remote sensing

MDPI

Editorial

Earth Observations for Sustainable Development Goals

Joan Maso [1,*], Alaitz Zabala [2] and Ivette Serral [1]

1 Grumets Research Group, CREAF, Edifici C, Universitat Autònoma de Barcelona, 08193 Cerdanyola del Vallès, Spain; ivette@creaf.uab.cat
2 Grumets Research Group, Geography Department, Universitat Autònoma de Barcelona, 08193 Cerdanyola del Vallès, Spain; alaitz.zabala@uab.cat
* Correspondence: joan.maso@uab.cat; Tel.: +34-935811771

check for updates

Citation: Maso, J.; Zabala, A.; Serral, I. Earth Observations for Sustainable Development Goals. *Remote Sens.* **2023**, *15*, 2570. https://doi.org/10.3390/rs15102570

Received: 25 April 2023
Revised: 28 April 2023
Accepted: 8 May 2023
Published: 15 May 2023

1. Introduction

In 2015, the United Nations adopted the 17 Sustainable Development Goals (SDGs), aiming at ending poverty, protecting the planet, and ensuring peace and prosperity. The SDG framework included 169 targets to be achieved by 2030 and 232 numerical indicators to measure the progress towards the targets. Indicators are classified by the Inter-agency and Expert Group on SDG indicators into three tiers based on their level of methodological development and the availability of data at the global level. In tier 1, an internationally established methodology to compute the indicator is available, and data needed as input for the methodology are regularly produced by countries for at least 50 per cent of the countries. Indicators in tier 2 have well established methodologies, but there is lack of data to execute the methodology. While there were some in the past, currently no indicator falls in tier 3, where no internationally established methodology exists. Initially, the indicators' calculation methodology was defined using mainly statistical agencies data. For those SDGs targeting the protection of the planet, Earth Observation, and particularly remote sensing, is an alternative data source to compute the indicators defined by the SDGs. The SDG indicators can be interpreted and measured through direct use of geospatial data itself or through integration with statistical data. Remote sensing data can be used as inputs for modeling and evaluation of measures in a variety of SDGs and targets (urban climate, water balance, soil protection, etc.) [1]. In addition, Earth Observation adds the benefit of measuring indicators at different levels of granularity, making it possible to find hot spots where the situation is further apart from the targets and more action is required.

This Special Issue intends to capture the latest research advances regarding Earth Observation technologies and their applications for computing the SDG indicators. Twelve original research articles, authored by seventy-two researchers, have been published in this Special Issue. Papers provide insights about SDGs and their indicators for SDGs 2, 3, 6, 11, 13, 14, and 15. Some are demonstrated at continental scale (e.g., Arctic region), regional scale (e.g., Hokkaido island), and at the local scale (e.g., inside cities or in gold mining). In the case of remote sensing, satellites used are mainly Sentinel 1, 2, and 5p, Landsat, and MODIS. The articles span multidisciplinary perspectives and methodologies. One paper, in particular, excels to demonstrate the capacity of Earth Observation for national reporting demonstrated in applications, such as water quality, phenological status, and crop production forecast to support the Bulgarian agriculture sector modernization [1]. The papers can be mainly clustered into four applications, each of them described in the following subsections.

2. Applications in Air Quality

One of the main benefits of Earth Observation for computing SDG indicators is the capability to define the spatial distribution below national scale. This is particularly important when studying air quality, as some pollutant distributions are very dependent on human activities, more present in industrial areas and cities. The SDG 11.6.2 indicator "Annual mean levels of fine particulate matter (e.g., $PM_{2.5}$ and PM_{10}) in cities (population weighted)" has huge implications on human health and climate. Current official reporting systems, based on in-situ monitoring networks (i.e., United Nations, Eurostat), are not able to represent the actual diversity of urban conditions and are not covering smaller cities. One paper proposes to supplement official reporting with Earth Observation, to enable calculating more representative and holistic values for the indicator, based on population density, as opposed to differing city definitions [2]. Another important aspect is that Earth Observation studies, similar to this one, not only support the monitoring of the SDG indicator, but also attempt to tackle the actual problem related to the SDG targets: in this particular case, to reduce city concentrations of particulate matter and, subsequently, the exposure of citizens to harmful substances.

While the previous cited paper has the focus in individual cities, remote sensing allows elaborating air quality analysis at the scale of a country, even if the country is as big as China [3]. Indeed, heavy air pollution caused by particulate matter ($PM_{2.5}$) and nitrogen dioxide (NO_2) can be analyzed by remote sensing. This data, when combined with census data from the Organization for Economic Co-operation and Development (OECD), can be used to estimate the SDG indicator 3.9.1: "Mortality rate attributed to household and ambient air pollution". Moreover, the beneficial effects of the lockdowns imposed by the authorities on the population to reduce the propagation of the COVID-19 are demonstrated as concentrations of $PM_{2.5}$ decreased by an average of 17% and of NO_2 by an average of 57%, reducing the number of premature deaths in almost 100,000 people.

To be able to calculate these and other SDGs indicators, such as SDG 11.3.1 and SDG 11.2.1 at intra-urban scale, better data on population distribution and density, and population internal migrations at city scale, are needed. Previous data about population numbers and population density were improved by adding building height information extracted from LIDAR and using height for site-specific weight values for population density correction [4]. By doing so, results presented an 8.6% decrease in previous estimations of population density in the region of Bari in southern Italy.

3. Applications in Ecosystems and Forestry

Ecosystem health can be monitored from remote sensing using Gross Primary Productivity (GPP). While there are global products derived from remote sensing, such as the MODIS GPP global product (MOD17), the resolution of those products does not allow for precise local studies. Deriving GPP from Sentinel 2 MSI data was tested in the Doñana National Park (DNP) as a contribution to the SDG targets 6.6 and 15.1 [5]. Results show the potentiality of Sentinel-2 data for the estimation of GPP at a finer scale. High spatial resolution products allow more detailed description of the distribution of GPP over the heterogeneous ecosystems, improving the understanding of ecosystem functions, which are highly correlated to their health condition. While some papers in this Special Issue focus on the calculation of indicators for SDGs, [6] goes beyond the SGD indicators for forest ecosystem (e.g., indicators 15.1.1 and 15.2.1) to look for ways to measure the ecosystem health in forests. This review found that the major stressor for the forest ecosystem is "climate change", followed by "insect infestation", while, for grasslands, it is "grazing", followed by "climate change". "Biotic interactions, composition, and structure" is the most important ecological attribute for both ecosystems. "Fire disturbance" is the second most important for forests, while, for grasslands, it is "Soil chemistry and structure".

4. Applications in Land Cover

Land cover maps are one of the common datasets used to filter particular land cover types before calculating SDGs indicators (e.g., SDG 2.4.1, SDG 15.1.1, SDG 15.3.1, etc.). Time series of land cover maps derived from remote sensing imagery can be used to assess projections of future land cover distribution [7]. In this study, Landsat data is used to analyze the temporal and spatial changes of land use in Hokkaido from 2000 to 2019. Three scenarios—natural development scenario (ND), cultivated land protection scenario (CP), and forest protection scenario (FP)—were made available to policy makers.

5. Applications in Climate

While climate is covered by the SDG 13, the indicator framework acknowledges that the United Nations Framework Convention on Climate Change is the primary international, intergovernmental forum for negotiating the global response to climate change and SDG 13 proposes only a limited number of indicators related to deaths due to climatic disasters and the development of strategies and finance to climate change, both not measurable by Earth Observation techniques. However, two papers in this Special Issue are related to climate and its impact.

One study synthesizes the key contributions of satellite observations into characterizing effects of the climate change in the Arctic and their amplification [8]. The study reveals that the satellites captured a number of important environmental transitions in the Arctic region. Additional efforts are needed to improve cross-sensor calibrations and retrieval algorithms, as well as to reduce uncertainties.

Secondly, another paper studies the additional injection of black carbon (BC) aerosol in the Amazon atmosphere that was produced in September 2019 due to the uncommonly extensive wildfires used to clear the land [9]. This injection was visible in MODIS imagery and forced a significantly change in the radiative balance and reduced the radiation reaching the top-of-atmosphere (TOA) in a 30% across the whole of South America continent compared to 2018. Most likely, this reduced the rainfall due to the cooling surface and enhanced thermodynamic stability of atmosphere due to the atmospheric heating effect.

6. Other Applications

An article in this Special Issue reviews the opportunities of using remote sensing technologies in addressing the persistent global challenges related to the artisanal and small-scale gold mining sector [10]. Case studies performed in the Democratic Republic of Congo and in Colombia using Open Data Cube demonstrate the identification and quantification of impacts of gold mining on land degradation and water turbidity. The article encourages governments to adopt remote sensing methods into their small-scale gold mining monitoring plans and policies.

Many SDGs indicators are related to human activities. Some of these activities are visible as small features that can be detected by remote sensing imagery, can be counted, and the evolution of their quantities with time can be studied. A paper in this special issue discusses the current capabilities and a modification of the YOLOv5 methodology for extracting objects from a bird's eye perspective of satellite photographs [11]. The modified YOLOv5 improves the mean Average Precision (mAP) by 0.071 on the DOTA dataset. The proposed method does not fully utilize spectral information, and the subsequent fusion of RGB images with multispectral data can be explored in the future.

In most papers of this Special Issue, the computation of SDG indicators using remote sensing data shows great potential. The use of remote sensing generates needs and requirements for in situ data that can be used for calibrating and validating remote sensing products and numerical models. It is important to collect these requirements in a systematic and centralized way to secure the continuous production of the necessary in situ data [12]. A database to collect in situ data requirements is proposed as an additional component for the GEOSS infrastructure.

This collection of articles addresses some of the knowledge gaps in the field of 'Earth Observations for Sustainable Development Goals' in general, and the potential for complementing the statistical methodologies for computing SDGs indicators. We hope this will encourage further investigation in this area and thus improve the performance of remote sensing technologies and data analysis techniques, as well as widen applications in research related to sustainable development, monitoring, and impact assessment.

Author Contributions: Conceptualization, J.M., writing—original draft preparation; J.M., writing; A.Z. and I.S., review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This work has been partially funded by e-shape and WQeMS, which received funding from the European Union's Horizon 2020 research and innovation Programme under Grant Agreement No. 820852 and No. 101004157. This work was also supported by the Catalan Government (SGR2021 00554).

Acknowledgments: I thank all the authors for their contributions and all the reviewers for their valuable comments and feedback.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Aleksieva-Petrova, A.; Mladenova, I.; Dimitrova, K.; Iliev, K.; Georgiev, A.; Dyankova, A. Earth-Observation-Based Services for National Reporting of the Sustainable Development Goal Indicators—Three Showcases in Bulgaria. *Remote Sens.* **2022**, *14*, 2597. [CrossRef]
2. Bailey, J.; Ramacher, M.; Speyer, O.; Athanasopoulou, E.; Karl, M.; Gerasopoulos, E. Localizing SDG 11.6.2 via Earth Observation, Modelling Applications, and Harmo-nised City Definitions: Policy Implications on Addressing Air Pollution. *Remote Sens.* **2023**, *15*, 1082. [CrossRef]
3. Liou, Y.; Vo, T.; Nguyen, K.; Terry, J. Air Quality Improvement Following COVID-19 Lockdown Measures and Projected Benefits for Environmental Health. *Remote Sens.* **2023**, *15*, 530. [CrossRef]
4. Aquilino, M.; Adamo, M.; Blonda, P.; Barbanente, A.; Tarantino, C. Improvement of a Dasymetric Method for Implementing Sustainable Development Goal 11 Indicators at an Intra-Urban Scale. *Remote Sens.* **2021**, *13*, 2835. [CrossRef]
5. Spinosa, A.; Fuentes-Monjaraz, M.; El Serafy, G. Assessing the Use of Sentinel-2 Data for Spatio-Temporal Upscaling of Flux Tower Gross Primary Productivity Measurements. *Remote Sens.* **2023**, *15*, 562. [CrossRef]
6. Soubry, I.; Doan, T.; Chu, T.; Guo, X. A Systematic Review on the Integration of Remote Sensing and GIS to Forest and Grassland Ecosystem Health Attributes, Indicators, and Measures. *Remote Sens.* **2021**, *13*, 3262. [CrossRef]
7. Chen, Z.; Huang, M.; Zhu, D.; Altan, O. Integrating Remote Sensing and a Markov-FLUS Model to Simulate Future Land Use Changes in Hokkaido, Japan. *Remote Sens.* **2021**, *13*, 2621. [CrossRef]
8. Esau, I.; Pettersson, L.; Cancet, M.; Chapron, B.; Chernokulsky, A.; Donlon, C.; Sizov, O.; Soromotin, A.; Johannesen, J. The Arctic Amplification and Its Impact: A Synthesis through Satellite Observations. *Remote Sens.* **2023**, *15*, 1354. [CrossRef]
9. Yuan, S.; Bao, F.; Zhang, X.; Li, Y. Severe Biomass-Burning Aerosol Pollution during the 2019 Amazon Wildfire and Its Direct Radiative-Forcing Impact: A Space Perspective from MODIS Retrievals. *Remote Sens.* **2022**, *14*, 2080. [CrossRef]
10. Moomen, A.; Lacroix, P.; Benvenuti, A.; Planque, M.; Piller, T.; Davis, K.; Miranda, M.; Ibrahim, E.; Giuliani, G. Assessing the Applications of Earth Observation Data for Monitoring Artisanal and Small-Scale Gold Mining (ASGM) in Developing Countries. *Remote Sens.* **2022**, *14*, 2971. [CrossRef]
11. Gong, H.; Mu, T.; Li, Q.; Dai, H.; Li, C.; He, Z.; Wang, W.; Han, F.; Tuniyazi, A.; Li, H.; et al. Swin-Transformer-Enabled YOLOv5 with Attention Mechanism for Small Object Detection on Satellite Images. *Remote Sens.* **2022**, *14*, 2861. [CrossRef]
12. Maso, J.; Brobia, A.; Voidrot, M.; Zabala, A.; Serral, I. G-reqs, a New Model Proposal for Capturing and Managing In Situ Data Requirements: First Results in the Context of the Group on Earth Observations. *Remote Sens.* **2023**, *15*, 1589. [CrossRef]