Using AI and Satellite Earth Observation to Monitor UN Sustainable Development Indicators

Lynn Miller[1*], Christoph Rüdiger[2], Geoffrey I. Webb[1]
[1]Faculty of Information Technology, Monash University, Australia
[2]Department of Civil Engineering, Monash University, Australia
{lynn.miller1, chris.rudiger, geoff.webb}@monash.edu

Abstract

There is widespread acceptance that data from earth observation satellites, combined with artificial intelligence, have the potential to play an important role to enable the quantification of the United Nations Sustainable Development Indicators (SDIs). However, building workflows that allow accurate and timely measurement of the SDIs from sub-national to global scales is proving challenging. We discuss a research program that aims to develop techniques to meet these challenges and help provide member states of the UN with effective methods of monitoring progress towards meeting the goals of the 2030 Agenda for Sustainable Development.

1 Introduction

In 2015 the member states of The United Nations adopted a program for enhancing the well-being of humanity known as the 2030 Agenda for Sustainable Development [United Nations, 2015]. Central to the program is a set of 17 sustainable development goals (SDGs), which collectively consist of 174 targets. Progress on each target is evaluated by measuring one or more indicators (SDIs) associated with each target. In total there are 231 indicators.

In adopting the sustainable development agenda, each member country committed to producing reports evaluating the progress made towards achieving each of the goals, but in many cases the variables required to measure each indicator are not well defined or the data are not easy to collect. Developing nations in particular may not have the resources to hold the regular surveys and censuses required to meet the reporting requirements [Oshri et al., 2018]. The United Nations [2020] have evaluated that as of December 2019, only half the indicators are tier 1 – that is, they have a defined methodology and standards, and at least 50% of countries are producing adequate data. The lack of data for measuring the SDIs poses a significant challenge; unless we are better able to measure the SDG indicators, we risk not meeting the targets of the 2030 agenda [Gennari & Navarro, 2020].

Satellite Earth Observation (EO) data has been suggested as a way of measuring some indicators [UN SIGDTT, 2017]. Several studies have identified the indicators that can be fully or partially measured using satellite data [Anderson et al., 2017; Andries et al., 2019]. Machine learning has been used with EO data to measure variables such as land cover and crop mapping [Kussul et al., 2019], which are required to measure several environmental SDIs. Other studies have explored how to use EO data to proxy measurements of human activity and built machine learning (ML) models for socio-economic indicators such as poverty levels [Xie et al., 2016] and infrastructure availability [Oshri et al., 2018]. The increasing availability of satellite data, together with further research will enable more indicators to be measured or estimated from earth observation data [Andries et al., 2019].

However, satellite earth observation data consist of inherently large, complex data sets [Tan et al., 2017], so measuring indicators on a large scale presents several challenges, which are discussed in section 3. Methods to overcome these challenges are needed before consistent wide-spread monitoring of the SDIs will be achievable.

We seek to use AI methods and EO data to develop robust methods of measuring the SDIs. Firstly, we will contribute to the literature evaluating the potential for using EO data to monitor the SDIs. Secondly, we will address the technical challenges preventing wide-spread adoption of AI to monitor the SDIs. Thirdly, we will develop AI workflows and pipelines for selected indicators to produce reports and maps of indicator measurements and progress. Finally, we will use explainable AI techniques to interpret the pipeline outputs to provide evidence to support reporting of progress and development of policy to achieve the SDGs.

The rest of this paper is structured as follows: in section 2 we discuss the benefits of using EO data to measure the SDIs and provide examples of common variables measurable using EO data. Section 3 outlines some of the main research

* Contact Author

challenges and in section 4 we discuss the aims of our research program.

2 Satellite Earth Observation

The benefits of using EO data to measure the SDIs have been discussed in several studies [Anderson et al., 2017; Paganini et al., 2018]. Polar-orbiting and geostationary satellites provide regular images covering the entire world without regard to geographic boundaries [Anderson et al., 2017]. Space agencies commit to long-term missions, ensuring continuity of data [Paganini et al., 2018], providing long-term sources of consistent and reliable data. Many agencies also make the images and derived data products open and freely available [Paganini et al., 2018].

These benefits help fill the data gap for measuring the SDIs, providing data for countries unable to collect it, and allowing SDIs to be measured more frequently than is possible using surveys. The global coverage of EO data allows consistency of data collection and preparation, and indicator computation [Anderson et al., 2017].

2.1 Using EO to Monitor the SDIs

Almost all satellite instruments used for earth observation sense electromagnetic radiation, which has been either reflected by or emitted from the Earth's surface or atmosphere. Active sensors, such as radars, emit a signal and measure how much of the signal is received back. Passive sensors measure radiation originating from another source, such as the sun, which is stored on the land surface and later released. Satellites also differ in the type of orbit (e.g., geostationary or polar orbit), the frequencies sensed (e.g., optical, infra-red or microwave), and the spatial, temporal, and spectral resolution. By varying these modalities, space agencies design instruments to collect data to support specific EO tasks [Paganini et al., 2018].

To extract meaningful information about objects, the raw sensor data must be converted into quantifiable variables [UN SIGDTT, 2017]. In this section we discuss such variables and the respective satellite platforms that collect data to estimate them, and provide examples of how these variables can be used to monitor SDIs.

Land Cover. Land cover classification is a well-studied application of EO data. As an example, Kussul et al. [2019] used land cover mapping to measure SDI 15.1.1 (Forest area as a proportion of total land area) for the Ukraine. Passive optical sensors such as the European Space Agency's (ESA) Sentinel-2 and NASA's Landsat are commonly used for this task, but some authors have suggested to complement this by using active radar systems such as Sentinel-1 [Asner, 2001].

Water Quality. Optical sensors with multiple narrow bands, such as NASA's Aqua MODIS and ESA's Sentinel-3, can detect variations in water coloration, allowing the measurement of water quality variables such as chlorophyll levels and turbidity. Sarelli et al [2018] have used these variables to monitor SDI 14.1.1 (Index of coastal eutrophication and floating plastic debris density) for western Europe, identifying areas of coastal eutrophication.

Nighttime Light. Nighttime light is a measure of the visual radiation emitted from earth at nighttime. As nighttime light is mainly from artificial sources it indicates the presence of human activity and has been used to estimate poverty levels for SDI 1.1.1 (Proportion of population below the international poverty line) [Xie et al., 2016] and access to electricity for SDI 7.1.1 (Proportion of population with access to electricity) [Falchetta et al., 2019]. Data from low-resolution optical sensors such as the VIIRS sensor on NASA's Suomi-NPP satellites are used to measure nighttime light.

2.2 AI Benefits

The development of artificial intelligence algorithms for big data provides methods of extracting additional information from EO data. Here we discuss recent research using AI and EO data that has led to new and improved techniques for monitoring the SDIs.

Improved Accuracy. Although land cover maps have been produced using single images of low and medium resolution data and simple statistical methods, the availability of long-term high-resolution data means it is possible to produce highly accurate land cover maps using machine learning methods. Gómez et al. [2016] showed the advantages of using a time series of satellite images (SITS), while Pelletier et al. [2019] showed the benefits of using both high-resolution images and deep learning techniques with SITS. Belgiu & Csillik [2018] combined SITS with image segmentation (OBIA) to develop an accurate and computationally efficient algorithm for crop classification.

Measure More Indicators. Machine learning methods such as deep learning allow information to be extracted from EO data that can be used as proxy variables for indicators that are not directly observable. Deep learning from EO data has been used to estimate poverty levels [Xie et al., 2016] and to detect possible sites of slave labor [Foody et al., 2019]. Innovative uses of ML such as these will allow more SDIs to be measured or monitored.

3 EO Data Challenges

EO data, although providing important information for measuring the SDIs, are large, complex datasets and present several challenges that need to be overcome before these benefits can be fully recognized. This section briefly discusses some of the main challenges.

Large Datasets. Analyzing high resolution satellite requires processing large volumes of data. The 10m resolution of the Sentinel-2 images means producing a land-cover map for the entire Earth requires the classification of about 1.5 trillion pixels. Many existing classification methods do not scale to these sized datasets. Shifaz et al. [2020] found that current state-of-the-art time-series classifiers took an infeasible length of time to run using a very modest sized training set.

Limited Training Data. The lack of reference data in some locations means that it is necessary to use data from other sources to train models. However, naively reusing a model trained on data from another location is likely to lead to poor results due to differing agricultural, physical, or climatic conditions [Tuia et al., 2016]. Domain adaptation methods (such as transfer learning) attempt to address this issue [Lucas et al., 2019].

Missing Data. Satellite images are vulnerable to missing data. In images from optical sensors, cloud cover is a major cause of missing data, especially in the tropics [Asner, 2001]. A common solution is to use composite images, where a single image is created by combining a time series of images. This however can introduce errors if the ground cover changes during the compositing time period [Holloway et al., 2019]. Other methods of handling missing data are to use spatial or temporal interpolation [Shen et al., 2015] or to use multiple sources of EO data [Asner, 2001].

Monitoring Over Time. In order to effectively monitor progress towards meeting the SDG targets, we need to not only evaluate the SDIs at specific times but quantify changes to them over time. Robust methods of detecting significant changes to the underlying variables are needed [Polykretis et al., 2020].

Interpretability. The lack of an explanation of the reasons why a model reached a specific decision is a well-recognized issue in machine learning [Bhatt et al., 2020]. Workflows incorporating explainable AI principles [Gunning and Aha, 2019] are needed to help decision makers understand issues and make evidenced-based policy decisions to help countries meet their SDG targets [Metternicht et al., 2020].

Bias. An advantage of satellite Earth observation is it provides a globally consistent method of collecting data [Anderson et al., 2017], however biases in field data or model selection processes may still arise and need to be controlled or accounted for [Mehrabi et al., 2019].

Uncertainty. Although all measurements involve a degree of uncertainty, it is recognised that measurements from EO data have more uncertainty than field-based measurements [UN SIGDTT, 2017]. To ensure transparency and enhance decision making, estimates of the uncertainties associated with the outputs are required.

4 Proposed Work

Overcoming the Technical Challenges. The challenges discussed in the previous section are common to many areas of AI and are active areas of research. We will incorporate appropriate solutions found into workflows for measuring SDIs, adapting them to meet the specific requirements of our program. Recent works that we expect to build on include ROCKET [Dempster et al., 2019], which made a substantial advance towards a classifier capable of processing the large volumes of data contained in high-resolution SITS images; Lucas et al. [2019], who are helping us understand how domain adaptation can be applied to EO data; and Polykretis et al. [2020], who investigated using change vector analysis for land cover change detection, to detect both land cover type and magnitude changes.

Developing AI Pipelines. We will select indicators suitable for measuring using EO data and develop workflows and pipelines to measure and report on indicators, using methods such as those developed by the ERA-PLANET project [Kussul et al., 2019] as a guide. Heeding the advice of the UN Satellite Imagery and Geospatial Data Task Team [UN SIGDDT, 2017] to start small, we will start with indicators that are straight-forward to measure and for local (Australian) areas, before developing a pathway to scale to larger regions and more complex indicators.

Role of AI and EO Data. One of the contributions we are seeking to make is to build on previous analysis work that has identified the SDIs that can be monitored using EO data [Anderson et al., 2017; Andries et al., 2019]. When designing workflows, we will analyze the variables these indicators require to identify the EO instruments and modalities that are best suited to measuring these variables. This will provide further insights into variables shared between the SDIs, and important EO sources.

Interpreting the Results. The reason for monitoring the SDIs is not only to evaluate progress towards meeting the SDG targets but also to identify areas (locations, groups of people etc.) where intervention is needed and to inform policy makers of the types of intervention required [Paganini et al., 2018]. To achieve this, we aim to build workflows that not only present results but also provide explanations of decisions and associated uncertainties [Ribeiro et al., 2016].

5 Conclusion

The United Nations 2030 Agenda for Sustainable Development is an important global initiative towards building an equitable world capable of supporting the ongoing development of humanity. Monitoring the progress towards these goals using the SDIs is of critical importance towards meeting this agenda.

Satellite earth observation data are rich sources of information, especially where in-situ data are scarce or difficult to obtain, but the complexity of this data presents challenges to using it to its fullest potential. This research program aims to use AI techniques to meet these challenges and develop workflows capable of monitoring SDIs at all levels, thus providing a leading example of using AI for social good.

Acknowledgements

This research was supported by an Australian Government Research Training Program (RTP) Scholarship.

References

[Anderson et al., 2017] K. Anderson, B. Ryan, W. Sonntag, A. Kavvada, and L. Friedl. Earth observation in service of the 2030 Agenda for Sustainable Development. Geo-Spatial Inform. Sci., 20(2):77–96, 2017.

[Andries et al., 2019] A. Andries, S. Morse, R. J. Murphy, J. Lynch, and E. R. Woolliams. Seeing sustainability from space: Using Earth observation data to populate the UN sustainable development goal indicators. Sustain., 11(18), 2019.

[Asner, 2001] G. P. Asner. Cloud cover in Landsat observations of the Brazilian Amazon. Int. J. Remote Sens., 22(18):3855–3862, 2001.

[Belgiu and Csillik, 2018] M. Belgiu and O. Csillik. Sentinel-2 cropland mapping using pixel-based and object-based time-weighted dynamic time warping analysis. Remote Sens. Environ., 204(Sept 2017):509–523, 2018.

[Bhatt et al., 2020] U. Bhatt, A. Xiang, S. Sharma, A. Weller, A. Taly, Y. Jia, J. Ghosh, R. Puri, J. M. F. Moura, and P. Eckersley. Explainable machine learning in deployment. Proc. 2020 Conf. Fairness, Accountability, and Transparency: pages 648–657, 2020.

[Dempster et al., 2019] A. Dempster, F. Petitjean, and G. I. Webb. ROCKET: Exceptionally fast and accurate time series classification using random convolutional kernels. Data Min Knowl Disc, in press.

[Falchetta et al., 2019] G. Falchetta, S. Pachauri, S. Parkinson, and E. Byers. A high-resolution gridded dataset to assess electrification in sub-Saharan Africa. Scientific data, 6(1):110, 2019.

[Foody et al., 2019] G. M. Foody, F. Ling, D. S. Boyd, X. Li, and J. Wardlaw. Earth observation and machine learning to meet Sustainable Development Goal 8.7: Mapping sites associated with slavery from space. Remote Sens., 11(3):1–12, 2019.

[Gennari and Navarro, 2020] P. Gennari and D. K. Navarro. Are We Serious About Achieving the SDGs? A Statistician's Perspective, 2020.

[Gómez et al., 2016] C. Gómez, J. C. White, and M. A. Wulder. Optical remotely sensed time series data for land cover classification: A review. ISPRS J. Photogramm. Remote Sens., 116:55–72, 2016.

[Gunning and Aha, 2019] D. Gunning, and D. W. Aha. DARPA's Explainable Artificial Intelligence Program Deep Learning and Security. AI Magazine, 40(2), 2019.

[Holloway et al., 2019] J. Holloway, K. J. Helmstedt, K. Mengersen, and M. Schmidt. A decision tree approach for spatially interpolating missing land cover data and classifying satellite images. Remote Sens., 11(15), 2019.

[Kussul et al., 2019] N. Kussul, M. S. Lavreniuk, A. Kolotii, S. V. Skakun, O. Rakoid, and L. Shumilo. A workflow for Sustainable Development Goals indicators assessment based on high resolution satellite data. Int. J. Digit. Earth, 2019.

[Lucas et al., 2019] B. Lucas, C. Pelletier, J. Inglada, D. Schmidt, G. I. Webb, and F. Petitjean. Exploring Data Quantity Requirements for Domain Adaptation in the Classification of Satellite Image Time Series. 10th Int. Work. Anal. Multitemporal Remote Sens. Images, 2019.

[Mehrabi et al., 2019] N. Mehrabi, F. Morstatter, N. Saxena, K. Lerman, and A. Galstyan. A Survey on Bias and Fairness in Machine Learning. arXiv, 2019.

[Metternicht et al., 2020] G. Metternicht, N. Mueller, and R. Lucas. Digital Earth for Sustainable Development Goals. In Manual of Digital Earth, pages 443–471, Springer, Singapore. 2020.

[Oshri et al., 2018] B. Oshri, X. Chen, M. Burke, A. Hu, P. Dupas, D. B. Lobell, P. Adelson, J. Weinstein, and S. Ermon. Infrastructure quality assessment in Africa using satellite imagery and deep learning. Proc. ACM SIGKDD Int. Conf. Knowl. Discov. Data Min., pages 616–625, 2018.

[Paganini et al., 2018] M. Paganini, I. Petiteville, S. Ward, G. Dyke, M. Steventon, J. Harry, and F. Kerblat. Satellite Earth Observations in support of the Sustainable Development Goals. Technical report, European Space Agency, 2018.

[Pelletier et al., 2019] C. Pelletier, G. I. Webb, and F. Petitjean. Deep Learning for the Classification of Sentinel-2 Image Time Series. 2019 IEEE Int. Geosci. Remote Sens. Symp., pages 461–464, 2019.

[Polykretis et al., 2020] C. Polykretis, M. G. Grillakis, and D. D. Alexakis. Exploring the impact of various spectral indices on land cover change detection using change vector analysis: A case study of Crete Island, Greece. Remote Sens., 12(2), 2020.

[Ribeiro et al., 2016] M. T. Ribeiro, S. Singh, and C. Guestrin. "Why should I trust you?" Explaining the predictions of any classifier. Proc. ACM SIGKDD Int. Conf. Knowl. Discov. Data Min., pages 1135–1144, 2016.

[Sarelli et al., 2018] A. Sarelli, D. Sykas, M. Miltiadou, D. Bliziotis, Y. Spastra, and M. Ieronymaki. A novel automated methodology that estimates the United Nations (UN) Sustainable Development Goal (SDG) 14.1.1.: index of coastal eutrophication using the Copernicus Marine Environment Monitoring Service (CMEMS). 6th Int. Conf. Remote Sens. and Geoinf. Environ., 1077302(Aug 2018):50, 2018.

[Shen et al., 2015] H. Shen, X. Li, Q. Cheng, C. Zeng, G. Yang, H. Li, and L. Zhang. Missing Information Reconstruction of Remote Sensing Data: A Technical Review. IEEE Geosci. Remote Sens. Mag., 3(3):61–85, 2015.

[Shifaz et al., 2020] A. Shifaz, C. Pelletier, F. Petitjean, and G. I. Webb. TS-CHIEF: A scalable and accurate forest algorithm for time series classification. Data Min. Knowl. Discov., 2020

[Tan et al., 2017] C. W. Tan, G. I. Webb, and F. Petitjean. Indexing and classifying gigabytes of time series under time warping. Proc. 2017 SIAM Int. Conf. Data Min., pages 282–290, 2017.

[Tuia et al., 2016] D. Tuia, C. Persello, and L. Bruzzone. Domain adaptation for the classification of remote sensing data: An overview of recent advances. IEEE Geosci. Remote Sens. Mag., 4(2):41–57, 2016.

[UN SIGDTT, 2017] UN Satellite Imagery and Geospatial Data Task Team. Earth Observations for Official Statistics. Technical report, United Nations, 2017.

[United Nations, 2015] United Nations. Transforming our world: the 2030 agenda for sustainable development. Technical report, United Nations, 2015.

[United Nations, 2020] United Nations. Sustainable Development Goal indicators website. https://unstats.un.org/sdgs/, 2020.

[Xie et al., 2016] M. Xie, N. Jean, M. Burke, D. B. Lobell, and S. Ermon. Transfer learning from deep features for remote sensing and poverty mapping. 30th AAAI Conf. Artif. Intell., pages 3929–3935, 2016.