencies for the indicators supported by EO and the tier status of the indicators supported by EO, while raising awareness of the importance of EO for achieving the SDG goals and targets. This highlighted the opportunities and challenges to mainstream EO in the SDG processes, and provided different perspectives from various stakeholders regarding the integration of EO in the SDG framework, while showcasing the value of earth observation with practical examples. The analysis done by GEO on the relevance of EO for the SDG targets and indicators was re-used and built-upon –an independent analysis was not carried out. A number of statistics were added on the custodians and tier levels. The analysis concluded that 73 targets and 29 indicators in total could be supported by EO (45 % of tier 1 indicators and 24% of tier 2) and that the FAO was the custodian whose indicators could most benefit from EO, followed by UNEP and UN-Habitat. The report demonstrated the importance of EO for goals 6, 11, 14 and 15 in particular as their respective targets and indicators require information on land cover, land productivity, above ground biomass, water extent or quality characteristics, as well as air quality and pollution.

Key EO datasets for the SDG Global Indicator Framework

Custodian agencies have the mandate to mobilize resources, including data, in support of national efforts to monitor and report on the SDG indicators. The data mobilization includes the provision of global or regional datasets that can complement national data when not adequately available.

This compendium only addresses key, critical and freely accessible EO datasets at the time of writing and, as this is a rapidly evolving environment, precludes an exhaustive review of all possible global EO datasets of potential use for SDG reporting.

It is impossible to do an exhaustive review of all potential global EO-based tools (i.e. tools that allow access to global datasets) that could assist NSOs and indicator custodians with delivering and implementing EO-based methodologies. Below are a sample of key global products that cover major thematic areas of the biosphere and society such as land cover, vegetation productivity, forests, wetlands, surface water, human settlements and which can support the methodological development and measurement of a number of SDG indicators.

Global Forest Watch (GFW) *[URL-37]* is a platform, delivered by the World Resources Institute (WRI), which houses geospatial datasets related to forest cover, condition and use. It is the key visualisation tool for the Global Forest Change product produced by the University of Maryland in collaboration with Google Earth Engine. The Global Forest Change product depicts a global tree cover baseline for the year 2000 and shows losses of tree cover on an annual basis up to 2017. Gains in tree cover are also visible but not resolved to annual time steps. This platform serves datasets of key importance for reporting on indicator 15.1.1 (forest area).

Global Mangrove Watch (GMW) *[URL-38]*, developed under the JAXA’s Kyoto & Carbon initiative, provides geospatial information about mangrove extent and changes to the Ramsar Convention, national wetland practitioners, decision makers and NGOs. The global mangrove extent baseline map for the year 2010 is displayed on WRI’s Global Forest Watch portal. Data are available for baseline changes from 1996 and 1997 (JERS-1), 2007 to 20010 (ALOS) and from 2015 (ALOS-2).This provides invaluable data for indicators 6.6.1, and 15.1.1., 15.1.2 as well as indicators under target 13.1 on disaster risk reduction, recognizing that mangroves have a key role to play in mitigating climate–related hazards such as sea level rise.

The Global Urban Footprint (GUF) *[URL-39]* **/ World Settlement Footprint (WSF)** *[URL-21]*, produced by the DLR’s Earth Observation Centre, provides global mapping of built-up areas, as man-made built structures with a vertical component. The GUF 2012 provides a global map of built areas for the reference year 2012, based on TerraSAR-X and TanDEM-X imagery, from the Airbus Defense and Space company. It is currently available to the scientific research community, at ~12 m spatial resolution near the equator, with increasing spatial resolution towards the poles. A 75m resolution data is also available for public use. The WSF 2015 is a new, globally consistent map of the world’s human settlements at an unprecedented spatial resolution of 10 metres, generated from the joint processing of optical and radar imagery. WSF 2015 has been derived from Landsat 8 and Sentinel 1. A WSF evolution which will allow to map the urban development patterns over the last 30 years, based on the whole Landsat archive, is under preparation in cooperation with Google Earth Engine. The WSF 2019, to be released by the end of 2020, will be the first global dataset of human settlements based on Sentinel 1 and 2. Both GUF and WSF datasets are available through the ESA's Urban Thematic Exploitation Platform (U-TEP). These global data sets are important for reporting on indicator 11.3.1.

The Global Human Settlement Layer (GHSL) *[URL-40]*, produced by the European Commission's Joint Research Centre (JRC), provides global coverage of the human settlement at 30m spatial resolution for four time steps from 1975 through to the year 2015. It consists of spatial datasets of built-up areas, population density and human settlement. The degree of area built-up is measured as the proportion of building footprint area within the total area of the pixel. Although built-up area is expressed at 30m resolution, when combined with census data, the population metric layers are produced at 1km resolution.

The Global Surface Water Explorer *[URL-41]* **/ Surface Water Viewer** *[URL-42]*, produced by the European Commission's Joint Research Centre (JRC) and UN Environment respectively, provide global coverage of the world's surface water resources including their temporal dynamics over the last 32 years. The 30m resolution water products within these tools are based on the Landsat archive from 1984 to 2015 and could have a wide range of uses in the SDG framework, supporting applications including water resource management, climate modelling, biodiversity conservation and food security. Indicator 6.6.1, in particular, could benefit from the information contained in the Global Surface Water Explorer within the Explorer and the UN's Surface Water viewer.

The ESA Climate Change Initiative (CCI) Land Cover *[URL-43]* is a project that has produced long-term, consistent, global land cover time series from 300m spatial resolution satellite imagery based on the UN Land Cover Classification System (LCCS). The CCI project has also delivered a free user tool to allow users to customise the land cover product for the purpose of climate modelling. The ESA CCI land cover products are potentially key inputs to the indicator 15.3.1.

The Global Soil Organic Carbon map (GSOCMap) *[URL-44]*, utilises remote sensing imagery as prediction factors for global soil organic carbon mapping as traditional soil mapping involves a sampling based approach. This process of integrating remote sensing imagery in digital soil mapping of the world also paves the way for soil organic carbon (SOC) maps. The Global Soil Partnership (GSP), of the FAO, and its Intergovernmental Technical Panel on Soils (ITPS) has launched the GSOCMap, in support of the Sustainable Development Goal Indicator 15.3.1. The map, compiled from national SOC maps, can be used to assess soil condition, identify degraded areas, set restoration targets, explore SOC sequestration potentials and support the greenhouse gas emission reporting required by the UNFCCC.

The International Soil Reference and Information Centre (ISRIC) *[URL-45]* has produced a global maps of soil property and class called SoilGrids at 1 km / 250 m spatial resolutions.

The Global RAPP (Rangelands and Pasture Productivity) Map *[URL-29]* is an online geospatial tool that provides EO-derived information about the state and condition of global rangelands. It gives time-series data on the vegetation and environmental conditions, allowing national and regional tracking of the resources which sustains livestock production. It has been developed in Australia, and is currently hosted by Data61 with the assistance of IT resources and services from the National Computational Infrastructure (NCI), and the AusCover facility. RAPP Map is managed and supported by the Commonwealth Scientific and Industrial Research Organisation (CSIRO) and through funding from the Australian Government's National Landcare Programme.

In summary, there are global EO-derived data sets which are of direct relevance for some of the SDG indicators, yet there are some caveats to their use. In terms of computational resources, the global datasets can only be produced through automatic processing using enabling digital infrastructure such as cloud computing which necessitate high internet bandwidth, access costs, computing infrastructure and expertise. In terms of accuracy, the global accuracy reported by the dataset producer might not be reached at country level, simply because of the need to favour global coverage at the expense of local precision. Therefore most of these datasets should be validated at the country level in order to estimate their accuracy for national scale uses, and this is why GEO global initiatives like GEOGLAM have a network of in-country validation sites. With these caveats in mind, global EO datasets, produced by major global collaborative initiatives, under the auspices of GEO, are an important source of information to complement national data and may represent the only data source for data poor countries.

Methodology for analysis of EO for the SDGs

The analysis of EO potential was undertaken based on the tier status and methodologies as of in February 2019. The presentation of results in this Compendium has been subsequently updated to reflect changes arising from the 2020 comprehensive review of the Global Indicator Framework. Due to broad scope of all 232 indicators[3], it was necessary to first conduct a broad screening of all indicators and select the subset of indicators that would be analysed in depth and presented in this compendium. This initial screening exercise was necessary to identify only those indicators where EO could reasonably contribute to the development or implementation of their methodology. In order to do this systematically, a "traffic light" system of red, amber, green colours was applied across the full indicator suite to flag EO relevance, where:

Green: SDG Indicators for which Earth Observations have or have not been currently identified as a source of information but would make a definite contribution to their methodological development with relative ease

Amber: SDG Indicators for which Earth Observations has not been currently identified as a source of information but where there is potential to do so with further methodological development

Red: Earth Observation currently has no contribution to the methodology, i.e. all other SDG Indicators

The amber and green indicators resulted from a two –phase analysis: (i) an initial screening exercise based on an internal review of the full indicator suite with respect to EO potential and (ii) an in-depth analysis, according to the readiness and adequacy criteria, as described and presented in a series of "factsheets", one per indicator. This in-depth analysis followed a similar logic of a traffic colour system but this time applied across eight criteria per indicator which led to an overall rating of EO relevance for the indicator. The overall colour rating was deduced from a review of all the colours across the eight criteria and an informed judgement on the use of EO for the indicator. A brief justification is given to support the final colour assessment. The eight criteria are listed below (table 2), covering the readiness of EO for the indicator (1-4) and the adequacy for the indicator methodology (5-8). The criteria for their colour rating are explained at the end of each factsheet for reference purposes.

Readiness criteria:

1. Maturity of EO technologies: How tried and tested are the EO technologies and are they globally applicable?
2. Status of EO in indicator guidelines: Is EO explicitly mentioned in the indicator methodology?
3. Technical capacity required: What is the level of expertise required to use EO at the country level?
4. Availability of global EO data: Are global or regional datasets publicly available and free to use?

Adequacy criteria:

5. Compliance with reporting calendar: Does the EO methodology align with the proposed reporting calendar?
6. Sensitivity to change: Are the EO data sensitive to change in the parameter of interest?
7. Scalability (spatial): Are the EO data geographically scalable or can they only be retrieved at limited scale?
8. Substitutability of gaps: Is EO the only source of information for the methodology or are there alternative data sources which could fill gaps in the EO data record?

3 After the 2020 comprehensive review of the Global Indicator Framework, the number of indicators has been reduced from 232 to 231 indicators.

	Readiness				Adequacy				Supporting Comments
Criteria	**Maturity of EO technologies**	**Status of EO in indicator guidelines**	**Technical capacity required**	**Availability of global EO data**	**Compliance with reporting calendar[4]**	**Sensitivity to change**	**Is it scaleable (spatial)?**	**Is there a substitute for gaps in the EO record?**	
	Tried and tested and globally applicable	Frequently mentioned	Little capacity – easy to use and implement in country	Widely available and in public domain	Yes	Dynamic variables	Good	Yes, stable approaches found	
	Demonstrated on a limited scale	Suggested as part of other spatial approaches	Medium level of expertise needed, not all countries will implement	Publicly available but only for limited regions	Partly	Static variables--that may be relevant but not useful for change monitoring	Patchy	Some but not consistent	
	Experimental	Not mentioned or implied	High level of expertise, demanding	Not publicly available anywhere but maybe on request	No	Insensitive to change in parameter of interest	Poor or limited	EO is the only support for the methodology	

Table 2: Explanation of criteria used to assign the RAG colours for each of the criterion used to assess overall contribution of EO to the indicator

4 Baseline year and reporting interval as mentioned in metadata

Once the final colour rating was assigned and justified by an explanatory sentence in the comments column (either amber or green, as red indicators would already have been eliminated by the screening exercise), the factsheets were populated with more detailed information gleaned from the peer-reviewed and grey literature, while supplemented by examples taken from expert contributions. The factsheet itself is carefully structured, mirroring the sub-sections of the metadata guidelines produced by the indicator custodians, for ease of interpretation and transferability to indicator methodologies on the SDG indicator Metadata repository *[URL-27]*. The factsheets were finally reviewed by the same experts for consistency and content.

It is accepted that the colours assigned and information collated could be subject to debate and further dialogue throughout the SDG and EO community. Therefore, future versions of this compendium are envisioned as the maturity of EO technologies develops and the demands of the SDG indicator framework continue to evolve while taking on board expert opinion in future iterations of the analysis.

Structure of Factsheets

The core body of this document is the compendium of EO contribution to the SDG targets and indicators, consisting of 29 factsheets, one per target, covering 34 indicators where EO has a potential or definite contribution to the indicator methodology. When a target has more than one indicator, each indicator is addressed separately in a unique factsheet.

These factsheets are intended to be stand-alone so that they can be used a resource material for NSOs, line ministries, etc. The factsheets are structured consistently and are composed of following three main sections and in some cases sub-sections:

How can EO be used to help countries achieve the target?

This is intended to be a broad assessment of how EO can help countries achieve the target, in isolation from the indicators. This section draws out the contribution of EO to (i) setting national targets as part of their voluntary commitments to Agenda 2030 and (ii) planning/implementation of the targets. This latter part also involves proposing new EO-based indicators that could be useful for countries.

The potential of EO to support the SDG indicators

The next section, in the form of a table, is indicator specific. It contains a transparent and objective assessment of how EO can support the indicators of the target, as described above in the methodology section. Non-EO based indicators are listed in the table for reference only. For a supporting guide to NSOs on using EO to support official statistics, see the Satellite Imagery and Geospatial Data Task Team report of the United Nations Task Team on Satellite Imagery and Geospatial Data *[RD-13]*.

Short methodological guidelines illustrated with EO best practice examples

This section summarises (i) where EO can contribute to the methodology as currently written by the indicator custodian and (ii) also proposes changes to the methodology for better EO uptake (as explained below under computation method). As green indicators were considered to be more open to the possibility of EO integration into their methodologies, this section is elaborated in more detail than for amber indicators.

The section is filled out for tier 1 and tier 2 indicators only, following a logical order, mirroring the sub-sections of the Methodology in the metadata guideline structure provided by the UN Department of Economic and Social Affairs. Tier 3 indicators (as they were at the start of the analysis), in the absence of a published methodology, were not analysed at this level of detail.

Computation method
This sub-section reviews the computation method on how the indicator is to be computed and either (i) provides a summary of the EO methods proposed by the custodian, (ii) proposes a methodology where EO is not mentioned but has a potential or definite contribution or (iii) proposes a methodology for a better use of EO than what is indicated in the metadata file.

Disaggregation
This sub-section describes opportunities for spatial disaggregation of the indicators using EO data, and/or thematic disaggregation where non-EO data are available for this purpose.

Treatment of missing values
This sub-section summarises the possibility of missing values in the availability of EO source data and proposes substitutes for the EO data record.

Regional aggregates
This sub-section suggests how the EO-based method can mitigate the problem of regional aggregations when countries use different definitions or different methods.

Sources of discrepancies
This sub-section documents discrepancies in indicator values related to accuracies of EO methods. Discrepancies arising from the integration of EO with non-EO data are also discussed where applicable.

Limitations
This sub-section briefly lists some restrictions and constraints on the use of an EO-based approach in the indicator computation.

Data sources
This sub-section covers the main datasets, tools, platforms and services related to the EO method described. It covers the following main resources:

- Source satellite data: EO legacy data and present data (with long term perspectives, distinguishing between free and commercial)
- Global/regional datasets: Derived EO datasets, some of which have been described above
- Software, tools and platforms: Free of charge software toolboxes, which can be used to implement, in part or in full, the EO methods (e.g. software tools to handle EO data cubes). On-line computing infrastructures which facilitate the production and/or access to EO datasets for public and private users
- Operational or commercial services: Existing service centres where the EO data (global, downstream datasets) are delivered on an operational basis, either freely or with a service fee. These are merely examples of service providers but there are many more private and public service providers of EO data tools and products which could be of use for SDG reporting than could be listed here.

Reference List
This sub-section lists a few critical, selected references for further reading on the topic.

Key messages for countries
This sub-section is intended as a brief summary, in the form of short bullet points, of the analysis with some take home messages for countries on how EO can assist them in indicator reporting.

EO best practices and national experiences

This section describes EO best practices and national experiences for specific indicators, collated, where possible and available, from EO experts and national focal points through solicited requests. This section is intended to bring the theory and concepts explained to life and make the EO methodologies proposed relevant for countries. We document examples only for those indicators where we could find appropriate examples, this does not preclude that EO is being actively used to support indicator reporting and methodological development in other countries which are not documented here.

Definition of terms

Terms used throughout this compendium have been standardised for ease of interpretation. Term definitions are described below.

Spatial Resolution

Refers to the size of the area covered by a pixel in a satellite image. In optical and thermal remote sensing, each pixel in an image corresponds to a patch on the Earth's surface. It is also known as 'ground resolution' and is usually expressed in meters.

For the purpose of this analysis, the following categories of spatial resolution are considered:

- Very High Resolution ≤ 5m
- High Resolution ≤ 30m
- Medium Resolution: ≤100m
- Low Resolution >100m

Spectral resolution

Refers to the wavelength intervals in which a satellite sensor receives electromagnetic radiation. It describes the ability of a sensor to define narrow wavelength intervals. The finer the spectral resolution, the narrower the wavelength range for a particular channel or band. The following categories are generally used describing the requirement for spectral resolution:

- Panchromatic – 1 band (i.e. black and white image)
- Multispectral – 4 to ±15 bands
- Hyperspectral – hundreds of bands

Temporal frequency (resolution)

This is the required interval between two successive instances of a satellite observation in the same area and often expressed on an hourly, daily, weekly, monthly, yearly basis.

Reference documents

[RD-1] Addis Ababa Action Agenda, Third International Conference on Financing for Development, 13 to 16 July 2015, Addis Ababa (2015)
http://bit.ly/AAAAFundDev

[RD-2] A World That Counts, Mobilising the data revolution for sustainable development (2014)
http://www.undatarevolution.org/wp-content/uploads/2014/11/A-World-That-Counts.pdf

[RD-3] Cape Town Global Action Plan for Sustainable Development Data (2017)
https://unstats.un.org/sdgs/hlg/Cape_Town_Global_Action_Plan_for_Sustainable_Development_Data.pdf

[RD-4] Transforming our world: the 2030 Agenda for Sustainable Development, UN Resolution 70/1, 21 October 2015
https://undocs.org/A/RES/70/1

[RD-5] 2019 Sustainable Development Goals Report
https://unstats.un.org/sdgs/report/2019

[RD-6] UN High Level Political Forum meeting New York. July 2018
https://sustainabledevelopment.un.org/hlpf/2018

[RD-7] Belward & Skøien (2015) Who launched what, when and why; trends in global land-cover observation capacity from civilian earth observation satellites. ISPRS Journal of Photogrammetry and Remote Sensing. 103, 115-128.
https://doi.org/10.1016/j.isprsjprs.2014.03.009

[RD-8] UNCCD Good Practice Guidance, SDG Indicator 15.3.1
https://www.unccd.int/sites/default/files/relevant-links/2017-10/Good%20Practice%20Guidance_SDG%20Indicator%2015.3.1_Version%201.0.pdf

[RD-9] 1st Expert Group Meeting of the IAEG-SDGs Working Group on Geospatial Information, 12-14 December 2016, Mexico
http://ggim.un.org/meetings/2016-1st_Mtg_IAEG-SDG-Mexico

[RD-10] 3rd Expert Group Meeting of the IAEG-SDGs Working Group on Geospatial Information, 8-10 May 2017, Kunming, Yunnan, China
http://ggim.un.org/meetings/2017-3rd_Mtg_IAEG-SDG-China

[RD-11] GEO/CEOS joint report on "Earth Observations in support of the 2030 Agenda for Sustainable Development"
https://www.earthobservations.org/documents/publications/201703_geo_eo_for_2030_agenda.pdf

[RD-12] ESA Satellite Earth Observations in Support of the Sustainable Development Goals
http://eohandbook.com/sdg/files/CEOS_EOHB_2018_SDG.pdf

[RD-13] UN Statistics Satellite Imagery and Geospatial Data Task Team report (2017)
https://unstats.un.org/bigdata/task-teams/earth-observation

Online Resources

[URL-1] The UN Sustainable Development Knowledge Platform
https://sustainabledevelopment.un.org/sdgs

[URL-2] Sendai Framework for Disaster Risk Reduction
https://www.unisdr.org/we/inform/publications/43291

[URL-3] New Urban Agenda
http://habitat3.org/the-new-urban-agenda/

[URL-4] UN Global Working Group on Big Data team on Geo-spatial information and satellite imagery
https://unstats.un.org/bigdata/task-teams/earth-observation

[URL-5] The Inter-agency and Expert Group on SDG Indicators. Tier classification.
https://unstats.un.org/sdgs/iaeg-sdgs/tier-classification/

[URL-6] The Inter-agency and Expert Group on SDG Indicators
https://unstats.un.org/sdgs/iaeg-sdgs/

[URL-7] UN Fundamental Principles of Official Statistics
https://unstats.un.org/unsd/dnss/gp/fundprinciples.aspx

[URL-8] CEOS Data Cube | *https://www.opendatacube.org/ceos*

[URL-9] Earth System Data Cube (ESDC) | *http://earthsystemdatacube.net*

[URL-10] Digital Earth Australia ODC | *http://www.ga.gov.au/dea/odc*

[URL-11] Euro Data Cube
https://eurodatacube.com

[URL-12] Google Earth Engine | *https://earthengine.google.com/*

[URL-13] Open Data Cube | *https://www.opendatacube.org/*

[URL-14] DIAS, European Copernicus Programme
https://www.copernicus.eu/en/access-data/dias

[URL-15] Sentinel Hub | *https://www.sentinel-hub.com*

[URL-16] Coastal Thematic Exploitation Platform | *https://www.coastal-tep.eu*

[URL-17] Forestry Thematic Exploitation Platform | *https://f-tep.com*

[URL-18] Hydrology Thematic Exploitation Platform | *https://hydrology-tep.eu*

[URL-19] Geohazards Thematic Exploitation Platform | *https://geohazards-tep.eu*

[URL-20] Polar Thematic Exploitation Platform | *https://portal.polartep.io*

[URL-21] Urban Thematic Exploitation Platform | *https://urban-tep.eu*

[URL-22] Food Security Thematic Exploitation Platform | *https://foodsecurity-tep.net*

[URL-23] Trends.Earth |*http://trends.earth*

[URL-24] NextGEOSS | *https://nextgeoss.eu*

[URL-25] EO4SDG initiative | *http://eo4sdg.org*

[URL-26] GEO BON | *https://geobon.org*

[URL-27] AquaWatch | *https://www.geoaquawatch.org*

[URL-28] GEOGLAM | *http://geoglam.org*

[URL-29] GEOGLAM RAPP | *https://www.geo-rapp.org*

[URL-30] GEO Blue Planet | *https://geoblueplanet.org*

[URL-31] Global Forest Observation Initiative (GFOI) | *http://www.fao.org/gfoi*

[URL-32] GEO-Wetlands | *https://geowetlands.org*

[URL-33] GEO Human Planet Initiative (HPI) *https://www.earthobservations.org/documents/gwp20_22/HUMAN-PLANET.pdf*

[URL-34] GEO Global Network for Observation and Information in Mountain Environments *https://mountainresearchinitiative.org/activities/projects/geo-mountains*

[URL-35] GEO Land Degradation Neutrality *https://www.earthobservations.org/documents/gwp20_22/GEO-LDN.pdf*

[URL-36] CEOS Ad-Hoc Team on SDGs | *www.ceos.org/sdg*

[URL-37] Global Forest Watch | *https://www.globalforestwatch.org*

[URL-38] Global Mangrove Watch | *https://www.globalmangrovewatch.org*

[URL-39] Global Urban Footprint *https://www.dlr.de/eoc/en/desktopdefault.aspx/tabid-9628/16557_read-40454*

[URL-40] Global Human Settlement Layer | *https://ghsl.jrc.ec.europa.eu*

[URL-41] Global Surface Water Explorer | *https://global-surface-water.appspot.com*

[URL-42] Freshwater Ecosystems Explorer | *https://www.sdg661.app*

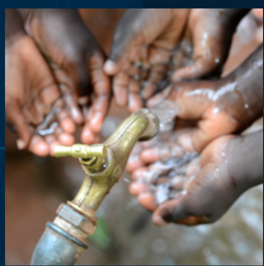
[URL-43] ESA Climate Change Initiative Land Cover *https://climate.esa.int/en/projects/land-cover*

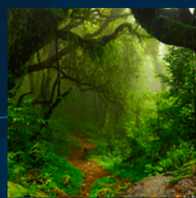
[URL-44] Global Soil Organic Carbon map | *http://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/global-soil-organic-carbon-map-gsocmap*

[URL-45] International Soil Reference and Information Centre *https://www.isric.org/explore/soilgrids*

[URL-46] SDG Indicators Metadata Repository | *https://unstats.un.org/sdgs/metadata*

COMPENDIUM OF EO CONTRIBUTION TO THE SDG TARGETS AND INDICATORS





GOAL 1

1 NO POVERTY

Target: 1.1

By 2030, eradicate extreme poverty for all people everywhere, currently measured as people living on less than $1.25 a day

Target: 1.2

By 2030, reduce at least by half the proportion of men, women and children of all ages living in poverty in all its dimensions according to national definitions

How can EO be used to help countries achieve the targets?

Targets 1.1 and 1.2 have been pooled together in this factsheet, due to their similarities.

Earth Observation (EO) data can be used to track and target poverty, and aid the allocation of scarce resources which can help improve human livelihoods. EO can be used to map spatial distribution of socioeconomic deprivations, as well as providing information that may indicate areas at risk of poverty (e.g. contribute towards famine early warning systems) (NASA, 2018). EO data can be used to forecast weather, monitor fires, determine populations at risk from flooding/landslides, analyse climate change and map land cover change (e.g. deforestation and degradation). These factors can all help identify areas currently at risk from poverty, and in the future.

Satellite images can also be used to estimate economic activity (e.g. through monitoring night lights) and mapping houses (e.g. slums), which can be identified through satellite images using physical parameters, clustering of structures with or without a road network, irregular and haphazardly grouped temporary, poorly-constructed or semi-permanent households (Montana et al., 2016). Further, these datasets can be combined with in-field survey data (from socioeconomic household surveys, social media, mobile phone networks) (Leidig & Teeuw, 2015), and often by additionally using machine learning algorithms (Jean et al., 2016), can estimate consumption expenditure and asset wealth of the region analysed. Such approaches can assist efforts to track and target poverty.

Current Indicator(s)

1.1.1 Proportion of population below the international poverty line, by sex, age, employment status and geographical location (urban/rural)

1.2.1 Proportion of population living below the national poverty line, by sex and age

1.2.2 Proportion of men, women and children of all ages living in poverty in all its dimensions according to national definitions

Short methodological guidelines illustrated with EO best practice examples

Indicator 1.1.1

Computation method

EO is not currently discussed in the methodological guidelines for these indicators, but there is scope for it to be used alongside the current methods. The guidelines set out a poverty standard, so that it can be consistently compared across different countries – the extreme poverty line is set at $1.90 per day in 2011 (World Bank, 2015). Once this is calculated, the working poverty rate can be calculated as = (employed persons living on less than $1.90 a day/total employment) x 100.

The level of poverty in an area is estimated through socioeconomic household surveys, which are based on census data. 'Big Data' has the potential to help understand poverty trends, e.g. through electronic money schemes. Most studies are limited to using single source data, such as mobile phone data or environmental data from satellite imagery, rather than amalgamating different sources together. However, new studies have combined these sources to create a more accurate representation of poverty.

EO data collects information on metrics such as night time lights, vegetation cover, meteorological conditions (e.g. flood or drought events), proximity to services (e.g. schools, hospitals), density of infrastructure (e.g. roads, railway, waterways). These data can be used alongside survey data to estimate the level of economic activity, food scarcity, households at risk of extreme events such as floods or droughts, and the services and infrastructure available. These data are useful, but lack information about population structure and other socioeconomic data that are directly (e.g. household income) or indirectly (e.g. child mortality) relating to poverty.

In many rural areas, e.g. sub-Saharan Africa, internet usage is low, although mobile phones are widely used and Call Data Records can capture how, when, where and, with whom individuals communicate. Further, electronic money schemes like M-Pesa provide information on the consumption patterns. These can capture spatial and temporal patterns of human interaction.

Limitations

In terms of in-situ data, the main limitation is the cost of the environmental surveys, as well as the time required to undertake them. Open Street Map is crowdsourced data which are used to map infrastructure, housing and buildings – and provide useful plans of unmapped areas; however the level of completeness varies. There is also selection bias in mobile phone ownership, some countries only have one provider, and mobile phone usage may not incorporate

some demographic subgroups like children and the ultra-poor. For EO data, there is varying spatial granularity at which the different datasets are available which requires an aggregation mechanism to merge them. Clouds can obscure data, especially in tropical and subtropical regions. Very high resolution data can be prohibitively expensive, and high expertise is required to process and analyse it.
When using EO data, it is often aggregated together from different time series, to combat issues of data gaps through cloud cover etc. However, data availability from other sources, such as access to mobile phone data, can often be an issue – e.g. access to call data records have to be obtained through individual telecommunication companies. In addition, EO data is complemented through the use of model fitting, e.g. through Gaussian Process regression (Pokhriyal & Jacques, 2017), and therefore there are challenges with variance and uncertainty.

Key messages for countries on EO contribution to the computation method

- EO data collects information on metrics such as night time lights, vegetation cover, meteorological conditions etc.
- These data can be used alongside other socioeconomic data that relate to poverty.
- Poverty can be inferred from a combination of these EO and non-EO datasets and mapped out spatially by geographic location but further statistics are required to disaggregate by gender and age.

Data sources

Data category	Data sources	Website
Source satellite data	WorldView, GeoEye, QuickBird, IKONOS satellite imagery	*https://www.maxar.com*
	Landsat satellites	*https://earthexplorer.usgs.gov*
Global/regional datasets	The Global Urban Footprint (GUF) / World Settlement Footprint (WSF)	*https://urban-tep.eu*
	The Global Human Settlement Layer (GHSL)	*https://ghsl.jrc.ec.europa.eu/data.php*
Software, tools and platforms	The GEO Human Planet initiative	*https://ghsl.jrc.ec.europa.eu/HPI.php*
	The Urban Thematic Exploitation Platform (U-TEP)	*https://urban-tep.eu*

Reference List

Jean, N., Burke, M., Xie, M., Davis, W. M., Lobell, D. B. & Ermon, S. (2016) Combining satellite imagery and machine learning to predict poverty. Science, 353 (6301) 790-794.

Leidig, M. & Teeuw, R. M. (2015) Quantifying and Mapping Global Data Poverty. PLoS ONE, 10 (11), e0142076.

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NASA (2018) US Uses Landsat satellite data to fight hunger, poverty. Landsat Science: Nasa. [Online] Available at: https://landsat.gsfc.nasa.gov/u-s-uses-landsat-satellite-data-to-fight-hunger-poverty/ [Accessed 28th June 2018]

Pokhriyal, N. & Jacques, D. C. (2017) Combining data sources for poverty mapping. Proceedings of the National Academy of Sciences. 114 (46) E9783-E9792.

World Bank (2015) FAQs: Global poverty line update. The World Bank. [Online] Available at http://www.worldbank.org/en/topic/poverty/brief/global-poverty-line-faq [Accessed 23rd July 2018]

Indicator 1.2.1

Computation method

EO is not currently discussed in the methodological guidelines for these indicators. However, there is potential for Earth Observation (EO) data to be used to track and target poverty, and aid the allocation of scarce resources which can help improve human livelihoods.

Currently, the formula for calculating the proportion of total, urban and rural population living below the national poverty line, or headcount index is:

$$P_0 = \frac{1}{N} \sum_{i=1}^{N} I(y_i < z) = \frac{N_p}{N}$$

Income data is gathered through nationally representative household surveys. National poverty rates use a country specific poverty line, which is reflective of the country's economic and social circumstances. This can be adjusted to reflect different regions within a country – i.e. costs of living are generally higher in urban areas than rural.

Limitations

National poverty estimates use a different methodology to international poverty. National poverty rates are defined at country-specific poverty lines in local currencies, which are different in real terms across countries, and different from the $1.90 a day international poverty line.

Key messages for countries on EO contribution to the computation method

- There currently are no EO products that can help establish poverty specifically by sex and age, however there is potential for EO to be used to track and target poverty, e.g. by mapping the spatial extent of informal settlements (see indicator 11.1.1).

Reference List

Jean, N., Burke, M., Xie, M., Davis, W. M., Lobell, D. B. & Ermon, S. (2016) Combining satellite imagery and machine learning to predict poverty. Science, 353 (6301) 790-794.

Leidig, M. & Teeuw, R. M. (2015) Quantifying and Mapping Global Data Poverty. PLoS ONE, 10 (11), e0142076.

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NASA (2018) US Uses Landsat satellite data to fight hunger, poverty. Landsat Science: Nasa. [Online] Available at: https://landsat.gsfc.nasa.gov/u-s-uses-landsat-satellite-data-to-fight-hunger-poverty/ [Accessed 28th June 2018]

Indicators		1.1.1 Proportion of population below the international poverty line, by sex, age, employment status and geographical location (urban/rural)	1.2.1 Proportion of population living below the national poverty line, by sex and age	1.2.2 Proportion of men, women and children of all ages living in poverty in all its dimensions according to national definitions
Custodian agency		World Bank; ILO	World Bank	
Tier		I	I	II
Status of step-by-step methodology document on the metadata repository		Published	Published	Published
Relevance of EO for the indicator criteria	Maturity of EO technologies			
	Status of EO in indicator guidelines			
	Technical capacity required			
	Availability of global EO data			
Robustness of proposed methodology Criteria	Compliance with Reporting calendar			
	Sensitivity to change			
	Is it scalable (spatial)?			
	Is there a substitute for gaps in the EO record?			
Overall EO relevance				
Comments to support criteria		EO is only partially relevant, due to lack of information in indicator guidelines and high technical capacity.	EO is also only partially relevant, for similar reasons as the above, in addition to the limited EO data products available. There currently are no EO products that can help establish poverty specifically by sex and age.	Not supported by EO. EO cannot be used to support any evidence of non-material poverty (e.g. education, knowledge, culture, lack of voice etc.).

Target 1.4

By 2030, ensure that all men and women, in particular the poor and the vulnerable, have equal rights to economic resources, as well as access to basic services, ownership and control over land and other forms of property, inheritance, natural resources, appropriate new technology and financial services, including microfinance.

How can EO be used to help countries achieve the target?

Improving human well-being and access to services, EO data can help develop various proxy indicators of human well-being, for example access to services such as electric power, as well as patterns of human interaction

Remote sensing and call data records can help monitor access to basic services. Call Data Records (CDR) provide information on where, when, how and with whom someone made a mobile phone call – mainly used for billing purposes, but also provide spatial information on patterns of human interaction. Mobile phone usage and movement can indicate household access to financial resources and services, for example, via electronic money schemes such as M-Pesa. Remote sensing can capture information on biophysical properties such as rainfall, temperature and vegetation cover as well to variables such as infrastructure (e.g. railway, main roads, waterways), distance to water sources and power plants, electricity use, agriculture productivity and distance to roads and urban areas (which reflects access to markets and information). The state of the road network (e.g. if it's a dirt track or an impervious road) can be derived through Open Street Map, but can be combined with remote sensing data to provide a more detailed picture.

Current Indicator(s)

Indicator 1.4.1 Proportion of population living in households with access to basic service.

Indicator 1.4.2 Proportion of total adult population with secure tenure rights to land, with legally recognized documentation and who perceive their rights to land as secure, by sex and by type of tenure.

Short methodological guidelines illustrated with EO best practice examples

Indicator 1.4.1

Indicator 1.4.1 was a Tier III indicator at the time of the analysis, and therefore had no published metadata. However, it has been considered within this analysis, as it is perceived that Earth Observation (EO) has clear potential to improve monitoring.

Data will be collected through routine national surveys, service providers, directly from country/local government data or websites, joint surveys with national agencies and international entities. This will be complemented through EO data and remote sensing techniques. For example, relative welfare can be measured through travel time to market towns, percentage of a village covered with woodland, percentage of a village covered with winter crop. Satellite data can be used to measure electrification, through measuring night-time luminosity (Ghosh et al., 2013). The level of technology use can be an indicator of access to services – for example number of households with internet access or mobile phone usage (Steele et al., 2016).

The work plan divides basic services into three categories: basic infrastructure services, social services, quality of life services. However, this list is not exhaustive. There is a lack of consistent definition on what constitutes a basic service, and this is likely to be interpreted differently, depending on who is collecting, reporting and using the data, respectively.

There are limitations to the proxies used to describe these services, e.g. in some rural villages, rural electrification is often not accurately measured due to intermittent power supply. Additionally remote sensing and call data records (e.g. where, when, how and with whom someone made a mobile phone call) mainly used for billing purposes, but also provide spatial information on patterns of human interaction. These are often generated at different spatial scales, which can be difficult to reconcile.

It is proposed that data will be collected through national surveys, service providers, directly from country/local government data or websites, joint surveys with national agencies and international entities. National statistic systems will be a key source of data: selected national statistical agencies will be consulted on methodological development and piloting in a limited set of countries.

As the methodology for indicator 1.4.1 was not yet finalised at the time of the analysis (still a Tier III), the EO-based methodology is not discussed in the same detail as Tier I and II indicators.

Data sources and tools

There are a number of global EO-based tools that are available that could assist NSOs and indicator custodians with delivering and implementing EO-based methodologies in relation to poverty. For example: The Global Urban Footprint (GUF) / World Settlement Footprint, The Global Human Settlement Layer (GHSL), The GEO Human Planet initiative.

Key messages for countries on EO contribution to the computation method

- Data will be collected through surveys, and there is scope for this to be complemented with EO data, such as night-time luminosity – which will give an indication of access to services.

Reference List

Ghosh, T., Anderson, S. J., Elvidge, C. D., Sutton, P. C. (2013) Using nighttime satellite imagery as a proxy measure of human well-being. Sustainability. 5, 4988–5019]

Pokhriyal, N. & Jacques, D. C. (2017) Combining disparate data sources for improved poverty prediction and mapping. Proceedings of the National Academy of Sciences. 46 (114), E9783-E9792.

Steele, J. E., Sundsøy, P. R., Pezzulo, C., Alegana, V. A., Bird, T. J., Blumenstock, J., Bjelland, J., Engø-Monsen, K., de Montjoye, Y-A., Iqbal, A. M., Hadiuzzaman, K. N., Lu, X., Wetter, E., Tatem, A. J. & Bengtsson, L. (2017) Mapping poverty using mobile phone and satellite data. Journal of the Royal Society Interface. 14 (127).

Indicators

		1.4.1 Proportion of population living in households with access to basic service.	1.4.2 Proportion of total adult population with secure tenure rights to land, with legally recognized documentation and who perceive their rights to land as secure, by sex and by type of tenure.
Custodian agency		UN-Habitat	UN-Habitat World Bank
Tier		I	II
Status of step-by-step methodology document on the metadata repository		Unpublished (Tier III at the time of the analysis)	Unpublished (Tier III at the time of the analysis)
Relevance of EO for the indicator criteria	Maturity of EO technologies		
	Status of EO in indicator guidelines		
	Technical capacity required		
	Availability of global EO data		
Robustness of proposed methodology Criteria	Compliance with Reporting calendar		
	Sensitivity to change		
	Is it scalable (spatial)?		
	Is there a substitute for gaps in the EO record?		
Overall EO relevance			
Comments to support criteria		EO data and GIS techniques can be applied to measure the distance to some basic services (e.g. road network, waterways, main cities etc.).	Not supported by EO.

Target 1.5

By 2030, build the resilience of the poor and those in vulnerable situations and reduce their exposure and vulnerability to climate-related extreme events and other economic, social and environmental shocks and disasters

How can EO be used to help countries achieve the target?

The frequency and severity of natural disasters have been increasing in the last decades. Research has revealed that it is generally the poor who tend to suffer worst from disasters. The fact that climate change is expected to increase the frequency and intensity of these events threaten to derail international efforts to eradicate poverty.

The importance of EO in disaster management and assessment has gained increasing significance over the past years. One of the ways EO can contribute to build resilience of vulnerable populations is through disaster-risk reduction. EO datasets and methods can contribute to disaster risk management and reduction by providing relevant information to the full cycle of disaster and environmental shock management: mitigation, preparedness, warning and response.

EO has proven successful for a wide range of disaster types, particularly for flooding, extreme drought events, earthquakes, landslides and volcanic eruptions. In fact, EO data is providing a reliable data basis for deriving useful information such as the extent of damaged area along with the land-use types as well as the population affected. This can be done through hazard mapping and risk modelling, real time monitoring, producing input data for feeding early warning systems, or for producing maps to support disaster response actions. For a comprehensive review on how EO can contribute to disaster-risk management, see ESA (2015). EO data lies also at the heart of climate modelling, which represent key tools to inform actions aiming to reduce vulnerability to climate change.

Current Indicator(s):

1.5.1: Number of deaths, missing persons and directly affected persons attributed to disasters per 100,000 population

1.5.2: Direct economic loss attributed to disasters in relation to global gross domestic product (GDP)

1.5.3: Number of countries that adopt and implement national disaster risk reduction strategies in line with the Sendai Framework for Disaster Risk Reduction 2015-2030

1.5.4: Proportion of local governments that adopt and implement local disaster risk reduction strategies in line with national disaster risk reduction strategies

Short methodological guidelines illustrated with EO best practice examples

Indicator 1.5.2

Computation method

Although Target 1.5 consists of four indicators, we are concentrating our analysis on 1.5.2 as it is the only indicator to which EO has a relevant contribution. The indicator measures the ratio of direct economic loss, defined as the monetary value of total or partial destruction of physical assets existing in the affected area, attributed to disasters in relation to the Gross Domestic Product (GDP).

EO datasets and methods can be used to gather useful information on the economic losses attributed to disasters and hence, the computation of indicator 1.5.2. Direct economic loss due to disasters can be estimated from the quantification of damaged areas (such as flooded surfaces, affected transport infrastructures, burnt areas, landslide scars, etc.) using optical imagery and radar data at different spatial resolutions. However very high spatial resolutions are particularly useful for mapping hotspots of damage such as in urban areas where high to medium spatial resolution imagery might underestimate the damaged area.

In detail, the indicator is a simple summation of five economic loss indicators divided by GDP, which include: (1) agricultural assets (based on crops, livestock, fisheries, apiculture, aquaculture and forest sectors as well as associated facilities and infrastructure); (2) other productive assets (disaggregated by economic sector, including services, according to standard international classifications); (3) housing (disaggregated according to damaged and destroyed dwellings); (4) critical infrastructure; and (5) cultural heritage. EO datasets and methods, combined with land cover maps and other thematic maps can help estimate such losses, especially for agriculture (FAO, 2017).

Treatment of missing values

Inconsistent and the lack of detailed data is a key issue. Systematic collection and cataloguing is required to make information robust enough for SDG reporting. This would require ground observations of damage to complement the damage mapped in EO imagery. Airplane and drone monitoring technologies could also replace missing EO derived estimates of damage if deployed on time.

Sources of discrepancies

Standardization of measurement approaches between countries is also a challenge but is being addressed (through Sendai and SDG processes).

Limitations

The indicator is based on many sub-indicators from multiple sectors and data sources and is therefore data-intensive. The area of damaged infrastructure reported using EO still needs to be converted to economic loss. Values of global GDP will need to be derived elsewhere. Different EO data will be needed to assess the impacts depending on the nature of the disaster.

Apart from the challenge on collecting such datasets, financial and technical capacity at the country level represent a challenge, too. Acquiring imagery at the time of the disaster can also be challenging and could require specific tasking of satellite assets. This approach is limited by resources and budgets and is largely in the domain of commercial image providers.

Key messages for countries on EO contribution to the computation method

- It is likely that an EO-based method for the indicator would have to be customised for the nature of the disaster (fire, floods, etc.).
- Current EO based assets for disaster monitoring mostly focus on post disaster recovery efforts but for this indicator would need to be enhanced to evaluate physical damage on infrastructures and productive lands.

Data sources

Data category	Data sources	Website
Global/regional datasets	The Global Urban Footprint (GUF) / World Settlement Footprint (WSF)	*https://urban-tep.eu*
	The Global Human Settlement Layer (GHSL)	*https://ghsl.jrc.ec.europa.eu/data.php*
	Emergency Events Database (EM-DAT)	*https://www.emdat.be*
	Disasters and conflicts: UNEP Data Explorer:	*http://geodata.grid.unep.ch/results.php*
Software, tools and platforms	The GEO Human Planet initiative	*https://ghsl.jrc.ec.europa.eu/HPI.php*
	Global Gridded Geographically Based Economic Data (G-Econ), v4 (1990, 1995, 2000, 2005)	*http://sedac.ciesin.columbia.edu/data/set/spatialecon-gecon-v4/docs*
	European Flood Awareness System	*https://www.efas.eu*
	European Forest Fire Information System	*http://effis.jrc.ec.europa.eu*
Operational or commercial services	The UN-SPIDER programme	*http://www.un-spider.org*

Reference List

European Space Agency (ESA) (2015). Satellite Earth Observations in Support of Disaster Risk Reduction. Special 2015 WCDRR Edition.

Food and Agriculture Organization of the United Nations (FAO) (2017) The Impact of disasters and crises on agriculture and Food Security.

UNISDR (2017) Technical Guidance for Monitoring and Reporting on Progress in Achieving the Global Targets of the Sendai Framework for Disaster Risk Reduction. For indicator 1.5.2, see Target C, pages 36-91 (55 pages). https://www.preventionweb.net/files/54970_techguidancefdigitalhr.pdf

Indicators		1.5.1 Number of deaths, missing persons and directly affected persons attributed to disasters per 100,000 population	1.5.2 Direct economic loss attributed to disasters in relation to global gross domestic product (GDP)	1.5.3 Number of countries that adopt and implement national disaster risk reduction strategies in line with the Sendai Framework for Disaster Risk Reduction 2015-2030	1.5.4 Proportion of local governments that adopt and implement local disaster risk reduction strategies in line with national disaster risk reduction strategies
Custodian agency		UNISDR			
Tier		II	II	II	II
Status of step-by-step methodology document on the metadata repository		Published	Published	Published	Published
Relevance of EO for the indicator criteria	Maturity of EO technologies				
	Status of EO in indicator guidelines				
	Technical capacity required				
	Availability of global EO data				
Robustness of proposed methodology Criteria	Compliance with Reporting calendar				
	Sensitivity to change				
	Is it scalable (spatial)?				
	Is there a substitute for gaps in the EO record?				
Overall EO relevance					
Comments to support criteria		Not supported by EO	Damage to infrastructure and productive land uses can be directly mapped from EO. However, GDP impact can only be inferred from such visible damage.	Not supported by EO	Not supported by EO

GOAL 2

2 ZERO HUNGER

Target 2.3

By 2030, double the agricultural productivity and incomes of small-scale food producers, in particular women, indigenous peoples, family farmers, pastoralists and fishers, including through secure and equal access to land, other productive resources and inputs, knowledge, financial services, markets and opportunities for value addition and non-farm employment.

How can EO be used to help countries achieve the target?

Smallholder farmers play a key role in global food production, particularly in developing countries. Is estimated that small-scale farming systems provide up to 80 percent of the food supply in Asian and sub-Saharan Africa. These systems usually host the majority of poor and hungry people worldwide. Therefore, increasing agricultural productivity in these systems would be key to achieve food security.

Even though EO has been proven potentially useful to contribute to the management of farming, pastoral and forestry systems at regional scales, particularly by generating data to feed crop simulation models and early warning systems, it still has limitations to provide the type of fine scale data needed to feed models operating at the farm scale. This is mainly due to the need for high spatial and temporal resolution and repeat monitoring on demand, which satellites cannot yet guarantee (Jin et al. 2018, Kasampalis et al. 2018). The Global Ecosystem Dynamics Investigation Lidar (GEDI), to be launched in 2018, is expected to produce promising data to fill this gap, at least for forestry systems.

Further efforts are needed in order to implement ways to put the information derived from crop simulation models and early warning systems in the hands of small-scale food producers, as required by this target. Recent pilot cases suggest that information derived from EO, such as weather forecasts, can be made accessible to small-scale food producers even in isolated areas in a way that can inform crop management decisions, such as the time to plant and crop variety selection (UNDP, 2016).

As this indicator was classified as Tier III at the time of the analysis, no internationally established methodology or standards were yet available.

Current Indicator(s):

There are two agreed indicators for this target:

2.3.1: Volume of production per labour unit by classes of farming/pastoral/forestry enterprise size.

2.3.2: Average income of small-scale food producers, by sex and indigenous status

Short methodological guidelines illustrated with EO best practice examples

Indicator 2.3.1

Computation method

The computational method for indicator 2.3.1 was not yet finalised and published at the time of the analysis. However, results from discussions so far suggest that the methodology will entail 3 different steps:

1) Identification of the target population ("small-scale food producers"),

2) Computation of the "volume of production per labour unit by classes of farming/pastoral/forestry enterprise size"

3) Calculation of "average income of small-scale food producers, by sex and indigenous status".

Much of the discussion during the development of this indicator has focused on an adoption of an international definition for "small-scale food producer". The custodian agency of this indicator, the FAO, proposes to define this concept based on the physical size of the food producer, as expressed by the amount of operated land and number of livestock heads in production, and the economic size of the food producer, as expressed by its revenues. Labour productivity is proposed to be computed as the ratio of the value of agricultural/livestock/fisheries/forestry production and the labour input (number of labour days per small scale farmer).

EO could help support the calculation indicator 2.3.1 by estimating some of the parameters needed for the calculation of these indicator. For example, EO could support the estimation of areas under cultivation, which is one of the required parameters to define "small-scale food producers" (GEOSS 2009), in addition to economic size. EO can also support the estimation of agricultural and forestry yields with reasonable accuracy.

Limitations

In addition of farm area and agricultural production, the methodology under discussion also requires the estimation of parameters such as the economic size (expressed through the gross monetary value of agricultural production) of the labour input (expressed as the number of labour days and number of small-scale food produced), which cannot be computed by EO.

Key messages for countries on EO contribution to the computation method

- EO is very well suited to support the increase of agricultural productivity through the estimation of crop yields, assessing nutritional and water requirements, and weed control. However, it still has limitations to provide the type of fine scale data needed to feed models operating at the farm scale.

- EO can also support the calculation of some of the parameters needed for the computation of this indicator, particularly for countries limited agricultural census data.

Data sources

Data category	Data sources	Website
Global/regional datasets	Copernicus Dry matter productivity product	*https://land.copernicus.eu/global/products/dmp*

Reference List

GEOSS (2009). Best practices for crop area estimation with Remote Sensing. Edited by Gallego J. Craig M., Michaelsen J., Bossyns B., Fritz S. Ispra, June 5-6, 2008

Jin, X. Kumar, L. Li, Z. Feng, H. Xu, X. Yang, G. Wang, J. (2018) A review of data assimilation of remote sensing and crop models. European Journal of Agronomy Vol 92: 141-152

Kasampalis, D.A., Alexandridis, T.K., Deva, C., Challinor, A., Moshou, D. and Zalidis, G. (2018) Contribution of Remote Sensing on Crop Models: A Review. Journal of Imaging, 4 (4). 52. ISSN 2313-433.

United Nations Development Programme (2016) Climate Information and Early Warning Systems Communications Toolkit. UNDP Programme on Climate Information for Resilient Development in Africa. Available at: https://reliefweb.int/sites/reliefweb.int/files/resources/communications-toolkit-v3.pdf

Indicators		2.3.1 Volume of production per labour unit by classes of farming/pastoral/forestry enterprise size.	2.3.2 Average income of small-scale food producers, by sex and indigenous status
Custodian agency		FAO	
Tier		II	II
Status of step-by-step methodology document on the metadata repository		Unpublished (Tier III at the time of the analysis)	Unpublished (Tier III at the time of the analysis)
Relevance of EO for the indicator criteria	Maturity of EO technologies		
	Status of EO in indicator guidelines		
	Technical capacity required		
	Availability of global EO data		
Robustness of proposed methodology Criteria	Compliance with Reporting calendar		
	Sensitivity to change		
	Is it scalable (spatial)?		
	Is there a substitute for gaps in the EO record?		
Overall EO relevance			
Comments to support criteria		As the metadata is not yet finalised, not all criteria could be assessed. However, based on criteria assessed, EO may support the computation of some of the parameters required to calculate the indicator	Not supported by EO.

Target 2.4

By 2030, ensure sustainable food production systems and implement resilient agricultural practices that increase productivity and production, that help maintain ecosystems, that strengthen capacity for adaptation to climate change, extreme weather, drought, flooding and other disasters and that progressively improve land and soil quality

How can EO be used to help countries achieve the target?

Continuing population and consumption growth is likely to increase the global demand for food in the next decades. The achievement of food security will require profound changes in the global food and agriculture system. At the same time, unsustainable agriculture expansion has created numerous environmental problems, such as soil erosion, water pollution as well as greenhouse gases emissions. This target aims to contribute to this goal by increasing the economic, social and environmental sustainability of agricultural practices, including through enhancing the resilience to climate change and extreme whether events.

EO methods can play an important role in increasing agricultural productivity as well as minimising the environmental impact of the agricultural sector. Some of the ways EO has proven successful to contribute to increase the sustainability of agricultural production include: (1) yield estimation, (2) vegetation vigour and drought stress monitoring, (3) assessment of crop phenological development, (4) crop acreage estimation and cropland mapping and (5) mapping of disturbances and land use/land cover (LULC) changes (Atzberger, 2014). EO datasets can also be used by countries to inform spatial land use planning and minimize the potential environmental impact of crop expansion through optimizing the allocation of lands (Laurence et al. 2014). In addition to crops, satellite remote sensing techniques can also be applied for rangeland monitoring and management (Ali et al. 2016). EO data and methods can be useful for assessing the future exposure to climate change as well as to extreme weather events, as explained in the 1.5.2 indicator factsheet.

Current Indicator(s)

2.4.1. Proportion of agricultural area under productive and sustainable agriculture.

Short methodological guidelines illustrated with EO best practice examples

Indicator 2.4.1

Computation method

The computational method for indicator 2.4.1 is under discussion and has not yet been finalised or officially published but is in work plan format. The suggested computation method is as follows:

SDG 2.4.1 = *Area under productive and sustainable agriculture / Agricultural land area* where:

The **denominator**, *Agricultural land area = arable land + permanent crops + permanent meadows and pastures*

The **numerator**, *Area under productive and sustainable agriculture*, captures the three dimensions of sustainable production: environmental, economic and social.

Much of the discussion during the development of this indicator has focused on a clarification of terms, particularly for the concept of 'sustainable agriculture'. Progress to date suggests that the intention is to design a threshold-based aggregate indicator which, through different sub-indicators, captures the economic, environmental and social main dimensions of sustainability. The estimation of proportion of agricultural area under sustainable agriculture, according to the work plan, will be based on data most likely collected through agricultural surveys and household surveys organized by the national statistical agencies, with support from the custodian agency (FAO) or other international agencies to ensure methodological harmonization. The opportunity for EO in supporting this indicator is mainly to benchmark the sustainability of farming practices. For example, it is unlikely that farmers would be able to assess the environmental impact of their farming practices on issues like fertilizer pollution or pesticide impact without a tool that can monitor impact in the wider landscape. An EO-based monitoring system can measure the impact of agriculture on the environment.

Regarding the computational method, EO technologies could particularly be useful to inform the agricultural land area. Agricultural land area is a common category in EO-derived land cover/land use maps. Satellite remote sensing has been used for several decades to support land cover mapping. It is the most cost-effective means for gathering spatially explicit information over large areas with high revisit frequency in a consistent and systematic manner.

EO could also be a tool to contribute to several sub-indicators of the environmental dimension of the indicator, such as farm output value per hectare, prevalence of soil degradation, variation in water availability and use of biodiversity-friendly practices. In addition, EO can provide support for cost-effective collection of agricultural and rural data by optimizing sampling designs and support to field surveys.

However, the current work plan specifies that this indicator will be assessed at the farm level. This is likely to require high to very high resolution EO-based data in order to produce meaningful results.

Limitations

In some cases, some of the definitions and assumptions of the EO-product might not match that of the sub-indicator, potentially leading to misleading numbers being reported. It could also be the case that validation has not been performed for a certain product for the conditions present in the country. Most freely available EO data might not be precise enough for field level monitoring. However field size can vary by country and in countries where industrial scale agriculture is practiced with commensurably large field sizes, VHR EO data might not be a necessity for computing this indicator.

Key messages for countries on EO contribution to the computation method

- The methodology for this indicator is in development but it is likely that EO will play a role in the computational method, particularly for supplementing farm survey data
- If this indicator is calculated at the farm level, high to very high resolution EO is likely to be needed (depending on national context of field sizes).
- EO could also be used to quantify the amount of agricultural area, using land-use/land-cover products.
- EO also has potential in assessing the impact of unsustainable farming and for monitoring the robustness of the indicator in monitoring the level of sustainability of agriculture with regards to wider landscape condition.

Data sources

Data category	Data sources	Website
Global/regional datasets	Copernicus Dry matter productivity product	*https://land.copernicus.eu/global/products/dmp*
Software, tools and platforms	GEO Global Agricultural Monitoring (GEOGLAM)	*https://cropmonitor.org/index.php/data-and-tools/cmet*
	Sentinel 2 for agriculture monitoring	*http://www.esa-sen2agri.org*
	Sentinels for Common Agriculture Policy	*http://esa-sen4cap.org*

Reference List

Ali, I., Cawkwell, F., Dwyer, E., Barrett, B. & Green, S. (2016) Satellite remote sensing of grasslands: from observation to management, Journal of Plant Ecology, 9 (6): 649–671

Atzberger, C. (2014) Advances in Remote Sensing of Agriculture: Context Description, Existing Operational Monitoring Systems and Major Information Needs. Remote Sensing (5): 949-981

FAO (2018) Methodological note, November 2018:http://www.fao.org/3/CA2639EN/ca2639en.pdf

Laurance, W.F., Sayer, J., & Cassman, K.G. (2014) Agricultural expansion and its impacts on tropical nature. Trends in Ecology & Evolution, 29 (2): 107-116

Indicators		2.4.1 Proportion of agricultural area under productive and sustainable agriculture.
Custodian agency		FAO
Tier		II
Status of step-by-step methodology document on the metadata repository		Methodological note available from November 2018
Relevance of EO for the indicator criteria	Maturity of EO technologies	
	Status of EO in indicator guidelines	
	Technical capacity required	
	Availability of global EO data	
Robustness of proposed methodology Criteria	Compliance with Reporting calendar	
	Sensitivity to change	
	Is it scalable (spatial)?	
	Is there a substitute for gaps in the EO record?	
Overall EO relevance		
Comments to support criteria		Household surveys have been identified as the main data collection instrument for this indicator. EO will have a supporting role, with a focus on environmental parameters that affect larger areas than the individual farm, or for parameters where it is unlikely that the farmers can evaluate the effects locally

GOAL 3

3 GOOD HEALTH AND WELL BEING

Target 3.3

By 2030, end the epidemics of AIDS, tuberculosis, malaria and neglected tropical diseases and combat hepatitis, water-borne diseases and other communicable diseases

How can EO be used to help countries achieve the target?

This target aims to end three of the world's major epidemics, which combined claim millions of lives per year (Murray et al., 2014). This makes this target one of the SDG targets with the greatest potential impact in terms of reducing mortality.

The utility of EO methods for improving the understanding, prevention, and control of vector-borne diseases has been extensively demonstrated, particularly for malaria (Gebreslasie, 2015). EO data has been used, for instance, to derive environmental data to feed malaria risk models, identification of potential vector habitats and to inform the development of early warning systems. Some of the EO-derived data that have been applied to malaria epidemiology include: land cover, land and sea surface temperature vegetation indices such as NDVI and enhanced vegetation index, precipitation and actual evapotranspiration. Results of the models developed with EO-derived data can be useful to identify locations where the risk of disease is highest and direct resources to the population most in need. EO-derived data can also be applied to develop risk models for other tropical diseases such as dengue or schistosomiasis, among others.

Current Indicator(s)

There are five indicators for this target:

3.3.1 Number of new HIV infections per 1,000 uninfected population, by sex, age and key populations

3.3.2 Tuberculosis incidence per 100,000 population

3.3.3 Malaria incidence per 1,000 population

3.3.4 Hepatitis B incidence per 100,000 population

3.3.5 Number of people requiring interventions against neglected tropical diseases

Short methodological guidelines illustrated with EO best practice examples

Indicator 3.3.3

Computation method

Incidence of malaria is defined at the country level as the number of new cases of malaria per 1,000 people at risk each year. The number of new cases of malaria is estimated from the number of malaria cases reported by the Ministry of Health of each country, using a series of statistical methods.

For some high-transmission countries where the quality of case reporting is considered insufficient for the above-mentioned method, estimates of the number of malaria cases are derived from the Malaria Atlas (https://map.ox.ac.uk/making-maps/) a geospatial model which is partly feed by EO-derived data, such as land surface temperature and vegetation indices (Bhatt et al., 2015)

Treatment of missing values

For missing values of the parameters a distribution based on a mixture of the distribution of the available values is used. When no reported data is available the number of cases is interpolated taking into account the population growth. EO datasets and methods could also represent an alternative way to fill the gaps in areas with missing values.

Limitations

While EO has great potential to contribute to reducing the impact of malaria and other vector-borne diseases, to be effective, it must be adopted as part of a holistic, multi-disciplinary approach, as it will necessarily involve coordination among different levels of government, health facilities, scientists and local population.

Key messages for countries on EO contribution to the computation method:

- The agreed methodology to compute this indicator is based on a series of statistical methods, EO-derived methods are only envisaged to be used when the quality of case reporting in high incidence countries is considered insufficient.

- EO derived data, combined with geospatial modelling, can also be useful to fill the gaps in areas with missing values elsewhere.

Data sources

Data category	Data sources	Website
Global/regional datasets	Malaria Atlas Project	*https://map.ox.ac.uk/making-maps*

Reference List

Bhatt, S., Weiss, D. J., Cameron, E., Bisanzio, D., Mappin, B., Dalrymple, U., … Gething, P. W. (2015). The effect of malaria control on Plasmodium falciparum in Africa between 2000 and 2015. Nature, 526, 207. Retrieved from http://dx.doi.org/10.1038/nature15535

Gebreslasie, M. T. (2015). A review of spatial technologies with applications for malaria transmission modelling and control in Africa. Geospatial Health, 10(2), 239–247. https://doi.org/10.4081/gh.2015.328

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Indicators 3 GOOD HEALTH AND WELL-BEING		3.3.1 Number of new HIV infections per 1,000 uninfected population, by sex, age and key populations	3.3.2 Tuberculosis incidence per 100,000 population	3.3.3 Malaria incidence per 1,000 population	3.3.4 Hepatitis B incidence per 100,000 population	3.3.5 Number of people requiring interventions against neglected tropical diseases
Custodian agency		UNAIDS	WHO	WHO	WHO	WHO
Tier		I	I	I	I	I
Status of step-by-step methodology document on the metadata repository		Published	Published	Published	Published	Published
Relevance of EO for the indicator criteria	Maturity of EO technologies					
	Status of EO in indicator guidelines					
	Technical capacity required					
	Availability of global EO data					
Robustness of proposed methodology Criteria	Compliance with Reporting calendar					
	Sensitivity to change					
	Is it scalable (spatial)?					
	Is there a substitute for gaps in the EO record?					
Overall EO relevance						
Comments to support criteria		Not supported by EO.	Not supported by EO.	Although current indicator methodology only envisages the use of EO derived data when the quality of case reporting is considered insufficient, the potential of geospatial modelling to provide accurate estimations of Malaria prevalence is high.	Not supported by EO.	Not supported by EO.

Target 3.9

By 2030, substantially reduce the number of deaths and illnesses from hazardous chemicals and air, water and soil pollution and contamination

How can EO be used to help countries achieve the target?

EO data can be used to monitor the level of air quality data (e.g. PM2.5, CO_2, CO, NOx, SO_2) (van Donkelaar et al., 2010) water quality data (E.g. Chlorophyll-a, turbidity) (Mohamed, 2015), as well as soil pollution data (e.g. concentration of hydrocarbons) (Karkush et al., 2014). These can be correlated with census data on human health and mortality to monitor progress towards reducing the number of deaths and illness from hazardous chemicals and air, water and soil and contamination. In order to reduce the number of deaths by creating public awareness, a wider forecasting system based on modelling EO data for the likely risk of danger from hazardous chemicals and air, water and soil pollution and contamination is needed.

Indicator(s)

3.9.1 Mortality rate attributed to household and ambient air pollution

3.9.2 Mortality rate attributed to unsafe water, unsafe sanitation and lack of hygiene (exposure to unsafe Water, Sanitation and Hygiene for All (WASH) services)

3.9.3 Mortality rate attributed to unintentional poisoning.

Short methodological guidelines illustrated with EO best practice examples

Indicator 3.9.1

Computation method

EO is not currently discussed in the methodological guidelines for these indicators, but there is scope for it to be used alongside the current methods.

Household census data on health and mortality (e.g. respiratory disease) can be used alongside pollution data. Satellite based observations can be used to estimate a number of pollutants. Anderson et al. (2012) used annual ground level PM2.5 concentrations by combining aerosol vertical profiles obtained from the global chemical transport model GEOS-Chem with total column aerosol depth obtained from 2 spectroradiometers (MODIS and MISR). Concentrations were averaged over a number of years. Similarly, NO_2 concentrations can be estimated by combining GEOS-Chem NO_2 profiles with tropospheric NO_2 columns obtained from the satellite Aura. O_3 concentrations can be modelled using the two-way nested TM5 Global Chemical Transport Model (Anderson et al., 2012).

Evans et al. 2013 used satellite data to derive PM2.5 concentration estimates, and then used previously developed concentration- response functions to calculate the relative risks of associations between PM2.5 and four cases of mortality: all causes, cardiopulmonary disease, lung cancer, and ischemic heart disease.

Data from Sentinel-5P has recently been made available – allowing O_3, CO and NO_2 data to be recorded. SO_2 data was made available in September 2018. The Sentinel-5P spacecraft uses a TROPOMI instrument which uses passive remote sensing techniques to measure at the Top Of Atmosphere (TOA) the solar radiation reflected by and radiated from the earth (ESAa, 2018). It is the first Copernicus satellite dedicated to monitoring the atmosphere. The TROPOMI instrument can provide highly detailed and accurate data about the atmosphere with a resolution up to 7 x 3.5km – detecting air pollution over individual cities (ESAb, 2018).

Aerosol dispersion varies spatially and temporally, therefore can display both local and regional patterns depending on their source. These characteristics limit the ability of fixed site ground-based PM monitors to capture large scale, regional and global PM distributions. Satellites can however detect this spatial variability both within the upper atmosphere and over broad regions. The choice of model parameters influenced the baseline estimates.

Limitations

Additionally, there are errors associated with satellite measurements. There are often a lack of PM2.5 sensors in rural regions. PM2.5 calculations are often based on stimulations, which have measures of uncertainty (Anenberg et al., 2010).

Key messages for countries on EO contribution to the computation method

- EO isn't currently discussed in the methodological guidelines for these indicators
- A number of satellites and instruments can be used to gather data on airborne pollutants, principally in the upper atmosphere, for example: Satellite Aura, Sentinel-5P and Spectroradiometers MODIS and MISR.
- EO data can be used to highlight the risk of dangerous air pollution, when the level of pollutants exceeds a background normal
- However, health information gathered through household census data is necessary to measure air pollution at the household level

Data sources

Data category	Data sources	Website
Source satellite data	Satellite Aura	*https://search.earthdata.nasa.gov* *https://scihub.copernicus.eu*
	Sentinel-5P	
	MODIS	
	MISR	
Software, Tools and Platforms	Water Observation and Information System (WOIS)	*http://www.tiger.esa.int/page_eoservices_wois.php*
	AquaWatch	*https://www.geoaquawatch.org/*

Reference List

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Anenberg, S. C., Horowitz, L. W., Tong, D. Q., West, J. J. (2010) An estimate of the global burden of anthropogenic ozone and fine particulate on premature human mortality using atmospheric modelling. Environmental Health Perspectives. 118, 1189–1195.

ESAa (2018) Sentinel-5P TROPOMI User Guide. ESA. [Online] Available at: https://sentinels.copernicus.eu/web/sentinel/user-guides/sentinel-5p-tropomi [Accessed 24th July 2018]

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Karkush, M. O., Ziboon, A. R. T. & Hussien, H. M. (2014) Studying the effects on soil properties using remote sensing. Journal of Engineering. 20 (6), 78-90.

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van Donkelaar, A., Martin, R. V., Brauer, M., Kahn, R., Levy, R., Verduzco, C. & Villeneuve, P. J. (2010) Global estimates of ambient fine particulate matter concentrations from satellite-based aerosol optical depth: development and application. Environmental Health Perspectives. 118 (6), 847-855.

Indicators 3 GOOD HEALTH AND WELL-BEING		3.9.1 Mortality rate attributed to household and ambient air pollution	3.9.2 Mortality rate attributed to unsafe water, unsafe sanitation and lack of hygiene (exposure to unsafe Water, Sanitation and Hygiene for All (WASH) services)	3.9.3 Mortality rate attributed to unintentional poisoning.
Custodian agency		WHO		
Tier		I	I	I
Status of step-by-step methodology document on the metadata repository		Published	Published	Published
Relevance of EO for the indicator criteria	Maturity of EO technologies			
	Status of EO in indicator guidelines			
	Technical capacity required			
	Availability of global EO data			
Robustness of proposed methodology Criteria	Compliance with Reporting calendar			
	Sensitivity to change			
	Is it scalable (spatial)?			
	Is there a substitute for gaps in the EO record?			
Overall EO relevance				
Comments to support criteria		An overall amber status: technology is available to use EO, and across different scales - highlighting sensitivity to change. However, there is currently little integration, and the technical capacity required to process and analyse is high.	Not supported by EO	Not supported by EO

GOAL 4

4 QUALITY EDUCATION

Target 4.a

Build and upgrade education facilities that are child, disability and gender sensitive and provide safe, non-violent, inclusive and effective learning environments for all

How can EO be used to help countries achieve the target?

EO data could be used to monitor aspects of education facilities, such as access to electricity and basic drinking water. However, it has limited capacity in measuring general effective learning environments. The target addresses the need to both build new and upgrade the existing education facilities. Hence, there is a gap for EO to contribute by identifying sites for development of education facilities, based on criteria such as proximity to human settlement and roads and upgrade damaged or defective buildings and other visible infrastructure. EO can therefore be used in urban and rural settings and as a planning tool for education facilities and help countries achieve their target. This will necessitate commercially produced very high resolution (VHR) imagery and may be a drawback for implementation of EO unless sufficiently financed.

Current Indicator(s)

4.a.1 Proportion of schools with access to (a) electricity; (b) the Internet for pedagogical purposes; (c) computers for pedagogical purposes; (d) adapted infrastructure and materials for students with disabilities; (e) basic drinking water; (f) single-sex basic sanitation facilities; and (g) basic handwashing facilities (as per the WASH indicator definitions)

Short methodological guidelines illustrated with EO best practice examples

Indicator 4.a.1

Computation method

EO is not currently discussed in the methodological guidelines for the indicator, but there is scope for it to be used alongside the current methods. The indicator is calculated as –

PSn,f = Sn,f

Where, PSn,f = percentage of schools at level n of education with access to facility f; Sn,f = schools at level n of education with access to facility f; Sn = total number of schools at level n of education.

EO could be integrated into calculations of the access to basic drinking water, which are mainly evaluated through survey data. However, one project in Lima, Peru has started to use EO to develop innovative solutions and planning tools for drinking water supply. It uses satellite-based remote sensing and water balance modelling alongside strategic decision-making tools and concepts for integrated water supply and wastewater disposal.

In addition, satellite data could be used to aid Demographic and Health Surveys (DHS). These surveys are nationally produced household survey data, which are collected in 90 countries worldwide, and record information on demographic, social, economic and health-related outcomes. The DHS monitors the time it would take to reach a source of drinking water in minutes – this can also be applied for schools. This can be complemented with satellite imagery for information about surface waterbody extent and water quality to estimate access to basic drinking water at schools.

Moreover, census data can also be used alongside satellite data. Currently census data provides information on electricity access, and satellite data can be used to complement this data by measuring electrification through measuring night-time luminosity (Min et al., 2013). Night light data can be easily downloaded from NOAA (National Oceanic and Atmospheric Administration). Many analyses only use the 'stable lights' datasets, which only includes locations with persistent lighting – excluding ephemeral events such as fires.

Limitations

Measuring night time luminosity through satellites will be less reliable in areas with constrained power supplies, and for detecting non-electrified villages.

Key messages for countries on EO contribution to the computation method

- EO isn't currently used to measure the percentage of schools by level of education with access to the given facility or service
- There is scope for EO to be used to complement survey data such as DHS and census surveys.

Data sources

Data category	Data sources	Website
Global/regional datasets	The Global Surface Water Explorer	*https://global-surface-water.appspot.com*

Reference List

Min, B., Gaba, K. M., Sarr, O. F. & Agalassou, A. (2013) Detection of Rural Electrification in Africa Using DMSP-OLS Night Lights Imagery. International Journal of Remote Sensing. 34 (22): 8118–8141.

Indicators		4.A.1 Proportion of schools with access to (a) electricity; (b) the Internet for pedagogical purposes; (c) computers for pedagogical purposes; (d) adapted infrastructure and materials for students with disabilities; (e) basic drinking water; (f) single-sex basic sanitation facilities; and (g) basic handwashing facilities (as per the WASH indicator definitions)
Custodian agency		UNESCO-UIS
Tier		II
Status of step-by-step methodology document on the metadata repository		Published
Relevance of EO for the indicator criteria	Maturity of EO technologies	
	Status of EO in indicator guidelines	
	Technical capacity required	
	Availability of global EO data	
Robustness of proposed methodology Criteria	Compliance with Reporting calendar	
	Sensitivity to change	
	Is it scalable (spatial)?	
	Is there a substitute for gaps in the EO record?	
Overall EO relevance		
Comments to support criteria		This is amber as there is currently limited integration and use of EO with this indicator.

GOAL 6

6 CLEAN WATER AND SANITATION

Target 6.1

By 2030, achieve universal and equitable access to safe and affordable drinking water for all

How can EO be used to help countries achieve the target?

One of the most essential uses of water is for domestic consumption within households. This purpose is captured in target 6.1, which seeks to guarantee safe and affordable drinking water for drinking and hygiene purposes for all. Households are an important share of total water use and therefore represent a significant sector in achievement of target 6.4 on water use efficiency. "Safe" water is considered to be free of contaminants and is determined by the quality of untreated water prior to human consumption. The necessity of the target, for a supply of high water quality in the first place, is threatened by conversion of wetlands, forests and woodlands to agriculture around populated areas and water catchments. This target is therefore linked to the protection of the water catchment which is the focus of target 6.6 and the quality of water in target 6.3. The use of land cover change data, particularly in models to estimate the impact on water supplies in the event of widespread deforestation and land conversion, is a powerful way to show how drinking water becomes both unsafe and unaffordable in the event of a water supply being compromised by the conversion of natural ecosystems which regulate it. As EO-based observations are primary inputs to such models, countries can be supported towards achievement of target 6.1 by implementing such models and to plan for better baseline water quality through regulation of land use in water catchments.

Current Indicator(s)

6.1.1 Proportion of population using safely managed drinking water services

Short methodological guidelines illustrated with EO best practice examples

Indicatior 6.1.1

Computation method

The current indicator methodology is based on household surveys and censuses. Although the notion of safe management of the water supply cannot be directly evaluated from EO, it can be inferred from the change in water quality before and after treatment, the former coming form EO-derived water quality maps and the latter from in-situ sampling.

State-of-the-art hyperspectral remote sensing-derived information on water quality is generating an increasing choice of products relevant to this indicator. These range from more accurate estimates of turbidity and transparency measures, chlorophyll, suspended matter and coloured dissolved organic matter concentration, to more sophisticated products such as particle size distributions, phytoplankton functional types or distinguishing sources of suspended and coloured dissolved matter, estimating water depth and mapping types of heterogeneous substrates (Giardino et al., 2018). As indicator 6.6.1 specifically requires comparison of water quality against international standards (faecal and chemical) from administrative reporting or regulatory bodies, these EO-derived parameters will need to be compliant with such standards. Another EO-based approach is through the provision of land cover and land use change layers for hydrological modelling and water quality assessment, e.g. to estimate nitrate leaching in groundwater (Abbaspour et al., 2015).

EO can also help to compute the level of access to basic services for each country, separately in urban and rural areas, though the provision of human settlement data, even at very high spatial resolutions, as discussed for indicator 11.1.1. Computing the proximity of these human settlements to a "safe" water supply would be a core part of an EO-based methodology.

Limitations

EO has limited relevance for evaluating the types of basic drinking water sources, whether piped or sourced from a well, or to evaluate the level of management and service of the water supply.

Key messages for countries on EO contribution to the computation method

- The EO methods that can support this indicator mostly relate to assessment of water quality and land cover / land use around water catchments
- While water quality can be used to assess the status of water supplies before treatment, in-situ sampling is required during and after treatment to assess the "safety" of water compared to international standards required for this indicator
- The planning for achievement of the target 6.1 can be supported by models of land use and hydrology which can use EO–derived information as inputs such as high resolution land cover. This is important to plan for water catchment management, ensuring that water supplies are as clean as possible before being supplied for domestic consumption

Data sources

Data category	Data sources	Website
Global/regional datasets	GlobWetland II	*http://www.globwetland.org/index.php*
	The Global Human Settlement Layer (GHSL)	*https://ghsl.jrc.ec.europa.eu/data.php*
	The Global Surface Water Explorer	*https://global-surface-water.appspot.com*
Software, tools and platforms	The Satellite-based Wetlands Observation Service (SWOS)	*http://portal.swos-service.eu/mapviewer/detail/1.html*
Operational or commercial services	Copernicus Global Land Service	*https://land.copernicus.eu/global/*

Reference List

Abbaspour, K. C., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H., & Kløve, B. (2015). A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high-resolution large-scale SWAT model. Journal of Hydrology, 524, 733–752. https://doi.org/10.1016/j.jhydrol.2015.03.027

Giardino, C., Brando, V. E., Gege, P., Pinnel, N., Hochberg, E., Knaeps, E., ... Dekker, A. (2018). Imaging Spectrometry of Inland and Coastal Waters: State of the Art, Achievements and Perspectives. Surveys in Geophysics. https://doi.org/10.1007/s10712-018-9476-0

Pesaresi, M., Blaes, X., Ehrlich, D., Ferri, S., Gueguen, L., Halkia, M., ... Zanchetta, L. (2013). A Global Human Settlement Layer From Optical HR/VHR RS Data: Concept and First Results. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 6(5), 2102–2131. https://doi.org/10.1109/JSTARS.2013.2271445

Indicators 6 CLEAN WATER AND SANITATION		6.1.1 Proportion of population using safely managed drinking water services
Custodian agency		WHO; UNICEF
Tier		II
Status of step-by-step methodology document on the metadata repository		Published
Relevance of EO for the indicator criteria	Maturity of EO technologies	
	Status of EO in indicator guidelines	
	Technical capacity required	
	Availability of global EO data	
Robustness of proposed methodology Criteria	Compliance with Reporting calendar	
	Sensitivity to change	
	Is it scalable (spatial)?	
	Is there a substitute for gaps in the EO record?	
Overall EO relevance		
Comments to support criteria		The proposed methodology is only partially supported because EO can support monitoring and modelling of water quality prior to treatment thus in quantifying "safe" levels of water quality. However quantifying proportion of population with access to safe water beyond the remit of EO.

Target 6.3

By 2030, improve water quality by reducing pollution, eliminating dumping and minimizing release of hazardous chemicals and materials, halving the proportion of untreated wastewater and substantially increasing recycling and safe reuse globally

How can EO be used to help countries achieve the target?

Target 6.3 aims to improve ambient water quality, important for protecting both ecosystem health and human health, by eliminating, minimizing and significantly reducing different streams of pollution into water bodies. The main sources of water pollution include wastewater from households, commercial establishments and industries (point sources), as well as run-off from urban and agricultural land (non-point sources). Water quality can be measured in different ways and EO methods of water quality detection differ from those based on in-situ assessment. Therefore EO support to this target will be limited by what can be detected based on current sensor technology. EO is important in ongoing, routine water quality monitoring of large water bodies, ideally in combination with in situ sampling. Yet it is feasible, although challenging, to use EO as a monitoring tool for illegal contamination of water supplies. The release of certain hazardous chemicals and materials, for example, can alter the opacity, turbidity and colour of lakes, rivers or other water bodies, which can be sensed from a multispectral or hyperspectral sensor. Armed with this EO-derived information on sudden declines in water quality, e.g. due to dumping of hazardous materials, water management authorities could track down polluters. However, the spatial resolution of the Sentinel 3 Ocean and Land Colour Imager (OLCI) is likely to be too coarse to accurately detect such events, while the Sentinel 2 Multi Spectral Imager (MSI), although better suited in terms of spatial resolution, is too sparse in terms of revisit time (5 days). A combination of commercial and free sensors (OLCI, S-2, L8, SPOT, RapidEye, IKONOS) could be an option for targeted, local efforts at detection of pollution events. EO can also support countries with the target by assessment of the risk of eutrophication of a country's water bodies by monitoring ambient nutrient pollution in standing waters.

Current Indicator(s):

6.3.1 Proportion of wastewater safely treated

6.3.2 Proportion of bodies of water with good ambient water quality

Potential new indicator(s) based on EO:

The number of cyanobacteria blooms in water supplies
The number of pollution events (including thermal) causing illegal contamination of water supplies

Short methodological guidelines illustrated with EO best practice examples

Indicator 6.3.1

Computation method

Indicator 6.3.1 is calculated as the amount of waste treated (off-site and on-site) divided by the total amount produced. The breakdown of treated wastewater into untreated versus treated can be calculated based on compliance records, related to national standards. Unless verified otherwise, through audited compliance records, the waste generated will be considered untreated. However it may be possible where there are no compliance records to use EO-derived nutrient concentrations present in standing waterbodies as an indicator of the amount of untreated / poorly treated wastewater entering these systems.
Parameters retrieved with medium to high confidence:

- Chlorophyll-a (chl-a),
- Colored dissolved organic matter (CDOM),
- Secchi disk depth (SDD),
- Turbidity,
- Total suspended matter (TSM)

Parameters retrieved with reduced resolution:

- Water temperature (WT): SST can be retrieved with quite good accuracy (and confidence) for the coarse resolution (large water bodies). Higher resolution data can provide relative temperature patterns (e.g. Landsat).
- Sea surface salinity (SSS): passive radar restricted to low spatial resolution (50km), which is not suitable for freshwater.

Limitations

The calculation of indicator 6.3.1 using an EO-based approach is limited because not all hazardous chemicals and materials, pollutants (such as litter) and untreated wastewater can be detected by multispectral or hyperspectral sensors. These errors of omission would need to be quantified before attempting an EO-based approach to this indicator. In coastal areas, Synthetic Aperture Radar (SAR) has been shown to be able to detect surface runoff plumes of biogenic substances associated with storm events (Svejkovsky & Jones, 2001), although the effectiveness of this method is dependent on weather conditions and sea surface state. However, its application in other aquatic environments, e.g. lakes, remains unproven.

Key messages for countries on EO contribution to the computation method:

- EO-based approaches to water quality monitoring are in varying levels of maturity with up to 7 physical and biological parameters currently retrievable from low to high confidence. Those parameters which do not have any optical (e.g. pathogens, salinity) can only be detected via proxy parameters (if at all) and are therefore retrieved with the lowest confidence and might contain the largest errors and need local adjustment, especially in optically complex waters.

- The safe treatment of wastewater is more challenging to evaluate from EO since it requires a prior knowledge of the status of the wastewater prior to treatment in order to deduce if the treatment has been "safe" according to acceptable standards. In addition water quality parameters, such as the presence of pathogens, are not retrievable from EO

- Standards of treatment will vary internationally, and establishing a wastewater quality baseline from EO alone is not possible, and will require compliance records obtained in-situ

- Water bodies include rivers, lakes and groundwater. Assessing the ambient water quality of ground water and very small rivers or lakes (e.g. 1km surface area) is not possible using EO

- Indicator 6.3.2 and 6.3.1 are interlinked because inadequate wastewater treatment leads to degradation in quality of the waters receiving the wastewater effluents.

Data sources

Data category	Data sources	Website
Global/regional datasets	The Global Surface Water Explorer	*https://global-surface-water.appspot.com*
Software, tools and platforms	Bio-physical parameters can be derived from Sentinel 2 and 3 using processors provided in the SNAP toolbox	*http://step.esa.int/main/*
Operational or commercial services	Copernicus Global Land Service	*https://land.copernicus.eu/global/*
	CyanoLakes	*http://www.cyanolakes.com/monitoring*
	EOMAP	*https://www.eomap.com/*
	Brockmann Consult	*https://web.brockmann-consult.de*

Reference List

Svejkovsky, J. & Jones, B. (2001) 'Satellite imagery detects coastal stormwater and sewage runoff', Eos, 82(50), pp. 624–625. doi: 10.1029/01EO00357.

Indicator 6.3.2

Computation method

Indicator 6.3.2 is computed as the proportion of all water bodies (river, lake and groundwater bodies) classified as having good quality, expressed as a percentage. The methodology considers a body of water to have good quality if at least 80% of all monitoring data from all monitoring stations within the water body are in compliance with the respective targets. Mapping the global extent and dynamics of water bodies from space has been well proven (Pekel et al., 2016). The mapping of water quality has been demonstrated in many different applications and services. EO can sense the water constituents that have an influence on the colour of the water and thus is providing a subset of parameters that are measured in-situ and used for indicator 6.3.2.

Parameters retrieved with medium to high confidence:

- Chlorophyll-a (chl-a),
- Colored dissolved organic matter (CDOM),
- Secchi disk depth (SDD),
- Turbidity,
- Total suspended matter (TSM)

Parameters retrieved with reduced resolution:

- Water temperature (WT): SST can be retrieved with quite good accuracy (and confidence) for the coarse resolution (large water bodies). Higher resolution data can provide relative temperature patterns (e.g. Landsat).
- Sea surface salinity (SSS): passive radar restricted to low spatial resolution (50km), which is not suitable for freshwater.

Treatment of missing values

Indicator 6.3.2: Missing values within water bodies could possibly be filled by spatiotemporal interpolation, e.g. using Data Interpolating Empirical Orthogonal Functions (DINEOF), an optimised gap filling procedure. However this risks introducing large uncertainties because bio-physical properties of water can vary over small distances. Another approach would be to use a time series of observations (e.g. yearly) and to calculate temporal statistics (e.g. mean, 25th and 75th percentiles, median). This would reduce the likelihood of a missed observation significantly.

Sources of discrepancies

Possible discrepancies will exist between national and international water quality datasets, derived from EO, if the input data are different. In addition compliance with water quality standards post-treatment will vary from country to country as do guidelines for acceptable standards of nutrient pollution.

Limitations

There is no information about ground water (or any sub-surface water) quality from EO for indicator 6.3.2. There is also a limitation in the comparison of EO-derived water quality products and the monitoring data collected for selected parameters at monitoring locations as required by the indicator for assessing "good" quality. This is because EO does not measure all water quality parameters but only bio-physical parameters, therefore it is not possible to comment on the overall water quality exclusively using EO data. For example, mapping ambient water quality of water bodies is a much more challenging prospect for two main reasons: (i) water quality is a combination of many biological, such as sedimentation, pathogens or algae, and physicochemical components, such as heavy metals, nutrient levels and dissolved minerals, etc. While EO can sense a limited number of these bio-physical components it cannot monitor chemical ones, e.g. heavy metals, nor water quality as a whole and (ii) spatial resolution of remote sensing instruments in the aquatic domain is generally coarse (>300m) meaning that groundwater bodies or small lakes or rivers are either undetectable or averaged out over large areas. Therefore EO is a useful source of supplementary information for in situ physicochemical water quality monitoring programmes but will never be a replacement for them. Seven such water quality parameters are directly measurable from EO, albeit with large uncertainties (Gholizadeh et al., 2016).

Key messages for countries on EO contribution to the computation method:

- EO-based approaches to water quality monitoring are in varying levels of maturity with up to 7 physical and biological parameters currently retrievable from low to high confidence. Those parameters which do not have any optical (e.g. pathogens, salinity) can only be detected via proxy parameters (if at all) and are therefore retrieved with the lowest confidence and might contain the largest errors and need local adjustment, especially in optically complex waters.

- Water bodies include rivers, lakes and groundwater. Assessing the ambient water quality of ground water and very small rivers or lakes is not possible using EO. With Sentinel-3 water bodies less than 1 km2 is not feasible to map, while Sentinel-2 can monitor water bodies down to approximately 150 by 150 meters (but limited by the spectral and temporal resolution).

- Indicator 6.3.2 and 6.3.1 are interlinked because inadequate wastewater treatment leads to degradation in quality of the waters receiving the wastewater effluents.

Data sources

Data category	Data sources	Website
Global/regional datasets	The Global Surface Water Explorer	*https://global-surface-water.appspot.com*
Software, tools and platforms	Bio-physical parameters can be derived from Sentinel 2 and 3 using processors provided in the SNAP toolbox	*http://step.esa.int/main/*
Operational or commercial services	Copernicus Global Land Service	*https://land.copernicus.eu/global/*
	CyanoLakes	*http://www.cyanolakes.com/monitoring/*
	EOMAP	*https://www.eomap.com/*
	Brockmann Consult	*https://web.brockmann-consult.de*
	DHI GRAS	*https://www.dhi-gras.com/solutions/water-quality/*

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Matthews, M. W. et al. (2018) The Integration of Earth Observation into the National Eutrophication Monitoring Programme.

Pekel, J.-F. et al. (2016) 'High-resolution mapping of global surface water and its long-term changes', Nature, 540(7633), pp. 418–422. doi: 10.1038/nature20584.

Two show cases for utilizing EO for waste water detection (indicator 6.3.1)

Target 6.3 aims for improved water quality, reduced pollution, eliminated dumping and minimized release of hazardous chemicals and materials as well as halving the proportion of untreated wastewater and substantially increasing recycling and safe reuse globally by 20130. The indicator 6.3.1 "Proportion of wastewater safely treated" addresses households as well as industry. The support that Earth Observation (EO) might give here is not in covering the treatment of wastewater itself. However, we would like to illustrate with two show cases what EO data can provide for the subject of waste water.

The first shows the detection of heat plumes at the outflow of cooling water from power plants into rivers. Landsat thermal data have been used to show temperature anomalies. Under certain conditions, the anomalies are clearly visible (showcase 1), while other images do not show any differences of cooling water and river water. Influencing factors are differences in temperature of the river water and the cooling water, the performance of the power plant, direction and strength of (tidal) currents and wind speed.

The second show case illustrates the monitoring of dredging activities in coastal waters (showcase 2). Human activities due to dredging and other coastal engineering work in coastal waters have a large impact on local and regional water quality and sedimentology. Depending on the source, dredging material can be contaminated with heavy metals and other organic or inorganic substances. Different water masses are identified by their colour and interpreted accordingly. The phenomena are of comparably small spatial scale and can be mapped with spatial high-resolution images such as Landsat-8 or Sentinel-2. The revisit time of the satellites limits the potential to run an operational monitoring scheme but can complement other methods.

Figure 3: Examples of Landsat images showing anomalies in temperature caused be cooling water from power plants (left and right: Landsat-7, middle: Landsat-8). Shown are power plants at the Elbe River (left and middle) and the Weser River in Germany. (Brockmann Consult service; image data: Landsat ©USGS)

Figure 4: Sentinel-2 observation of dumping activities. Above: True colour image, below: derived parameter: absorption (humic substances), differentiating between dumped water and coastal waters. (Brockmann Consult service; image

South Africa: The Earth Observation National Eutrophication Monitoring Programme (indicator 6.3.2)

The "Integration of Earth Observation into the National Eutrophication Monitoring Programme" (EONEMP) Project (funded by the Water Research Commission, ZAR 3 Million, 2015-2018) used earth observation satellite remote sensing to monitor cyanobacteria blooms (fig.1) and nutrient pollution (eutrophication, fig.2) in South Africa's large and medium-sized (>900 m) fresh waterbodies (Matthews et al., 2018). Using EO, it determined the status and severity of nutrient enrichment and the health risks from cyanobacteria blooms, for both the previous decade (2002 to 2012) and for the year 2016/17. A prototype online near real-time monitoring service website was developed (fig.3) through which chlorophyll-a and associated data were delivered to, and integrated into, the Water Management System database of the national governmental Department of Water and Sanitation to supplement in situ monitoring and fill information gaps. The satellite information was ultimately used for reporting to Parliament on the nutrient pollution levels and risks from cyanobacteria in South Africa's water supply reservoirs. The project demonstrates how EO can produce invaluable environmental records for reporting on and analysing pollution of standing waters by shedding light on the impacts from poorly or untreated wastewater which is known to be a significant problem in South Africa's infrastructure.

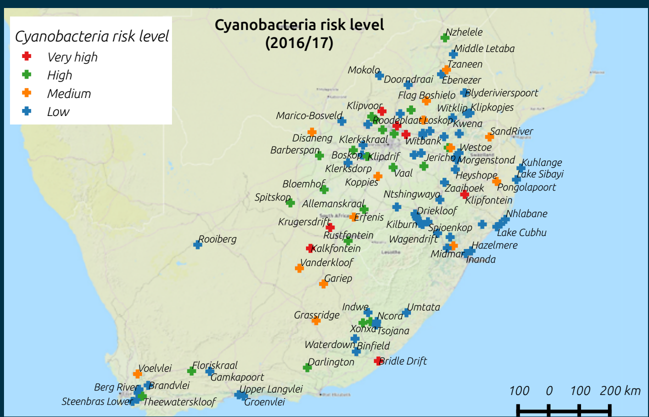

Figure 5: The cyanobacteria risk level derived from Sentinel-3 OLCI for 2016/17 for 102 South African waterbodies.

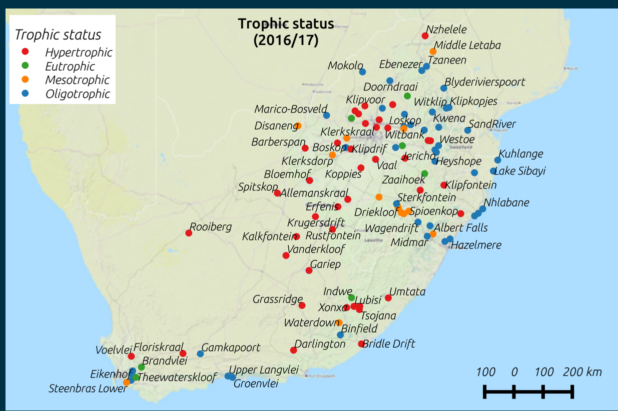

Figure 6: The nutrient pollution level (trophic status) derived from Sentinel-3 OLCI for 2016/17 for 102 South African waterbodies

Figure 7: The online monitoring service developed by CyanoLakes during the EONEMP project for monitoring nutrient pollution and cyanobacteria health risks in waterbodies in near real-time.

Target 6.4

By 2030, substantially increase water-use efficiency across all sectors and ensure sustainable withdrawals and supply of freshwater to address water scarcity and substantially reduce the number of people suffering from water scarcity

How can EO be used to help countries achieve the target?

Target 6.4 addresses water scarcity, aiming to ensure there is sufficient water for the population, the economy and the environment by increasing water-use efficiency across all sectors of society. Finding a balance between demands for water from environmental requirements and human demand is essential to maintaining ecosystem health and resilience. An imbalance due to unsustainable levels of demand can result in water stress with negative effects on economic development, increasing competition and potential conflict among users. This requires effective supply and demand management policies and an increase in water-use efficiency.

EO has an obvious – if yet unrecognised – contribution to the monitoring of the target in quantifying surface water changes over time, water consumed by key water-user sector such as agriculture, as well as soil moisture deficits. Therefore EO can help countries achieve water use efficiency gain targets by identify areas of current and future surface water deficits, e.g. through hydrological models, based on EO parameters such as evapotranspiration, soil moisture and surface water, and by modelling supply and demand across sectors based on land use change. In agricultural areas, EO can monitor how effectively water uptake by vegetation is translated into crop yield, using a metric that is referred to as agriculture water productivity (yield/m^3 of water consumed). This can ultimately help countries to plan for water deficits in advance of stresses such as climate extremes or when demand is excessive. The number of people suffering from or potentially affected by such water deficits could then be calculated based on demographic statistics A range of options exists for coping with water scarcity that address the supply side or the demand side or a combination of the two, depending on the bio-physical and socio-economic context.

Current Indicator(s)

6.4.1 Change in water-use efficiency over time

6.4.2 Level of water stress: freshwater withdrawal as a proportion of available freshwater resources

Potential new indicator(s) based on EO:

Proportion of the population suffering from water scarcity
Water productivity

Short methodological guidelines illustrated with EO best practice examples

Indicator 6.4.1

Computation method

Indicator 6.4.1 defines water use efficiency as the volume of water used divided by the value added of a given major sector. Traditionally the sectors considered are agriculture; forestry; fishing and MIMEC (mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply; construction) and services (i.e. the public distribution network). Efficiency is defined as the change in the ratio of the value added (by the sector) to the volume of water use, over time. The sectoral approach is designed to identify economic sectors where value added is small relative to water use at the national scale and therefore where gains in water use efficiency can be made over time. Data on volumes of used and distributed water are collected at country level from the municipal supply utilities records and reported in questionnaires. Services value added is obtained from national statistics, deflated to the baseline year. There is currently no mention of EO in the indicator guidelines.

EO-based methods of measuring water use efficiency for this indicator include the concepts of water productivity for agriculture and rain use efficiency for environmental applications. Both concepts are based on production of vegetation in relation to water usage. Net Primary Production (NPP) is the total carbon fixed by photosynthesis during a period and is the rate of organic biomass growth or accumulation by plants. EO NPP models can be divided into models based on empiric relationships with the Normalised Difference Vegetation Index, radar backscatter or another simple satellite-derived parameter, and in physical models using the absorbed photosynthetically active radiation (fPAR). Methods based on EO derived fPAR have been successfully used to measure biomass production across scales, climates, and ecosystems.

Timeseries of optical and radar EO images can be very useful for separating the landscape into land use and land cover classes focused specifically on water use. Examples of such classes are irrigated and non-irrigated agriculture or individual crop types. Such maps can be produced at high enough accuracy (up to 10 m when using open data) to capture individual fields or linear landscape features such as riparian zones.

EO is increasingly being used to compute actual evapotranspiration, thereby allowing for a direct estimation of the amount of water consumed in each spatial unit (pixel). When that information is associated to land use maps (mostly EO-based), it becomes possible to calculate water consumption by land use class (e.g. irrigated agriculture, rainfed agriculture, water bodies, different crops etc.)

This concept can be applied to water use efficiency in the agricultural sector, e.g. where EO-based approaches have been used to estimate crop water productivity based on water uptake (Bastiaanssen and Steduto 2017). Recently, FAO, IHE-Delft, IWMI, and other partners have been joining forces to develop an open-access database that monitors water productivity in Africa and the Near East (WaPOR) using satellite derived information (FAO, 2018).

Other water using sectors, like industry, energy, or domestic use, have different impacts on water resources (like deteriorating water quality, or altering its temporal availability) that are not captured through evapotranspiration and are not easily detectable through EO.

Sources of discrepancies

When using EO for the total freshwater withdrawn (TWW) component (explained further in the section on 6.4.2), there would not be discrepancies expected as optical image inputs (Leaf Area Index, the crop height, vegetation indices, surface albedo, and land surface temperature) are usually standard and are required for most ET models which also use thermal data.

Limitations

For TWW the spatial resolution of satellite thermal images is not commensurate with the size of small agricultural fields. Since the pixels contain broad mixtures and densities of crops, the land surface temperature signals are mixed and the evapotranspiration retrievals are difficult to interpret. For example, the pixel size ranges from 100 m for the thermal sensor on board Landsat 8 to 375m for VIIRS to 1000 m for MODIS-AQUA, MODIS-TERRA and Sentinel-3 (Allen et al. 2011). This might not pose a problem for national reporting on the TWW component of indicator 6.4.2, but might pose a challenge for disaggregation by hydrological units (river basins, aquifers), with the caveat that if a thermal-based model is being used, low spatial resolutions, e.g. the 1km of the Sentinel-3 SLSTR, might be just adequate for river basins but is not enough for individual fields. Various techniques exist for improving the spatial resolution of thermal data using high-resolution optical observations. However, caution should be exercised when using such fused data for detailed field-scale analysis.

For the total renewable freshwater resources (TRWR), only wetlands reservoirs and similar water bodies are quantifiable from EO but it's not clear how they are counted in the internal renewable water resource.

There also imitations on the accuracy of model inputs derived from EO such as land use and meteorological data such as rainfall (Karimi & Bastiaanssen 2015).

Finally, as the indicator also depends on the economic value of the output, and hence on fluctuations in prices, the monetary value component cannot be estimated from EO.

Key messages for countries on EO contribution to the computation method:

- These indicators are based on quantifying water consumption across different sectors - domestic, industrial, services and agriculture and comparing it to a baseline or background water storage in order to ascertain water use efficiency

- There are both experimental and robust applications of EO in the computational methodologies. For example the estimation of ground water storage from microwave remote sensing is in its infancy compared to surface water extent and depth mapping based on optical sensors and scanning radiometry

- EO technologies to quantify water use efficiency of vegetation, both natural and agricultural, by assessing the vegetation productivity – NPP, biomass production – versus the water consumption – actual evapotranspiration- have matured in the scientific community and found their way to commercial and open applications.

- Therefore it is easier to quantify water use over time for certain sectors, e.g. agriculture, than others, e.g. domestic use and for evaluating surface parts of the freshwater budget, e.g. reservoirs and lakes

- Methods applied to rain water use efficiency in meteorology are now employed for water use efficiency in agriculture and are based on evapotranspiration models where a range of EO parameters are used

- Spatial resolution and accuracy of retrieval will vary for certain optical and thermal properties which should be considered for national circumstances

- EO technology offer the opportunity to change not only the way but also what we measure. For example traditional methodologies only capture water extracted for irrigation, while satellite earth observation can also measure water usage by natural vegetation, forest plantations, and rainfed agriculture.

- The use of EO for calculation of the indicators in the agricultural sector has a number of advantages compared to the currently available dataset (Graveland et al., 2016):

    - Agricultural water use derived from remote sensing, which is actual ET, can be made for each country relatively easily;
    - A number of AET data sources are already publicly available;
    - Historical archives make it possible to assess the trend in water use efficiency, even when no prior information has been collected;

- The methodology can be consistently implemented in each country, making cross-country comparison for AET possible; and
- It has a high level of spatial and temporal resolution, which will enable more targeted policies to improve agricultural water use efficiency.

Data sources

Data category	Data sources	Website
Global/regional datasets	ESA CCI Land Cover	*https://climate.esa.int/en/projects/land-cover*
	Global Map of Irrigation Areas (GMIA) of FAO	*http://www.fao.org/nr/water/aquastat/irrigationmap/index10.stm*
	Global Irrigated Area Map (GIAM) of IWMI	*http://waterdata.iwmi.org/Applications/GIAM2000*
	The FAO portal to monitor Water Productivity through Open access of Remotely sensed derived data (WaPOR)	*https://wapor.apps.fao.org*
	Dry matter productivity (yield) and water bodies map from Copernicus Land Services	*https://land.copernicus.eu/global*
Operational or commercial services	IrriSAT	*https://irrisat-cloud.appspot.com*
	FruitLook (for South Africa)	*https://www.fruitlook.co.za*

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EO for improving water-use efficiency in the agricultural sector in South Africa for indicator 6.4.1

FruitLook – supporting farmers to increase water use efficiency

Like in many other countries, South Africa is facing a growing demand for water while at the same time water availability is under threat from climate change. Recently South Africa experienced one of the worst droughts in centuries with a strong impact on urban and agricultural communities. In Western Cape Province, the fruit and wine industry represents almost a third of the province's exports but is also a large consumer of irrigation water. Optimizing production while minimizing the ecological impact of the sector will have both economic and environmental benefits and calls for innovative solutions.

FruitLook (http://www.FruitLook.co.za) is an online platform for fruit and grape farmers powered by satellite Earth Observation data, developed by the Dutch company eLEAF and supported by the Department of Agriculture: Western Cape. It provides farmers with weekly updates on their crop's water and growth status. FruitLook has been available since 2010 and services an area of 9 million ha, including 200,000 ha of fruit crops.

FruitLook helps farmers to make better management decisions which are reflected in more efficient and productive water usage (Figure 8). Farmers use FruitLook to monitor crop development, detect and locate growth problems, evaluate and improve water management, and generally optimize use of resources. And with success: the water use efficiency of FruitLook users has already increased by between 10% and 30%.

Earth Observation technologies help farmers to address the challenge of producing more with less input, in response to a growing population, climate change, increased competition for water, and rising input costs. The PiMapping® technology behind the FruitLook application is applicable on any land surface, and the concept can be expanded to other countries and crops to assist farmers all over the world in attaining more sustainable, efficient and resilient water resource management.

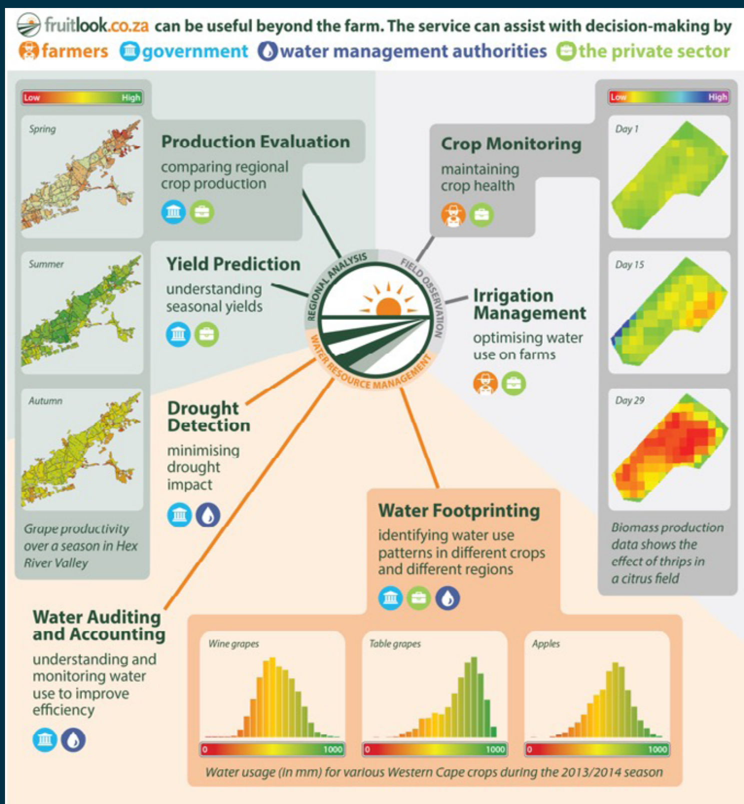

Figure 8: Fruitlook helps farmers to achieve water use efficiency in the agricultural sector using EO technology

Open access water productivity data for Africa and the Near East for indicator 6.4.1

Achieving food security in the future while using water resources in a sustainable manner will be a major challenge in the face of climate change. Agriculture is a key water user and is one of the key sectors for computing indicator 6.4.1. In order to monitor the performance of water use in agriculture, FAO developed a publicly accessible near real time database using EO data.

The FAO portal to monitor Water Productivity through open access of remotely sensed derived data (WaPOR) can be used to report on agricultural water productivity over Africa and the Near East from 2009 to present. It provides open access (through its portal and dedicated Application Programming Interfaces) to various spatial data layers related to land and water use. It allows for direct data queries, time series analyses, area statistics and data download of key variables to estimate land and water productivity gaps in irrigated and rainfed agriculture, monitor trends of water use in irrigated areas and assess the influence of droughts on agricultural production.

Land productivity is assessed in terms of production (biomass production or yield) in kg/ha while water used for agricultural production is expressed in actual evapotranspiration. When combined these datasets result in the water productivity: production per volume of water in kg/m3. Data is available at three different spatial resolutions (Figure 9) and generated by the FRAME consortium members, eLEAF and VITO, with financial support from the Dutch Ministry of Foreign Affairs.

WaPOR can help countries to improve the understanding of trends in water productivity and contributing factors, provides evidence on risks and their impact, advocates management with water accounting, defines strategies and prioritization, and plans interventions more effectively. Moreover, WaPOR is a powerful instrument to help in the computation of indicator 6.4.1 and more broadly to achieve and measure progress towards SDG6.

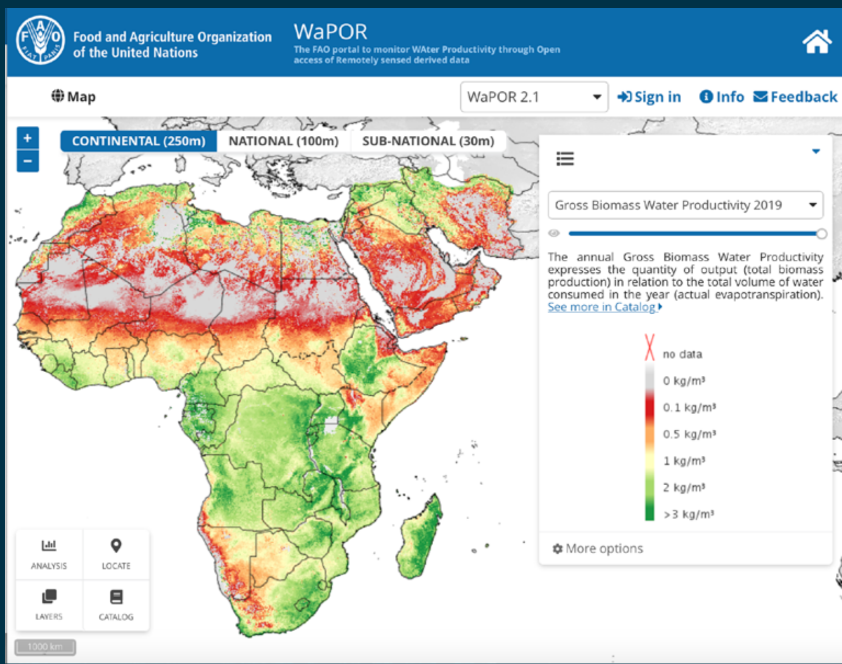

Figure 9: Water Productivity through open access of remotely sensed derived data (WaPOR) is a new tool developed by the FAO to report on agricultural water productivity over Africa and the Near East from 2009 to present

Indicator 6.4.2

Computation method

Indicator 6.4.2 is computed as the total freshwater withdrawn (TWW) divided by the difference between the total renewable freshwater resources (TRWR) and the environmental water requirements (Env.), multiplied by 100. To compute this indicator by sector (as is required), data for each of the relevant sectors (agriculture, municipalities and industry) are needed. Like 6.4.1, there is currently no mention of EO in the indicator guidelines.

However, EO data can be used to quantify both the TWW and TRWR components of the indicator. For TWW, most water withdrawals are for agricultural irrigation. The amount of water used by irrigation can be estimated/modelled as incremental evapotranspiration, using EO data on actual evapotranspiration (see computational method for 6.4.1) in irrigated agriculture as compared to the surrounding rainfed land, and rainfall.

It is important to realise EO data provides a new way to measure water use, which goes beyond the traditional ways of measuring water withdrawals by sectors. Through actual evapotranspiration modelling it is now possible to determine water usage by not only irrigated agriculture, but also by rainfed agriculture, forest, and natural vegetation.
Secondly the TRWR is expressed as the sum of internal and external renewable water resources. Internal renewable water resources are defined as the long-term average annual flow of rivers and recharge of groundwater for a given country generated from endogenous precipitation. Precipitation is another parameter that can largely benefit from improved EO-based techniques. External renewable water resources refer to the flows of water entering the country. Groundwater has been inferred from EO through gravimetric measurements, however this is not yet a robust approach (Chen et al., 2016) and also limited in terms of detail. Arguably, reservoirs are a component of the internal renewable water resource. Water reservoirs and their evolution over time can be mapped from EO, providing data on water surface area, water surface height and volume. The available time period and update frequency depends on the satellite sensors used, but using only Landsat data one can have monthly updates at a global scale for reservoirs larger than one hectare. Optical sensors such as Landsat and SPOT can easily identify reservoirs of size down to one hectare. In cloudy areas SAR observations can fill the gaps or provide the complete reservoir map with comparable levels of accuracy to optical data, except when wind and other weather conditions distort the water surface (Huilin, 2015).

In summary, EO can contribute to quantifying the TWW and TRWR components of the indicator – in the former case only for the agricultural sector (Ferrant et al., 2017), and in the latter case only for reservoirs and other open water bodies. Moreover, EO can be very useful for the spatial disaggregation of the indicator at sub-national/basin level
Another way of estimating the level of water stress is looking at the transpiration deficit, which is based on the ratio of actual water consumption and the potential water consumption.

Treatment of missing values

For indicator 6.4.2, An EO-based approach will contain missing values due to cloud as the approaches proposed are based on optical or thermal data. Gaps in observed Evapotranspiration (ET) are usually interpolated using meteorological data. Also work is being done on all-weather ET estimation using microwave temperature (Holmes et al., 2018).

Key messages for countries on EO contribution to the computation method:

- These indicators (6.4.1 and 6.4.2) are based on quantifying water consumption across different sectors - domestic, industrial, services and agriculture and comparing it to a baseline or withdrawal (water stress)

- There are both experimental and robust applications of EO in the computational methodologies. For example the estimation of ground water storage from microwave remote sensing is in its infancy compared to surface water extent and depth mapping based on optical sensors and scanning radiometry

- EO technologies to quantify water use efficiency of vegetation, both natural and agricultural, by assessing the vegetation productivity – NPP, biomass production – versus the water consumption – actual evapotranspiration - have matured in the scientific community and found their way to commercial and open applications.

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- Methods applied to rain water use efficiency in meteorology are now employed for water use efficiency in agriculture and are based on evapotranspiration models where a range of EO parameters are used

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- It has a high level of spatial and temporal resolution, which will enable more targeted policies to improve agricultural water use efficiency.

Data sources

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	Global Irrigated Area Map (GIAM) of IWMI	*http://waterdata.iwmi.org/Applications/GIAM2000*
	The FAO portal to monitor Water Productivity through Open access of Remotely sensed derived data (WaPOR)	*https://wapor.apps.fao.org*
	Dry matter productivity (yield) and water bodies map from Copernicus Land Services	*https://land.copernicus.eu/global*
Operational or commercial services	IrriSAT	*https://irrisat-cloud.appspot.com*
	FruitLook (for South Africa)	*https://www.fruitlook.co.za*

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Indicators

6 CLEAN WATER AND SANITATION

		6.4.1 Change in water-use efficiency over time	6.4.1 Level of water stress: freshwater withdrawal as a proportion of available freshwater resources
Custodian agency		FAO	
Tier		I	I
Status of step-by-step methodology document on the metadata repository		Published	Published
Relevance of EO for the indicator criteria	Maturity of EO technologies		
	Status of EO in indicator guidelines		
	Technical capacity required		
	Availability of global EO data		
Robustness of proposed methodology Criteria	Compliance with Reporting calendar		
	Sensitivity to change		
	Is it scalable (spatial)?		
	Is there a substitute for gaps in the EO record?		
Overall EO relevance			
Comments to support criteria		EO can support estimations of water use efficiency in agriculture in terms of yield gained per unit of water added.	EO-based mapping of terrestrial ecosystems that can monitor freshwater resources, e.g. wetland extent. Most of water withdrawals are for agricultural irrigation, whose extent can be estimated based on EO data.

Target 6.6

By 2020, protect and restore water-related ecosystems, including mountains, forests, wetlands, rivers, aquifers and lakes

How can EO be used to help countries achieve the target?

For the purposes of this target, water-related ecosystems are grouped into five categories: 1) vegetated wetlands, 2) rivers and estuaries, 3) lakes, 4) aquifers, and 5) artificial waterbodies. Water-related ecosystems contain and maintain the global stock of freshwater, from which water related services flow to society. They are characterised by high biodiversity and because they are carbon-rich, are important for climate change mitigation. In terms of services they provide micro climate regulation, e.g. minimising the negative impacts of urban heat islands. They capture and store water and maintain water quality since they can decompose and/or absorb water pollutants. In addition they are important for fisheries and provision of construction materials. Therefore this target promotes the sustainable management of water catchment ecosystems such as wetlands, rivers, lakes, reservoirs and groundwater, as well as water-related forests and mountains, which are crucial for provision of these services. The ecosystem based approach is important for flood regulation, public water supply and access to clean drinking water. In this respect, target 6.6 is the starting point for other water-related targets as it aims to protect water at source. As water-related ecosystems are often highly complex and very diverse, management is challenging and monitoring is expensive and time consuming. Therefore EO provides a standardised monitoring approach which can capture the multiple dimensions of change from hydrological to biophysical processes. However as this target is focused on the watershed EO at high spatial resolution, e.g. Landsat and Sentinel-1/-2 (10-30m) should be acquired. For example, high resolution land cover change can be used to track changes in water-related ecosystems, to assess the success of catchment-wide restoration efforts and the effectiveness of protection measures or to identify threats to sensitive habitat. Other EO products such as the extent of water bodies and their temporal dynamics, as well as digital terrain models, are inputs to models that assess the availability of surface and ground water.

Current Indicator(s)

6.6.1 Change in the extent of water-related ecosystems over time

Potential new indicators based on EO:

Proportion of land restored to wetland

Short methodological guidelines illustrated with EO best practice examples

Indicator 6.6.1

Computation method

The Indicator 6.6.1 is composed of 5 sub-indicators:
Sub-Indicator 1 – spatial extent dynamics of water-related ecosystems
Sub-Indicator 2 – water quality of lakes and artificial water bodies
Sub-Indicator 3 – quantity of water (discharge) in rivers and estuaries
Sub-Indicator 4 – water quality imported from SDG indicator 6.3.2
Sub-Indicator 5 – quantity of groundwater within aquifers

As this indicator is composed of sub-indicators, for global reporting on percentage change of Indicator 6.6.1, each sub-indicator must be aggregated up to form a single score for each country. Scores of each sub-indicator should also be kept.

Currently the sub-indicator 1 (spatial extent dynamics) methodology does employ EO but is based on a two-tier approach – a global approach to map the four major global datasets on the spatial extent of water related ecosystems: spatial extent of lakes, rivers, and estuaries; spatial extent of artificial waterbodies; spatial extent of vegetated wetlands.; and (in the tropics/sub-tropics) spatial extent of mangroves. The second tier consists of a national approach to validate these global layers. Once validated, the global datasets are used to calculate percentage change of spatial extent over time, using a 2001-2005 baseline period. Subsequent five year averages are compared to this baseline.

Three EO-derived products are important for calculating sub-indicator 1 - land use and land cover (LULC), open water and the effective wetland area (in order to demarcate the boundaries of infrequently flooded wetlands as well as the permanently flooded). The Global Surface Water Explorer (GSWE) is now the official product for calculating indicator 6.6.1 (Pekel et al., 2016). The GSWE documents the spatiotemporal dynamics of the world's open water from the long time series of the Landsat satellite series, spanning the 1984-2015 era. The GSWE contains unique data on water seasonality (documenting the intra-annual persistence) and water recurrence (documenting the inter-annual variability of surface water presence). However ecological definitions of wetland are complex to map from an EO point of view and usually require accurate in situ information and other ancillary data. For example, the Copernicus high resolution layer "combined Water and Wetness product" scheme contains only four classes: (1) permanent water, (2) temporary water, (3) permanent wetness and (4) temporary wetness. In addition to the physical properties of the water surface, it is necessary to map the different types of wetland ecosystems using a dedicated LULC product. The computational method suggests mapping 6 types of vegetated Wetlands –swamps, fens, peatlands, marshes, paddies, and mangroves which aligns with the Ramsar Convention on Wetlands definition of wetlands (Robelo et al., 2018).

Although useful for the above applications, optical data has serious limitations in detecting vegetated wetlands, where long wavelength-band (L-band) Synthetic Aperture Radar (SAR) has the unique capability to detect standing water (inundation extent) under a closed forest canopy, e.g. in mangroves (Bunting et al., 2018). Mapping of inundation extent and dynamics in forested wetlands by L-band SAR has been demonstrated over semi-continental scales e.g. in the Amazon and Congo river basins (Chapman et al., 2015). In order to capture the full extent of vegetated wetlands, a multi-annual time series of L-band radar (or in the case of open water, optical imagery) should be constructed then re-evaluated through a moving time window (e.g. 2015-2017, 2016-2018, 2017-2019, etc.) in order to avoid missing "dormant" wetlands which do not recur on an annual basis. In order to conduct a wetland inventory with EO, it is necessary to delineate a zone for wetland potential. Potential wetland is derived from a number of EO-derived parameters for topography, hydrology, climate and soil characteristics (e.g. soil moisture). This layer includes all open areas (without a dense vegetation cover) that are permanently or temporarily flooded and could also include ecosystems that are converted wetlands, like agricultural lands or urban zones (e.g. former wetlands that are converted by human activities). Areas with high potential wetland value could be considered as the functional area of the effective wetlands, however this still needs to be demonstrated.

For sub-Indicator 2, the EO methods are focused on chlorophyll a (Chl) and total suspended solids (TSS) within lakes and artificial water bodies globally, as these parameters are retrievable with higher confidence from EO. Historically, water quality products were derived from Envisat MERIS (no longer operational), MODIS and VIIRS data but Sentinel-3 Ocean and Land Colour Imager (OLCI) provides similar capacity for quantitative measures of chlorophyll a, suspended sediments and coloured dissolved organic matter (CDOM) (ESA, 2017). Sentinel 2 and Landsat 8 can also be used to retrieve water quality parameters at higher resolutions. However, these sensors are limited by the spectral bands available - they don't have all the spectral bands available to make an accurate retrieval. This is in comparison to MERIS, Sentinel-3 OLCI, MODIS and VIIRS, which are set at 300m spatial resolution. EO-derived water quality parameters can be used as indicators of eutrophication, physical disturbance and contamination in the water body.

For sub-Indicator 3, there are two EO based approaches to streamflow measurement by EO – direct estimation and modelling (Tan et al., 2014). Estimation consists of mapping inundation directly by classification of satellite imagery and/or water level estimation by satellite altimetry. A study combining both satellite altimetry and MODIS imagery was able to estimate river discharges at the basin scale for rivers greater than 800m wide (Sichangi et al., 2016). Streamflow modelling involves a range of EO data including snow cover and evapotranspiration estimates to understand the potential capacity of stream flow given a range of terrain and meteorological parameters. River discharge can also be modelled with a hydrodynamic model calibrated with all available in-situ observations and water-surface elevation observations from radar altimetry. Then the calibrated model can be used to predict discharge, as has been done for the Ogooué River in Africa using multi-mission EO data (Kittel et al., 2018). Although the sub-Indicator 3 methodology proposes in-situ measurements by gauging stations or discharge meters, the EO-based approaches described above, based on direct observations and modelling, have potential for areas were no in situ data exists.

As water is such a complex medium to observe from space, the choice of satellite imagery is key to the success of EO in measuring the sub-indicators. Therefore the complementarity of SAR and optical measurements should be considered as both have advantageous properties for water detection. In the optical domain Landsat and Sentinel-2 provide adequate spectral range and resolution to characterise surface water and its dynamics (especially Sentinel -2 with a more regular revisit time than Landsat 8). Sentinel-1 is also relevant to detect surface water dynamics. It provides high temporal resolution (six days for Sentinel-1A and -1B at the Equator), high spatial resolution, cloud-penetrating qualities, illumination independence and wide swath allowing for a much-needed operational change detection system (Muro et al., 2016). Other comparable radar datasets are the (L-band) Synthetic Aperture Radar (SAR) satellite series operated by JAXA: JERS-1 SAR (1992-1998), ALOS PALSAR (2006-2011) and ALOS-2 PALSAR-2 (2014-present) which are provided by JAXA as annual 25m global mosaics. The sensitivity of the long wavelength L-band to vegetation structure is especially useful in detecting densely vegetated wetlands as show in boreal zones (Whitcomb et al., 2009) and for mapping of inundation extent and dynamics in tropical wetlands (Rosenqvist and Birkett, 2002; Hess et al., 2003). All these data are cost-free. For water quality, the main source of data is the OLCI on board the Sentinel-3 satellite and Terra/Aqua MODIS, and the Visible Infrared Imaging Radiometer Suite (VIIRS) weather monitoring system. For freely available global satellite precipitation data sets, see table 1 in Tan et al. (2014). Finally, radar altimetry has the potential to determine changes (through the measurements of water levels) in water volumes both in lakes and rivers.

Treatment of missing values

Gaps in EO time series can be filled by alternative climatic proxies such as inundation regime recorded by flood gauges or precipitation levels from meteorological stations. However point measurements are sparse and might represent local precipitation events. Gap filling should always be used with caution and – should be based on evidential reasoning approaches.

Sources of discrepancies

Discrepancies could be introduced for all sub-indicators where EO data are merged over multi-annual baselines, e.g. where there are five year baseline reference periods. Within this period it is feasible that a country would merge satellite imagery with different spatial and temporal characteristics, especially in order to fill gaps due to cloud and other areas without adequate EO coverage. It should also be noted that satellite coverage and technology has evolved over time. We therefore cannot be as accurate for the baseline 2001-2005, as we will be for 2016-2020.

Limitations

For sub-indicator 1, the application of EO to mapping wetland extent in areas of dense vegetation cover is limited. This is because optical sensors and short wavelength (C-band, X-band) radar sensors are constrained to measuring the top of the vegetation canopy. Long wavelength radar sensors (L-band) can penetrate the canopy to the water surface in most conditions, although data availability can be a limitation outside the tropics/sub-tropics where most L-band SAR time-series data have been collected to date. This poses challenge because of the reporting frequency of the indicator on a 5 year basis without any overlap.

In addition, SAR alone would not allow to accurately map open water, e.g. the occurrence of the water. Even if all the observations are considered valid, for water it's not necessarily the case. For example, the presence of surface waves on a lake can strongly increase radar backscattering – expressed as a distortion of the imagery. This would be a significant source of omission error and therefore a source of underestimation of the water occurrence. The 2001–2015 dataset GSWE dataset includes freshwater and saltwater rivers, lakes and estuaries greater than 30 m2, however this will be reduced to at least 20 m2 for Sentinel-1 and Sentinel-2 (possibly even 10 m2, at the native resolution of Sentinel-2's visible and near infrared bands). Yet, the vast majority of rivers, however, are not captured as they are too narrow to detect or are blocked by the vegetation canopy.

For sub-indicator 2, the main limitation is that the global EO-based approach for water quality proposed is limited to parameters measurable by satellite remote sensing. These parameters are therefore biophysical in nature, properties that alter the water colour. However there are many water quality factors such as heavy metals and pathogens that have no impact on water colour and are not measurable from EO. In order to overcome this limitation, the more comprehensive water quality indicator (6.3.2), that must adhere to standards, is imported as sub-Indicator 4.

For sub-indicator 3, precipitation products, for example from the Tropical Rainfall Measuring Mission radar data, comprise high spatial variability problems that lead to uncertainties in model estimates (Strauch et al., 2012). TRMM Is also limited with respect to the spatial coverage. However, there is a multitude of other satellite based precipitation datasets available, e.g. GPCP, CMAP, etc.

Key messages for countries on EO contribution to the computation method:

- Indicator 6.6.1 has 5 sub-indicators but the first two are the most appropriate for an EO-based methodology (with the exception of sub-indicator 4 on water quality imported from indicator 6.3.2)

- Sub-indicator 1 requires extent of water related ecosystems information in 3 categories: open and natural surface waters, artificial water bodies and vegetated wetlands (this is further divided into different vegetated wetland types)

- Optical EO can distinguish open surface water with higher accuracy than vegetated wetland but is challenged to separate artificial (e.g. reservoir) from natural water bodies (e.g. glacial lake). In order to separate these categories, the methodology would need ancillary data, e.g. on water infrastructure or land use

- Vegetated wetlands present complicated surfaces for EO sensors as the water underneath the canopy is not possible to detect by optical methods especially where water is seasonal and is only sometimes present. SAR presents a more useful tool, especially L-band SAR, which can in most cases penetrate vegetation canopies to the water surface underneath, e.g. in forested wetlands. An optimised wetland mapping strategy should consider both optical and radar sources of EO imagery.

- For sub-indicator 2, EO-based methods are mature for total suspended solids and chlorophyll concentrations, which can be used to report on some aspects of water quality of lakes and artificial water bodies but it's not a complete assessment of water quality. Sentinel 2 and Landsat 8 will be particularly applicable, as these have a higher spatial resolution, but with a lower accuracy in water quality retrieval.

- For sub-indicator 2, all ocean colour scanner like MODIS, VIIRS, MERIS have the potential to measure water quality of inland water bodies with variable results. However, the OLCI is designed for water quality monitoring in both inland and ocean settings. The main limitation for OLCI, as with pervious sensors such as MERIS, is the spatial resolution (300m). Issues associated with strong haze over large water bodies and sun glint have also been reported (ESA, 2019).

Data sources

Data category	Data sources	*Website*
Source satellite data	Landsat	*https://earthexplorer.usgs.gov*
	Sentinel data (1,2 and 3) from the Copernicus Open Access Hub	*https://scihub.copernicus.eu*
	L-Band SAR satellite series operated by JAXA: JERS-1 SAR (1992-1998), ALOS PALSAR (2006-2011) and ALOS-2 PALSAR-2 (2014-present)	*https://www.eorc.jaxa.jp/ALOS/en/palsar_fnf/fnf_index.htm*
	Terra/Aqua MODIS	*https://search.earthdata.nasa.gov*
	Visible Infrared Imaging Radiometer Suite (VIIRS) weather monitoring system	*https://earthdata.nasa.gov/earth-observation-data/near-real-time/download-nrt-data/viirs-nrt*
Global/regional datasets	The Global Surface Water Explorer	*https://global-surface-water.appspot.com*
	FLO1K, a consistent streamflow dataset at a resolution of 30 arc seconds (~1 km) and global coverage	*https://www.nature.com/articles/sdata201852*
	CMAP (CPC Merged Analysis of Precipitation) refers to a collection of precipitation data sets, though the 2.5° x 2.5° global monthly version is probably the most widely used.	*https://climatedataguide.ucar.edu/climate-data/cmap-cpc-merged-analysis-precipitation*
	GCP (Global Precipitation Climatology Project)	*https://precip.gsfc.nasa.gov*
	GMW (Global Mangrove Watch), consistent dataset of mangrove extent from 2010 (and from Feb 2019, also from 1996, 2007-2009, 2015-2017)	*https://www.globalmangrovewatch.org*
Software, tools and platforms	The Satellite-based Wetlands Observation Service (SWOS), developed by a Horizon 2020 consortium led by Jena Optronik, Germany which has tools and workflows for the following wetland products: · LULC, long/short term changes · Surface Water Dynamics · Wetland inventory and delineation · Water Quality · Land Surface Temperature	*http://portal.swos-service.eu*
	GlobWetland Africa – a joint product of the Ramsar Convention and ESA - provides a toolbox rather than a dataset, although maps are produced for selected pilot sites in Africa. It provides workflows for wetland inventory, wetland habitat mapping, inundation regimes, Water quality, hydrological modelling and mangroves	*http://globwetland-africa.org*

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Global Mangrove Watch – an example of EO for SDG 6.6.1

A time-series of maps of the global mangrove extent has been generated within the framework of the Global Mangrove Watch (GMW) project (Bunting et al. 2018), based on 25 meter resolution global satellite mosaic data from the Japanese radar satellites (JERS-1, ALOS and ALOS-2), combined with optical (Landsat) satellite data. As of November 2018, maps for seven annual epochs have been produced: 1996, 2007, 2008, 2009, 2010, 2015 and 2016 (and with 2017 foreseen to be completed in late 2018). By comparing maps from different years in the time-series, the corresponding change maps can be derived. In addition to reporting on SDG 6.6.1 (sub-indicator 1), mangrove extent maps can be used for reporting on the Nationally Determined Contributions under the Paris Agreement and the UN Reducing Emissions from Deforestation and forest Degradation scheme (REDD+) under the UN Framework Convention on Climate Change (UNFCCC).

The Global Mangrove Watch maps provide an effective means for periodic mapping and monitoring over national to regional and global scales, in a uniform manner as the same type of data and classification algorithms are used over all areas and over several temporal epochs. Using these data enable a more consistent comparison of extent between different countries and regions as well as analysis of changes over time from a defined baseline, in comparison to the use of data obtained from different sources. It should, however, not be expected that global datasets can achieve the same high level of accuracy everywhere as a local scale map derived through ground surveys; global mapping exercise using consistent data and methods which typically necessitates a trade-off in terms of accuracy at the local scale. Yet, for countries with incomplete or out-dated geospatial information about their mangrove resources, the GMW maps can provide important first baseline maps, and support field survey planning by indicating areas of potential past or recent changes.

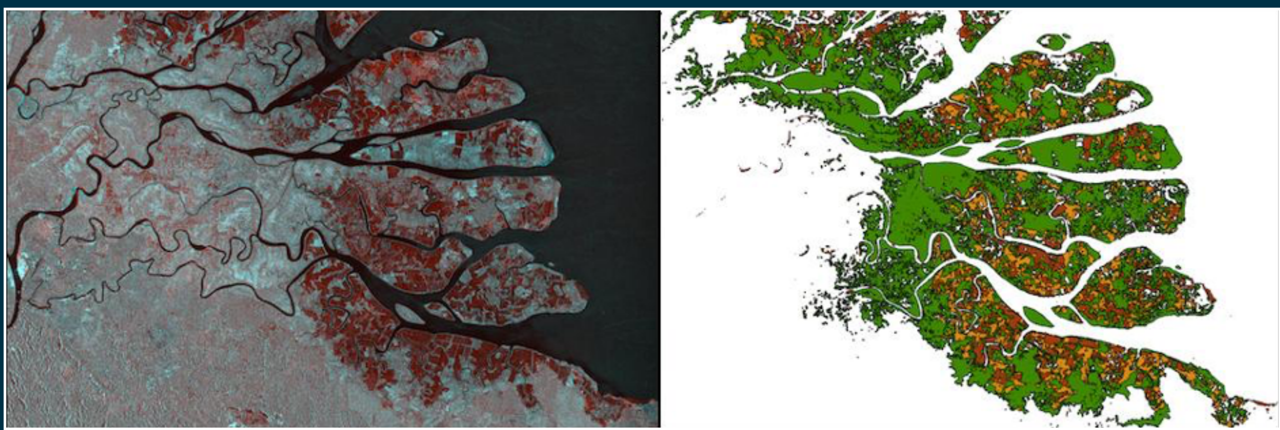

Figure 10: An example of GMW data for the Kahan River Delta, North Kalimantan, Indonesia. [Left] Multi-temporal radar image composite (1996 JERS-1 SAR and 2016 ALOS-2 PALSAR-2); [Right] Global Mangrove Watch extent and change map; Red – mangrove loss 1996-2007; Orange – loss 2007-2016; Green – mangrove cover in 2016. (Satellite image copyright JAXA/METI).

EO-based Wetland Inventory of Uganda supporting the monitoring of SDG indicator 6.6.1

A consistent mapping and monitoring of global wetland ecosystems is essential for tracking wetland changes and trends in support of the Sustainable Development Goals indicator 6.6.1, on the extent of water-related ecosystems. Although EO data are ideal for large-scale inventorying of wetlands, the tremendous diversity of wetland ecosystems makes remote detection particular challenging and no global dataset on the distribution of wetlands is yet available. Thus, within the framework of several projects (Copernicus Pan-European 2015 High-Resolution Layer on Water and Wetness, ESA project GlobWetland Africa, ESA EO4SD Water Resource Management), a methodology has been developed to detect and monitor wetlands in a highly automated manner to support the sustainable management of wetland ecosystems. This approach has also been applied to Uganda, for which the Global Partnership for Sustainable Development Data (GPSDD) funded a project to compile an EO-based wetland inventory and to develop a monitoring and reporting platform for SDG indicator 6.6.1.

One of the major challenges when mapping wetlands by EO-based techniques is due to their diversity and high temporal variability compared to other land cover types. To properly address these challenges, a multi-temporal and multi-sensor approaches is most valuable and provides the best-possible information. Therefore, a hybrid sensor approach making use of both radar and optical imagery has been developed which leads to a more robust wetland delineation compared to traditional (either optical or radar) approaches with optical imagery being more sensitive to the vegetation cover and radar imagery to soil moisture content. The methodology does not detect wetlands in the ecological sense, but rather identifies the physical properties of water and wet soils. The main output is the Water and Wetness (wet soil) Presence Index which can be translated into categorical classes showing areas which are permanently or seasonally flooded as well as areas permanently or seasonally water-logged vegetated/bare areas in Uganda (cf. Figure 11).

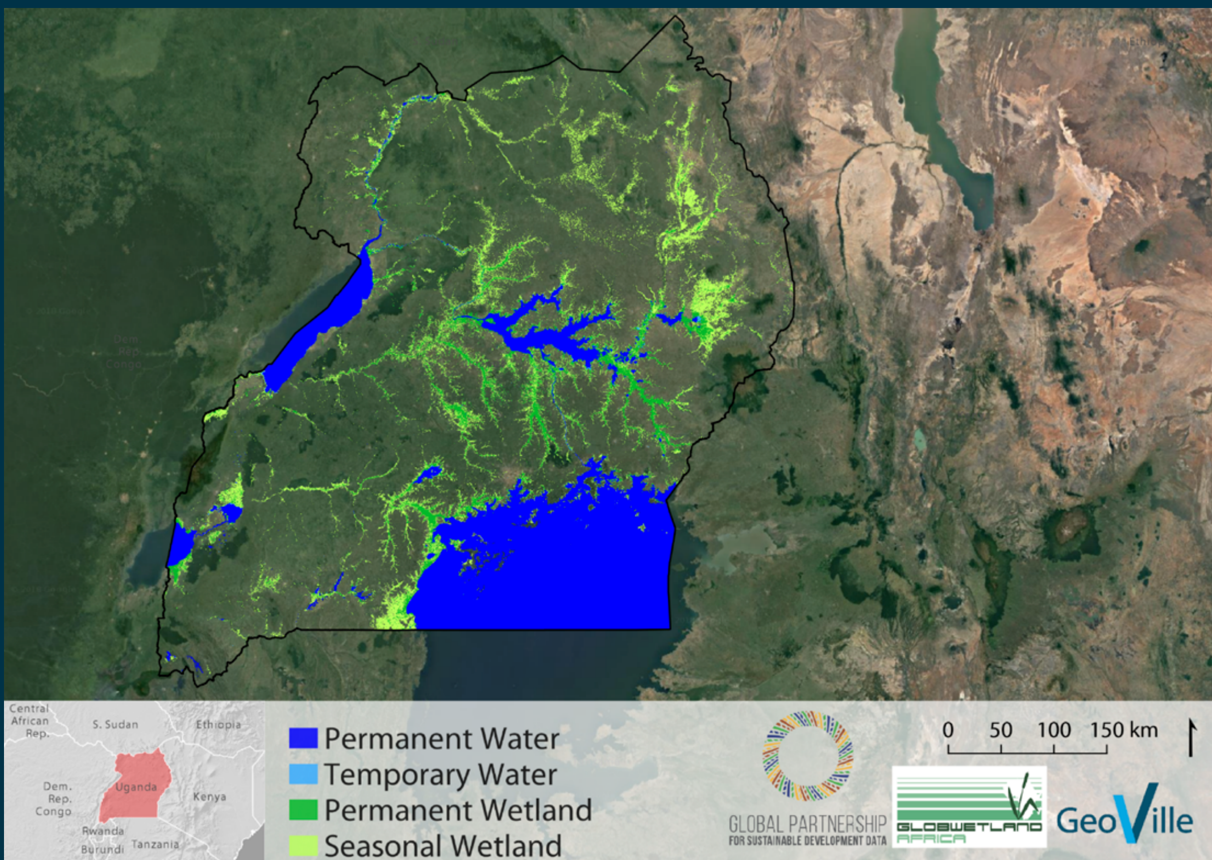

Figure 11: Wetland inventory of Uganda based on Sentinel-1 radar and Sentinel-2 optical imagery using data from the years 2016 and 2017 in support of SDG Indicator 6.6.1 on the extent of water-related ecosystems.

Indicators		6.6.1 Change in the extent of water-related ecosystems over time	Sub-Indicator 1: spatial extent dynamics	Sub-Indicator 2: water quality (lakes/ artificial water bodies)	Sub-Indicator 3: water quantity	Sub-Indicator 4: water quality imported from SDG indicator 6.3.2	Sub-Indicator 5: groundwater quantity in aquifers
Custodian agency		UN Environment; Secretariat of the Ramsar Convention on Wetlands					
Tier		I	n/a	n/a	n/a	n/a	n/a
Status of step-by-step methodology document on the metadata repository		Two methodologies published by co-custodians					
Relevance of EO for the indicator criteria	Maturity of EO technologies						
	Status of EO in indicator guidelines						
	Technical capacity required						
	Availability of global EO data						
Robustness of proposed methodology Criteria	Compliance with Reporting calendar						
	Sensitivity to change						
	Is it scalable (spatial)?						
	Is there a substitute for gaps in the EO record?						
Overall EO relevance							
Comments to support criteria			A variety of EO methods are available to map water bodies and surrounding land covers. However there are no EO established methods for vegetated wetland areas.	A variety of EO methods are available to monitor water quality at different spatial resolutions and with different accuracies.	A challenge for EO to estimate discharge, but methods using hydrological models have been successful in a limited number of studies	EO data can be used to find hotspots (e.g. eutrophic lakes) where these WQ parameters should be field sampled.	Currently not robust enough to consider EO as a tool

GOAL 7

7 AFFORDABLE AND CLEAN ENERGY

Target 7.1

By 2030, ensure universal access to affordable, reliable and modern energy services

How can EO be used to help countries achieve the target?

Approximately 1 billion people still have no access to electricity, 50% of which live in sub-Saharan Africa. Access to energy is essential for achieving many sustainable development goals, from poverty reduction, improved health care, gender equity, and education to combating climate change. Energy accounts for around 60% of total global greenhouse gas emissions and while energy sources are transitioning from coal, to natural gas, to renewables, global energy use is still primarily based on fossil fuels. In this context, Target 7.1 can be achieved and monitored with the integration of EO data. Applicable on a larger scale, remote sensing data is able to give information that by field surveys alone would be more time consuming and often difficult to gain because of the accessibility of many locations. The regular collection of EO ensures the long-term availability of data to monitor the status of remote and rural settlements. A useful data source is nigh-time luminosity data, which can collect daily variations at sufficiently low light levels to detect artificial lights at night across remote and rural areas. Night time lights products have been used for a vast range of purposes for more than 50 years, including to map the distribution of economic activity, poverty levels and to generate CO2 emission maps. In particular, the NASA's Black Marble product suite can be used to monitor in near-real time areas not reached by centralized electricity services, and then inform the development of investment and implementation plans for electrical infrastructures aiming to protect and/or increase energy access by the highest number of people in a country.

EO-based technologies for monitoring access to different types of energy resources varies depending on the details of the information needed. For instance, the type of energy source (e.g. solar panels, diesel power generators, nationwide electrical networks) can only be acquired using high resolution EO data in combination with sophisticated statistical techniques, but various use cases (e.g., from Zambia to Pakistan) show the high potential that EO have to monitor several aspects of this target.

Current indicators:

7.1.1 Proportion of population with access to electricity

7.1.2 Proportion of population with primary reliance on clean fuels and technology

Short methodological guidelines illustrated with EO best practice examples

Indicator 7.1.1

Computation method

Data for access to electricity are collected entirely from household surveys, such as Demographic and Health Surveys (DHS), Living Standards Measurement Surveys (LSMS), Multi-Indicator Cluster Surveys (MICS), the World Health Survey (WHS), and other nationally developed and implemented surveys, including those by various government agencies (for example, ministries of energy and utilities).

Household surveys even if more precise and capable to provide a more comprehensive set of information, have the disadvantages of being more expensive, time-consuming and often unable to gain data from remote locations, not easily accessible. This results in an uncomplete view of the energy access of a country. EO using solar irradiance, meteorological, urban build up, and night time lights can enable systematic monitoring of electricity access, complementing nationwide household surveys. Global and freely available data also at high spatial resolution and at a wide radiometric detection range, can be utilised to report the proportion of population with access to electricity.

Night luminosity data are particularly helpful to detect artificial lights at night across remote and rural areas. The NASA's Black Marble product suite, available at 500 m resolution since January 2012 (Román et al., 2018) and produced with data captured by the Suomi –NPP and NOAA-20 VIIRS Day/Night Band sensors, allows to disaggregate at sufficient spatial and temporal granularity the daily patterns in night time lights, to monitor abrupt, seasonal, and gradual changes associated with electrification and other human activities, such as conflict, rapid electrification, and cultural holidays. In particular, recent studies have combined Black Marble nighttime lights with EO-derived human settlement data to estimate access to electricity at very spatial (Zheng et al., 2018) and high temporal resolution.

Disaggregation

Using nighttime lights, spatial disaggregation is now possible at the neighbourhood level. The use of additional spectral channels, machine learning algorithms, and high resolution satellite imagery would further augment disaggregation down to the parcel level.

Treatment of missing values

Missing values can be obtained using household surveys or through interpolation using known data.

Limitations

The energy access to villages located inside forests are more difficult to detect using night lights imagery. In this case a different approach, such as household surveys, might be more appropriate. The use of high resolution EO and more advanced techniques based on SAR data can be used when possible (Esch et al., 2013, 2017). The difficulty in discriminating the use of generators to produce electricity from other sources can overestimate the access to sustainable energy.

Erratic power supply in rural areas can potentially bias the final results, because of the fluctuations in the nighttime luminosity between satellite orbits. Traditionally, this problem has been overcome by using image-based composites of a high number of images from monthly and annual averages of moon- and cloud-free radiances. This has limited the use of nighttime lights maps to annual intervals, or roughly half of available acquisitions during the lunar cycle (Elvidge et al., 2017). Recent studies have uncovered additional sources of measurement error, particularly when image compositing methods are used. This includes biases resulting from aerosol contamination, seasonal vegetation cycles, and snow effects (Levin & Zhang, 2017). These findings point to an increasing need by the EO community to ensure that night time lights data sources are of sufficient quality and traceability to address Target 7.1 objectives.

Key messages for countries on EO contribution to the computation method

- There are several challenges surrounding energy access, Reisser et al. (2018) have identified the four key ones: the potential expansion of the use of fossil fuels driven by the countries' need of expanding energy access; the social and environmental impact (habitat loss, displacement of people, etc.) caused by renewables, in particular hydropower; the negative relationship between population growth and energy access, where population is exploding (e.g. Africa and India) the energy access is lower than where population is stagnant (e.g. Japan, Europe); and finally how to address the economic and livelihood needs resulting from greater demand for modern energy services.
- The regular availability and on a large spatial scale of EO data provides the opportunity to monitor access to electricity in a systematic way and inform the implementation of electrical infrastructures development plans.
- Nighttime lights imagery have been widely used to map human presence and as a proxy measure of human well-being and can be used to monitor potential presence of electrical power.
- Nighttime lights have been used to track the effectiveness of rural electrification projects in West Africa (e.g. Ivory Coast) and in disaster-afflicted communities (e.g. Puerto Rico after Hurricane Maria) where electricity restoration often relies on self-reporting from local utilities.
- Quantifying the proportion of population with access to electricity is more difficult as it requires human settlement data from which distance to the electrical grid can be calculated. However human settlement data can also be mapped from EO and global data are available (e.g. The Global Human Settlement Layer).

Data sources

Data category	Data sources	Website
Global/regional datasets	NASA's Black Marble night-time lights product suite (VNP46)	*https://earthobservatory.nasa.gov/Features/Night-Lights/page3.php*
	NOAA VIIRS Night Lights Annual Composites	*https://www.ngdc.noaa.gov/eog/viirs.html*
	POWER	*http://power.larc.nasa.gov*

Reference List

Elvidge, C. D. et al. (2017) 'VIIRS night-time lights', International Journal of Remote Sensing. Taylor & Francis, 38(21), pp. 5860–5879. doi: 10.1080/01431161.2017.1342050.

Esch, T. et al. (2013) Urban footprint processor-Fully automated processing chain generating settlement masks from global data of the TanDEM-X mission. IEEE Geosci Remote Sens Lett 10(6):1617–1621.

Esch, T. et al. (2017) Breaking new ground in mapping human settlements from space -The Global Urban Footprint. arXiv Prepr arXiv170604862.

Levin, N. and Zhang, Q. (2017) A global analysis of factors controlling VIIRS nighttime light levels from densely populated areas. Remote Sens Environ 190:366–382.

Reisser, W. J. and Reisser, C. (2018) Energy Resources: From Science to Society. Oxford University Press.

Román, M. O. et al. (2018) 'NASA's Black Marble nighttime lights product suite', Remote Sensing of Environment, 210 (November 2017), pp. 113–143. doi: 10.1016/j.rse.2018.03.017.

Zheng, Q. et al. (2018) "A new source of multi-spectral high spatial resolution night-time light imagery—JL1-3B." Remote Sensing of Environment 215: 300-312.

Further reading and resources

Best practice resources:

Eckman, R. S. and P.W. Stackhouse, Jr., (2012) CEOS Contributions to Informing Energy Management and Policy Decision Making Using Space-Based Earth Observations. Applied Energy, 90, pp. 206-210

Gelaro, R., et al. (2017) The Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2). J. Climate, 30, 5419–5454, https://doi.org/10.1175/JCLI-D-16-0758.1

Stackhouse, Jr., P.W. et al. (2011) The NASA/GEWEX Surface Radiation Budget Release 3.0: 24.5-Year Dataset. GEWEX News, 21, No. 1, February, 10-12.

Stackhouse, Jr., P. W. et al. (2012) Usage of NASA's Near Real-time Solar and Meteorological Data for Monitoring Building Energy Systems Using RETScreen International's Performance Analysis Module. Proceedings of the World Renewable Energy Forum 2012 (American Solar Energy Society), May 13-17, Denver, Colorado

Supervised object detection methodologies for the detection of solar panels:

Malof, J. M. et al. (2016) Automatic Detection of Solar Photovoltaic Arrays in High Resolution Aerial Imagery, arXiv preprint arXiv: 1607.06029v1, 183, pp. 229–240. doi:10.1016/j.apenergy.2016.08.191.

Machine learning algorithms to detect High Voltage towers that have been tested in Pakistan, Nigeria and Zambia:

Development Seed (2018) Mapping the electric grid. A report developed for World Bank. Available at: http://devseed.com/ml-grid-docs/

Expansion of reliance on clean fuels and technology by coupling EO with decision support tools

Besides monitoring, EO is a critical component toward enabling communities to adopt and increase reliance upon clean fuels and technology. This is accomplished by coupling EO with financial and engineering decision support tools that enables the planning, design and feasible of clean energy technologies. One example is the coupling between the solar and meteorological data sets produced by NASA's Prediction of Worldwide Energy Resource (POWER) and the RETScreen clean energy management software system (https://www.nrcan.gc.ca/energy/software-tools/7465).

RETScreen Expert, the advanced premium version of the software, helps to make sound decisions on clean energy. Developed by the Government of Canada, the software is used by more than 600,000 energy professionals and decision-makers globally, including energy engineers, facility managers, researchers, instructors, architects, financial planners and policy analysts. RETScreen is also used for teaching and research in over 1,000 universities and colleges around the world. The tools supports project development in 36 different languages, allowing for global partnerships to aid in the adoption of clean energy technologies. The tool also enables measurement and verification of the actual and ongoing energy performance of a wide range of buildings, factories and power generation facilities. The global applicability of the RETScreen Expert tool is enabled thanks to the ongoing partnership with the NASA POWER project that provides global climatological solar energy information coupled with surface meteorological parameters up to a few days of real-time (Eckman and Stackhouse, 2012; Stackhouse et al., 2012). The solar and meteorological parameters are derived from NASA research projects using a combination of remote sensing analysis (Stackhouse et al., 2011) and the NASA's global atmospheric data assimilation products from the Modern-era Retrospective Analysis for Research and Applications (MERRA-2; Gelaro et al., 2017). Thus, project planners and officials evaluate the feasibility of clean energy projects and their subsequent performance even in areas where surface measurements of those quantities are not readily available.

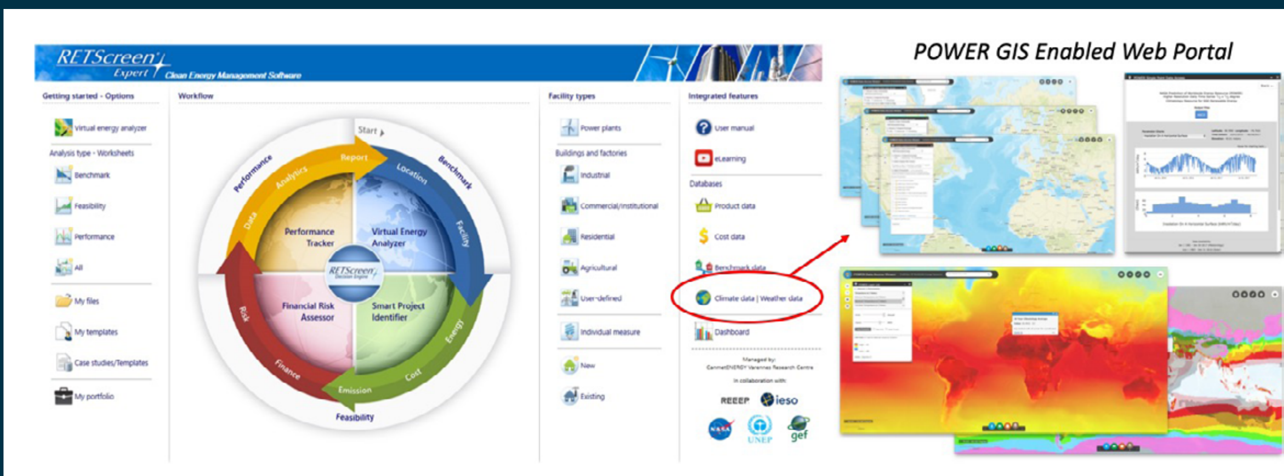

Figure 12: RETScreen Expert and NASA partnership couples Earth Observations with a decision support tool aimed at enabling clean energy projects worldwide

Indicators 7 AFFORDABLE AND CLEAN ENERGY		7.1.1 Proportion of population with access to electricity	7.1.2 Proportion of population with primary reliance on clean fuels and technology
Custodian agency		World Bank	WHO
Tier		I	I
Status of step-by-step methodology document on the metadata repository		Published	Published
Relevance of EO for the indicator criteria	Maturity of EO technologies		
	Status of EO in indicator guidelines		
	Technical capacity required		
	Availability of global EO data		
Robustness of proposed methodology Criteria	Compliance with Reporting calendar		
	Sensitivity to change		
	Is it scalable (spatial)?		
	Is there a substitute for gaps in the EO record?		
Overall EO relevance			
Comments to support criteria		Observations of night-time lights have been widely used to map human presence and availability of electricity at global and regional scales. There are fewer examples of the use of this method at national and sub-national level, but several studies show a high potential for its application to monitor this indicator.	Not supported by EO

GOAL 9

9 INDUSTRY, INNOVATION AND INFRASTRUCTURE

Target 9.1

Develop quality, reliable, sustainable and resilient infrastructure, including regional and trans-border infrastructure, to support economic development and human well-being, with a focus on affordable and equitable access for all

How can EO be used to help countries achieve the target?

Infrastructures that are sustainable, durable and disaster-resilient, provide the basic and essential structures to a country to effectively function, but also allow to generate employment and wealth and drive economic development. This target is strongly linked to other sustainable development goals, including zero hunger, no poverty, good health and well-being, as well as quality education. Rural development processes, including access to markets, education and health services, cannot succeed without a reliable access to roads year-round. EO data can inform the production of efficient and effective plans for infrastructures development and management. The global coverage of remote sensing images allows the identification of areas currently lacking infrastructures for transportation or energy access. These data coupled with information on topography, land cover, precipitation patterns, climate change scenarios, can support the development of climate resilient infrastructures. EO data has been widely used to extract infrastructures such as urban areas, roads and dams using data at different spatial resolution (e.g. rural roads can be detected just with high resolution images) and different techniques (e.g. supervised and unsupervised classification, neural networks, and mathematical morphology). Research is also currently focused on using high resolution or radar data to monitor the status of infrastructures, particularly in areas prone to natural disasters, such as flooding, but also in areas affected by conflicts. The need to plan for regional and trans-border infrastructure is also well served by EO since it is technology that crosses borders and is not limited by a single country's or region's national data collection systems. In theory, open access EO data should help countries collaborate on shared infrastructure projects.

Current indicators

9.1.1 Proportion of the rural population who live within 2 km of an all-season road

9.1.2 Passenger and freight volumes, by mode of transport

Short methodological guidelines illustrated with EO best practice examples

Indicator 9.1.1

Computation method

A final methodology to measure rural access is currently under development by the World Bank with support from the Research for Community Access Partnership (ReCAP) funded by the Department for International Development (DFID) of the United Kingdom. This new method has been anticipated to use spatial data, obtained directly from country database/website, Joint survey/compilation with national agency and international entity, satellite images, remote sensing. Georeferenced information on road conditions, will be collected through consultations with line ministries and Road Agencies.

All season roads defined as "roads motorable all year round by the prevailing means of rural transport (often a pick-up or a truck which does not have four-wheel drive), with some predictable interruption of short duration during inclement weather (e.g. heavy rainfall) allowed" (Roberts et al., 2006) can be identified from satellite images based on features such as geometry, photometry, topology, function and texture, or using a road model (Wang et al., 2016; Ahmad & Deore, 2016). Several factors affect the effective extraction of roads from EO data, such as sensor type, spectral and spatial resolution, weather, cloud cover, variation and ground characteristics.

Manual digitalisation and automatic or semi-automatic classification can be used for the extraction of roads, but often is preferable to utilise a combination of methods. Even though manually digitising an image can be time consuming in many areas with several linear features, manual editing is required for the elimination of segments that are not roads (Brandão and Souza, 2006).

The methods that have been used to extract roads from RS images are classification based methods (supervised and unsupervised), knowledge based methods, mathematical morphology methods usually combined with image segmentation techniques, active contour models and dynamic programming and grouping (Wang et al., 2016). These techniques consider different features, such as spectral information of the pixels, edge detection, length and width of the feature, texture, etc.; all of them have both advantages and disadvantages and require different technical skills. A combination of methods, including digitisation should be used, and ground truth activities should complement the analyses.

In order to produce more accurate road products, high spatial resolution satellite images, such as Spot 6/7 (Transport & ICT, 2016), should be used. Landsat images have also been successfully utilised to extract roads using bands 3 (Red) and 5 (Shortwave Infrared - SWIR), in a dense forest environment, where these bands appear with a brighter intensity, contrasting with areas of dense forest. The linear features with brighter intensity can thus be digitised (Brandão & Souza, 2006).

The resulting road map using any of the approaches above and a settlement layer, such as the Global Human Settlement Layer and the Global Urban Footprint, can be used to calculate the distance from the nearest road.

Treatment of missing values

Missing values can be treated using higher resolution images and field surveys or composites.

Sources of discrepancies

Discrepancy can be determined by misclassification of roads and omission errors, based on the methods and satellite images used.

Limitations

In areas with high could cover radar images are required. Technical capacity, expensive high resolution images and time-intensity when the detection is country-wide, are other main limitations.

Key messages for countries on EO contribution to the computation method

- EO data has been widely and successfully used to extract different types of infrastructures including roads;
- Plans for the development of climate resilient infrastructures can be generated using the location of roads and spatial data on topography, land cover, precipitation patterns, and climate change scenarios;
- Infrastructures located in areas prone to natural disasters can be efficiently monitored using EO imagery.

Data sources

Data category	Data sources	Website
Source Satellite Data	Landsat	*https://earthexplorer.usgs.gov*
	Sentinel data (1,2 and 3) from the Copernicus Open Access Hub	*https://scihub.copernicus.eu*
	Pleiades	*https://www.intelligence-airbusds.com*
	WorldView, GeoEye, QuickBird, IKONOS	*https://www.maxar.com*
Global/regional datasets	OpenStreetMap	*https://www.openstreetmap.org*

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Ahmad, N. and Deore, P. J. (2016) 'Road detection from satellite images', International Journal of Recent Trends in Engineering and Research, 2(4), pp. 299–304.

Brandão, A. O. and Souza, C. M. (2006) 'Mapping unofficial roads with Landsat images: A new tool to improve the monitoring of the Brazilian Amazon rainforest', International Journal of Remote Sensing, 27(1), pp. 177–189. doi: 10.1080/01431160500353841.

Hoppe, E., et al. (2016) 'Transportation Infrastructure Monitoring Using Satellite Remote Sensing'. In Materials and Infrastructures 1 (Eds J. Torrenti and F. La Torre). doi:10.1002/9781119318583.ch14

Transport and ICT (2016) 'Measuring Rural Access: Using New Technologies'. Washington DC: World Bank, License: Creative Commons Attribution CC BY 3.0
Wang, W., et al. (2016) 'A review of road extraction from remote sensing images'. Journal of Traffic and Transportation Engineering (English Edition). doi:10.1016/j.jtte.2016.05.005

Further reading and resources

Roberts, P., et al. (2006) 'Rural Access Index: A Key Development Indicator'. Transport Papers TP-10. The World Bank Group, Washington, DC.

Indicators		9.1.1 Proportion of the rural population who live within 2 km of an all-season road	9.1.2 Passenger and freight volumes, by mode of transport
Custodian agency		World Bank	ICAO
Tier		II	I
Status of step-by-step methodology document on the metadata repository		Unpublished (Tier III at the time of the analysis)	Published
Relevance of EO for the indicator criteria	Maturity of EO technologies		
	Status of EO in indicator guidelines		
	Technical capacity required		
	Availability of global EO data		
Robustness of proposed methodology Criteria	Compliance with Reporting calendar		
	Sensitivity to change		
	Is it scalable (spatial)?		
	Is there a substitute for gaps in the EO record?		
Overall EO relevance			
Comments to support criteria		EO imagery has been widely used to extract the location and in some cases the status of roads, using different techniques (e.g. supervised and unsupervised classification, neural networks, and mathematical morphology).	Not supported by EO

Target 9.4

By 2030, upgrade infrastructure and retrofit industries to make them sustainable, with increased resource-use efficiency and greater adoption of clean and environmentally sound technologies and industrial processes, with all countries taking action in accordance with their respective capabilities

How can EO be used to help countries achieve the target?

EO data can be used to measure pollutants that arise from industries and infrastructure. Satellite data can also be used to locate potential pollutant hotspots through analysis of global emissions, and monitoring pollution plumes. Satellites also collect weather and climate data, which can aid decision-making in relation to clean energy installations. For example, satellites can be used to forecast surface wind field data to guide operations of wind turbines, and predict their energy input into power grids. It can also be used to map photovoltaic solar electricity potential, based on solar irradiance climatology – which can be used to aid solar energy installation.

Current indicator(s)

9.4.1 CO2 emission per unit of value added

Short methodological guidelines illustrated with EO best practice examples

Indicator 9.4.1

Computation method

EO is not currently discussed in the methodological guidelines for the indicator, but there is wide availability of EO products, which would be able to complement the current methods. The indicator is based on the following equation:

$$\textit{CO}_2\ \textit{emission per unit of value added} = \frac{\textit{CO}_2\ \textit{emission from manufacturing (kg)}}{\textit{(Manufacturing value added (constant 2010 USD)}}$$

Gases Observing Satellite (GOSAT) and the orbiting Carbon Observatory-2 (OCO-2) have been used to measure atmospheric column-averaged concentrations of the key greenhouse gases CO2 and CH4. These can be used to complement the current methods, through use in flux inversions to provide estimates of natural fluxes of CO2.
In general methods for monitoring ambient pollutant levels are, however, better established than monitoring emission levels. Several strategies are being developed to use atmospheric CO2 data for estimating fossil fuel CO2 emissions (Hardwick & Graven, 2016), including targeting strong emitters such as large power plants and megacities (Velazco et al., 2011), and measuring other gases (e.g. CO and NOx) that help distinguish fossil fuel-derived CO2 from natural emissions (Reuter et al., 2014). GHGSat, a company that undertakes global emissions monitoring, has used its demonstration satellite, Claire, to detect methane emissions, to monitor targeted sites – this could be used more widely.

However currently, there is limited capacity of using EO data to measure CO2 emissions per unit of value added (the ratio between CO2 emissions from fuel combustion and the value added of associated economic activities). However, if the methodology of using satellites to measure CO2 emissions are developed further, there is potential for it to be combined with business data to create a unit of value added.

One development which will aid this is the data from Sentinel-5P, which has recently been made available – allowing O3, CO, SO2 and NO2 data to be recorded. The Sentinel-5P spacecraft uses a TROPOMI instrument uses passive remote sensing techniques to measure at the Top Of Atmosphere (TOA) the solar radiation reflected by and radiated from the earth. It is the first Copernicus satellite dedicated to monitoring the atmosphere. The TROPOMI instrument can provide highly detailed and accurate data about the atmosphere with a resolution up to 7 x 3.5km – detecting air pollution over individual cities.

A project by the University of Denmark, looks to improve the assessment of wind energy resources, through combining EO methodologies. It will use Copernicus Global and pan-European products to describe vegetation properties, in combination with digital elevation models to derive the surface drag force, to lead to more accurate wind modelling for turbine placement, which will aid emission reduction.

Limitations

The ability to distinguish manmade CO2 emissions from natural sources using EO data is currently not well established.

Key messages for countries on EO contribution to the computation method

- EO data is not currently used to monitor CO2 emission per unit of value added, but there are many products and methodologies available to do so.

Data sources

Data category	Data sources	Website
Global/regional datasets	Gases Observing Satellite (GOSAT)	*http://www.gosat.nies.go.jp/en/index.html*
	Carbon Observatory-2 (OCO-2)	*https://ocov2.jpl.nasa.gov*
	Sentinel 5-P	*https://sentinel.esa.int/web/sentinel/missions/sentinel-5p/data-products*

Reference List

Hardwick, S. & Graven, H. (2016) Satellite observations to support monitoring of greenhouse gas emissions. Grantham Institute Briefing Paper No. 16 [Online] Available at: https://www.imperial.ac.uk/media/imperial-college/grantham-institute/public/publications/briefing-papers/Satellite-observations-to-support-monitoring-of-greenhouse-gas-emissions-Grantham-BP-16.pdf [Accessed 27th June 2018]

Reuter, M., M. Buchwitz, A. Hilboll, A. Richter, O. Schneising, M. Hilker, J. Heymann, H. Bovensmann & J. P. Burrows (2014) Decreasing emissions of NOx relative to CO2 in East Asia inferred from satellite observations, Nature Geoscience, 7, 792-795.

Velazco, V. A., M. Buchwitz, H. Bovensmann, M. Reuter, O. Schneising, J. Heymann, T. Krings, K. Gerilowski & J. P. Burrows (2011) Towards space based verification of CO2 emissions from strong localized sources: fossil fuel power plant emissions as seen by a CarbonSat constellation, Atmos. Meas. Tech., 4, 2809–2822.

Indicators		9.4.1 CO2 emission per unit of value added
Custodian agency		IEA; UNIDO
Tier		I
Status of step-by-step methodology document on the metadata repository		Published
Relevance of EO for the indicator criteria	Maturity of EO technologies	
	Status of EO in indicator guidelines	
	Technical capacity required	
	Availability of global EO data	
Robustness of proposed methodology Criteria	Compliance with Reporting calendar	
	Sensitivity to change	
	Is it scalable (spatial)?	
	Is there a substitute for gaps in the EO record?	
Overall EO relevance		
Comments to support criteria		Overall amber relevance, due to high technical capacity required, but the wide availability, especially as a result of the recent release of Sentinel-5P.

GOAL 11

11 SUSTAINABLE CITIES AND COMMUNITIES

Target 11.1

By 2030, ensure access for all to adequate, safe and affordable housing and basic services and upgrade slums

How can EO be used to help countries achieve the target?

"Currently, an estimated 1.6 billion people live in inadequate housing globally, of which 1 billion live in slums and informal settlements". The rapid urban growth of recent decades has led to an increase of slums and informal settlements, as well as air pollution and inadequate basic services and infrastructure. The lack of proper urban planning and management can bring tenure insecurity, increase poverty, pollution, health risks, as well as a higher vulnerability and exposure to natural and technological hazards. To make urban spaces more inclusive, safe, resilient and sustainable the development, monitoring and management of better forms of urban plans are urgently needed. Many local governments ignore the extent of slums. "Slums disappear not through being removed, but by being transformed", and in order to carry out this transformation the extent, the physical characteristics as well as the dynamics of slums, such as their densification and expansion, need to be understood and monitored. EO can help both understanding and monitoring slums, but can also link their morphology with socio-economic data, as well as help to identify hazardous areas where many of these settlements are located. An increased number of studies in the last 15 years have been published on the use of EO to understand geography and dynamics of slums, thanks to the availability of very-high-resolution (VHR) data and the advances in the methodologies to analyse them. The use of EO can support monitoring of slums and informal settlements growth, thanks to their frequent coverage of large areas, for which it would be difficult to regularly undertake on the ground household surveys. By knowing the dynamics and the extent of slums, sustainable urban plans and slum improvement polices can be developed and monitored, including the improvement of the building structures, access to water, electricity and other basic needs. VHR images are also increasingly used by slum communities and NGOs as a basis for mapping and enumeration, who then use the data to negotiate for recognition and their right to the city and its services.

Current indicators

11.1.1 Proportion of urban population living in slums, informal settlements or inadequate housing.

Short methodological guidelines illustrated with EO best practice examples

Indicator 11.1.1

Computation method

The current computation method to report on this indicator, used two components the Slum/Informal Settlement households (SISH = 100 * [N. of people living in SISH households/city population]) and the Inadequate housing households (IHH = 100 * [N. of people living in IHH/city population]).

The data for slums and informal settlements are derived from census and national household surveys, including Demographic and Health Surveys (DHS) and Multiple Indicator Cluster Surveys (MICS). The data for the inadequate housing component can be computed through income and household surveys that capture housing expenditures.

Census and national household surveys, can compile several types of information at once, but have three main disadvantages: a long temporal gap between surveys, often 10 years; the time needed to check and analyse raw data; and the underestimation of the population living in slums/informal settlements, because of the un-transparent and often subjective set of criteria used to categorize them (Kit et al., 2013).

Two main initiatives have produced a database of built-up areas, the Global Human Settlement Layer (GHSL) (Esch et al., 2012) and the Global Urban Footprint (Pesaresi et al., 2013), but none of them have been able to fully account for slums, because of their different morphology from planned built-up areas and the resolution of the currently used images for GHSL which does not allow the distinction between slum and non-slum areas.

The use of EO data can help in standardizing the criteria used to identify slums/informal settlements by setting clear physical characteristics identifiable with remote sensing. The Generic Slum Ontology (GSO), for example, consists of a list of slum characteristics at three spatial levels: object level (building characteristics, access network), slum settlement level (density and shape) and the slum environment (location and neighbourhood characteristics) (Kohli et al., 2012; Kuffer et al., 2016). The GSO by being adapted to local conditions, can account for specific characteristics within the same city or among cities. Several techniques have been used to detect slums and informal settlements and thanks to the increased availability of high and very-high-resolution (HR & VHR) imagery, with spatial resolutions between less than 1 m to 5 m produced by sensors such as Ikonos, QuickBird, WorldView, the detailed spatial analyses, required to detect slums and informal settlements, are now feasible. In general for building objects the spatial resolution needed is 2 m, for footpaths 1–2 m, and for minor roads 5 m. If detailed building object information are required than a resolution of 0.5 m is necessary. For very dense slum areas such as those found in India, the highest resolutions are required if individual buildings are to be identified and mapped.

Three main approaches can be used to map slums and informal settlements from EO imagery:

- **Proxies**. Various proxies capable of identifying slums have been tested (Kuffer et al., 2016), also using high resolution imagery (e.g., Landsat, Sentinel 2 and 3, Terra ASTER). Vegetation cover, for example, has been proven to be negatively correlated to slum areas, sparser vegetation being associated to slum-like areas (Stoler et al., 2012). Depending on the context specific proxies can be identified.

- **Object-Based Image (OBIA or GEOBIA)**. This technique accounts for spatial, spectral and contextual characteristics of the slum surface (building characteristics and density, shape, access networks, location, etc.). It works well for the extraction of objects (e.g. roofs and roads) on settlement level. It is recommended that a combination of ontological indicators adapted to local levels, and converted into object-based parameters, such as texture, spectral range, and geometry are used to identify slums from VHR satellite images (Kohli et al., 2016).

- **Machine learning techniques (e.g. Random Forest, Neural Networks, Support Vector Machines)**. These techniques, based on the use of a large and rich set of training data, are successful in extracting slum areas at the city scale. Building up a sufficiently large and diverse training set is critical for global slum mapping with EO.

Location and extent of slum areas can be mapped quickly using any of these three approaches or a combination of them. The proportion of population living in the slum areas identified can then be calculated using municipal data like election wards. In some contexts, where multi-storey slum buildings exist (e.g. India, Egypt, Brazil, Colombia) stereo images may be useful to estimate building volume as well as density, in order to allow better estimates of population to be made.

Disaggregation

A temporal disaggregation using EO data is possible, since for normal circumstances daily images are not required, and in the case of fast growing cities, annual or bi-annual images are enough. This also allows the use of VHR images, which are characterized by a low temporal frequency. A thematic disaggregation can also be performed using income levels.
Treatment of missing values

For areas where VHR satellite images cannot be acquired due to cloud cover, radar could be used as well as airborne/UAV data. In-situ data derived from household surveys can be used for areas where data are missing. An increasing number of NGOs are doing this (e.g. Know your City programme of Slum/Shack Dwellers International)

Sources of discrepancies

The criteria to identify slums, if not objective, can generate discrepancies and the extent of slums can be underestimated. Delineating the boundary of the slums can also be challenging and thus generate discrepancies (Kohli et al., 2016). Informal/slum areas receive a multiplicity of names in many languages, dialects and slangs all over the world and their definition (UN HABITAT, 2015) includes far more than morphological and contextual aspects as for example cultural, legal, security, level of deprivation ones – some of them are not directly observable using EO techniques.

Limitations

EO data have technical challenges for characterizing slums such as mixed pixels or the obliqueness of images introducing shadowing effects, even with VHR images, in situations where slums and very tall buildings are closely packed (e.g. Mumbai, Cairo). Choosing the right specifications for image acquisition can thus be very important. Also, the cost and processing of VHR data can often be prohibitive, but slum mapping should not be a standalone application, it should be combined with other applications, so that the cost/benefit ratio improves.

In areas with persistent cloud cover the use of VHR is limited and the use of other data such as radar has to be preferred.

Open source tools and platforms

Key messages for countries on EO contribution to the computation method

- EO can be used to regularly monitor the extent and densification of slums without waiting for the implementation of census or national household surveys;

- Monitoring slums through EO, helps understanding their pattern, density, location and distribution, enabling the development of sustainable, disaster risk resilient and inclusive urban plans.

Data sources

Data category	Data sources	Website
Source satellite data	Landsat	*https://earthexplorer.usgs.gov*
	Sentinel	*https://scihub.copernicus.eu*
	Terra ASTER	*https://terra.nasa.gov/data/aster-data*
	WorldView, GeoEye, QuickBird, IKONOS	*https://www.maxar.com*
	Pleiades	*https://www.intelligence-airbusds.com*

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Further reading and resources

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Predicting informal settlement dwellers' deprivations from space: a pilot study in Dhaka for planning for target 11.1

One of the most pressing development challenges is how to respond to the unmet demand for basic infrastructure services, like adequate housing, clean water, and sanitation, for the 1 billion people living in informal settlements. One of the main difficulties when looking at approaches to support informal settlement upgrading initiatives is the lack of adequate spatial data.

With an eye towards using innovative data analytics to support the formulation of interventions and policies to upgrade informal settlements, in 2017, World Bank Group Water Global Practice launched, under the "Water Supply and Sanitation in Rapid Urbanization" umbrella, a pilot study in Dhaka (Bangladesh). A city particularly challenged due to congestions, poor infrastructures and regular flooding. The main objective was to create an analytical tool to support decision-making leading to improved pro-poor policy interventions. The project was conducted through a collaboration between the WASH Poverty Diagnostic team in Bangladesh, the remote sensing service company GISAT, a member of an EO4SD Urban consortium working for the European Space Agency (ESA), and researchers from the University of Massachusetts Boston. As part of this project, a novel, predictive model combining spatial characterization analysis, with statistical modelling to identify and delineate informal/informal settlement areas and characterize informal settlement deprivation, was devised and tested. Two sources of data were combined: VHR EO data and analytics of informal areas/ informal settlements for the whole Dhaka Metropolitan area, and an in-depth household survey conducted in 2016. Multiple variables derived from EO data were found to be statistically significantly associated with measures of deprivation. For example, distance to Central Business Districts, arterial roads, average dwelling size, percentage of informal, local primary, secondary and tertiary streets in informal settlements, were found to increase the relative risk of overall deprivation. The results from this analysis, because of their potential ability to predict future scenarios, will be able to support the development of inclusive policies and targeted planning interventions to help populations living in informal settlements.

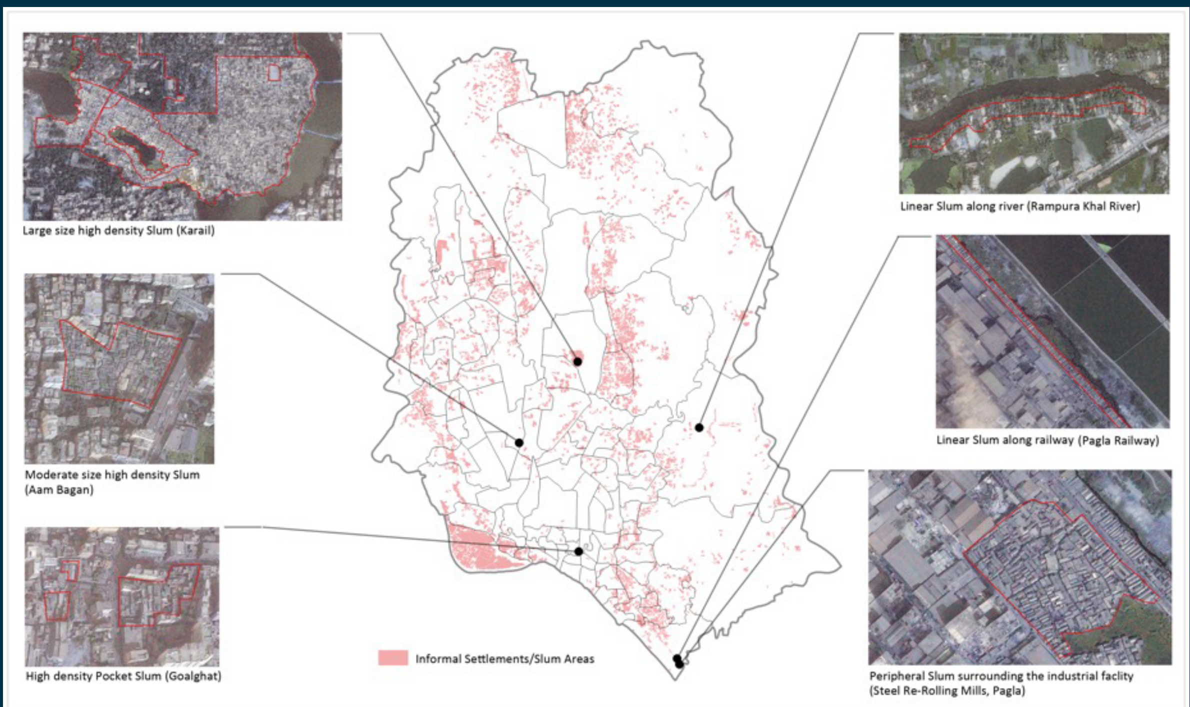

Figure 13: VHR EO data and analytics of informal areas/slums for the Dhaka Metropolitan area

Indicators		9.4.1 Proportion of urban population living in slums, informal settlements or inadequate housing.
Custodian agency		UN-Habitat
Tier		I
Status of step-by-step methodology document on the metadata repository		Published
Relevance of EO for the indicator criteria	Maturity of EO technologies	
	Status of EO in indicator guidelines	
	Technical capacity required	
	Availability of global EO data	
Robustness of proposed methodology Criteria	Compliance with Reporting calendar	
	Sensitivity to change	
	Is it scalable (spatial)?	
	Is there a substitute for gaps in the EO record?	
Overall EO relevance		
Comments to support criteria		The increased number of studies and advancement of technology allows the use of EO to map slums and informal settlements, but due to broad definition and complex structure, it still requires more research to identify their physical characteristics in order to develop more robust proxies and generalised slum models. Many studies and methods are developed and tested for specific contexts. Upscaling to global level is the next challenge.

Target 11.2

By 2030, provide access to safe, affordable, accessible and sustainable transport systems for all, improving road safety, notably by expanding public transport, with special attention to the needs of those in vulnerable situations, women, children, persons with disabilities and older persons.

How can EO be used to help countries achieve the target?

EO data can inform the production of efficient and effective plans for road infrastructures and shipping routes (although, the global coverage of remote sensing images allows the identification of areas currently lacking infrastructures for transportation. This data can be combined with census data to provide more detailed information on public transport that cannot be measured through EO (e.g. railways and subways), as well as data on vulnerable people. EO data has been widely used to extract infrastructures such as urban areas, roads and dams using data at different spatial resolution (e.g. rural roads can be detected just with high resolution images) and different techniques (e.g. supervised and unsupervised classification, neural networks, and mathematical morphology). Research is also currently focused on using high resolution or radar data to monitor the status of infrastructures, particularly in areas prone to natural disasters, such as flooding, but also in areas affected by conflicts (Roberts et al., 2006). The need to plan for regional and trans-border infrastructure is also well served by EO since it is technology that crosses borders and is not limited by a single country's or region's national data collection systems. In theory, open access EO data should help countries collaborate on shared infrastructure projects.

Current indicator:

11.2.1 Proportion of population that has convenient access to public transport, by sex, age and persons with disabilities

Short methodological guidelines illustrated with EO best practice examples

Indicator 11.2.1

Computation method

The indicator methodology currently uses earth observation in relation to urban planning, however there is scope for it to be integrated further, especially in relation to road identification.

All season roads can be identified from satellite images based on features such as geometry, photometry, topology, function and texture, or using a road model (Wang et al., 2016; Ahmad and Deore, 2016). A combination of methods, including digitisation should be used, and ground truth activities should complement the analyses.
In order to produce more accurate road products, very high spatial resolution satellite images, such as Spot 6/7 (Transport and ICT, 2016), WorldView, GeoEye or Pleiades (spatial resolution = 0.6 metre). An important ancillary dataset that can be used in conjunction with the VHR data is OpenStreetMap.

Limitations

While EO can identify access to public transport, there currently isn't any capacity to identify this specifically by sex, age and persons with disabilities.

Harmonised global/local data on urban transport systems do not exist, nor are they comparable at the global level. It is also recognised that there are various forms of public transport in the member countries that are not fully defined or captured.

Manual digitalisation and automatic or semi-automatic classification can be used for the extraction of roads, but often is preferable to utilise a combination of methods. Even though manually digitising an image can be time consuming in many areas with several linear features, manual editing is required for the elimination of segments that are not roads.

Open source tools and platforms

There are a number of global EO-based tools that are available that could assist NSOs and indicator custodians with delivering and implementing EO-based methodologies. For example, the GEO Human Planet initiative, the Global Urban Footprint/World Settlement Footprint, and the Global Human Settlement Layer. OpenStreetMap, is a useful resource, however the accuracy of this data is unknown.

Key messages for countries on EO contribution to the computation method

- EO is currently used to monitor the indicator in relation to urban planning
- EO can be further used to identify different roads and shipping routes

Data sources

Data category	Data sources	Website
Source satellite data	Landsat	*https://earthexplorer.usgs.gov/*
	Sentinel data (1,2 and 3) from the Copernicus Open Access Hub	*https://scihub.copernicus.eu/*
	Pleiades	*https://www.intelligence-airbusds.com*
	WorldView, GeoEye, QuickBird, IKONOS	*ttps://www.maxar.com*
Global/regional datasets	The Global Urban Footprint (GUF) / World Settlement Footprint	*https://urban-tep.eu*
	The Global Human Settlement Layer (GHSL)	*https://ghsl.jrc.ec.europa.eu/data.php*
Software, tools and platforms	The GEO Human Planet initiative	*https://ghsl.jrc.ec.europa.eu/HPI.php*
	OpenStreetMap	*https://www.openstreetmap.org*

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Indicators 11 SUSTAINABLE CITIES AND COMMUNITIES		11.2.1 Proportion of population that has convenient access to public transport, by sex, age and persons with disabilities
Custodian agency		UN-Habitat
Tier		I
Status of step-by-step methodology document on the metadata repository		Published
Relevance of EO for the indicator criteria	Maturity of EO technologies	
	Status of EO in indicator guidelines	
	Technical capacity required	
	Availability of global EO data	
Robustness of proposed methodology Criteria	Compliance with Reporting calendar	
	Sensitivity to change	
	Is it scalable (spatial)?	
	Is there a substitute for gaps in the EO record?	
Overall EO relevance		
Comments to support criteria		There is an overall amber relevance. Urban accessibility can be measured through percentage of street space in cities and number of intersections/km2 from analysis of earth observations and/or city maps.

Target 11.3

By 2030, enhance inclusive and sustainable urbanization and capacity for participatory, integrated and sustainable human settlement planning and management in all countries

How can EO be used to help countries achieve the target?

Urban areas are rapidly expanding to accommodate the growing number of people moving to cities. "From 2000 to 2015, in all regions of the world, the expansion of urban land outpaced the growth of urban populations". An uncontrolled urban sprawl can lead to the increase of carbon emissions, poverty, health and safety risks, social inequalities, and vulnerability to natural disasters. The achievement of this target will ensure that land is used efficiently, allowing sustainability and inclusiveness, but it also provides the foundation for attaining other sustainable development goals related to health, food security, energy, safety and poverty. Urban growth needs to be monitored and managed to ensure the sustainable use of land. The improvement of EO technology and the availability of high temporal and spatial resolution images, as well as the advancement in the methodologies proposed to identify built up areas from satellite images, have created a good opportunity to plan and monitor urban development. EO has been used for the direct monitoring and dynamic simulation of urban expansion since the '60s and new models and methods are continually being proposed and tested. Remote sensing data can support the generation of country specific urban expansion models and inform the development of sustainable urban plans. In particular, they can inform the development of urban plans that include the increase of green spaces where these are lacking, identify where these spaces have the capacity to mitigate natural hazard such as floods, and therefore should be prioritise for protection, which are the most vulnerable areas to disaster, as well as to enhance infrastructures such as roads or access to energy, in poorer areas of the city, to include its inclusiveness. The effectiveness of these plans can then be regularly monitored and adapted through EO.

Current indicators:

11.3.1 Ratio of land consumption rate to population growth rate

11.3.2 Proportion of cities with a direct participation structure of civil society in urban planning and management that operate regularly and democratically

Short methodological guidelines illustrated with EO best practice examples

Indicator 11.3.1

Computation method

The current computation method includes the estimate of two components, the population growth rate and the land consumption rate, which indicates the progressive expansion of a city. The land consumption rate can be calculated using the total areal extent of built-up areas for a past year, and the current year, divided by the number of years between the two measurement periods. Similar approach is used to derive the population growth rate, and the combination of the two rates will provide the final indicator "Ratio of land consumption rate to population growth rate". Satellite images are indicated as the source of data to extract the extent of built up areas.

Countries can report on the expansion of built up areas, by using image acquisitions of multiple dates. Satellite sensors derive information about the earth surface with a range of spatial resolutions ranging from a low resolution (e.g. MODIS, MERIS, Sentinel-3), medium resolution (e.g. Sentinel-1/-2, Landsat, ASTER, Radarsat) and high to very high resolution (e.g. TerraSAR-X, COSMO Sky-Med, QuickBird, WorldView, GeoEye, Pléiades) including aerial images and images derived from drone campaigns. The remote sensing sensors acquire information also in different wavelengths of the electromagnetic spectrum. Three main types can be classified in optical sensors (e.g. Sentinel-2, Landsat, WorldView, etc.), microwave (SAR) sensors (e.g. Sentinel-1, TerraSAR-X, Radarsat) and thermal sensors (ASTER, Sentinel-3). Some of the above mentioned satellite missions provide images in various spatial resolutions and spectral ranges. Medium resolution sensors are suitable to monitor large areas up to the entire globe. EO-based thematic baseline layers such as the Global Human Settlement Layer and the Global Urban Footprint (GUF) / World Settlement Footprint (WSF) are derived of sensors with this resolution. The Sentinel missions with their systematic and long-term operational service guarantee represent a unique, but yet to be fully realised, opportunity for advancing global urban mapping. High and very high resolution sensors are suitable for city and sub-city scale applications.

Night time lights (NTL) derived of optical sensors can provide also information on settlement areas. NTL data from the Defense Meteorological Satellite Program's Operational Line-Scan System (DMSP-OLS) can also be used to measure artificial illumination and extract built-up areas, for example by combining vegetation indices and night-time light urban areas (Goldblatt et al., 2018). Night time lights data are a valuable source in particular when the goal is to gain information on poverty and energy consumption, and when analysing climate/heat related aspects of built-up areas. A useful products that combine population statistics and nightlights is the Global Rural Urban Mapping Project (GRUMP). It provides a series of multi-temporal grids (1990-1995-2000) at approximately 1 km spatial resolution, but can under-estimate countries where the illumination footprint is not as strong as in developed countries (Melchiorri et al., 2018).

Built-up areas can be characterized by thermal sensors by a higher land surface temperature than that of suburban, with lower density, and rural areas due to the heat emissions from the residences, traffics, industries and manual labour in the built-up area. The thermal infrared band of EO data, such as Landsat TM, ETM+, OLI, TIRS, can be used to extract the land surface temperature. Boundaries are then drawn around areas with higher temperature (Wang et al., 2018).

A huge variety of methods to delineate urban areas using remote sensing data is documented in the scientific literature. Many approaches combine multiple workflows. Most methods use the spectral and structural properties of built-up areas to classify urban and non-urban areas. Two widely used methods are described below:

- **Machine learning techniques.**
The machine learning techniques that are commonly used to detect built-up areas are supervised classification approaches such as Support Vector Machines, Random Forest or decision tree technology (Corbane et al., 2017; Esch et al., 2013). These methods basically link the image data to a defined collection of semantic layers based on training data sets. Training data can be any representative data that allows to approximate the built-up areas class. The resulting classification models can then be used for deriving human settlements information from satellite imagery – e.g., Sentinel-1 and Landsat data (Esch et al., 2018; Corbane et al., 2017). Deep learning methods emerged also in this domain in the last years.

- **Geographic object-based image analysis (GEOBIA)**.
This technique typically uses very high resolution satellite imagery (<5m), usually between 2 and 0.5m (Herold et al., 2012; Wezyk et al., 2016; Molenaar, 2001). The objects to be analysed, in this case built-up areas, can be obtained from image segmentation and then classification of the segments. Image segments are representative clusters of neighbouring pixel with similar spectral properties. This approach requires a high processing effort and it is realistically applicable just at local to regional scale.

Disaggregation

EO-based products can be used to disaggregate types of built-up structure (residential, industrial, etc.). Disaggregation is often used to distribute population data, as well as socio-economic data, such as income level. Using the data from indicator 11.1.1 residential areas can be differentiated from slums/informal settlements.

Treatment of missing values

At a local scale missing values can be obtained using ground truth surveys or very high resolution EO data. Temporal interpolation is also feasible as long as a reasonable time series is available.

Sources of discrepancies

One of the main source of discrepancy derives from the definition of built up area, this can be avoided by using the same baseline datasets. Other sources of discrepancy are the underlying imagery (sensor), the classification method, the training data and the quality assurance procedure. If the NTL approach is used, discrepancies can be generated from the use of different thresholds for the pixel value at which the category urban development is assigned.
Limitations
Missing data in areas with high cloud cover prevent the mapping of entire sections of built-up areas leading to the underestimation of the real extent of urban areas. The calculation of rate of change in land consumption is limited by the number of acquisitions the EO satellite can obtain of built up area, which has to be consistent at the national scale, requiring longer compositing periods, several years in the case, for example, of tropical regions. The use of SAR data and of improved methods (e.g. TimeScan) can overcome some of these issues. At a local scale, missing data can be obtained using ground truth surveys or very high resolution EO data.

Key messages for countries on EO contribution to the computation method

- EO are a valuable source of data, to monitor urban growth and have been widely used to map and model the expansion of cities;

- EO can support the development of urban plans that use efficiently and sustainably the available land;

- The combination of several types of EO data and products, such as topography, climate change scenarios, land cover and precipitation patterns, can inform the development of natural disaster resilient urban plans.

Data sources

Data category	Data sources	Website
Source satellite data	Landsat	*https://earthexplorer.usgs.gov/*
	Sentinel data (1,2 and 3) from the Copernicus Open Access Hub	*https://scihub.copernicus.eu/*
	MODIS	*https://search.earthdata.nasa.gov*
Global/regional datasets	The Global Urban Footprint (GUF) / World Settlement Foot-print (WSF)	*https://urban-tep.eu*
	NASA's Black Marble nighttime lights product suite (VNP46)	*https://earthobservatory.nasa.gov/Features/NightLights/page3.php* *https://www.ngdc.noaa.gov/eog/viirs.html*
	NOAA. N.d. "Version 4 DM-SP-OLS Nighttime Lights Time Series."	*https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html*
	'GHS built-up grid, derived from Landsat, multitemporal (1975, 1990, 2000, 2014)'. European Commission, Joint Research Centre (JRC) [Dataset]	*http://data.europa.eu/89h/jrc-ghsl-ghs_built_ldsmt_globe_r2015b*
	'GHS Settlement grid follow-ing the REGIO model 2014 in application to GHSL Landsat and CIESIN GPW v4-multitemporal (1975-1990-2000-2015)'. Euro-pean Commission, Joint Research Centre (JRC) [Dataset]	*http://data.europa.eu/89h/jrc-ghsl-ghs_smod_pop_globe_r2016a*
Software, tools and platforms	Trends.Earth Urban Mapper from Conservation International	*https://geflanddegradation.users.earthengine.app/view/trendsearth-urban-mapper*
	Global Rural-Urban Mapping from the Centre for Internation-al Earth Science Information Network (CIESIN), Columbia University.	*http://sedac.ciesin.columbia.edu/data/set/grump-v1-urban-extents*
	Urban Thematic Exploitation Platform (U-TEP)	*https://urban-tep.eu*

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Further reading and resources

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A new dataset and online platform to plan for inclusive and sustainable urbanisation for SDG target 11.3

Satellites enable a spatially and temporally continuous observation of Earth's surface. Recently, the German Aerospace Centre (DLR) and the 6 team have succeeded in deploying a newly developed method to map the growth of human settlement extent at 30m spatial resolution on a yearly basis over three decades from 1985 to 2015. The generation of this World Settlement Footprint (WSF) Evolution dataset is based on a multi-temporal analysis of more than six million satellite images of the Landsat mission.

To facilitate an effective and joint exploration of data collections related to the built environment – e.g. the new WSF Evolution that will be accessible on a free and open basis in 2019 – a consortium funded by the European Space Agency (ESA) and led by DLR has set-up the Urban Thematic Exploitation Platform (U-TEP). U-TEP represents a web-based, open and collaborative virtual environment providing services for high-performance data access, processing, analysis and visualization. At the same time this enabling technology aims at supporting the development and sharing of technical solutions, thematic data and knowledge related to sustainable cities and communities in general.

One key use scenario of U-TEP's analytics and visualization toolbox includes the implementation of a service for the worldwide on-demand calculation of SDG 11.3.1 "Ration of land consumption rate to population growth rate" based on the WSF Evolution and the statistics of the World Bank Open Data Catalogue (https://data.worldbank.org).

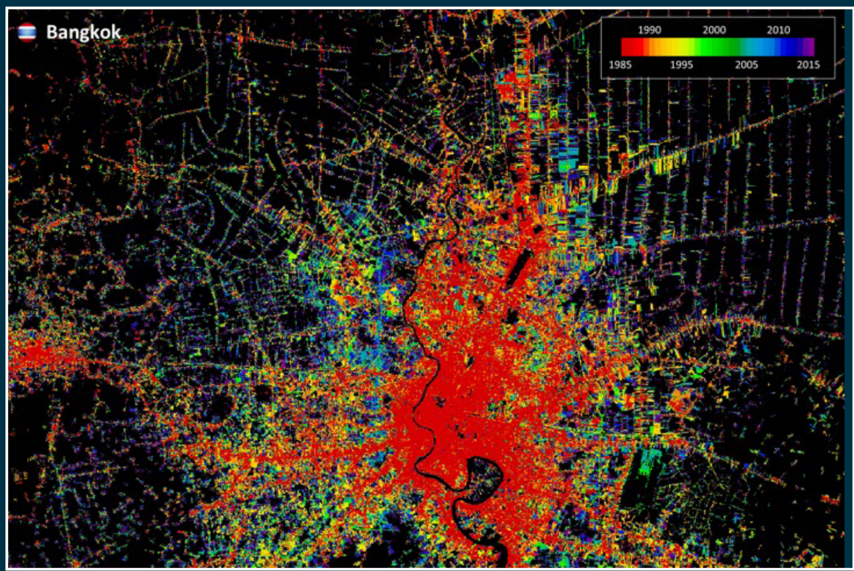

Figure 14: WSF Evolution of Bangkok region, Thailand. Red corresponds to the urban extent in 1985 and yellow-green-blue indicates the growth to 2015. Credit: DLR

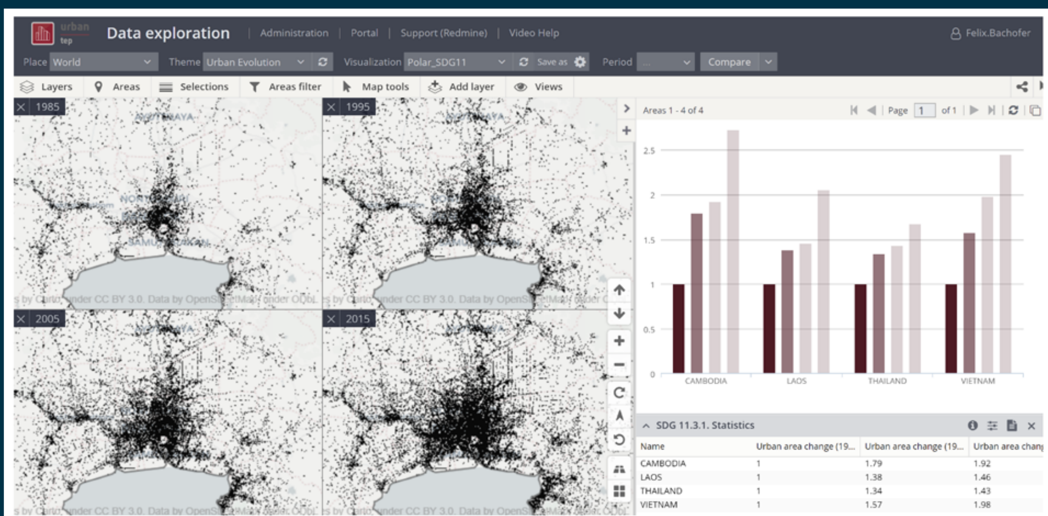

Figure 15: Calculation of indicator "Ratio of land consumption rate to population growth rate" (SDG 11.3.1) with the Urban Thematic Exploitation Platform. The bar chart and table show the Population Change normalized by Settlement Area Change (www.urban-tep.eu). Credit: DLR/Gisat

Indicators 11 SUSTAINABLE CITIES AND COMMUNITIES		11.3.1 Ratio of land consumption rate to population growth rate	11.3.2 Proportion of cities with a direct participation structure of civil society in urban planning and management that operate regularly and democratically
Custodian agency		UN-Habitat	Unknown
Tier		II	II
Status of step-by-step methodology document on the metadata repository		Published	Unpublished (Tier III at the time of the analysis)
Relevance of EO for the indicator criteria	Maturity of EO technologies		
	Status of EO in indicator guidelines		
	Technical capacity required		
	Availability of global EO data		
Robustness of proposed methodology Criteria	Compliance with Reporting calendar		
	Sensitivity to change		
	Is it scalable (spatial)?		
	Is there a substitute for gaps in the EO record?		
Overall EO relevance			
Comments to support criteria		EO has been used to monitor urban growth since the 60s. Several techniques have been tested and new ones are under development, but technical expertise are required to implement these methods. Systematic and comparative accuracy assessment of thematic products (derived from EO data) and related methods are required.	Not supported by EO

Target 11.5

By 2030, significantly reduce the number of deaths and the number of people affected and substantially decrease the direct economic losses relative to global gross domestic product caused by disasters, including water-related disasters, with a focus on protecting the poor and people in vulnerable situations

How can EO be used to help countries achieve the target?

This target seeks to reduce the adverse effects of natural disasters. It recognises the growing impact of natural disasters around the world and the heightened risk, especially to vulnerable populations, e.g. in unplanned urban settlements without adequate protection or planning. It targets both slow-onset, climate related disasters such as sea level rise and extreme weather events. Human loss is the main focus of the target, both in terms of mortality and injury, and negative economic impacts of disasters. This target also relates to targets 1.3, 1.5, 3.6, 3.9, 15.3, 12.1 and 14.2 as well as related targets in the Sendai Framework for Disaster Risk Reduction 2015-2030. EO can play a role in both planning and achievement of this target. For planning purposes, EO can map both the areas that are vulnerable to disasters, e.g. coastal, low-lying areas or areas of deforested, steep slope, susceptible to landslides as well as to map vulnerable populations, e.g. through informal urban settlement mapping. EO also has a role to play in planning for natural disasters by the provision of early warnings systems where flooding, fires and landslides pose a risk to people and their material goods. In order to achieve the target EO can be used to assess the overlap or proximity between vulnerable population and areas prone to disaster and the extent of change in this overlap area in order to ascertain if the human related loss is increasing or decreasing over time. Although not EO-derived, globally gridded GDP data can contribute to the achievement of this target by mapping the geographic location of the poor (see indicators 1.2.2 and 1.2.1).

Current Indicator(s)

11.5.1 Number of deaths, missing persons and persons affected by disaster per 100,000 people

11.5.2 Direct economic loss in relation to global GDP, damage to critical infrastructure and number of disruptions to basic services, attributed to disasters

Short methodological guidelines illustrated with EO best practice examples

Indicator 11.5.1

Computation method

Indicator 11.5.1 relies on a long-established method of quantifying natural disaster loss - the national disaster loss database compiled at a national scale and reported to the United Nations Office for Disaster Risk Reduction (UNISDR). This approach involves registering physical damage value (housing unit loss, infrastructure loss etc.), which needs conversion to monetary value. The converted global, monetary value is divided by global GDP calculated from the World Bank Development Indicators. Spatial gridded GDP data are available globally but these are derived from statistical data, not EO (Nordhaus, 2006).

Although the computational method does not employ EO data currently, mapping and quantifying the economic value of physical damage to housing and roads is a developing area for EO, particularly on disaster preparedness/warning and response/monitoring (Bello & Aina, 2014). The EO methods are designed to relay information on sites of damage to authorities as quickly as possible to minimise disruption and loss of life. Such information, compiled over time, could be fed into a national disaster loss database. An important EO based Emergency and Disaster Mapping Service hitherto not used for the assessment of Indicators of Target 11.5, is the European Commission supported Copernicus Emergency Management Service (EMS) which "uses satellite imagery and other geospatial data to provide free of charge mapping service in cases of natural disasters, human-made emergency situations and humanitarian crises throughout the world,"(http://emergency.copernicus.eu/mapping/ems/emergency-management-service-mapping). The programme provides a "Rapid mapping" service to assess extent of damage shortly after an event as well as a "Risk & Recovery Mapping" Service.

The power of EO to monitor and map damage from natural disasters has been demonstrated notably for: assessing shoreline damage following tsunamis (Bello & Aina, 2014); building damage following earthquakes using very high resolution optical imagery at spatial resolution of 1m (Chesnel, Binet, & Wald, 2007); and flood-related damage to roads using very high resolution optical imagery, a digital elevation model and SAR for flooded area detection (Frey & Butenuth, 2009). Fusion of optical and SAR data and more detailed use of radiometric elements of the optical imagery is encouraged for detecting manmade objects and their destruction, particularly for mapping usable roads post-flooding (Butenuth et al., 2011). With the advent of the Sentinel suite of EO data and the Copernicus EMS programme, the impact of a natural disaster on a population can be assessed using the EMS products in conjunction with geo-spatial population density data.

All the above examples require vector-based maps to support the analysis in a GIS environment, e.g. building footprints and road networks, comparing them before and after disaster, to evaluate loss. However, those layers could potentially be derived from the imagery used to map disaster areas.

Limitations

The area of damaged infrastructure reported using EO still needs to be converted to economic loss. Values of global GDP will need to be derived elsewhere. More generally, the type of EO data used varies with the nature of the disaster, i.e. whether slow onset or from extreme weather or events. Slow onset events require an EO-based monitoring system which is commensurate with the rate of change and the change in disaster risk level. The use of EO to monitor sudden events is limited to post-disaster recovery efforts, e.g. in surveying infrastructure damaged and therefore needs careful selection and combination with other types of spatial data such as the pre-disaster road network.

Key messages for countries on EO contribution to the computation method

- This indicator follows a well-established methodology based on related indicators, e.g. for the Sendai Framework, from national disaster loss databases.
- An EO-based method for the indicator would have to be customised for the nature of the disaster, whether long-term onset or sudden, and whether in coastal, inland or mountainous settings.
- Current EO based assets for disaster monitoring mostly focus on post disaster recovery efforts but for this indicator would need to be enhanced to evaluate physical damage and the proportion of the population affected by the disaster
- The EO based methods for infrastructural damage assessment are more advanced than those for assessing human impact (mortality, injury, relocation etc.)
- However, combining advances made in EO-based human settlement mapping with the ability to evaluate physical damage in disaster zones could pave the way for the use of EO in the indicator computation

Data sources

Data category	Data sources	Website
Global/regional datasets	The Global Urban Footprint (GUF) / World Settlement Footprint (WSF)	*change hyperlink to*
	The Global Human Settlement Layer (GHSL)	*https://ghsl.jrc.ec.europa.eu/data.php*
Software, tools and platforms	The GEO Human Planet initiative	*https://ghsl.jrc.ec.europa.eu/HPI.php*
	Global Gridded Geographically Based Economic Data (G-Econ), v4 (1990, 1995, 2000, 2005)	*http://sedac.ciesin.columbia.edu/data/set/spatialecon-gecon-v4/docs*
Operational or commercial services	The UN-SPIDER programme	*http://www.un-spider.org/*
	Copernicus Emergency Management Service (EMS) The GEO Human Planet initiative	*http://emergency.copernicus.eu/mapping/ems/emergency-management-service-mapping*

Reference List

Bello, O. M., & Aina, Y. A. (2014). Satellite Remote Sensing as a Tool in Disaster Management and Sustainable Development: Towards a Synergistic Approach. Procedia - Social and Behavioral Sciences, 120, 365–373. https://doi.org/10.1016/j.sbspro.2014.02.114

Butenuth, M., Frey, D., Nielsen, A. A., & Skriver, H. (2011). Infrastructure assessment for disaster management using multi-sensor and multi-temporal remote sensing imagery. International Journal of Remote Sensing, 32(23), 8575–8594. https://doi.org/10.1080/01431161.2010.542204

Chesnel, A.-L., Binet, R., & Wald, L. (2007). Quantitative assessment of building damage in Urban area using very High Resolution images. 2007 Urban Remote Sensing Joint Event, URS. https://doi.org/10.1109/URS.2007.371865

Frey, D., & Butenuth, M. (2009). Multi-Sensorial Imagery for Near-Realtime Disaster Management, XXXVIII, 3–4. Nordhaus, W. D. (2006). Geography and macroeconomics: New data and new findings. Proceedings of the National Academy of Sciences of the United States of America, 103(10), 3510 LP-3517. Retrieved from http://www.pnas.org/content/103/10/3510.abstract

Indicators

11 SUSTAINABLE CITIES AND COMMUNITIES

		11.5.1 Number of deaths, missing persons and persons affected by disaster per 100,000 people	11.5.2 Direct economic loss in relation to global GDP, damage to critical infrastructure and number of disruptions to basic services, attributed to disasters
Custodian agency		UNISDR	
Tier		II	II
Status of step-by-step methodology document on the metadata repository		Published	Published
Relevance of EO for the indicator criteria	Maturity of EO technologies		
	Status of EO in indicator guidelines		
	Technical capacity required		
	Availability of global EO data		
Robustness of proposed methodology Criteria	Compliance with Reporting calendar		
	Sensitivity to change		
	Is it scalable (spatial)?		
	Is there a substitute for gaps in the EO record?		
Overall EO relevance			
Comments to support criteria		Not supported by EO	Damage to critical infrastructure and disruption to services can be directly mapped from EO while GDP impact can only be inferred from such visible damage.

Target 11.6

By 2030, reduce the adverse per capita environmental impact of cities, including by paying special attention to air quality and municipal and other waste management

How can EO be used to help countries achieve the target?

Minimising the per capita environmental impact of cities is challenged by traffic congestion, lack of funds to provide basic services, a shortage of adequate housing, declining infrastructure and rising air pollution within cities. This target covers aspects of waste generated by cities and aims to reduce the amount of solid waste generated and air polluted, while encouraging better waste management. Therefore EO can be used in three major aspects of this target – the spatial mapping of cities and the sources of pollution, the identification and treatment of waste in and around cities and in planning better waste management for per capita pollution reduction.

Firstly, satellite observations of human settlement are increasingly more sophisticated allowing the impact of cities to be assessed based on their spatial extent and density. EO-derived maps of cities allow the size, shape and other metrics of urban setting (e.g. urban population) to be monitored from which likely environmental impact could be inferred. Within cities there are identifiable sources of aerosol emissions such as power plants and various industrial processes. These sources generate significant amounts of particulates, e.g. fine particulate matter (PM2.5), which can have adverse effects on human health. Remote sensing of dry PM2.5 mass concentration near the ground is now feasible. In addition to particulates, trace gases that affect air quality are now routinely monitored over large urban areas.

In addition to air pollution, solid waste management can be supported in cities by using EO as a tool to evaluate the impact of different phases of the waste cycle. In particular, very high resolution EO has been shown to be effective in the detection of illegal waste disposal sites through visual image interpretation and classification as well as the monitoring of the spread of municipal landfill sites using multi-temporal thermal Landsat imagery.

Current Indicator(s):

11.6.1 Proportion of urban solid waste regularly collected and with adequate final discharge out of total urban solid waste generated, by cities

11.6.2 Annual mean levels of fine particulate matter (e.g. PM2.5 and PM10) in cities

Potential new indicator(s) based on EO:

The number of illegal waste sites identified and eradicated in cities

Short methodological guidelines illustrated with EO best practice examples

Indicator 11.6.2

Computation method

For indicator 11.6.2 the annual urban mean concentration of PM2.5 is estimated by modelling satellite remote sensing data with ground measurements from the 2016 WHO ambient (outdoor) air quality database, which serves for calibration of the satellite data (WHO, 2016). EO-derived aerosol optical depth data are typically retrieved at low spatial resolutions, e.g. Aerosol Optical Depth product from VIIRS at 750m resolution (NOAA STAR, 2018). Derived products such as particle size describe the nature of the aerosol and can be used to estimate the size of the particulate matter (e.g. <2.5µg). Annual mean concentrations of particulates over cities are then combined with the corresponding number of inhabitants to derive the population-weighted exposure to particulate matter in cities.

Treatment of missing values

Missing values are currently excluded from the regional and global averages. However, there is potential to use models (e.g. the Copernicus Atmosphere Monitoring Service outputs from the ECMWF) to fill data gaps.

Sources of discrepancies

Pixel-based satellite measurements and cell-based chemical transport modelling are fundamentally different approaches and vary in their ability to capture different microscale features that may be reflected in the ground measurements. All three sources of data will be subject to error, which may not be consistent with each other. The variance in spatial resolution between ground monitors (point locations) and estimates from satellite and chemical transport models (grid cells) has led to the use of spatially varying coefficient models, which are often referred to as downscaling models (Shaddick et al., 2018).

Limitations

Ground station measurements of air particulates are needed to validate the EO-derived measurements, therefore this indicator remains partly measurable with EO.

Key messages for countries on EO contribution to the computation method

- Air quality is a relatively well established area of EO application, in particular in the detection of aerosols from fossil fuel combustion – both industrial and domestic sources in cities

- The indicator methodology already integrates EO with ground data to estimate levels of air pollution over cities but as the method relies on ground data for validation and ground level air pollution levels, it is only partly measurable with EO
- The estimate of per capita impact requires the total number of city inhabitants to be accurately estimated so that the indicator can be correctly computed. Such information should be readily available at the national level.

Data sources

Data category	Data sources	Website
Source satellite data	GOSAT-2	*http://global.jaxa.jp/activity/pr/brochure/files/sat38.pdf*
	Sentinel- 5P	*https://sentinel.esa.int/web/sentinel/missions/sentinel-5p/data-products*
	MODIS Aerosol Product	*https://modis.gsfc.nasa.gov/data/dataprod/mod04.php*
	Sentinel-3 Aerosol Optical Depth Product	*https://sentinel.esa.int/web/sentinel/technical-guides/sentinel-3-olci/level-2/aerosol-optical-thickness*
Operational or commercial services	The Copernicus atmosphere monitoring service	*https://www.ecmwf.int/en/about/what-we-do/environmental-services/copernicus-atmosphere-monitoring-service*

Reference List

NOAA STAR. (2018). STAR Product Catalog. Retrieved July 23, 2018, from https://www.star.nesdis.noaa.gov/portfolio/productListings.php

Shaddick, G., Thomas, M. L., Green, A., Brauer, M., van Donkelaar, A., Burnett, R., ... Prüss-Ustün, A. (2018). Data integration model for air quality: a hierarchical approach to the global estimation of exposures to ambient air pollution. Journal of the Royal Statistical Society. Series C: Applied Statistics, 67(1), 231–253. https://doi.org/10.1111/rssc.12227

WHO. (2016). Ambient air pollution: a global assessment of exposure and burden of disease, WHO Geneva. Geneva.

Indicators		11.6.1 Proportion of urban solid waste regularly collected and with adequate final discharge out of total urban solid waste generated, by cities	11.6.2 Annual mean levels of fine particulate matter (e.g. PM2.5 and PM10) in cities
Custodian agency		UN-Habitat; WHO	
Tier		II	I
Status of step-by-step methodology document on the metadata repository		Published	Published
Relevance of EO for the indicator criteria	Maturity of EO technologies		
	Status of EO in indicator guidelines		
	Technical capacity required		
	Availability of global EO data		
Robustness of proposed methodology Criteria	Compliance with Reporting calendar		
	Sensitivity to change		
	Is it scalable (spatial)?		
	Is there a substitute for gaps in the EO record?		
Overall EO relevance			
Comments to support criteria		Not supported by EO	EO based methods for fine particulate matter detection over cities are routine and operational

Target 11.7

By 2030, provide universal access to safe, inclusive and accessible, green and public spaces, in particular for women and children, older persons and persons with disabilities

How can EO be used to help countries achieve the target?

Green and public spaces in cities are important for human well-being and economic development and should be sustainable spaces for all to use equally. Increasingly there are inadequate, poorly designed, or privatized public spaces in cities that generate exclusion and marginalization for inhabitants, especially those who are vulnerable. This target addresses the drastic reduction in the quality of green and public space in cities and seeks to make them safe and inclusive for all regardless of gender, age or level of mobility. Public space is made of streets and green and open spaces in public use. EO can help countries to achieve this target because it is a useful tool to establish the extent of urban areas as well as to do an inventory of open space in cities, especially green open space. The challenge in using EO to complete the target will be in discerning what private and public space is as they will have the same spatial characteristics from an EO point of view. Furthermore the notion of access is complicated as it implies freedom of movement and this not a practically measurable quantity from EO. Therefore while certain aspects of the target can be planned for using EO, much will depend on other in situ data sources or local ancillary data such as cadastral records, land use or basic topography.

Current Indicator(s)

11.7.1 Average share of the built-up area of cities that is open space for public use for all, by sex, age and persons with disabilities

11.7.2 Proportion of persons victim of physical or sexual harassment, by sex, age, disability status and place of occurrence, in the previous 12 months

Short methodological guidelines illustrated with EO best practice examples

Indicator 11.7.1

Computation method

The computational method for indicator 11.7.1 was still under discussion and not yet finalised and published at the time of the analysis. Much of the discussion has focused on a clarification of terms, e.g. of 'built-up area'. Nevertheless the method for the estimation of area of public space, according to the work plan, will consist of three steps: a) spatial analysis to delimit the built-up area of the city; b) estimation of the total open public space and; c) estimation of the total area allocated to streets. EO is mentioned in the methodology as a potential source of data in step 1 to map built up area (urban delimitation), in combination with the methodology "National Sample of Cities" proposed by UN-Habitat[1] . Land use maps can be used to identify the public space within the built up area. Estimation of the land allocated to street is based on an in situ sampling regime or, as proxy, using of open datasets (e.g. OSM) when available and EO is not foreseen as a method here.

Limitations

The main limitation expected will be in the acquisition of optical imagery at the required spatial resolution to delineate open space within 'locales'. There are some small green open spaces (local parks) that cannot be distinguished due to the limited spatial resolution of free and open satellite images. The possibility of small urban space detection increases with VHR imagery. However such imagery is rarely free and would put the burden on city authorities to purchase expensive imagery. The variance in definition of open space between cities (and countries) will also be a challenge for an EO-based approach.

Key messages for countries on EO contribution to the computation method

- This methodology is in development but it is likely that EO will play a role in the computational method. The spatial resolution of images is a key factor to use them in 11.7.1 calculation, the higher the resolution, the better the classifications can be to differentiate green, built-up and street areas.
- Countries need to make a choice between the delimitation of built up area from EO imagery by themselves or to use existing EO products

1 https://unhabitat.org/national-sample-of-cities/

- Very high resolution EO imagery to delineate the built-up area and small green areas will obligate countries to pay for commercially acquired imagery. Although at the edge of applicability in an urban context with 10m resolution, Sentinel-2 images are free of charge. A world-wide data archive is currently being built up.

- Countries can use ready-to-use products, such as the EO-derived GHSL or GUF listed above, in which case it is not necessary to acquire any new satellite images.

- EO will not be used to quantify the amount of open, public space within the built up area and the estimation of area covered by streets which is more feasible using local land use and urban datasets

- Readily available and global EO products are already being used for built up area mapping, e.g. as part of the GEO Human Planet initiative, but the definition of built up area has not yet been finalised in the indicator methodology and it may differ from the definition used in these data products

Data sources

Data category	Data sources	Website
Global/regional datasets	The Global Urban Footprint (GUF) / World Settlement Footprint (WSF)	*https://urban-tep.eu*
	The Global Human Settlement Layer (GHSL)	*https://ghsl.jrc.ec.europa.eu/data.php*
Software, tools and platforms	Night time lights data	*https://sos.noaa.gov/datasets/nighttime-lights/*
	Urban Thematic Exploitation Platform	*https://urban-tep.eu*
Operational or commercial services	Copernicus Services: Urban Atlas	*https://land.copernicus.eu/local/urban-atlas*
	Copernicus High Resolution Layers	*https://land.copernicus.eu/pan-european/high-resolution-layers/imperviousness*

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Esch, T., Marconcini, M., Felbier, A., Roth, A., Heldens, W., Huber, M., … Dech, S. (2013). Urban Footprint Processor-Fully Automated Processing Chain Generating Settlement Masks From Global Data of the TanDEM-X Mission. IEEE Geoscience and Remote Sensing Letters, 10(6), 1617–1621. https://doi.org/10.1109/LGRS.2013.2272953

Lee, H. (2018). Quantifying public spaces for better quality of urban assets. World Bank Group Sustainable Cities Blog, 10/24/2018, https://blogs.worldbank.org/sustainablecities/quantifying-public-spaces-better-quality-urban-assets.

Pesaresi, M., Blaes, X., Ehrlich, D., Ferri, S., Gueguen, L., Halkia, M., … Zanchetta, L. (2013). A Global Human Settlement Layer From Optical HR/VHR RS Data: Concept and First Results. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 6(5), 2102–2131. https://doi.org/10.1109/JSTARS.2013.2271445

Planning for target 11.7: Earth Observation for Transforming Cities through Public Spaces

VHR satellite imagery is being used in a framework to examine how urban green and open areas (GOA) can transform urban environments by promoting inclusive green growth and enhance liveability in megacities. This framework has been developed by the World Bank Group UrbanScapes Team which has initiated an Advisory Services and Analytics (ASA) activity to support ongoing investment in operations on the ground. The framework is being piloted in Karachi (Pakistan) and Dhaka (Bangladesh, fig.1). Overall cooperation under this ASA aims to:

(i) Develop an enhanced diagnostic on the nature of public spaces, and the opportunities and challenges;

(ii) Provide a concrete body of evidence on public spaces-related policies and programs, for the Bank operations to assist cities with strategic advice and inputs to public spaces;

(iii) Gain a better understanding of the state and problems of urban public spaces, focusing on selected cities, and to identify future investments and implementation strategy;

(iv) Provide a platform for related knowledge exchange and policy dialogue with practitioners, academics, and clients.

As part of this program, the UrbanScapes multidisciplinary team cooperated with GISAT – a remote sensing company, on developing a series of analytical projects focused on characterizing land use and identification of public municipal assets (e.g. public spaces) using high resolution satellite imagery, and to better define intervention areas during project preparation. The EO part of the project is supported by the EO4SD (Earth Observation for Sustainable Development) ESA initiative and builds on previous successful ESA-World Bank collaborations. These joint projects aim to achieve a step change in the use of satellite-based environmental information in the World Bank's regional and global programs. Although the project is being piloted at two locations in the preparation phase, there is potential for streamlining the approach to future World Bank UrbanScapes projects (Lee, 2018).

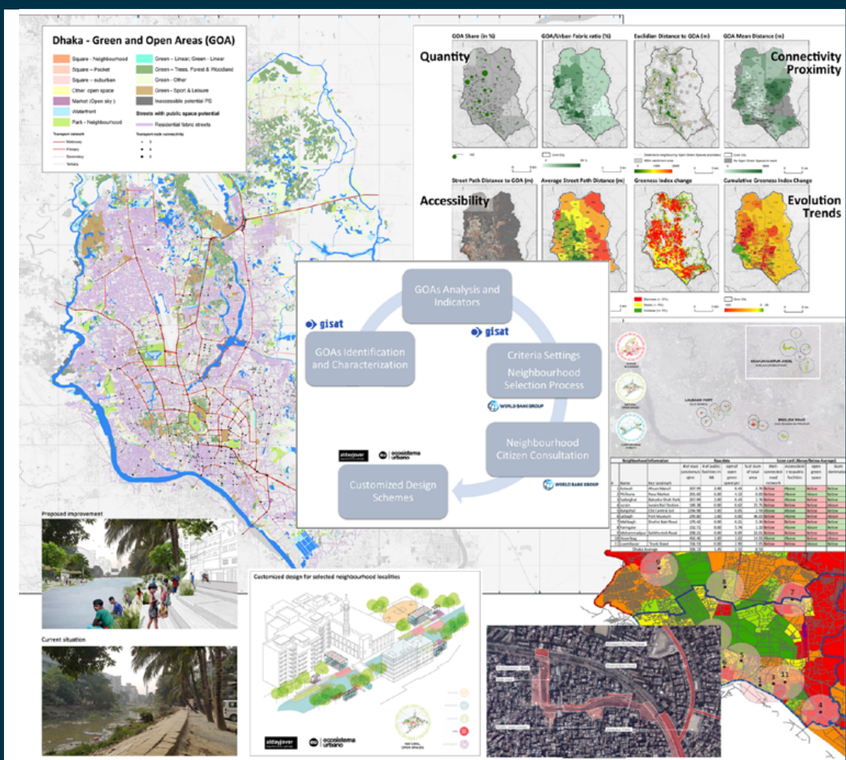
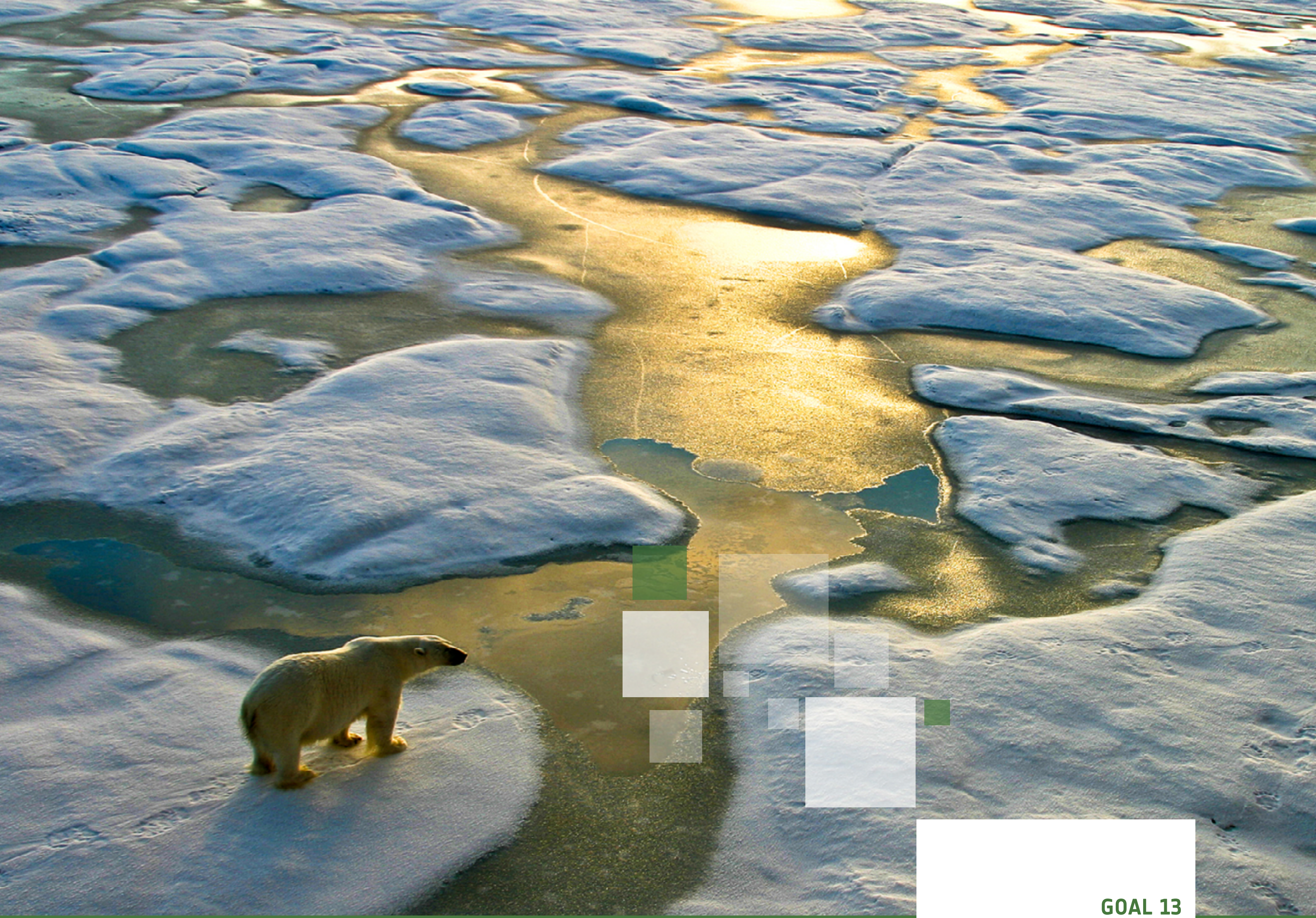


Figure 16: Very high resolution satellite imagery has been used in cooperation between the World Bank and ESA EO4SD Urban project to promote urban green growth. An example map of Green and Open (GOA) areas is shown here for one of the pilots - Dhaka, Bangladesh.

Indicators 11 SUSTAINABLE CITIES AND COMMUNITIES		11.7.1 Average share of the built-up area of cities that is open space for public use for all, by sex, age and persons with disabilities	11.7.2 Proportion of persons victim of physical or sexual harassment, by sex, age, disability status and place of occurrence, in the previous 12 months
Custodian agency		UN-Habitat	UNODC
Tier		II	II
Status of step-by-step methodology document on the metadata repository		Work plan only	Not published (Tier III at the time of the analysis)
Relevance of EO for the indicator criteria	Maturity of EO technologies		
	Status of EO in indicator guidelines		
	Technical capacity required		
	Availability of global EO data		
Robustness of proposed methodology Criteria	Compliance with Reporting calendar		
	Sensitivity to change		
	Is it scalable (spatial)?		
	Is there a substitute for gaps in the EO record?		
Overall EO relevance			
Comments to support criteria		EO is useful to map open and green spaces within urban areas. EO is very limited in mapping socioeconomic variables associated with this indicator.	Not supported by EO



GOAL 13

13 CLIMATE ACTION

Target 13.1

Strengthen resilience and adaptive capacity to climate-related hazards and natural disasters in all countries

How can EO be used to help countries achieve the target?

This target is complementary to the global targets of the Sendai Framework for Disaster Risk Reduction, specifically targets A and B. The definition of hazard, according to the open-ended intergovernmental expert working group of the UNISDR (United Nations Office for Disaster Risk Reduction (UNISDR) and United Nations General Assembly (UNGA), 2016), is "a process, phenomenon or human activity that may cause loss of life, injury or other health impacts, property damage, social and economic disruption or environmental degradation". Hazards may be natural, anthropogenic or socio-natural in origin.

EO can be used by countries in two ways, both in planning for the target, though a more robust system of identifying, monitoring and preparing for climate related hazards and natural disasters and in achieving the target, through improved resilience to disasters through ecosystem-based adaptation strategies. For the former, EO is a powerful monitoring technology to track natural, anthropogenic or socio-natural hazards on the land or sea surface. Populations in the path of disasters can be prepared and alert to disasters before they occur if EO is used effectively in an early warning system, e.g. in tracking hurricanes approaching coastlines, tracking wildfires near human settlements or in detecting terrain movements prior to volcanic eruptions. For the latter, strengthening resilience and adaptive capacity to disasters requires longer term planning. Ecosystem-based approaches to climate change adaptation are included in many disaster risk reduction strategies as they provide a natural buffer to hazards while providing other ecosystem services to surrounding communities. EO is useful as a national planning tool for the target in ecosystem-based adaptation to natural disasters because it can map the extent of such ecosystems as well as potential areas for increasing the extent and composition of these ecosystems to strengthen resilience. For example coastal ecosystems such as mangroves are readily mapped through EO and can be conserved and resorted to strengthen resilience to coastal hazards such as storm surges and wave damage.

Current Indicator(s):

13.1.1 Number of deaths, missing persons and directly affected persons attributed to disasters per 100,000 population

13.1.2 Number of countries that adopt and implement national disaster risk reduction strategies in line with the Sendai Framework for Disaster Risk

13.1.3 Proportion of local governments that adopt and implement local disaster risk reduction strategies in line with national disaster risk reduction strategies

Short methodological guidelines illustrated with EO best practice examples

Indicator 13.1.1

Computation method

The relevant global indicators for the Sendai Framework will be used to report for this indicator.

Indicator 13.1.1. is calculated as a summation of related indicators (deaths, missing people, and affected people) from national disaster loss databases, divided by the total population of the area concerned, derived from relevant global or national databases (e.g. World Bank or UN Statistics information). Affected people, whether directly or indirectly, are defined as those that "experience short-term or long-term consequences to their lives, livelihoods or health and to their economic, physical, social, cultural and environmental assets. In addition, people who are missing or dead may be considered as directly affected" (United Nations Office for Disaster Risk Reduction (UNISDR) and United Nations General Assembly (UNGA), 2016).

Although EO is not mentioned as a potential source of data for the indicator, an EO-based approach could be used to estimate the extent of area impacted by the disaster from which the impact to "physical or economic assets" could be inferred, according to the UNISDR definition above. Census data would be required for the area's population while counting in-situ the number of deaths, missing persons and directly affected persons. To be consistent with the indicator, a conclusion on the number of affected persons would have to account for those indirectly and directly affected by the disaster. For this distinction, the UNISDR proposes the estimation of "directly affected" as a proxy for the number of affected. Directly affected are those "People who have suffered injury, illness or other health effects; who were evacuated, displaced, relocated or have suffered direct damage to their livelihoods, economic, physical, social, cultural and environmental assets". This could be feasibly estimated by overlaying a population density map on a disaster zone map derived from high to very high resolution EO data, perhaps stratifying zones into areas with the highest to the lowest impact based on variables for proximity to the disaster, vegetation cover, slope and topographic factors etc. Clearly, the type of disaster would determine the parameterisation of such a model.

There are also limits to the type of disaster that could be monitored with EO but the main applications would be in earthquakes, in particular using SAR interferometry for ground motion detection, e.g. from Sentinel-1 (ESA, 2015, 2018b), COSMOS-Skymed or TerraSAR-X data; Sentinel-1 for floods (Twele et al., 2016) and tropical cyclones/storm surges (Guo, 2010). Newer applications have shown the potential of EO for monitoring dangerous heat waves (or urban heat islands) , e.g. from MODIS Land Surface Temperature (Clinton & Gong, 2013) and dangerous emissions from natural sources such as wildfires (Zielinski et al., 2016) and volcanoes (Prata et al., 2015). Other disasters that could be directly monitored with EO are wildfires (ESA, 2018a), industrial fires, drought (Sinergise, 2018), ice (sea ice and icebergs), landslides (Casagli et al., 2016), oil spills and volcanoes (Rothery, 1992; CEOS, 2015).

Limitations

Use of multi-sensor/satellite information will introduce errors and potentially gaps where certain sources of imagery don't exist. There are limitations on the use of remotely sensed EO data for landslide studies including the high cost of VHR imagery for detailed geomorphologic mapping and the size of ground deformations in relation to the capacity of radar interferometry to detect motion. The use of polar and geostationary orbiting weather satellites for volcano monitoring (ash clouds, toxic emissions, heat etc.) is limited by cloud cover (meteorological cloud as well as volcanic cloud), reduced capability at night and limited ability to detect small-scale events (meteorological satellites have very coarse resolutions >1km) (Rothery, 1992). In addition the polar regions have less coverage than the rest of the planet.

Key messages for countries on EO contribution to the computation method:

- There are a wide variety of disaster impacts which EO can monitor, especially those that produce material damage, such as earthquakes and hurricanes. Longer-term, slower onsets disasters such as urban heat island impacts and drought can be monitored remotely but their impact is less easily quantified.
- This indicator requires a quantification of the number of directly affected people as well as deaths and missing persons. For these accurate head counts are required which cannot be readily by EO methods.
- However EO can be used to map the extent and intensity of impact of the affected area and theoretically population density maps could be overlaid to infer the numbers of those directly affected by a disaster while missing person would remain unquantifiable.
- Even with an EO-based method, for accurate reporting of this indicator, ground based methods would still be needed to count the numbers of persons in the different categories within and around the disaster zone

Data sources

Data category	Data sources	Website
Software, tools and platforms	The ESA Thematic Exploitation Platform (TEP) on Geohazards	*https://geohazards-tep.eu*

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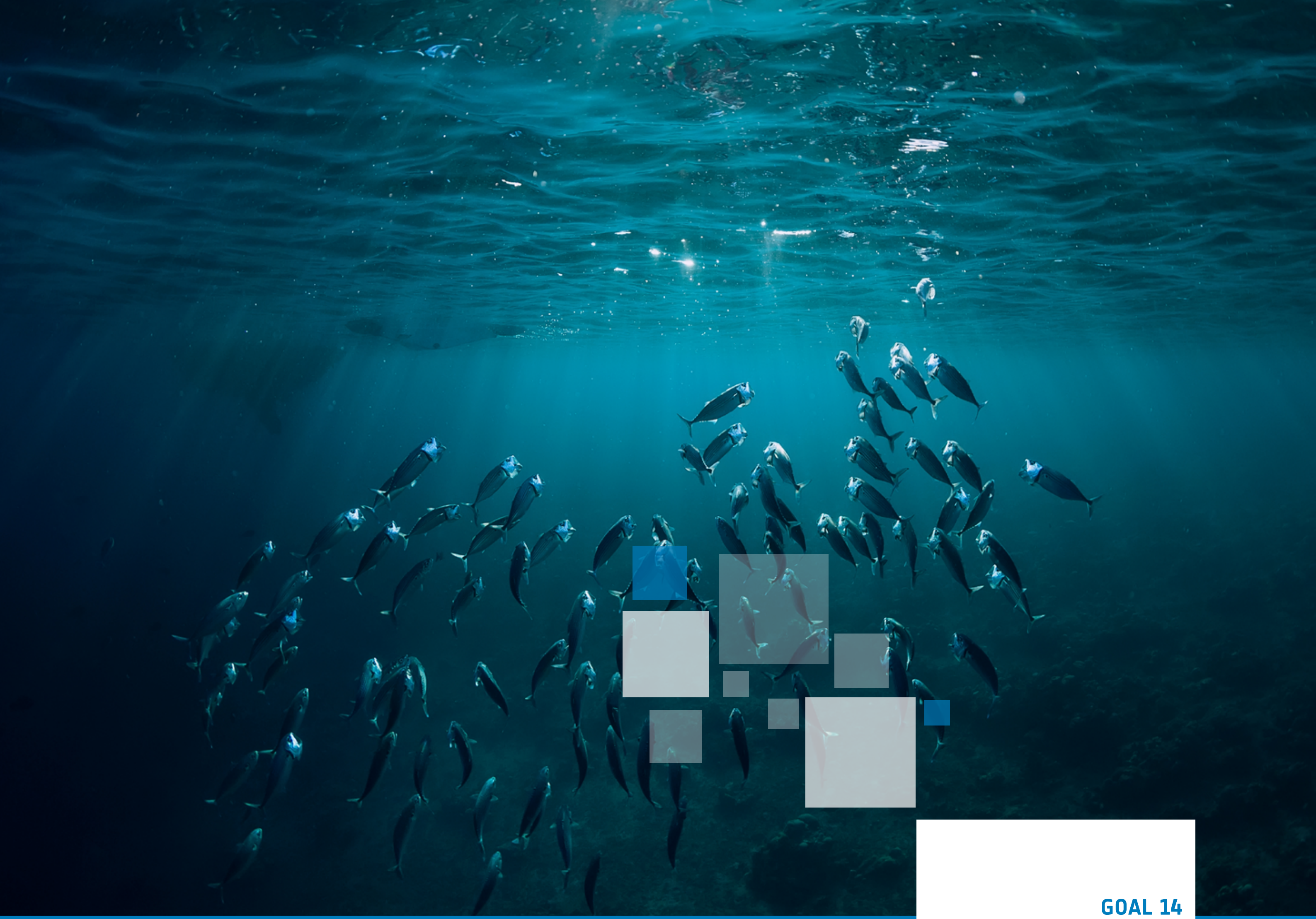
Further Reading and Resources:

Space-based information for disaster management and emergency response
http://www.un-spider.org/

Indicators		13.1.1	13.1.2	13.1.3
		Number of deaths, missing persons and directly affected persons attributed to disasters per 100,000 population	Number of countries that adopt and implement national disaster risk reduction strategies in line with the Sendai Framework for Disaster Risk	Proportion of local governments that adopt and implement local disaster risk reduction strategies in line with national disaster risk reduction strategies
Custodian agency		UNISDR		
Tier		II	II	II
Status of step-by-step methodology document on the metadata repository		Published	Published	Not published (Tier III at the time of the analysis)
Relevance of EO for the indicator criteria	Maturity of EO technologies			
	Status of EO in indicator guidelines			
	Technical capacity required			
	Availability of global EO data			
Robustness of proposed methodology Criteria	Compliance with Reporting calendar			
	Sensitivity to change			
	Is it scalable (spatial)?			
	Is there a substitute for gaps in the EO record?			
Overall EO relevance				
Comments to support criteria		Number of directly affected people could be inferred from EO-based maps of the extent of affected area in combination with population data	Not supported by EO	Not supported by EO



GOAL 14

14 LIFE BELOW WATER

Target 14.1

By 2025, prevent and significantly reduce marine pollution of all kinds, in particular from land-based activities, including marine debris and nutrient pollution

How can EO be used to help countries achieve the target?

This target addresses the need to reduce marine pollution by recognising the land-based sources that emit pollutants such as nutrients and plastic debris. It is therefore an interconnected target that seeks to join land and sea based approaches to pollution reduction and prevention. In setting a deadline for achievement of this target by 2025, the community must act quickly towards global pollution reduction. EO is useful in relation to this target because it has both land, sea and coastal coverage thereby enabling integrated monitoring, e.g. of land based debris which accumulates on shorelines before being transported seaward. Equally, EO can monitor the location and extent of inland waterways, including their water quality as mentioned in relation to SDG 6, enabling the transport of land based, water-dissolved pollutants such as excessive nutrients to be monitored. At sea, the detection of surface, coarse marine debris is an experimental area for EO but with increasing sophistication this technique could yield results in being able to map large debris fields and plot their movement for subsequent intervention and clean up. Evaluation of coastal eutrophication status, anomalies and trends is a challenging but evolving application of EO and contributes to the land-based pollution reduction aspect of this target.

Current Indicator(s)

14.1.1 Index of Coastal Eutrophication and floating plastic debris density

Short methodological guidelines illustrated with EO best practice examples

Indicator 14.1.1

Computation method

Due to the complexity of this indicator, the methodology will be divided into multiple primary and secondary sub-indicators. The data for the sub-indicators will be based on two levels of data:

1. **Global level data derived from satellite observations, and**
2. **National and regional in situ data.**

The identification and development of secondary sub-indicators is currently in progress. Information about two potential sub-indicators is outlined below.

Sub-Indicator 1: Index of Coastal Eutrophication

Provisional sub-indicator 1.1: Surface water chlorophyll a as a proxy for phytoplankton biomass (chlorophyll a trends, anomalies and annual maximum)

Sub-Indicator 2: Floating plastic debris density

Provisional sub-indicator 2.1: Beach litter

14.1.1 Provisional sub-indicator 1.1: Surface Chlorophyll-a concentration as an indicator of phytoplankton biomass

Chlorophyll-a is a pigment contained in plants, algae and phytoplankton that provides a proxy indicator for eutrophication. It can be measured by EO using ocean colour radiometry sensors. Data on Chlorophyll-a is freely accessible on a number of data portals, data bases and satellite missions (see data sources) (ESAa, 2018). These data sources can be used to identify satellite Chlorophyll-a data for the national waters under consideration but the use of the satellite Chlorophyll-a for reporting on this indicator is restricted because current methods are designed for open ocean applications. As a result they produce spurious results in optically complex coastal (and inland) waters (see limitations section).

Chlorophyll-a trends should be monitored due to seasonal changes in phytoplankton growth, rainfall and oceanographic processes that impact surface nutrient concentrations such as upwelling and stratification.

To use Chlorophyll-a as a proxy for eutrophication, national Chlorophyll-a eutrophication threshold levels have to be defined (i.e. the Chlorophyll-a levels in µg l-1 at which eutrophication occurs in national waters). However, due to the uncertainties inherent in EO retrievals, it would be more realistic for this to be a percent change over time of Chlorophyll-a concentrations rather than a specific ug/l value. These can be calculated using historical data, modelling outputs and expert judgement. Historical data for satellite-remote sensing derived Chlorophyll-a levels is available (see data sources).

To determine Chlorophyll-a concentrations, the satellite data should be analysed using appropriate algorithms for the prediction of apparent optical properties of coastal waters, as shown in a study by Zheng & DiGiacomo (2017). Initial in-situ measurements are required to ground truth these algorithms. A number of software packages, online toolboxes and web portals are available to support the processing and analysis of satellite data (see data sources). Chlorophyll-a concentrations will need to be compared to time series data to identify trends. Chlorophyll-a anomaly data can also serve as a proxy for harmful algal bloom occurrence/potential eutrophication. This can be done for representative water bodies which are then monitored and statistical indicators are generated per water body, as per the approaches of the EU'S Water Framework and Marine Strategy Framework Directives.

14.1.1 Sub-indicator 2: floating plastic debris density, and provisional sub-indicator 2: beach litter

Floating plastic in coastal areas could be observed using optical data (e.g. Sentinel-2 and Landsat 7/8), with the caveat that the resolutions will be max 10m (for Sentinel-2) and 30m (for Landsat), indicating that only large (>10m) floating plastic and/or beach litter can be observed and even still with large uncertainties. Therefore it is currently impossible to implement a robust monitoring strategy for marine plastic debris using direct EO measurements.

However one potential application which is currently being explored is the identification of distinct spectral signature of plastic picked up from Sentinel-2 SLSTR and Sentinel-3 OLCI data. In addition the Research & Development domain is working on a new generation of multi to hyper spectral near infrared (NIR) & short wave infrared (SWIR) sensors which are able to pick up the spectral signature of micro plastic in the sea. These two latter activities, together with detailed observation of the ocean dynamics in boundary habitats such as frontal zones (known to be hot spots of surface polymer aggregation), could eventually enable the monitoring of the floating plastic debris density indicator. However these technologies are not yet operational. As an alternative solution, efforts should focus on a robust characterization of the cycle of marine plastic, with EO being used to measure parameters at key points in the cycle where it is most suited. For example, one of the main entry points for plastic waste is rivers. However this requires an assumption of the percentage of total waste that is plastic. EO data could then inform models of river discharge, as suggested for indicator 6.6.1 (sub-indicator 3), form which plastic volume supplied to oceans could be inferred.

Chlorophyll-a data can be obtained from a number of optical satellite missions, including:

Sentinel-2 MSI[1] EU Copernicus satellite, supporting land and monitoring studies, including the monitoring of vegetation, soil and water cover, as well as observation of inland waterways and coastal areas.

Sentinel-3 OLCI EU Copernicus satellite(s), launched by ESA (European Space Agency) and operated by EUMETSAT (European Organisation for the Exploitation of Meteorological Satellites). Data available from 2016. Global coverage, max spatial resolution 300m, orbit cycle 27 days. Currently 1 satellite but shortly become a constellation of 2. The two in-orbit SENTINEL-3 satellites enable a short revisit time of less than two days for OLCI (Ocean and Land Colour Instrument).

ASTER-Terra NASA satellite carrying the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER). Global coverage. Data available form 1999.

MODIS-Aqua NASA satellite carrying a Moderate Resolution Imaging Spectroradiometer (MODIS). Global coverage, max spatial resolution 300m. Data available from 2002.

Landsat 8 NASA satellite. Launched in Feb 2013. Carrying the Thermal Infrared Sensor (TIRS) with 100m spatial resolution, and the Operational Land Imager (OLI) with 30m spatial resolution.

Archive satellite data sources:

SeaWiFS Sea-Viewing Wide Field-of-View Sensor. NASA satellite, no longer operational. Global coverage, spatial resolution 1.1km, historical data are available covering the period 1997-2010.

CZCS Coastal Zone Color Scanner. NASA satellite, no longer operational. Global coverage, max spatial resolution 800m, historical data available covering period 1978-1986.

Treatment of missing values

Missing values (e.g. due to cloud cover) can be estimated using models (hydrodynamic or mathematical gap filling procedures). In the absence of modelling, statistical measures could be taken, e.g. of monthly and seasonal average of the water body. This would ensure issues such as missing pixels are effectively corrected for and enable the compilation of year on year relative changes

Sources of discrepancies

For 14.1.1 (sub-indicator 1), remote sensing sensors detect Chlorophyll-a based on its absorption signal, meaning that a constant value between absorption and concentrations (called specific absorption coefficient) is assumed. However each phytoplankton species are present in different oceans and seas, resulting in distinctly different bloom seasons in many waterbodies. This requires different specific absorption coefficients, depending on the coastal

1 Some combination of S2 and S3 is needed – S2 channels are not optimized for Chlorophyll-a retrieval but S2/S3 fusion can enable extension of S3 measurements into areas requiring higher resolution data such as estuaries and lagoons

setting. This modification of the coefficients for different groups of phytoplankton species could introduce unwanted discrepancies when comparing Chlorophyll-a retrievals at the global level.

Limitations

For 14.1.1 (sub-indicator 1), the availability of ocean colour data from optical satellite imagery is dependent on the absence of clouds. However this is less of a problem than for other surface parameters as algal bloom growth is slower in cloudy conditions due to the lower light intensity. Nevertheless, a merged multi-sensor satellite remote sensing Chlorophyll-a dataset is available, covering the period 1997 to now. The sensors included in this merged product are: SeaWIFS, MERIS, MODIS, VIIRS and OLCI-A. Where data gaps exist, these can be filled by modelling or estimates based on data aggregates.

The achievable accuracy of the estimation of chlorophyll from optical satellite imagery depends greatly from the type of waters considered. In a most common classification, sea waters are classified as Case 1 and Case 2 waters (Morel & Bélanger, 2006). Case 1 waters belongs mostly to open sea areas or to oligotrophic coastal areas, in such areas the accuracy that can be achieved by EO data is very high. Case 2 waters are sediments dominated waters: for such waters the challenge is to separate the contribution to the measured signal of the water turbidity and of the atmosphere, and within the former to distinguish the component related to the chlorophyll (phytoplankton). Different algorithms exist which rely on different approaches to measure chlorophyll for Case 2 waters (for example, Moses et al., 2009) and in most cases while it is difficult to measure absolute values of chlorophyll with high accuracy, it is possible to find/evaluate trends and anomalies. For both Case 1 and Case 2 algorithms, the availability of reliable in situ measures/sampling to be used for calibration and validation is essential to achieve a high accuracy in the chlorophyll measurement.

Without measurement of further eutrophication parameters, it is not possible to determine whether Chlorophyll-a concentrations are linked to an (anthropogenic) increase in nutrients. Therefore, where possible, Chlorophyll-a should be supplemented by monitoring further eutrophication parameters, by means of traditional at sea sampling/measurements and/or by using of models which are able to merge different information (also satellite ones) to predict with good accuracy values of parameters like nitrates or dissolved oxygen. In addition, for many coastal areas it is necessary to understand the local ocean conditions (currents, temperature etc.) to understand what is driving Chlorophyll-a concentration variations.

For 14.1.1, (sub-indicator 2), there are serious limitations to what is possible to directly measure from EO. Therefore, as the bulk of marine plastic debris at sea originates on land, EO methods will focus on quantifying the land contribution of plastic debris, e.g. through river outflow.

Key messages for countries on EO contribution to the computation method

- This indicator is composed of two sub-indicators, on coastal eutrophication and floating plastic debris, for which provisional sub-indicators have been agreed until the sub-indicator methodologies have been finalised, due for roll-out by 2021.
- The agreed indicator for 14.1 is the Index of Coastal Eutrophication (ICEP); the ICEP methodology is currently being developed; it is based on concentrations and ratios of nitrogen, phosphorous and silica, which currently cannot be directly measured by remote sensing.
- The provisional sub-indicator 1 methodology, based on chlorophyll-a, does mention EO as a possible source of data. Furthermore, eutrophication can also be monitored remotely through images of harmful algal blooms and coloured dissolved organic matter.
- In coastal and inland waters chlorophyll-algorithms and methods are all experimental and site specific. There is no global and universally applicable EO method for Chlorophyll-a in the coastal zone.
- Many countries do not have validation data for satellite chlorophyll and absolute values of Chlorophyll-a (ug/l) will not be accurate. Hence a % change measure is recommended to report on the indicator.

Data sources

Data category	Data sources	Website
Source satellite data	Landsat 8	https://earthexplorer.usgs.gov/
	Sentinel data (1,2 and 3) from the Copernicus Open Access Hub	https://scihub.copernicus.eu/
	ASTER-Terra	http://asterweb.jpl.nasa.gov/
	MODIS-Aqua & Terra	https://oceancolor.gsfc.nasa.gov/
	SeaWiFS	https://oceancolor.gsfc.nasa.gov/data/seawifs/
	CZCS	https://oceancolor.gsfc.nasa.gov/data/czcs/

Data category	Data sources	Website
Software, tools and platforms	SeaDas (National Aeronautics and Space Administration)	https://seadas.gsfc.nasa.gov/
	Coastal Thematic Exploitation Platform	https://www.coastal-tep.eu/portal
	Sentinel Application Platform (SNAP)	http://step.esa.int/main/toolboxes/snap/
	Ocean Virtual Laboratory	https://ovl-project.oceandatalab.com/home
	Global Marine Information System	https://ec.europa.eu/jrc/en/scientific-tool/global-marine-information-system
	NOAA (National Oceanic and Atmospheric Administration) CoastWatch/OceanWatch	https://coastwatch.noaa.gov/cw_html/index.html
	NASA (National Aeronautics and Space Administration) OceanColor Web	https://oceancolor.gsfc.nasa.gov/data/overview/
	ChloroGIN data portal	www.chlorogin.org/index.php
	GlobColour	http://www.globcolour.info
Operational or commercial services	Copernicus Marine Environment Monitoring Service (CMEMS)	http://marine.copernicus.eu
	NASA Ocean Color	https://oceancolor.gsfc.nasa.gov/

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Reporting on coastal eutrophication in the Italian coastal zone using EO, in support of indicator 14.1.1

In Italy the Ministry for the protection of Environment and Sea (MATTM) is responsible to provide law directives for the SDG 14.1. For indicator 14.1.1, related to coastal eutrophication, the adopted benchmark values are those indicated by the Italian implementation of the European Marine Strategy Framework Directive (MSFD) through the legislative decree D.lgs 190/2010.

In particular the ministerial decree D.M. of 17/10/2014 specifies the environmental targets to determine the Good Environmental State (GES) and the following ministerial decree D.M. of 11/2/2015, identifies the specific indicators to be measured to evaluate coastal eutrophication. In this way chlorophyll and nitrates concentrations have been adopted as key parameters for 14.1.1

Current practice is based on in situ measurements and samplings performed regularly (usually monthly or bi-monthly) by local environmental authorities. Even if some pilots services have been implemented for evaluating the use of Earth Observation data for the MSFD (in particular chlorophyll and turbidity), currently it is not routinely employed in the measurement of chlorophyll due to these limitations: poor spatial resolution of existing satellite missions dedicated to measurement of ocean colour (ranging from 300m to few kilometres) and the lack of an extensive validation over the Italian territory. A promising improvement is currently being provided by hydrological and ecosystem models that merges different kinds of satellite data and (when) available in situ measurements to scale down the former and enrich the water parameters that can be evaluated. Some implementations based on models can be found in the Copernicus Marine Environment Monitoring Service (see data sources), which provides measurements of nitrates and chlorophyll. Such products have been used by ISPRA (Superior Institute for the Environmental Protection and Research) to obtain qualitative synergic views over the Italian coasts (see Figure 17), but they are not used as official sources mainly due to their coarse spatial resolution.

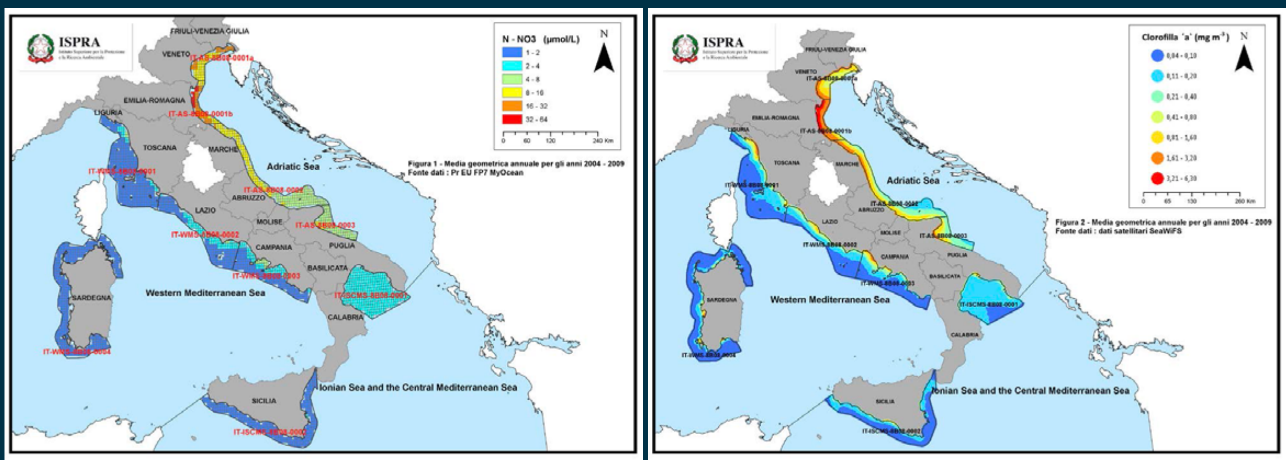


Figure 17: Geometric means of Nitrates concentration (left) and Chlorophyll-a concentration (right) for the years 2004-2009 obtained using products from the Copernicus Marine Environment Monitoring Service (former MyOcean) over the Italian coasts.
Credit: The Italian position with respect to the 17 SDGs http://www.minambiente.it/sites/default/files/archivio/allegati/sviluppo_sostenibile/posizionamento_Italia_SDGs_3.1_16012017_2.pdf

Indicators		14.1.1	Sub-Indicator 1: Index of Coastal Eutrophication	Provisional Sub-Indicator 1.1: Surface water chlorophyll	Sub-Indicator 2: Floating plastic debris density	Provisional Sub-Indicator 2.1: Beach litter
Custodian agency		UN Environment				
Tier		II	II	n/a	II	n/a
Status of step-by-step methodology document on the metadata repository		Unpublished (Tier III at the time of the analysis)	Unpublished (Tier III at the time of the analysis)	n/a	Unpublished (Tier III at the time of the analysis)	n/a
Relevance of EO for the indicator criteria	Maturity of EO technologies					
	Status of EO in indicator guidelines					n/a
	Technical capacity required					
	Availability of global EO data					
Robustness of proposed methodology Criteria	Compliance with Reporting calendar		n/a	n/a	n/a	
	Sensitivity to change					
	Is it scalable (spatial)?					
	Is there a substitute for gaps in the EO record?					
Overall EO relevance						
Comments to support criteria		See primary sub-indicators and provisional secondary sub-indicators for assessment	EO is applicable to this sub-indicator		EO is mentioned as a potential data source in the work plan for this sub-indicator; however, the EO methodology for measuring floating plastic debris density is still experimental.	This is being considered as a sub-indicator that is used provisionally while the methodology for floating plastic debris density is under development. EO methodology for measuring beach litter is still experimental.

Target 14.3

Minimize and address the impacts of ocean acidification, including through enhanced scientific cooperation at all levels

How can EO be used to help countries achieve the target?

As the ocean's biology and biochemistry is largely under sampled, this target presents a significant challenge for countries hence the stated need to enhance scientific cooperation at all levels. Nevertheless, this enhanced scientific cooperation should involve the remote sensing community, at least at the target level. For instance, EO can support countries in planning for and setting targets on minimising ocean acidification, as part of a wider climate change monitoring/management strategy. EO could help countries with significant marine areas to identify areas at risk from acidification and estimate their extent, e.g. of waters with aragonite close to its saturation level, below which organisms find it more difficult to form and retain their shells. EO can also be used as a diagnostic tool, e.g. to map the impacts of ocean acidification on coral reefs. The utility of the satellite measurements comes in obtaining a synoptic view where few or no in situ measurements of the carbonate system exist. Although EO is limited to the ocean surface layer, these observations are important because the change in carbonate chemistry due to atmospheric CO2 occurs in the ocean surface first.

Current Indicator(s)

14.3.1 Average marine acidity (pH) measured at agreed suite of representative sampling station

Short methodological guidelines illustrated with EO best practice examples

Indicator 14.3.1

Computation method

Indicator 14.3.1 adopts the International Panel on Climate Change (IPCC) Workshop on Impacts of Ocean Acidification (OA) on Marine Biology and Ecosystems definition of OA as "a reduction in the pH of the ocean over an extended period, typically decades or longer, which is caused primarily by uptake of carbon dioxide from the atmosphere, but can also be caused by other chemical additions or subtractions from the ocean." The indicator computational method is based on an in-situ sampling strategy in order to calculate the mean (monthly or annual) surface seawater pH and aragonite saturation state, based on ocean acidification observations. These observations must include: two parameters of the carbonate system (Dissolved Inorganic Carbon, total pH, pCO2, and total alkalinity), in situ seawater temperature, salinity, as well as relevant metadata, to be measured at an agreed suite of representative sampling stations. An agreed suite of representative sampling stations are sites that: 1) have a measurement frequency adequate to describe variability and trends in carbonate chemistry to deliver critical information on the exposure of and impacts on marine systems to ocean acidification, and 2) provide data of sufficient quality and with comprehensive metadata information to enable integration with data from other sites in the country.

Although EO is not mentioned in the work plan, satellites such as NASA's Aquarius (no longer operational), NASA's salinity sensor SMAP, and ESA's SMOS can measure ocean salinity globally. Coupled with EO-derived sea surface temperature (SST) measurements and surface chlorophyll-a, pH can be estimated using the empirical relationship derived from in-situ data. As EO based estimation of ocean acidity is reliant upon in-situ data observations, EO based methods cannot replace the need for in-situ data collection, however it could be used to derive spatially explicit datasets. Furthermore the utility of the EO-based method could be useful for identifying regions at risk from OA and the study of complex systems challenging for in situ monitoring such as river plumes and upwelling areas. The Copernicus Marine Environment Monitoring service (CMEMS) is launching a new product on Ocean Health in April 2019, which includes Ocean Acidification. The pH estimates in this product relies on in situ data from buoys, EO data on SST and salinity, auxiliary data on nitrate and dissolved silica and combines this within a modelling environment. The exact details of the product and accuracy assessments are not currently available.

Limitations

The EO algorithms in their current state have quite large uncertainties, unless at relatively coarse spatial resolutions, rendering them unsuitable for detecting fine-scale changes in pH expected from OA. The current proposed methodology requires that sample station observations must include: two parameters of the carbonate system (Dissolved Inorganic Carbon, total pH, pCO2, total alkalinity) and in situ seawater temperature and salinity. However only direct EO-based observations of salinity and sea surface temperature are currently feasible. The indicator methodology would have to be adapted to incorporate these observations globally while still relying on carbonate parameters from sampling stations. As salinity and temperature can be sampled relatively simply in-situ the use of EO-derived salinity and temperature from space is really in broad scale ocean acidification mapping, e.g. over a square kilometre or more. The utility of the satellite measurements therefore comes in obtaining a synoptic view where few or no in situ measurements exist (as mentioned in the introduction for target 14.3).

Key messages for countries on EO contribution to the computation method:

- This indicator methodology uses an ocean in-situ (buoys and ships) sampling approach for key parameters of importance for ocean pH in order to determine average pH from which anomalous deviations could indicate an acidification risk

- The methodology does not currently mention EO as a data source but models of global ocean acidification risk, inferred from EO derived salinity and sea surface temperature measurements (and possibly chlorophyll-a). These together with empirical algorithms to estimate carbonate system parameters, have been used to map OA risk, albeit at coarse spatial resolution (>1km) and with large uncertainties

- EO is therefore not yet ready for the precise monitoring required for the indicator but as EO based methods improve, there is a possibility that it could therefore become integrated into future iterations of the methodology, especially if enhanced scientific cooperation (between modellers, remote sensing experts and ocean scientists) is achieved in line with target 14.3

- The upcoming product from CMEMS on Ocean Acidification will allow easy access to updated data based partly on EO inputs. The accuracy of the product for national reporting should be evaluated before being used for SDG indicator reporting.

Data sources

Data category	Data sources	Website
Source satellite data	ESA Soil Moisture and Ocean Salinity (SMOS)	https://smos-diss.eo.esa.int/oads/access
	NASA Aquarius (no longer operational but a source of historical data):	https://aquarius.nasa.gov/data.html
	NASA Soil Moisture Active Passive (SMAP)	Meissner, T. and F. J. Wentz, (2016) Remote Sensing Systems SMAP Ocean Surface Salinities Level 3, Version 2.0 validated release. Remote Sensing Systems, Santa Rosa, CA, USA. Available online at www.remss.com/missions/smap, doi: 10.5067/SMP20-3SMCS
Operational products	Copernicus Marine Environment Monitoring Service - Ocean Health Monitoring Indicator	http://marine.copernicus.eu/science-learning/ocean-monitoring-indicators/catalogue

Reference List

Land, Peter E et al. 2015. "Salinity from Space Unlocks Satellite-Based Assessment of Ocean Acidification." Environmental Science & Technology 49(4): 1987–94. https://doi.org/10.1021/es504849s.

Salisbury, Joseph et al. 2015. "How Can Present and Future Satellite Missions Support Scientific Studies That Address Ocean Acidification?" Oceanography 25(2): 108–21. https://tos.org/oceanography/article/how-can-present-and-future-satellite-missions-support-scientific-studies-th.

Indicators		14.3.1 Average marine acidity (pH) measured at agreed suite of representative sampling station
Custodian agency		IOC-UNESCO
Tier		II
Status of step-by-step methodology document on the metadata repository		Unpublished (Tier III at the time of the analysis)
Relevance of EO for the indicator criteria	Maturity of EO technologies	
	Status of EO in indicator guidelines	n/a
	Technical capacity required	
	Availability of global EO data	
Robustness of proposed methodology Criteria	Compliance with Reporting calendar	
	Sensitivity to change	
	Is it scalable (spatial)?	
	Is there a substitute for gaps in the EO record?	
Overall EO relevance		
Comments to support criteria		EO algorithms for direct estimation of OA/pH have quite large uncertainties rendering them unsuitable for operational use, but EO products on salinity and SST are mature and are used in the CMEMS OA product.

Target 14.4

By 2020, effectively regulate harvesting and end overfishing, illegal, unreported and unregulated fishing and destructive fishing practices and implement science-based management plans, in order to restore fish stocks in the shortest time feasible, at least to levels that can produce maximum sustainable yield as determined by their biological characteristics

How can EO be used to help countries achieve the target?

This target is aimed at regulation through consistent reporting of overfishing as well as restoration of already depleted fish stocks. The most conservative estimates suggest that illegal, unreported and unregulated (IUU) fishing on the high seas, affecting species such as tunas and sharks, is worth US$1.25 billion annually (Global Ocean Commission, 2014). Current measures taken for implementing, monitoring and enforcing plans for fish stock conservation at the national level are mostly inadequate. Satellite remote sensing has the potential to improve plans for monitoring and management of fisheries in a number of ways (Stuart et al. 2011a). For example satellite data on ocean parameters such as temperature, salinity, phytoplankton and chlorophyll-a concentrations can help identify ocean areas where fish tend to aggregate (e.g. thermal fronts) and to estimate primary production. Studies have shown that satellite remote sensing of primary production in the ocean could be used to support fish stock assessments, for example, using ocean colour images to infer primary production and estimate global fish biomass. This would be particularly useful for this target given that the fish stock assessments demand high levels of technically capacity and data, which is currently lacking at country level. However, the uptake of satellite remote sensing in fisheries management has so far been limited. This is due to a number of reasons, including the spatial and temporal inadequacy of available ocean colour data for fisheries management purposes, lack of technical capacity to analyse remote sensing data sets, and the limited accuracy of ocean colour algorithms for coastal areas, where most fishing activities take place (Stuart et al. 2011b, Wilson 2011).

Current Indicator(s)

14.4.1 Proportion of fish stocks within biologically sustainable levels

Short methodological guidelines illustrated with EO best practice examples

Indicator 14.4.1

Computation method

The indicator measures the sustainability of fishery resources based on stock assessments (fish catch statistics, fishing effort, biological information, population dynamics models. The methodology is very well established and FAO has maintained and reported on this indicator since 1974. Yet; satellite remote sensing data can support fish stock assessments over vast areas of the ocean both within and outside national waters through estimates of ocean primary productivity. Non-EO data such as tracking fishing vessel movements could be used to strengthen the estimate of over fishing in areas of high primary productivity.

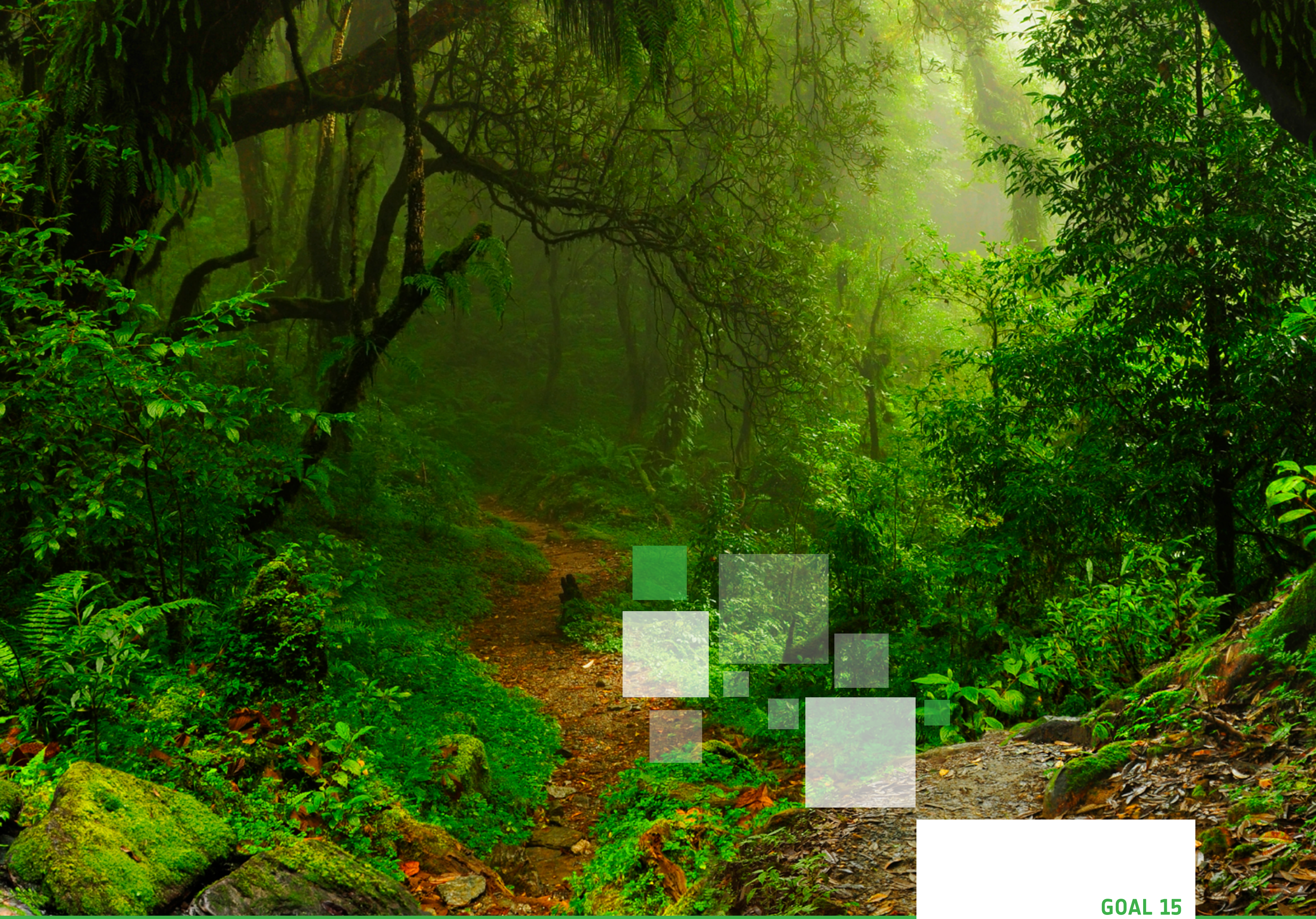
Limitations

The accuracy of ocean colour algorithms for coastal areas is limited, where most fishing activities take place.

Key messages for countries on EO contribution to the computation method

- Unregulated and unlicensed fishing is causing extreme pressure on global fish stocks as well as lost revenue for countries
- This indicator reports on the proportion of fish stocks within biologically sustainable levels
- It is using a tried and tested statistical methodology
- EO can however help improve estimates of fish socks especially in open ocean, based on the levels of ocean primary productivity inferred form measurements of ocean colour
- Areas of high primary productivity generally support higher fish stocks than area of lower productivity
- Non-EO data such as illegal fishing vessel movement tracking can be used to complement EO data and in order to identify where fish stocks are being unsustainably depleted, e.g. by overlaying on areas of high primary productivity or on zones where fisheries are protected

Indicators		14.4.1 Proportion of fish stocks within biologically sustainable levels
Custodian agency		FAO
Tier		I
Status of step-by-step methodology document on the metadata repository		Unpublished (Tier III at the time of the analysis)
Relevance of EO for the indicator criteria	Maturity of EO technologies	
	Status of EO in indicator guidelines	
	Technical capacity required	
	Availability of global EO data	
Robustness of proposed methodology Criteria	Compliance with Reporting calendar	
	Sensitivity to change	
	Is it scalable (spatial)?	
	Is there a substitute for gaps in the EO record?	
Overall EO relevance		
Comments to support criteria		Ocean colour remote sensing technologies are well established from which fish stocks can be inferred. Further work needed to estimate the sustainability of stocks from remote sensing.



GOAL 15

15 LIFE ON LAND

Target 15.1

By 2020, ensure the conservation, restoration and sustainable use of terrestrial and inland freshwater ecosystems and their services, in particular forests, wetlands, mountains and drylands, in line with obligations under international agreements.

How can EO be used to help countries achieve the target?

This target aims to ensure sustainable management and monitoring, and use of terrestrial ecosystems including freshwater ecosystems and their restoration. It is an ambitious target which considers the interrelatedness of life in different elements of terrestrial ecosystems - mountains, wetlands, arid lands and forests and that the health of one part impacts the other.

EO can play multiple roles in achieving the target as it is a crucial part of the monitoring strategies for conservation, restoration and sustainable use of terrestrial ecosystems. The availability of multi-decadal time series datasets of the (global) land surface from multiple satellite sensors means that there are fewer remote sensing data gaps and greater ability to monitor long term changes over greater areas. Multi-scale land-cover information can be retrieved over whole countries which, complemented with field data, can support integrated land use plans, including evaluation of the services provided by terrestrial and freshwater ecosystems. Remote sensing data coupled with modelling tools can support the identification of priority areas for ecosystem services provision that needs specific management activities. It can also be used to monitor the effectiveness of restoration activities planned for these sites or to assess their status over time. Optical or radar sensors, or a combination of the two, can detect not just forest cover area, but also other attributes as wetlands, lakes and to estimate their biophysical parameters, as well as surface and volume measures.

Existing indicators primarily report on the extent to which areas are conserved (15.1.2) or sustainably used (15.1.1), therefore, there is a gap for an indicator on the restoration of these ecosystems. For example, indicator 15.1.1 only includes forest areas – drylands and mountains are considered under indicators 15.3.1, 15.4.1 and 15.4.2. Similarly, freshwater ecosystems are monitored using indicator 6.6.1 – so are not considered under target 15.1.

EO has a lot of potential here as it can effectively monitor land cover change over time with high accuracy both at very high to high spatial resolution. The identification of terrestrial and inland freshwater ecosystems which have been modified by humans paves the way for a tool that could identify areas for habitat restoration. Moreover, FAO is custodian of these SDGs and will work closely with other partners.

Current Indicator(s):

15.1.1 Forest area as a proportion of total land area

15.1.2 Proportion of important sites for terrestrial and freshwater biodiversity that are covered by protected areas, by ecosystem type

Potential new indicator(s) based on EO:

Proportion of terrestrial and freshwater ecosystems restored

Short methodological guidelines illustrated with EO best practice examples

Indicator 15.1.1

Computation method

This indicator is calculated from national data on forest that FAO has been collecting since 1946, as part of the Global Forest Resources Assessment (FRA). Each country provides this data to FAO following a standard format, which includes raw data files. Based on this national data, forest statistics are produced and archived in the FAO Statistical Database (FAOSTAT). This data is complemented with data from the global Remote Sensing survey conducted by FAO in conjunction with the European Commission's Joint Research Centre (JRC) for 1990, 2000 and 2010. However, in the 2020 FRA the online reporting platform provides correspondents with access to global remote sensing products via Collect Earth (Bey et al., 2016).

EO, mostly in combination with ground observations, are widely used to produce forest cover maps at the national and sub-national level, and thus to determine the proportion of land covered by forests. Freely available Landsat satellite images at 30m resolutions and Sentinels missions' data from the European Copernicus programme can be processed to generate national, regional or global forest cover maps, e.g. as has been done for the Global Forest Change product (Hansen et al., 2013). In particular Sentinel-2 mission can provide high-resolution imaging (from 10 to 60m resolution) for land monitoring, including imagery of vegetation, soil and water cover, inland waterways and coastal areas.

Different land cover classification techniques can be used, classifiers such as Random Forest, Gaussian Mixture Model classifier, Support Vector Machines or K-Nearest neighbours, have been widely used and tested (Noi & Kappas, 2017). Validation using ground truth data is a critical final step that ensures the accuracy of the final map (Rwanga & Ndambuki, 2017).

Countries can also opt to generate the statistics on their national forests based on a sample based approach. Therefore, they can use freely available tools such as the Collect Earth developed by FAO's Open Foris initiative (FAO Forestry Department), which enables to collect land cover/ land use at point locations using Google Earth imager in a user-friendly and easy way.

Global products, such as the Global Forest Change developed by independent laboratories such as the University of Maryland's Global Land Analysis and Discover laboratory (GLAD) (Hansen et al., 2013), and by initiatives such as the Global Forest Watch, which builds on GLAD data, can also be used and aggregated at the country level and complemented with field surveys if necessary. These products should be validated at the country level in order to be used as data for national use. The combination of EO based products with reference data not only reduces bias, but also provides an estimate of uncertainty for the indicator in the form of a confidence interval.

Disaggregation

Disaggregation can be by spatial unit, such as administrative districts, or by forest type, but only by broad categories such as deciduous, coniferous and mixed forests for example. This is because the seasonality of the vegetation within these forest types is relatively easy to discriminate with time series of satellite imagery. Spatial disaggregation requires sufficient reference data and class disaggregation is heavily dependent on spectral and phenological behaviours of different forest types. It is also important that all countries use the same definition of forest (such as the FAO definition) – this will allow easier comparison.
Treatment of missing values

Missing values because of cloud cover can be treated using different EO sensor types such as radar (e.g. a new algorithms under development using Sentinel-1), using ground observations or image composites.

Regional aggregates

Regional aggregation is possible, by disaggregation of a global forest product for example, but when the forest classification is performed at the national scale, the use of different types of EO as well as different techniques can hinder the possibility of meaningfully aggregating the country products.

Sources of discrepancies

Different definitions of forests across countries can generate discrepancies, as well as the use of different products, at different resolution across countries. The quality of input imagery and training data as well as classification methods are also a large source of discrepancy.

Limitations

The definition of forest used (FAO, FRA or other) as well as the difficulties in discriminating among land cover types, in particular in dry areas, is a limitation in using EO. Moreover, if the goal is to map land use, field data or other auxiliary data are required. Using optical EO data in cloudy regions is challenging and it might require the use of radar data. The technical capacity necessary to process images can be a limitation in many countries.

Key messages for countries on EO contribution to the computation method:

- EO are widely used to report on forest cover extent and strong methodologies are established to accurately classify forest/non forest areas.
- Dry forest systems are more difficult to map using optical EO data, because can be easily confused with grasslands. The use of radar and/or VHR data is preferable for this forest type. Radar data should also be used in regions characterised by persistent cloud cover.
- The availability of online platforms and free global data, e.g. through Collect Earth, allows countries to easily report on forest cover extent, but this should always be combined with ground observations to validate and improve upon forest cover estimates derived from global EO products

Data sources

Data category	Data sources	Website
Source satellite data	Landsat data	*https://earthexplorer.usgs.gov/*
	Sentinel from the Copernicus Open Access Hub	*https://scihub.copernicus.eu/*
Global/regional datasets	Global Forest Watch	*https://www.globalforestwatch.org/*
	University of Maryland's Global Land Analysis and Discovery laboratory	*https://glad.umd.edu/*
Software, tools and platforms	Open Foris, of the FAO, a collection of free and open source tools for EO-based environmental monitoring	*http://www.openforis.org*
	SEPAL: System for Earth Observation Data Access, Processing and Analysis for Land Monitoring	*https://sepal.io*
	Forestry TEP	*https://f-tep.com*

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Bey, A.; Sánchez-Paus Díaz, A.; Maniatis, D.; Marchi, G.; Mollicone, D.; Ricci, S.; Bastin, J.-F.; Moore, R.; Federici, S.; Rezende, M.; Patriarca, C.; Turia, R.; Gamoga, G.; Abe, H.; Kaidong, E.; Miceli, G. (2016) Collect Earth: Land Use and Land Cover Assessment through Augmented Visual Interpretation. Remote Sensing, 8, 807.

Hansen, M. C., et al. (2013) 'High-Resolution Global Maps of 21st-Century Forest Cover Change' Science 342 (15 November): 850–53. Data available on-line from: http://earthenginepartners.appspot.com/science-2013-global-forest.

Mitchard, E. (2016) 'A Review of Earth Observation Methods for Detecting and Measuring Forest Change in the Tropics'. Ecometrica, Edingburgh, UK

Noi, P.T. and Kappas, M. (2017) 'Comparison of Random Forest, k-Nearest Neighbor, and Support Vector Machine Classifiers for Land Cover Classification Using Sentinel-2 Imagery'. Sensors. 18, 18.

Rose et al. (2014) 'Ten ways remote sensing can contribute to conservation'. Conserv. Biol. 29, 350–359.
Rwanga, S.S. and Ndambuki, J.M. (2017) 'Accuracy Assessment of Land Use/Land Cover Classification Using Remote Sensing and GIS'. International Journal of Geosciences, 8, 611-622.

Sass, G. Z. et al. (2012) Defining protected area boundaries based on vascular-plant species richness using hydrological information derived from archived satellite imagery. Biol. Conserv. 147, 143–152.

Townshend, J. R. et al. (2012) 'Global characterization and monitoring of forest cover using Landsat data: Opportunities and challenges', International Journal of Digital Earth. Taylor & Francis, 5(5), pp. 373–397. doi: 10.1080/17538947.2012.713190.

Further Reading and Resources

FAO and SDGs (2018) Keeping an eye on SDG 15 – Working with countries to measure indicators for forests and mountains. Available to download at: http://www.fao.org/3/a-i7334e.pdf

GFOI (2016) 'Integration of remote-sensing and ground-based observations for estimation of emissions and removals of greenhouse gases in forests: Methods and Guidance from the Global Forest Observation Initiative'. Edition 2.0, Food and Agriculture Organization, Rome.

Hestir, E.L. et al. (2015) 'Measuring freshwater aquatic ecosystems: The need for a hyperspectral global mapping satellite mission'. Remote Sensing of Environment. 167, 181-195.

IUCN (2016) A Global Standard for the Identification of Key Biodiversity Areas, Version 1.0. First edition. Gland, Switzerland: IUCN.

McRoberts, R.E. (2011) 'Satellite image-based maps: Scientific inference or pretty pictures?' Remote Sensing of Environment, 115(2), 715-724.

UNEP-WCMC (2017). World Database on Protected Areas User Manual 1.5. UNEP-WCMC: Cambridge, UK. Available at: http://wcmc.io/WDPA_Manual

Forest cover mapping in Gabon to calculate forest area (indicator 15.1.1)

Forest cover maps were produced in collaboration with the Gabonese Agency for Space Studies and Observations (AGEOS) for 1990, 2000, 2010 and 2015 for the whole country. The maps were constructed using a combination of a semi-automated classification procedure and manual enhancements to ensure the highest possible level of accuracy. A two-stage area frame sampling approach was adopted to collect reference data for assessing the accuracy of the forest cover maps and to produce forest cover and forest cover change area estimates. A total of 665 2x2 km segments or primary sample units (PSUs) were visually interpreted by a team of photo-interpreters independently from the production team and produced a reference data set representing about 1% of the study area. Paired observations were extracted from the forest cover map and the reference data for a random selection of 50 pixels or secondary sample units (SSUs) for each PSU. Overall map accuracies greater than 0.95 were achieved. PSUs and SSUs outputs were used to produce forest cover and forest cover change area estimates using both direct expansion and model-assisted regression (MAR) estimators. All area estimates were similar, but the variances of the MAR forest cover area estimates were smaller by factors as great as 50 than direct expansion estimates. In 2010, 88.30 ± 0.26% of Gabon is covered by forest. In addition despite large overall map accuracies, deforestation estimates obtained from the maps alone can be misleading as indicated by the finding that the adjusted estimates of net change were twice the non-adjusted map estimates (for periods 1990-2000 and 1990-2010). The results confirmed the expected generally low level of deforestation for Gabon. However, net deforestation appears to have almost stopped in the last 10 years, which could be linked to the implementation of forest concession management plans from 2000 onward. Deforestation increased again from 2010 to 2015 largely due to the development of large project as shown below:

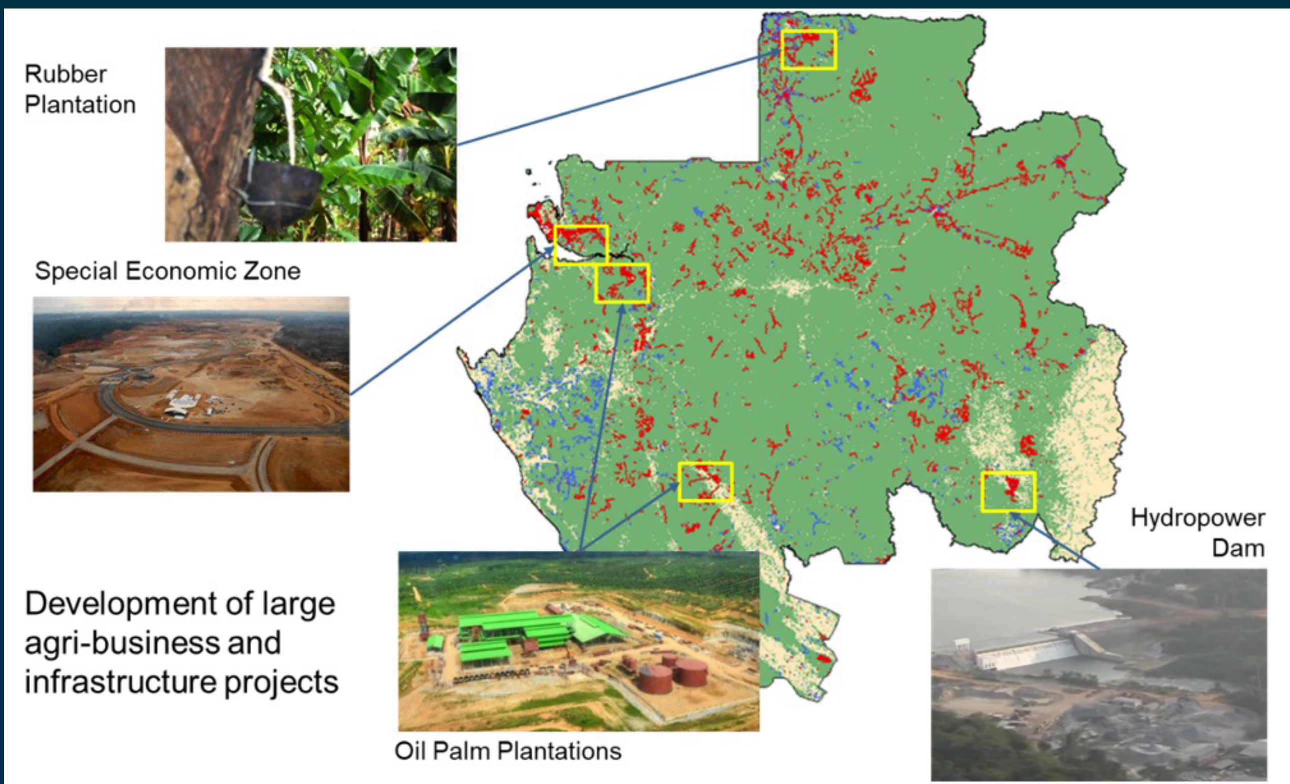

Figure 18: Extent of forest in Gabon in 2015 and main causes of deforestation.
Credit: Christophe Sannier

Indicator 15.1.2

Computation method

This indicator is calculated from data derived from a spatial overlap between digital polygons for protected areas from the World Database on Protected Areas (IUCN & UNEP-WCMC 2017) and digital polygons for terrestrial and freshwater Key Biodiversity Areas (KBA) from the World Database of KBA, including Important Bird and Biodiversity Areas, Alliance for Zero Extinction sites, and other KBA. The indicator tracks the mean percentage [%] of each KBA that is covered by protected areas in order to better reflect trends in protected area coverage for countries or regions with few or no KBA.

As discussed above, EO are widely used to derive information on biophysical aspects of terrestrial and inland freshwater ecosystems and their services. Protected Areas and KBAs are often correlated with biophysical aspects, e.g. by following a mountain ridge or a river but their boundaries are not defined by such biophysical aspects (Sass et al 2012). Instead, both PAs and KBAs have their boundaries defined through a diverse series of potential mechanisms, for example participatory mapping involving local communities. EO does have the potential in helping define KBA boundaries, for example through using 'extent of suitable habitat' to define proportion of a global population of a species (criteria A1, B1, B2) or extent of a threatened habitat (criteria A2). These criteria are explained in the KBA standard document (IUCN, 2016).

Limitations

The singular limitation of using EO data to calculate indicator 15.1.2 is the inability of automated remote-sensed data to capture spatially defined areas that reflect human decision-making rather than physical/biological features. EO data could conceivably aid in the delineation of KBAs and PAs, but not in their identification.

Key messages for countries on EO contribution to the computation method:

- Indicator 15.1.2 is based on a well-established methodology that uses the mean percentage [%] of each Key Biodiversity Area that is covered by protected areas in order to better reflect trends in protected area coverage for countries or regions with few or no Key Biodiversity Areas (KBA)
- EO data can be successfully used to (i) separate terrestrial from freshwater ecosystems and map their ecosystem types and (ii) delineate the edges of protected areas, e.g. based on biophysical features such as lake shores, as well as to assess certain KBA criteria such as extent of suitable habitat
- EO will not be able to replace certain aspects of the indicator computational such as participatory mapping by communities in proximity to KBAs

Data sources

Data category	Data sources	Website
Global/regional datasets	World Database on Protected Areas	*https://www.protectedplanet.net/*
	World Database on Key Biodiversity Areas	*http://www.keybiodiversityareas.org/home*

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Ban, Y., Gong, P. and Giri, C. (2015) 'Global land cover mapping using Earth observation satellite data: Recent progresses and challenges', ISPRS Journal of Photogrammetry and ..., 103, pp. 1–6. doi: 10.1016/j.isprsjprs.2015.01.001.

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Sass, G. Z. et al. (2012) Defining protected area boundaries based on vascular-plant species richness using hydrological information derived from archived satellite imagery. Biol. Conserv. 147, 143–152.

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Further Reading and Resources

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Hestir, E.L. et al. (2015) 'Measuring freshwater aquatic ecosystems: The need for a hyperspectral global mapping satellite mission'. Remote Sensing of Environment. 167, 181-195.

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UNEP-WCMC (2017). World Database on Protected Areas User Manual 1.5. UNEP-WCMC: Cambridge, UK. Available at: http://wcmc.io/WDPA_Manual

Indicators 15 LIFE ON LAND		15.1.1 Forest area as a proportion of total land area	15.1.2 Proportion of important sites for terrestrial and freshwater biodiversity that are covered by protected areas, by ecosystem type
Custodian agency		FAO	UNEP-WCMC; UNEP; IUCN
Tier		I	I
Status of step-by-step methodology document on the metadata repository		Published	Published
Relevance of EO for the indicator criteria	Maturity of EO technologies		
	Status of EO in indicator guidelines		
	Technical capacity required		
	Availability of global EO data		
Robustness of proposed methodology Criteria	Compliance with Reporting calendar		
	Sensitivity to change		
	Is it scalable (spatial)?		
	Is there a substitute for gaps in the EO record?		
Overall EO relevance			
Comments to support criteria		Reliable methods are established and widely used to extrapolate forest cover data from EO. One of the strengths of using EO is the possibility of detecting change, unless the area of interest is located in cloudy regions. The combination of EO based products with sampled reference data can produce reliable change estimates.	EO can separate terrestrial from freshwater ecosystem types (e.g. wetland, mangrove, forest, grassland etc.). However the indicator uses management as well as biophysical factors to identify important sites for biodiversity.

Target 15.2

By 2020, promote the implementation of sustainable management of all types of forests, halt deforestation, restore degraded forests and substantially increase afforestation and reforestation globally

How can EO be used to help countries achieve the target?

Forests are a key terrestrial ecosystem, providing various ecosystem services, including food, biodiversity, protection from soil erosion, climate change mitigation. This ecosystem is rapidly disappearing, "thirteen million hectares of forests are being lost every year while the persistent degradation of drylands has led to the desertification of 3.6 billion hectares", and this indicates the need for effective strategies to reduce deforestation and implement sustainable forest and land management practices. Together with target 15.1, this target ensures that forests are efficiently managed, and a sustainable balance between conservation and the use of natural resources is achieved. EO can be used to assess the change in forest extent and quality (e.g. degradation), but also to plan for the effective implementation of activities aiming to achieve the sustainable management of forest. Satellite images and subsequent analyses can help to identify sites where to implement reforestation and afforestation activities, as well as areas that are at higher risk of deforestation because of past forest clearing for agriculture or because of the proximity to infrastructures such as roads, and their protection should be prioritised. Different types of EO sensor systems are available (optical, radar and LiDAR) and can be used to map forest change based on type of forest, climatic conditions, technical capacity available in the country. Mapping forest degradation and biomass change is generally more challenging than monitoring forest extent, but new promising methods are being developed and tested.

Current indicator(s)

15.2.1 Progress towards sustainable forest management

Short methodological guidelines illustrated with EO best practice examples

Indicator 15.2.1

Computation method

Countries already report directly to the FAO on forest area, biomass stock, forest area within protected areas, forest area under a management plan and forest area under an independently verified forest management scheme. FAO then applies the compound interest formula to make estimates of the forest area net change rate, as well as the proportion of forest area within protected area and under a management plan. Countries report on forest cover using a combination of remote sensing data and national forest inventory.

Sub-indicator a: Forest area net change rate
Sub-indicator b: Above-ground biomass stock in forest
Sub-indicator c: Proportion of forest area located within legally established protect areas
Sub-indicator d: Proportion of forest area under a long term forest management plan
Sub-indicator e: Forest area under an independently verified forest management certification scheme

Sub-Indicator a – Forest area net change rate: EO are widely used to monitor forest extent. Freely available Landsat images (30m resolution) and Sentinel-2 images (10 – 20m resolution) can be used to map changes of forest at the national and sub-national scale. This approach can be easily used for monitoring deforestation in medium/low cloud regions like boreal forests. However, for regions with high cloud cover such as the Amazon forest, the Congo Basin, and Malaysia/Indonesia, or where the biophysical environment is complex, forest monitoring is more challenging (Mitchard, 2016). Combinations of Landsat and Sentinel-2 can be used to increase their individual temporal resolution and further combinations with Sentinel-1 in areas where cloud cover is persistent, but in many cases Radar can be the best option. Forest area mapping approaches are reliant on 2D classification of SAR backscatter or automated change analysis applied to calibrated time-series. Estimates of forest height and biomass are possible using L-band data. P-band SAR penetrates vegetation canopies to a greater depth, but there are no currently operational P-band SARs. However, the European Space Agency P-band BIOMASS mission is scheduled for launch around 2021. A lot of radar datasets are commercial datasets, such as ALOS PALSAR (12.5 m) and TerraSAR-X (6 m). Therefore, data availability can be an issue in using Radar to monitor deforestation.

As described in Mitchard (2016) at least three approaches can be used to estimate deforestation, comparing one-time layers, time series analyses and machine learning algorithms. The first approach, which is the most widely used, compares classified forest layers (e.g. forest/no-forest) at different points in time. The accuracy of the input layers are critical for this method to be valid. The time series analyses compare a series of observations of the same forest parameter for example the Normalised Difference Vegetation Index (NDVI) using a specific algorithm. These time-series should include more than one observation/year in order to avoid errors due to seasonality or cloud cover. Algorithms, such as pixel-based Break detection For Additive Seasonal Trends (BFAST) monitor (Mitchell et al., 2017), try to distinguish either a sudden break-point (for example due to a deforestation/degradation event) or a long-term trend (for example forest regrowth/forest degradation), from the natural variation that can be due just to seasonality (Mitchard, 2016). Machine learning algorithm, for example artificial neural networks, based on back propagation training algorithm, have also been used, mostly when more than one vegetation parameter

or spectral band, are used to detect forest change. The initial computational development of the algorithm can be expensive, but once the specific algorithm has been developed can be run easily. The model developed is valid just for the type of forests for which it has been trained, for different contexts new models needs to be generated.
Global and regional deforestation datasets are also currently freely available and can be used as baselines or downscaled at the national level. The coverage of these datasets goes from global to regional or at the country level (GLAD; Hansen et al., 2013 and 2016; Camara et al., 2013; PRODES 2016); their spatial resolution from 30m to 500 m and their temporal resolution can be annual, monthly or bi-weekly. Considering the reporting frequency of 5 years the use of the global products downscaled at the country level can be used and provide a more systematic reporting of this indicator. Initiatives such as Open Foris by FAO and Global Forest Watch provide tools that can easily be used by countries to map their forest. In particular within Open Foris the tool Collect Earth enables country to collect data through Google Earth and assess their forest cover extent and to monitor its changes. The Global Forest Observation Initiative provides methodological advice on the joint use of remotely sensed and ground-based data to countries for forest monitoring and Green House Gas reporting (GFOI MGD 2.0, 2016).

Sub-Indicator b – Above-ground brown biomass stock in forest: Above-ground brown biomass, i.e. woody components such as the tree trunk and branches, requires the use of field plots and EO data. Traditional SAR and optical observations can be used to extract biomass values, but ground truth training data is required (Laurin et al., 2018).

Artificial neuronal network (ANN) techniques have been used to integrate remotely-sensed satellite data and field inventory data and thus estimate forest biomass. Some studies show that vegetation indices such as normalized difference vegetation index (NDVI), shortwave infrared (SWIR) band reflectance, transformed normalized difference vegetation index (TNDVI), soil adjusted vegetation index (SAVI), principal component analysis (PCA) and difference vegetation index (DVI) are suitable to predict forest biomass, by using optical EO data, but field plots are still necessary to calibrate the models at the country level (Nandy et al., 2017).

The biomass change is more difficult to detect using current EO technology. LiDAR and SAR tomography are the only suitable techniques, but are both rather expensive and need high technical expertise. Global data on biomass are also available and can potentially be downscaled at the national level and be used as baseline. The main datasets are Avitabile et al. (2016) at 1 km resolution and GlobBiomass (Santoro et al., 2018) developed using Radar data at 100m resolution. The Global Forest Observation Initiative (GFOI) has also developed a set of methods and guidelines for estimating carbon stocks using EO data such as Landsat and Sentinel, and ground based observations, which can support countries.

Recently launched (ICESat-2, SAOCOM) and upcoming missions (GEDI, MOLI, NISAR, ALOS-4, BIOMASS) from various space agencies have biomass estimation as primary or secondary objective. It is expected that they will have a strong impact on the accuracy of biomass estimation from space.

Sub-Indicator c – Proportion of forest area located within legally established protect areas, **Sub-Indicator d** – Proportion of forest area under a long term forest management plan, **Sub-Indicator e** – Forest area under an independently verified forest management certification scheme: the proportion of forest located within these forest management categories can be extracted from the forest datasets used to detect changes in forest extent, as long as updated shapefiles of the boundaries of these forest management areas of interest are available.

Disaggregation

Spatial disaggregation can be carried out to downscale the data at the protected area level and other forest management types scale. Temporal disaggregation can also be performed thanks to the regular production of EO data.

Treatment of missing values

The combination of different types of EO data, such as the use of radar in cloudy areas, and at different resolutions (e.g. EO at less than 10m resolution) can be used to treat missing values. Regional and global products can also be used to fill gaps.

Regional aggregates

If using global products the regional aggregations is possible, but in case different deforestation detection methods are used the aggregation can be more difficult.
Sources of discrepancies

Discrepancies related to forest changes can arise based on the techniques used to detect deforestation and to the definition of forest used. The regional aggregation can also produce discrepancies if different forest change detection methods are used. National definitions of forest sometimes contradict the biophysical view of EO sensors that just observe tree cover. Furthermore the use of the tree cover, e.g. for industrial logging, is not easily discerned from EO data. The discrepancies between EO-derived forest extent and national statistics have been well documented (Tropek et al., 2014). Discrepancies related to forest biomass are associated with uncertainties in retrieval but also the prevailing environmental conditions which can vary between acquisitions even for the same forest area. SAR sensitivity to biomass also varies with frequency, with C-and X-band tending to saturate at low biomass levels while L and P bands are more sensitive to medium and high biomass respectively. Data fusion approaches may help overcome sensor specific limitations such as saturation, operating modes and temporal gaps.

Limitations

The main limitations are related to the persistent cloud cover in many areas when using optical EO data for forest area and change mapping, the complexity of some ecosystems, seasonality and the technical capacity required to perform the EO data analyses often unavailable. Errors of commission or omission appear in EO-derived forest cover change products based on the techniques used to detect deforestation. While SAR is a powerful alternative it is limited by less frequent observation relative to optical sensors and fewer source of freely available data.

Biomass does not change naturally as quickly as other forest parameters and is often driven by subtle processes of degradation not easily detectable using optical sensors. Although the use of LiDAR could overcome these issues, airborne LiDAR is currently not sufficiently affordable to governments to acquire multi-year and wall-to-wall, other than for local projects. Although not yet spaceborne, there are experimental space LIDAR missions such as GEDI which had just been launched from the International Space Station (ISS) by NASA. The technical capacity required to estimate biomass from EO and ground-observation, can represent a limitation for many countries.

Key messages for countries on EO contribution to the computation method

- The sustainable management of forest can be monitored and planned through EO thanks to well established methodologies and the availability of global datasets and open source platforms

- Monitoring forest biomass stock and their changes through EO is challenging, but new technologies and methods are becoming available to users with the required technical capacity to work with radar data for example. Consensus methods which combine optical, SAR, Interferometric SAR (InSAR) and LiDAR tend to be the most effective at overcoming the limitation of each of these EO technologies used in isolation.

- Ground observations are still needed to complement EO data to monitor forest cover change and biomass stocks

Data sources

Data category	Data sources	Website
Source satellite data	Landsat	https://earthexplorer.usgs.gov/
	Sentinel data (1,2 and 3) from the Copernicus Open Access Hub	https://scihub.copernicus.eu/
Global/regional datasets (forest biomass)	Pan-tropical biomass map	https://www.wur.nl/en/Research-Results/Chair-groups/Environmental-Sciences/Laboratory-of-Geo-information-Science-and-Remote-Sensing/Research/Integrated-land-monitoring/Forest_Biomass.htm
	GlobBiomass (global terrestrial biomass map for 2010)	http://globbiomass.org/products/global-mapping
Global/regional datasets (forest cover and change)	University of Maryland's Global Land Analysis and Discovery laboratory generates near real time deforestation alerts	https://glad.umd.edu
	Global Forest Watch (global change 2000-2017)	https://www.globalforestwatch.org/
	PRODES (Amazon change 2004 to 2018)	http://www.obt.inpe.br/prodes/index.php
Software, tools and platforms	Global Forest Observation Initiative (GFOI) Methods and Guidance Documentation aimed at REDD+ Measurement, Reporting, and Verification	http://www.gfoi.org/methods-guidance/
	Open Foris, of the FAO, a collection of free and open source tools for EO-based environmental monitoring	http://www.openforis.org
	SEPAL: System for Earth Observation Data Access, Processing and Analysis for Land Monitoring	https://sepal.io
	Forestry TEP	https://f-tep.com

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Further reading and resources

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Indicators 15 LIFE ON LAND		15.2.1	Sub-Indicator a: Forest area net change rate	Sub-Indicator b: Above-ground biomass stock in forest	Sub-Indicator c: Forest area within legally established protect areas	Sub-Indicator d: forest area under a management plan	Sub-Indicator e: Forest area under management certification scheme
Custodian agency		FAO					
Tier		I	n/a	n/a	n/a	n/a	n/a
Status of step-by-step methodology document on the metadata repository		Published					
Relevance of EO for the indicator criteria	Maturity of EO technologies						
	Status of EO in indicator guidelines						
	Technical capacity required						
	Availability of global EO data						
Robustness of proposed methodology Criteria	Compliance with Reporting calendar						
	Sensitivity to change						
	Is it scalable (spatial)?						
	Is there a substitute for gaps in the EO record?						
Overall EO relevance							
Comments to support criteria			EO are widely used to map forest cover, but in several context the misinterpretation of forest as non-forest or the detection of degraded forest can be challenging and requires higher technical capacity.	Changes in biomass can be detected using EO tool such as LiDAR and SAR tomography, but the technology is not fully mature, often expensive and requires a high level of expertise.	Forest area can be derived from EO. However, boundaries of protected areas are required, which cannot be derived from EO data.	Only possible in combination with in-situ data.	Only possible in combination with in-situ data.

Target 15.3

By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world

How can EO be used to help countries achieve the target?

Land degradation, defined as "a state whereby the amount and quality of land resources necessary to support ecosystem functions and services and enhance food security remain stable or increase within specified temporal and spatial scales and ecosystems" (decision 3/COP.12, UNCCD, 2015a) is negatively impacting the well-being of billions of people (IPBES, 2018). Already at this point, there have been a number of global initiatives aiming to halt land degradation and restore degraded land. The global community's efforts to halt desertification, maintain and restore land and soil productivity, and to mitigate the effects of drought are spearheaded by the United Nations Convention to Combat Desertification (UNCCD) which was adopted in Paris on 17 June 1994. As the dynamics of land, climate and biodiversity are intimately connected, the UNCCD collaborates closely with the other two Rio Conventions; the Convention on Biological Diversity (CBD) and the United Nations Framework Convention on Climate Change (UNFCCC). The vision of the UNCCD aligns in particular with the CBD's Aichi Biodiversity Target 15, which aim to restore at least 15% of degraded ecosystems; the Bonn Challenge (2011) and its regional initiatives to restore more than 150 million hectares; and most recently, the UN Sustainable Development Goals (SDGs) (Sims et al. 2017). Target 15.3 is strongly aligned with the land degradation neutrality (LDN) target setting process of the UNCCD which is supporting interested countries (now) through a dedicated target setting programme (TSP), including the definition of national baselines, targets and associated measures to achieve LDN by 2030. While 120 countries are in the process of setting voluntary targets, 80 countries already have. As part of the TSP, the UNCCD has selected data partners to assist countries with data for target setting in the absence of national data. These include the ISRIC soil grids, the JRC Land productivity dynamics data layer and the ESA-CCI land cover. All of these global datasets are reliant on EO data as inputs thereby directly contributing to countries in the LDN Target Setting Program.

Current Indicator(s)

15.3.1: Proportion of land that is degraded over total land area, with three sub-indicators capturing trends in land cover, land productivity, and carbon stocks.

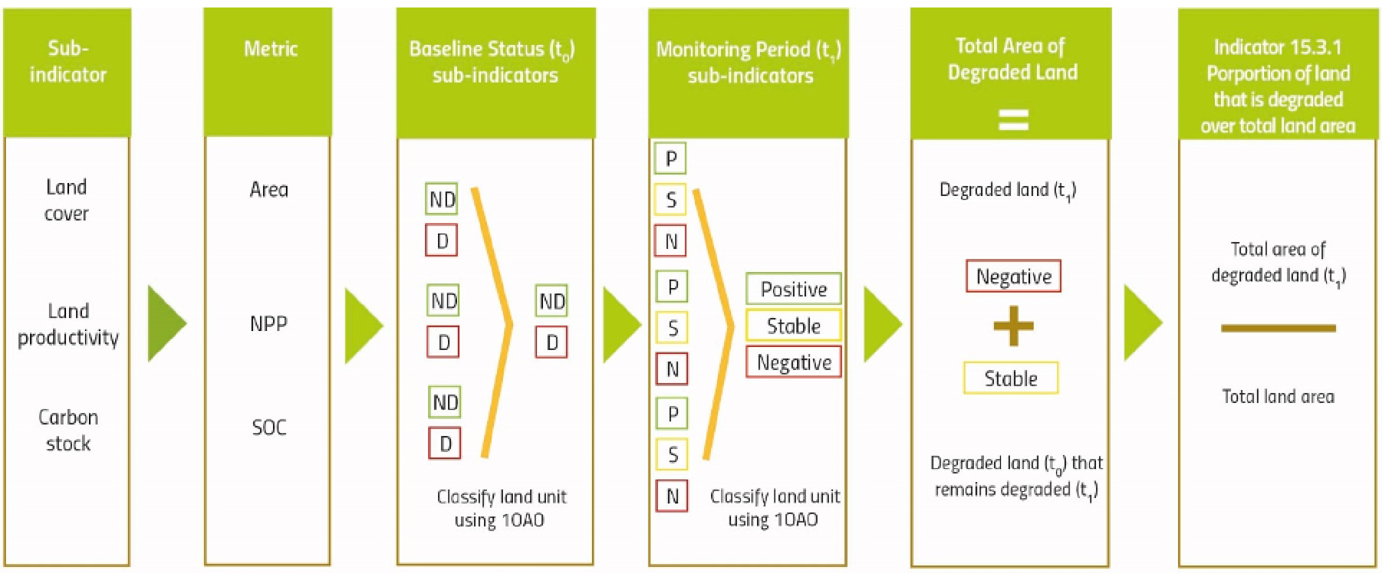
Short methodological guidelines illustrated with EO best practice examples

Indicator 15.3.1

Computation method

The indicator falls under official reporting to the UNCCD, and as custodian agency it has already established a universal methodology for reporting on SDG 15.3.1, documented in the Good Practice Guidance (GPG, Version 1.0, 2017), which explicitly considers EO for reporting purposes. However, the potential for land degradation can already be detected using EO to estimate other drivers of change, as is used in the convergence of evidence approach (see discrepancies section).

The current indicator 15.3.1 methodology is a binary - degraded/not degraded - quantification based on the assessment of available data for three sub-indicators, namely Land cover and land cover changes, land productivity changes and carbon stock changes, to be validated and reported by national authorities. The sub-indicators were adopted by the UNCCD's governing body in 2013 as part of its monitoring and evaluation approach. They represent proxies that ought to reflect the capacity of the land to deliver ecosystem services and changes have to



be assessed and depicted as (i) positive or improving, (ii) negative or declining, or (iii) stable or unchanging.

Based on the evaluation of the changes, the proportion of land that is degraded over total land area (%) is calculated following a "One out all out" (1OAO) principle, defined by the Scientific Conceptual Framework of the LDN (Land Degradation Neutrality) (see Figure below). That is, if one of the sub-indicators is negative (or stable when degraded in the baseline or previous monitoring year) for a particular land unit, the particular area is considered as degraded. The baseline for assessment is established over the period 2000 to 2015, with the base year being 2015. All changes are assessed relative to the baseline value with a reporting interval of 4 years, starting in the year 2018. Countries are responsible for submitting national reports to UNCCD.

For each of the sub-indicators, countries can access a wide range of global and generic data sources, including Earth observation (EO) and geospatial information, while at the same time ensuring national ownership.

For land cover and land cover change, a range of global EO-derived products are available at coarse resolution (see Data Sources section), which generally detail the distribution of vegetation types, water bodies and human-made infrastructure, and reflect the use of land resources (i.e., soil, water and biodiversity) for agriculture, forestry, human settlements and other purposes. These datasets differ in the number of classes in which they describe the landscape, their spatial resolution and duration. National land cover datasets can more accurately represent the range of land cover types that exists in the respective country.

There is an international standard for land cover which includes the Land Cover Meta Language (LCML), a common reference structure (statistical standard) for the comparison and integration of data for any generic land cover classification system. LCML is also used for defining land cover and ecosystem functional units used in the SEEA, and closely linked to the Intergovernmental Panel on Climate Change (IPCC) classification on land cover/land use. The IPCC land use change legend suggests six main classes (forest land, grassland, cropland, wetlands, settlements and other lands) which should be considered as a minimum set. Changes in landcover are identified as degradation or not using a transition matrix, in which reporting authorities have the opportunity to nominate which transitions to identify as degraded for their country (see below).

Note: This sub-indicator is also expected to be used for reporting on SDG indicators 6.6.1, 11.3.1 and 15.1.1.

A large variety of methods exist to estimate land productivity and its associated changes from EO data sources. The sub-indicator refers to the total above-ground net primary production (NPP) defined as the energy fixed by plants minus their respiration which translates into the rate of biomass accumulation that delivers ecosystem services. While the ability to calculate changes in NPP in specific units such as tonnes/ha is preferred, changes in a unitless proxy of productivity, such as the NDVI or other vegetation index, can equally be used to identify degradation through relative changes in productivity over time. However, calibration and validation of the EO-based observations of productivity against field data can be a challenging task and requires a solid in situ data basis.

The sub-indicator on carbon stocks, above and belowground is currently represented as a provisional proxy by Soil Organic Carbon (SOC) stocks. In UNCCD decision 22/COP.11, soil organic carbon (SOC) stock was adopted as the metric to be used with the understanding that this metric will be replaced by total terrestrial system carbon stocks,

Final Class

Original Class

IPCC Class	Forest Land	Grassland	Cropland	Wetlands	Settlements	Other Land
Forest Land	Stable	Vegetation loss	Deforestation	Inundation	Deforestation	Vegetation loss
Grassland	Afforestation	Stable	Agricultural expansion	Inundation	Urban expansion	Vegetation loss
Cropland	Afforestation	Withdrawal of Agriculture	Stable	Inundation	Urban expansion	Vegetation loss
Wetlands	Woody Encroachment	Wetland drainage	Wetland drainage	Stable	Wetland drainage	Wetland drainage
Settlements	Afforestation	Vegetation establishment	Agricultural expansion	Wetland establishment	Stable	Withdrawal of Settlements
Other Land	Afforestation	Vegetation establishment	Agricultural expansion	Wetland establishment	Urban expansion	Stable

once operational. SOC is an indicator of overall soil quality associated with nutrient cycling and its aggregate stability and structure with direct implications for water infiltration, soil biodiversity, vulnerability to erosion, and ultimately the productivity of vegetation, and in agricultural contexts, yields. For carbon stocks, IPCC (2006 & 2019) contains the most relevant definitions and standards related to soil infrastructure, and data transfer. EO methods can also be used to estimate aboveground carbon stocks, but SOC will be used until methods to measure total terrestrial carbon stock is operational and robust. The methodological approaches range from using default values based on land cover type which are modified by a range of use factors similar to those described in the IPCC processes, to highly detailed country-specific digital soil mapping, calibrated and validated using process-based models.

Already at this point, Conservation International (CI) together with Lund University, and the National Aeronautics and Space Administration (NASA), have developed a platform for monitoring land change using EO in an innovative desktop and cloud-based system with the support of the Global Environment Facility (GEF). The Trends.Earth tool box draws on a variety of different data sources including the Normalized Difference Vegetation Index (NDVI), soil moisture, precipitation, evapotranspiration, land cover, soil carbon, agro-ecological zones as well as administrative boundaries. The toolbox is able to estimate the three sub-indicators for monitoring the achievement of LDN and can be used by countries to analyse the data as well as to report to UNCCD.

Treatment of missing values

In case no data or information is available at country level for any sub-indicator, there exists a wide range of regional and global EO derived products with an acceptable spatial resolution to derive estimates for all three sub-indicators (See data sources section). The land area of countries with missing values (with no default data) are proposed to be excluded from regional and global aggregation.

Sources of discrepancies

Differences between global and national figures may arise due to differences in spatial resolution of datasets, classification approaches (i.e. definition of land cover classes or difference in classifying methods) and/or contextualization with other indicators, data and information. In such cases, the use of regional and global datasets derived from EO can play a role in clarifying such discrepancies. Alternatively, the convergence of evidence approach, adopted by the World Atlas of Desertification of the JRC, could be used to resolve discrepancies arising from the 1OAO principle. Convergence of reliable, global evidence of human environment, in the form of global change issues (GCIs) at a location suggests a potential for land degradation (at least in some form). The GCIs are a mixture of biophysical and socio-economic drivers, and were selected because of their availability as global data and their usefulness as factors associated with land degradation (WAD, 2018).

Limitations

While access to remote sensing imagery has improved dramatically in recent years, there is still a need for essential historical time series that is currently only available at coarse to medium spatial resolution. This resolution can represent an issue especially in mountainous areas, small island states and highly fragmented landscapes (GEO, 2017). There is an urgent need to move to high resolution datasets (GEO, 2017).

Some aspects of land degradation, such as the loss of biodiversity and ecosystems services are not currently included in the UNCCD definition of Land Degradation and may also be not well captured by EO methods.

While land productivity is not difficult to monitor from an EO points of view, for example by using a vegetation index time series, it is more difficult to determine if the land productivity trend observed corresponds to degradation. For example, bush encroachment or the presence of invasive plant species will feature a positive trend in land productivity but it is seen as land degradation.

Although, global coarse to medium resolution EO datasets are delivering acceptable results for reporting of the progress under Agenda 2030, efforts should be focused on the incorporation of high resolution satellite EO imagery as a starting point for the further development and improvement of the SDG reporting system of indicator 15.3.1

For raw data, data sources include:

- Landsat-5 to 8 archive to derive the baseline period as well as the base year 2015
- Sentinel-2 for monitoring and reporting starting from the year 2016 and onwards
- Sentinel-1 (evaluate potential for integration)

Existing products (with coverage exceeding national or regional initiatives) include:

- Pan-European Copernicus High resolution Layers (HRL) for imperviousness, forest, grasslands, water and wetness as well as small woody features for the year 2015 at 20m resolution
- S2 prototype LC 20m map of Africa 2016
- Copernicus Dynamic Land Cover map at 100 m resolution produced annually for the entire globe

Key messages for countries on EO contribution to the computation method

- The sub-indicators of indicator 15.3.1 are theoretically well suited to an EO-based methodology but the strengths and limitations of the EO approach must be carefully understood in order to be compliant with the sub-indicator requirements, e.g. on assessing land degradation from a land productivity point of view not a biophysical one

- The sub-indicator on carbon stocks, above and belowground is currently the most challenging. It will take more time to harmonise EO-based methods of above ground carbon assessment with other methods of soil organic carbon quantification before this sub-indicator is robust enough for EO.

- The other sub-indicators can use EO more readily as methods for land cover and land productivity mapping are well established. However, the limitations are that these sub-indicators may not be available at the appropriate spatial scale and that land productivity must be quantified from a degradation perspective

- Although indicator 15.3.1 adopts the “One out all out” principle, a convergence of evidence approach was used in the World Atlas of Desertification to map areas vulnerable to land degradation. Some of the global change issues which could indicate degradation at a location are mapped by EO.

Data sources

Sub-indicator 15.3.1 on Land Cover and Land Cover Change

Data category	Data sources	Website
Global/regional datasets	ESA CCI Land Cover	https://climate.esa.int/en/projects/land-cover
	SEEA-MODIS	https://search.earthdata.nasa.gov
	Copernicus Global Land Cover	https://land.copernicus.eu/global/products/lc
	World Atlas of Desertification	https://wad.jrc.ec.europa.eu/

Sub-indicator 15.3.1 on Land Productivity

Data category	Data sources	Website
Global/regional datasets	Copernicus Global Land Service products	*https://land.copernicus.eu/global/*
	SEEA-MODIS	*https://search.earthdata.nasa.gov*
	Land Productivity Dynamics	*http://publications.jrc.ec.europa.eu/repository/handle/JRC80541*
	World Atlas of Desertification	*https://wad.jrc.ec.europa.eu/*

Sub-indicator 15.3.1 on Carbon Stocks, Above and Belowground

Data category	Data sources	Website
Global/regional datasets	Harmonized World Soil Database (HWSD)	*http://webarchive.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML*
	SoilGrids	*https://soilgrids.org*
	Global Soil Organic Carbon Map (GSOC)	*http://54.229.242.119/GSOCmap/*
	World Atlas of Desertification	*https://wad.jrc.ec.europa.eu/*

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Further Reading and Resources

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Tutorials on UNCCD PRAIS reporting: https://knowledge.unccd.int/knowledge-products-and-pillars/access-capacity-policy-support-technology-tools/tutorials-unccd
Trends.Earth: a platform from Conservation International for monitoring land change using earth observations in an innovative desktop and cloud-based system.

LDN Scientific Conceptual Framework (2017). Scientific Conceptual Framework for Land Degradation Neutrality. A report of the Science-Policy Interface. Available at: https://www.unccd.int/publications/scientific-conceptual-framework-land-degradation-neutrality-report-science-policy

Earth as a tool for calculating 15.3.1 in Uganda

Trends.Earth, developed by Conservation International in corporation with NASA and Lund University, under funding of the Global Environment Facility, is a tool to integrate national level data with globally available EO datasets to calculate SDG indicator 15.3.1 (proportion of degraded land). It is based on standardised methods, while also providing the flexibility for customisation to local conditions. The tool uses data from three sub-indicators –land cover, vegetation productivity and soil organic carbon - to estimate the degraded land area and is able to produce spatial explicit information (Figure 19).

For each Sub-indicator, changes have to be assessed and depicted as (i) positive or improving, (ii) negative or declining, or (iii) stable or unchanging. Based on the evaluation of the changes in these three sub-indicators, the proportion of land that is degraded over total land area (%) is calculated and reported as a binary (i.e. degraded/not degraded) quantification as required by SDG target indicator 15.3.1.

Figure 19: Overview of the SDG 15.3.1 Sub-Indicators.

The quantification follows the so called “One out all out” (1OAO) principle. That is, if one of the sub-indicators is negative (or stable when degraded in the baseline or previous monitoring year) for a particular land unit, then the particular area would be considered as degraded. The baseline is established over the period 2000 to 2015, with the base year being 2015. All changes are assessed relative to the baseline value with a reporting interval of 4 years, starting in the year 2018. The land degradation assessment is illustrated in Figure 20.

The method for calculating SDG indicator 15.3.1 is extensively described in the Good Practice Guidance (GPG) developed by UNCCD. In collaboration with UNCCD, the Trends. Earth team, as of November 2018, has trained over 400 people – from representatives of national statistics offices and ministries of environment, to academic and non-profit users – on how to use the tool for reporting purposes. Access to simplified summaries of spatial outputs were greatly appreciated by users to simplify obtaining the data they needed directly in the format required for reporting.

Lessons learned:
A key need that Trends.Earth users identified is the importance of support for local and nationally available information to supplement EO data. Particularly for analyses of land cover and carbon stocks, country representatives noted the limitations of globally available EO data in some areas.

Figure 20: Schematic illustration of Trends.Earth processing and results for Uganda.

Credit: Franziska Albrecht (GeoVille)

Indicators		15.3.1	Sub-Indicator on Trends in land cover	Sub-Indicator on trends in land productivity	Sub-Indicator on trends in carbon stocks, above and below ground.
Custodian agency		UNCCD			
Tier		II	n/a	n/a	n/a
Status of step-by-step methodology document on the metadata repository		Published			
Relevance of EO for the indicator criteria	Maturity of EO technologies				
	Status of EO in indicator guidelines				
	Technical capacity required				
	Availability of global EO data				
Robustness of proposed methodology Criteria	Compliance with Reporting calendar				
	Sensitivity to change				
	Is it scalable (spatial)?				
	Is there a substitute for gaps in the EO record?				
Overall EO relevance					
Comments to support criteria			There is sufficient evidence to suggest that EO could fully support countries in the production of this indicator as land cover is widely available and routinely monitored.	There is sufficient evidence to suggest that EO could fully support countries in the production of this indicator as land productivity proxies are routinely monitored.	Carbon stock monitoring using EO data has advanced but challenges remain to trend detection as comparability between different time periods is limited by changes in EO and lack of robust time series

Target 15.4

By 2030, ensure the conservation of mountain ecosystems, including their biodiversity, in order to enhance their capacity to provide benefits that are essential for sustainable development

How can EO be used to help countries achieve the target?

Mountain ecosystems are hotspots of biodiversity and provide essential ecosystem services for population living in and beyond mountain areas. Accordingly, their safeguard is of primary importance to help achieving certain SGDs. This is explicitly recognized in SDG 15 through this target, which is fully dedicated to conserving mountain ecosystems so that their biodiversity and the services that flow from them are not in peril and are sustained in the long term.

EO can help support the conservation and sustainable management of mountain ecosystems through multiple ways. The applicability of EO to monitor land use dynamics and the drivers of land use change, such as expansion of human settlements or crop conversion, as well as their implications for biodiversity, has been extensively proven. EO data, such as Digital Elevation Models (DEMs) or data on climate and dynamic processes, can also be used to feed models that assess the supply of and demand for mountain ecosystem services. These models, in turn, could be combined with information derived from climate or land use change scenarios to assess how the provision of ecosystems services could be affected by them, allowing to identify priority areas to implement adaptation actions.

Current Indicator(s):

15.4.1 Coverage by protected areas of important sites for mountain biodiversity

15.4.2 Mountain Green Cover Index.

Potential new indicator(s) based on EO

Given that mountain ecosystems have been highlighted as one of the most vulnerable to climate change, the degree of vulnerability to climate change could also be considered by countries in order achieve this target. Mountain snow and ice are the main control parameters of the hydrological cycle of many watersheds. The melting glaciers and decrease in snow volume may therefore affect water availability for the population living in and outside mountain areas. An indicator focusing on the proportion of snow and ice cover in mountain areas could easily be developed using EO methods and would provide valuable insights on the effects of climate change on regional water availability.

While indicator 15.4.2 is relevant, it may not be able to fully capture some of the main drivers of mountain ecosystem degradation processes such as overgrazing, pollution, invasive species and fuelwood extraction or timber extraction, as these processes do not always translate into land cover/land use conversion. An additional indicator focusing on ecosystem functioning, such as vegetation productivity, may be appropriate to complement the current set of indicators.

Given the importance of human pressures on mountain biodiversity and ecosystem service use and demand, an EO-based socio-economic indicator, such as population density in mountain areas would possibly be meaningful as well; especially also in view of the link between demography and land use.

Short methodological guidelines illustrated with EO best practice examples

Indicator 15.4.1

Computation method

This indicator is calculated from data derived from a spatial overlap between digital polygons of protected areas included in the World Database on Protected Areas (IUCN & UNEP-WCMC 2017), Key Biodiversity Areas (from the World Database of Key Biodiversity Areas, including Important Bird and Biodiversity Areas, Alliance for Zero Extinction sites, and other Key Biodiversity Areas; available through the Integrated Biodiversity Assessment Tool), and mountains (UNEP-WCMC 2002). The indicator is computed as the mean percentage of each mountain Key Biodiversity Area currently recognised that is covered by protected areas.

Sources of discrepancies

Protected areas are not static measures, they continually change in response to the varying pressures they face. Despite concerted efforts by UNEP-WCMC in collaboration with national, regional and international partners the World Database on Protected Areas (WDPA) is not always entirely up-to-date. As such, there can be discrepancies between national statistics and those calculated by state parties on national protected area coverage.

Limitations

The indicator does not measure the effectiveness of protected areas in reducing biodiversity loss, which ultimately depends on a range of management and enforcement factors not covered by the indicator. Regarding important sites, the biggest limitation is that site identification to date has focused on specific subsets of biodiversity, for example birds (for Important Bird and Biodiversity Areas) and highly threatened species (for Alliance for Zero Extinction sites).

An additional limitation is that PAs don't protect elevational gradients uniformly across continents (Elsen et al., 2018) and not sufficiently either to preserve biodiversity, especially under climate change.

Key messages for countries on EO contribution to the computation method:

- Indicator 15.4.1 is based on a well-established methodology that uses the mean percentage [%] of each mountain Key Biodiversity Area that is covered by protected areas in order to better reflect trends in protected area coverage for countries or regions with few or no mountain Key Biodiversity Areas (KBA).
- It is not employing any EO data in the computational method but could feasibly use it to (i) identify mountain ecosystem types (such as mountain bioclimatic belts) by incorporating a Digital Elevation Models (Körner et al., 2011) and (ii) delineate the edges of protected areas in mountains, e.g. based on biophysical features such as lake shores, as well as to assess certain KBA criterion such as extent of suitable habitat.
- Besides topography, direct use of EO for 15.4.1 is not obvious but their indirect use for the monitoring and assessment of biodiversity and ecosystems (and change therein) is easy to imagine.

Data sources

Data category	Data sources	Website
Global/regional datasets	The World Database on Protected areas, as accessible via Protected Planet	*www.protectedplanet.net*
	The World Database on Key Biodiversity Areas, as accessible via BirdLife	*http://www.keybiodiversityareas.org/home*
	Global Mountain Explorer	*https://rmgsc.cr.usgs.gov/gme*
	Socio-Economic Data and Application Center:	*http://sedac.ciesin.columbia.edu*

Reference List

Bey, A.; Sánchez-Paus Díaz, A.; Maniatis, D.; Marchi, G.; Mollicone, D.; Ricci, S.; Bastin, J.-F.; Moore, R.; Federici, S.; Rezende, M.; Patriarca, C.; Turia, R.; Gamoga, G.; Abe, H.; Kaidong, E.; Miceli, G. (2016) Collect Earth: Land Use and Land Cover Assessment through Augmented Visual Interpretation. Remote Sensing, 8, 807.

Elsen, P. R., Monahan, W. B. and Merenlender, A. M. (2018) 'Global patterns of protection of elevational gradients in mountain ranges', Proceedings of the National Academy of Sciences, 115(23), p. 6004 LP-6009. Available at: http://www.pnas.org/content/115/23/6004.abstract.

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Körner, C., Paulsen, J. and Spehn, E. M. (2011) 'A definition of mountains and their bioclimatic belts for global comparisons of biodiversity data', Alpine Botany, 121(2), p. 73. doi: 10.1007/s00035-011-0094-4.

Open access EO data and web tools for watching over the Alps for planning towards target 15.4

Remoteness and complex topographies represent major challenges for the acquisition of data on the state of and trends in mountain ecosystems, their biodiversity, and the ecosystem resources they provide, including water and timber. Yet such data are critically needed to develop sustainable pathways towards the long-term conservation of mountain ecosystems and their biodiversity. EO is therefore a critical component toward acquiring the biological and physical parameters to monitor environmental processes in mountains and support the proactive management of natural assets. In the European Alps, the acquisition and delivery of reliable up-to-date information is achieved with the Sentinel Alpine Observatory (SAO). The SAO is an initiative of Eurac Research-Institute for Earth Observation that gathers more than 10 years of expertise in remote sensing-based environmental monitoring in the alpine region of South Tyrol, Italy. Thanks to innovative methodologies for the exploitation of the new sensor technology on board the Copernicus Sentinel satellites, the SAO provides users of Earth Observation data in the alpine region with a range of map products related to key environmental parameters extracted from Sentinel data as well as a range of services. The products comprise:

- Level 2 data (Sentinel-2 RGB, Sentinel-2 surface reflectance, Sentinel-1 backscatter),
- Water and cryosphere data (snow, glacier, permafrost, evapotranspiration, soil moisture)
- Vegetation and land use dynamics data (grass leaf area index, Normalized Difference Vegetation Index, forest cover change)
- Natural hazards data (landslide monitoring)

These products are made available for unrestricted use to the scientific community through a user-friendly web GIS platform. Services include a catalogue to publish and access data at different scales, cloud-computing services to perform customized analysis on the data, and web tools for visualization and interactive analysis of Sentinel data time series.

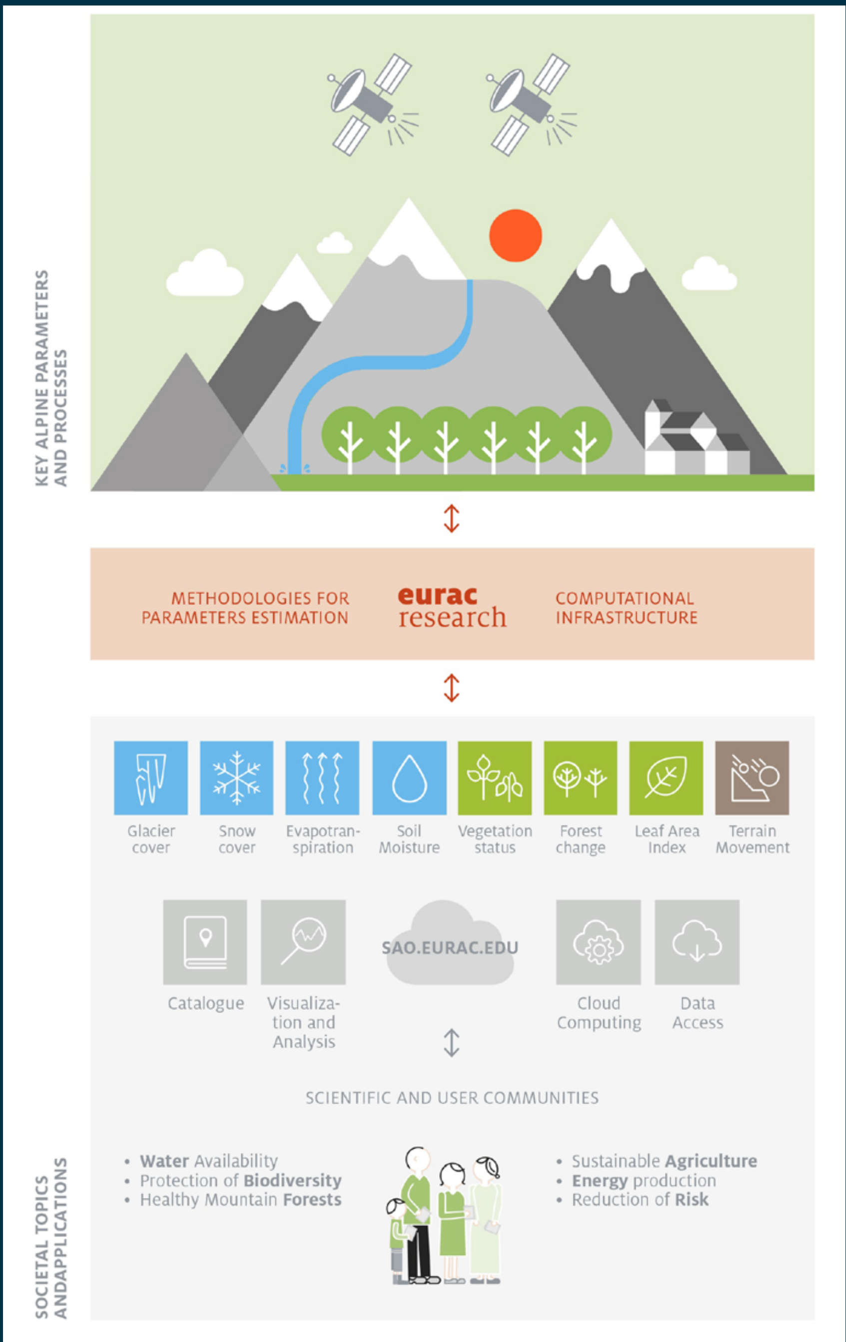

Figure 21: Sentinel Alpine Observatory (Source: http://sao.eurac.edu/sao/#mission)

Indicator 15.4.1

Computation method

The Mountain Green Cover Index, or SDG indicator 15.4.2, measures changes in the area of green vegetation in mountain areas. Mountain areas are defined according to UNEP-WCMC (Kapos et al. 2000), which classifies mountains in 6 different classes based on a combination of elevation and ruggedness. These classes are:

Class 1: elevation > 4,500 metres
Class 2: elevation 3,500 – 4,500 metres
Class 3: elevation 2,500 – 3,500 metres
Class 4: elevation 1,500 – 2,500 metres and slope > 2
Class 5: elevation 1,000 –1,500 metres and slope > 5 or local elevation range (LER 7 kilometre radius) > 300 meters
Class 6: elevation 300 – 1,000 metres and local elevation range (7 kilometre radius) > 300 meters

Changes in the area of green vegetation are reported as the change of the proportion of the area covered by 3 IPCC land cover/land use classes (forest, grassland/shrubland and cropland). This figure is expressed as a percentage of the total mountain area.

Remote sensing methods can contribute to the assessment of changes in land cover in mountain areas. As indicated in the indicator's metadata, these changes can be estimated using Collect Earth (Bey et al. 2016), based on the visual interpretation of medium to high resolution multi-temporal satellite images from DigitalGlobe, SPOT, Sentinel 2, Landsat and MODIS imagery within Google Earth, Bing Maps and Google Earth Engine. Image resolution ranges from 3 cm to 250 meters. Data and images are stored and made globally available for any year from 2000. The changes in land cover are assessed using a sample-based approach. Collect Earth allows the user to distribute sampling plots in 3 different ways: Systematic, Random and Stratified Random. The result is a grid of sampling plots, in which each plot is classified according to the dominant land cover by the user.

Disaggregation

This indicator is disaggregated by the mountain classes defined by Kapos et al. (2000). The disaggregation by mountain areas can be carried out with the help of EO derived products such as digital elevation models. A global map of mountains based on UNEP-WCMC classification was produced using these products in 2015 by the Mountain Partnership Secretariat at the Food and Agriculture Organization of the United Nations.

Treatment of missing values

The visual interpretation of satellite images can give rise to missing values due to cloud cover, especially in tropical areas. However, considering that only one value of land cover class is needed per year for a given area, the proportion of missing values is expected to be very low, given the high variety of imagery available in Collect Earth. In cases with persistent cloud cover, radar data could be potentially used as a substitute.

Sources of discrepancies

Protected areas are not static measures, they continually change in response to the varying pressures they face. Despite concerted efforts by UNEP-WCMC in collaboration with national, regional and international partners the World Database on Protected Areas (WDPA) is not always entirely up-to-date. As such, there can be discrepancies between national statistics and those calculated by state parties on national protected area coverage.

Limitations

The sampling density established by FAO (a systematic grid of 500 000 plots, half hectare each plot, 16 km grid) may not be high enough to produce a fully representative dataset for all countries. Some countries may need to complement this and collect more data, especially for countries with highly heterogeneous mountain landscapes.

Key messages for countries on EO contribution to the computation method:

- Indicator 15.4.2 is fully based on EO data, but does not allow to fully capture some of the main drivers of mountain ecosystem degradation processes affecting vegetation such as overgrazing, fuelwood and timber extraction or forest to cropland conversion, which has important implications for biodiversity in mountain ecosystems of the world.

Data sources

Data category	Data sources	Website
Global/regional datasets	Shuttle Radar Topography Mission (SRTM) 1 arc-sec global	*https://earthdata.nasa.gov/nasa-shuttle-radar-topography-mission-srtm-version-3-0-global-1-arc-second-data-released-over-asia-and-australia*
	ASTER DEM 30 m global	*https://asterweb.jpl.nasa.gov/gdem.asp*
	Precise Global Digital 3D Map "ALOS World 3D"	*https://www.eorc.jaxa.jp/ALOS/en/aw3d/index_e.htm*
	OpenTopography	*https://opentopography.org/*
Software, tools and platforms	Collect Earth	*http://www.openforis.org/tools/collect-earth.html*
	Global Mountain Explorer	*https://rmgsc.cr.usgs.gov/gme/*

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Körner, C., Paulsen, J. and Spehn, E. M. (2011) 'A definition of mountains and their bioclimatic belts for global comparisons of biodiversity data', Alpine Botany, 121(2), p. 73. doi: 10.1007/s00035-011-0094-4.

Indicators 15 LIFE ON LAND		15.4.1 Goverage by protected areas of important sites for mountain biodiversity	15.4.2 Mountain Green Cover Index
Custodian agency		UNEP-WCMC; UNEP; IUCN	FAO
Tier		I	I
Status of step-by-step methodology document on the metadata repository		Published	Published
Relevance of EO for the indicator criteria	Maturity of EO technologies		
	Status of EO in indicator guidelines		
	Technical capacity required		
	Availability of global EO data		
Robustness of proposed methodology Criteria	Compliance with Reporting calendar		
	Sensitivity to change		
	Is it scalable (spatial)?		
	Is there a substitute for gaps in the EO record?		
Overall EO relevance			
Comments to support criteria		EO data could be useful if there are a set of mountain-specific essential biodiversity variables that are identified and if EO data get collected at the right resolution for these variables, accounting for the fact that mountain ranges vary greatly in their nature, topography, ecology, etc. between countries.	The methodology to assess this indicator is fully based on EO data. The methodology proposes the use of a tool (Collect Earth) that is freely available and for which training materials are abundant.

LIST OF ACRONYMS AND ABBREVIATIONS

AAAA	Addis Ababa Action Agenda
AET	Actual Evapotranspiration
AGEOS	Gabonese Agency for Space Studies and Observations
AHT SDG	Ad-Hoc Team on Sustainable Development Goals
ALOS	Advanced land Observing Satellite
ANN	Artificial Neuronal Network
ASA	Advisory Services and Analytics
ASAR	Advanced Synthetic Aperture Radar
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
ATSR	Along Track Scanning Radiometer
AVHRR	Advanced Very High Resolution Radiometer
BFAST	pixel-based Break Detection for Additive Seasonal Trends
BLI	BirdLife International
CCI	Climate Change Iniative
CDOM	Colored dissolved organic matter
CEOS C	ommittee on Earth Observation Satellites
CMEMS	Copernicus Marine Environment Monitoring Service
CSIRO	Commonwealth Scientific and Industrial Research Organisation
CZCS	Coastal Zone Color Scanner
DAAC	Distributed Active Archive Centre
DEM	Digital Elevation Model
DG-JRC	Directorate General – Joint Research Council
DHS	Demographic and Health Surveys
DLR	German Aerospace Centre
EDC	Euro Data Cube
EG-ISGI	Expert Group on the Integration of Statistica and Geospatial Information
EM-DAT	Emergency Events Database
EMS	Copernicus Emergency Management Service
EO	Earth Observations
EO4SDG	Earth Observation for Sustainable Development Goals
ESA	European Space Agency
ESDC	Earth System Data Cube
ET	Evapotranspiration
ETM+	Enhanced Thematic Mapper Plus
EVI	Enhanced Vegetation Index
FAPAR	Fraction of Absorbed Photosynthetically Active Radiation
FAO	Food and Agricultural Organisation
FAOSTAT	FAO Statistical Database
FEWS	RFE Famine Early Warning Systems Rainfall Estimates
fCover	fraction of Green Vegetation Cover
fPAR	fraction of Photosynthetically Active Radiation
FRA	Forest Resources Assessment
GEDI	Global Ecosystem Dynamics Investigation Lidar
GEO	Group on Earth Observations
GEOBIA	Geographic Object-Based Image Analysis
GEO BON	Group on Earth Observations Biodiversity Observation Network
G-Econ	Geographically based Economic data
GEOGLAM	Group on Earth Observations Global Agricultural Monitoring
GEO-GNOME	Global Network for Observation and Information in Mountain Environments
GEOSS	Global Earth Observation System of Systems
GES	Good Environmental State
GCP	Global Precipitation Climatology Project
GFOI	Global Forest Observation Initiative
GFW	Global Forest Watch
GIS	Geographic Information System
GHSL	Global Human Settlement Layer
DLR	German Aerospace Center
GMW	Global Mangrove Watch
GMIA	Global Map of Irrigation Areas
GOCI	Geostationary Ocean Color Imager
GOSAT	Greenhouse Gas Observation Satellite
GPS	Global Positioning System
GPSDD	Global Partnership for Sustainable Development Data
GRACE	Gravity Recovery and Climate Experiment mission

GRUMP	Global Rural Urban Mapping Project
GSO	Generic Slum Ontology
GSOC	Global Soil Organic Carbon
GSP	Global Soil Partnership
GUF	Global Urban Footprint
GWOS	Global Wetlands Observation System
HLPF	High Level Political Forum
HPC	High Performance Computing
HWSD	Harmonized World Soil Database
IAEG-SDGs	Inter Agency Expert Group on SDG Indicators
ICAO	International Civil Aviation Organization
ICEP	Index of Coastal Eutrophication
IEA	International Energy Agency
ILO	International Labour Organization
IOC	Intergovernmental Oceanographic Commission
IOC-UNESCO	Intergovernmental Oceanographic Commission of UNESCO
IOOS	Integrated Ocean Observing System
IPCC	International Panel on Climate Change
IRS	Indian Remote Sensing satellite
ISPRA	Superior Institute for the Environmental Protection and Research
ISRIC	International Soil Reference and Information Centre
ITPS	Intergovernmental Technical Panel on Soils
IUCN Nature	International Union for Conservation of
JERS	Japanese Earth Resources Satellite
JAXA	Japanese Aerospace Exploration Agency
JRC	Joint Research Centre
KBA	Key Biodiversity Areas
LAI	Leaf Area Index
LCCS	Land Cover Classification System
LDN	Land Degradation Neutrality
LiDAR	Light Detection and Ranging
LSMS	Living Standards Measurement Surveys
LULC	Land Use and Land Cover
MAR	Model-assisted Regression
MATTM	Italian Ministry for the protection of Environment and Sea
MDG	Millennium Development Goal
MEA	Multilateral Environmental Agreement
MERIS	Medium Resolution Imaging Spectroradiometer
MICS	Multiple Indicator Cluster Surveys
MISR	Multi-angle Imaging SpectroRadiometer
MODIS	Moderate Resolution Imaging Spectrometer Sensor
MOOC	Massive Open Online Course
MSFD EU	Marine Strategy Framework Directive
NASA	National Aeronautics and Space Admin istration
NDVI	Normalized Difference Vegetation Index
NGO	Non-Government Organisation
NIR	Near Infrared
NMCA	National Mapping and Cadastral Authorities
NOAA	National Oceanic and Atmospheric Association
NPP	Net Primary Productivity
NSO	National Statistic Office
MSI:	Multi Spectral Imager
OA	Ocean Acidification
OBIA	Object-based Image
OCO	Orbiting Carbon Observatory
OLCI	Ocean and Land Colour Imager
OLI	Operational Land Imager
PALSAR	Phased Array Synthetic Aperture Radar
PAR	Photosynthetically Active Radiation
PRODES	Programa de Cálculo do Desflorestamento da Amazônia (Deforestation in Brazil)
PSU	Primary Sample Units
REDD+	United Nations Reducing Emissions from Deforestation and forest Degradation Scheme
SAO	Sentinel Alpine Observatory
SAR	Synthetic Aperture Radar
SeaWiFS	Sea-Viewing Wide Field-of-View Sensor
SEPAL	System for Earth Observation Data Access, Processing and Analysis for Land Monitoring
SDD	Secchi Disk Depth
SDMX	Statistical Data and Metadata Exchange
SISH	Slum/Informal Settlement Households
SMAP	Soil Moisture Active Passive satellite mission
SMOS	Soil Moisture Ocean Salinity satellite mission

SNAP	Sentinel Application Platform
SPOT	Systeme Pour l'Observation de la Terre (French satellite)
SSS	Sea Surface Salinity
SST	Sea Surface Temperature
SSU	Secondary Sample Units
SDG	Sustainable Development Goal
SWOS	Satellite-based Wetlands Observation Service
TEP	Thematic Exploitation Platforms
TIRS	Thermal Infrared Sensor
TOMS	Total Ozone Mapping Spectrometer
TOA	Top Of Atmosphere
TRMM	Tropical Rainfall Measuring Mission
TRWR	Total Renewable Freshwater Resources
TSM	Total Suspended Matter
TSS	Total Suspended Solids
TWW	Total freshwater withdrawn
UAV	Unmanned aerial vehicle
UN	United Nations
UNAIDS	United Nations Programme on HIV/AIDS
UN CBD	Convention on Biological Diversity
UNCCD	UN Convention to Combat Desertification
UN ECOSOC	UN Economic and Social Council
UNFCCC	United Nations Framework Convention on Climate Change
UNEP	United Nations Environment Programme
UNGA	United Nations General Assembly
UN-GGIM	UN Committee of Experts on Global Geospatial Information Management
UNICEF	United Nations International Children's Emergency Fund
UNIDO	United Nations Industrial Development Organization
UNISDR	United Nations International Strategy for Disaster Reduction
UNEP-WCMC	UN Environment World Conservation Monitoring Centre
UNESCO	United Nations Educational, Scientific and Cultural Organization
UNESCO-UIS	UNESCO Institute for Statistics
UNFCCC	UN Framework Convention on Climate Change
UNSD	United Nations Statistics Division
USGS	United States Geological Survey
UV	Ultraviolet
VCF	Vegetation Continuous Field
VCI	Vegetation Condition Index
VPI	Vegetation Productivity Index
VHR	Very High Resolution
VIIRS	Visible Infrared Imaging Radiometer Suite
VIS	Visible Spectrum
WaPOR	Water Productivity Open-access portal
WASH	Water, Sanitation and Hygiene for All
WGGI	Working Group on Geospatial Information
WHO	World Health Organization
WOIS	Water Observation and Information
WRI	World Resources Institute
WSF	World Settlement Footprint
WSSD	World Summit on Sustainable Development
WT	Water Temperature