Recent Advances in Machine Learning for Remote Sensing Toward the Sustainable Development Goals

THE United Nations (UN) has defined a set of 17 "Sustainable Development Goals (SDGs)," which provide a policy framework to end poverty and protect the planet. These goals address several challenges related to inequality, poverty, climate, environmental degradation, and justice, and provide a blueprint for action. Progress toward these goals is measured using a data-driven approach, which involves analyzing data from sources such as surveys, imagery, and statistics. For example, imagery acquired from satellites and airborne and unmanned aerial vehicles (UAVs) is used to monitor natural ecosystems and track environmental changes over time.

Advances in machine learning (ML) have enabled the transformation of remote sensing (RS) data into products that can be used for applications such as mapping crop types, delineating agricultural fields, mapping urban areas and slums, managing forests sustainably, and disaster monitoring and response. These example efforts are well-aligned with the SDGs, such as attaining Zero Hunger (SDG 2), Good Health and Well-Being (SDG 3), Sustainable Cities and Communities (SDG 11), Climate Actions (SDG 13), Life on Land (SDG 15), and Secure Property Rights (multiple SDGs).

The Image Analysis and Data Fusion Technical Committee (IADF TC) of the IEEE GRSS organized a special stream on ML applied to RS data for contributing to the SDGs. This stream received a total of 42 submissions, and after review, as per GRSL policy, a total of 12 articles were published. This closing article summarizes the articles accepted in the special issue and also discusses the future directions in applying ML methods to RS data toward the SDGs.

The articles published in this special stream proposed ML approaches that contribute toward the SDGs and highlighted the benefits of using ML approaches to measure and monitor the progress toward these goals. For instance, a fuzzy classifier is proposed [1] to identify plant species from hypertemporal satellite data. The information about plant species can help in better management of terrestrial ecosystems and addresses SDG 15 (Life on Land). In a separate work [2], a deep learning-based semantic segmentation for resource constraint settings is proposed to identify marine debris (SDG 14: Life Below Water).

I. ML Methods in RS Toward SDGs

The works published in this special stream offer methodologies that directly or indirectly address the targets and indicators associated with the SDGs. The data acquired from Earth observation (EO) satellites contain rich temporal information at multiple scales that can be utilized to monitor Earth and its ecosystems as well as to track progress toward the SDG targets. In addition, a few works focused on improving the quality of the acquired data [3] or tuning hyperparameters of the model [4]. These efforts can enhance the accuracy of ML models and offer improved insights for achieving the SDGs. This section summarizes the current efforts in applying ML methods in RS toward SDGs.

A. ML Applications Contributing Directly to SDGs

1) SDG 2: Zero Hunger: With the increase in the global population, there is an urgent need to increase agriculture production through sustainable practices while reducing food wastage and improving the global supply chain. SDG 2 aims to eradicate hunger and improve nutrition while promoting sustainable agriculture to provide food security to all. Specifically, one of the targets (Target 2.3) of SDG 2 is to double the productivity and income of small-scale farmers. Leveraging ML techniques to analyze RS data holds significant promise in boosting the yields and profitability of these small-scale farmers, contributing to the overall goal of sustainable food security for all.

A new benchmark dataset (AI4SmallFarms) for crop field delineation from Sentinel 2 data is proposed in [5]. This is the first publicly available benchmark dataset for determining field boundaries for small-scale farmers of Southeast Asia. Agricultural field boundaries can record important information such as crop type, soil characteristics, and yield, and can provide valuable information to the government and other agencies. The dataset contains 439 001 field polygons divided into 62 nonoverlapping tiles of approximately 5×5 km distributed across Vietnam and Cambodia. The agricultural boundaries in each tile are manually annotated by visual inspection of Sentinel 2 data and the corresponding Google map images. This work also presented a segmentation-based baseline model to predict the agricultural boundaries and discussed the challenges in identifying field boundaries in AI4SmallFarms, such as small field size, heavy cloud presence, and imbalanced classification. This publicly available dataset will advance research in identifying agricultural field boundaries from EO images and contribute to increasing the productivity and income of small-scale farmers.

Monitoring of soil organic carbon (SOC) is essential to ensure soil health and contributes directly toward food security and nutrition. An ML-based approach is presented in [6] to estimate the SOC by integrating soil spectral libraries (SSLs) with hyperspectral sensing data. Unlike the existing SSL-based approaches, which rely on regular soil collection and suffer from a lack of consistent calibration libraries,

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this approach involves creating synthesized SSL in controlled laboratory conditions and integrating it with hyperspectral data (PRISMA) using ML algorithms such as support vector machine (SVM), random forests, and statistical regression models, for estimating SOC. This method shows that synthetic SSL can speed up the development of ML models with limited ground-truth data for predicting SOC in croplands, which could greatly benefit farmers and aid in tracking progress toward the SDGs.

2) SDG 14: Life Below Water: The ocean is the planet's largest ecosystem, and marine resources must be conserved and sustainably used to stop the decline of the ocean's health. In recent years, existing ocean-based industries (sea trade and tourism) have grown significantly, and at the same time, new industries, such as offshore wind and offshore aquaculture, are gaining momentum. With the increase in human activities and growing human population, there is a decline in ocean health, which has adversely affected its ecosystems, species, and genetic diversity. Target 14.1 of the SDGs aims to prevent and significantly reduce marine pollution, in particular from land-based activities, including marine debris. Accurately detecting marine debris would be the first step in reducing marine pollution. In this context, octonion neural network is proposed for marine debris segmentation in [2]. In this work, octonion, which belongs to the hypercomplex number family, is utilized, and all convolution operations are replaced by octonion-based convolution in the UNet-based segmentation. This method was evaluated on the MARIDA dataset, which contains Sentinel 2 images over water areas from 11 countries. The proposed octonion UNet outperformed the traditional UNet in terms of mean intersection over union (mIoU) but with a higher number of parameters. However, the octonion-based segmentation model achieved competitive mIoU and $F1$-scores compared to other segmentation methods such as feature pyramid network (FPN) with significantly reduced parameters. This parameter-efficient model opens the possibility of analyzing data onboard the satellite.

3) SDG 11: Sustainable Cities and Communities: Most of the world's population lives in cities, and it is estimated that 70% of the global population will reside in cities by 2050. The migration of people in huge numbers will further strain the public infrastructure already grappling with challenges such as a rise in urban slums, poor air quality, lack of public spaces and streets, and insufficient public transport. SDG 11 aims to make cities and human settlements inclusive, safe, resilient, and sustainable. The EO data can help map urban public spaces and directly address SDG 11's target 11.7 to provide universal access to public spaces. In one such study, a MixLabel autoencoder is proposed in [7], which uses labels as prior information to extract discriminative features from limited training images. This encoder is used as a feature extractor for downstream segmentation tasks to identify urban public spaces in RS images. This encoder is pretrained for RS images and learns much richer visual semantics than the traditional masked autoencoder (MAE) trained on the ImageNet dataset. The approach is validated on optical RS images from the Gaofen-1 satellite from 17 provincial capitals in China. The experimental results demonstrate that the performance of the proposed encoder on the downstream segmentation tasks was much superior to that of pretraining only on ImageNet and MAE pretrained on RS data. Accurately identifying urban public spaces from optical RS images using the proposed approach helps map the urban public spaces and contributes toward SDG 11.

A separate study [8] develops an ML model to identify the peripheral areas of a major urban city in India. Over the past few years, the major urban centers have expanded significantly, giving rise to peri-urban areas near the periphery. This study utilized a thresholding approach on land use/land cover data, along with indices such as nighttime light (NTL), normalized difference vegetation index (NDVI), and land surface temperature (LST) to create a dataset for distinguishing between peri-urban and rural regions. This dataset was then used to train an SVM classifier to accurately identify the peri-urban areas of Hyderabad, India. This study revealed a 107% increase in peri-urban areas, in contrast to a 9% increase in urban areas over the last seven years. By highlighting the rapid expansion of the peri-urban area due to economic growth and population shift, this study emphasized the importance of delineating peri-urban areas to assist government agencies in effectively planning for urban expansion.

4) SDG 13: Climate Action: Human activities have adversely impacted the Earth and its ecosystem. Global warming is increasing at an alarming rate. It has led to a twofold increase in the rate of sea level rise over the past ten years, accompanied by a rise in the frequency and severity of natural disasters. There is an immediate need to move toward climate-resilient development and secure a sustainable future in line with SDG 13. Determining the crop phenotyping and adapting cropping systems resilient to climate change would contribute to combating climate change and its impact. One such study uses an ML-based approach to identify water stress in groundnuts using hyperspectral images (HSIs) from UAVs [9]. This work designed an ensemble feature selection approach to determine the optimal waveband for identifying water stress. Subsequently, the performance of three traditional classifiers (SVM, random forest, and gradient boosting) was evaluated on the selected features. The proposed approach [9] was validated using a field experiment conducted in Hyderabad, which contains well-watered and water-stressed plants. This study shows the benefits of using ML approaches on HSIs and creating an early warning system for identifying water stress and aiding crop phenotyping.

In recent years, there has been a noticeable increase in the occurrence of natural disasters, such as forest fires, leading to significant damage to the ecosystem, property, and human lives. A real-time wildfire detection system is proposed in [10], which explores distributed satellite systems and onboard processing to identify the locations of wildfires. The approach uses a 1-D convolutional neural network (CNN) for on-board processing of HSIs from PRISMA. The presented results demonstrate that the approach can be used for near real-time monitoring of wildfires in Australia using the chosen satellite constellation. The ML-on-edge, along with the distributed satellite constellation for disaster monitoring, demonstrates the application of EO data toward SDGs.

Identifying the areas affected by disaster is an essential step for efficiently managing postdisaster relief and rescue efforts and directly addressing SDG 13. In one such study [11], an encoder–decoder segmentation module is proposed to segment the disaster-affected areas from multiple RS data. This module consists of a multibranch encoder that inputs synthetic aperture radar (SAR) data and digital elevation model (DEM)/hydrology maps. These inputs are then processed through channel attention and spatial attention modules to extract features. The extracted features are combined using a fusion module and passed through a channel spatial attention fusion module-based decoder to create a segmentation map. The method is evaluated for the identification of flooded regions and the mapping of landslides. This work illustrates the effectiveness of using multimodal RS data to identify areas affected by natural disasters.

Earthquakes are another natural disaster that can worsen other climate-related hazards. While earthquakes are not directly caused by climate change, they cause disasters such as tsunamis and flooding. It is imperative to build earthquake resilience through preparedness and warning systems to address target 13.1 of SDG 13. An ML-based early warning earthquake prediction system is proposed in [12]. The geomagnetic field data were analyzed using the wavelet scattering transform to extract scattering coefficients (or features) in time and frequency domains. This study evaluated the performance of various classical ML models such as k-nearest neighbors, decision trees, neural networks, Naïve Bayes, and SVMs in predicting earthquakes. The analysis utilized geomagnetic field data and earthquake data from the period 1970–2021. This study found that the neural network model provided the best performance, and demonstrated the effectiveness of ML models in predicting earthquakes.

5) SDG 15: Life on Land: The loss of forest cover, along with the degradation of land cover and extinction of species, poses a serious threat to the people and the Earth's ecosystem. SDG 15 (Life on Land) aims to protect, restore, and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt land degradation and biodiversity loss. One target (15.2) of this goal is to measure the progress toward sustainable forest management. The analysis of EO data can be utilized for mapping plant species as demonstrated in [1] and assist in their management and conservation. This work explores the use of hypertemporal data from PlanetScope for single species (*Acacia catechu*) extraction in heterogeneous forests. This work suggests using the "individual sample as mean" method to train the classifier and evaluate the performance of three fuzzy classifiers for identifying the *A. catechu* species. This study demonstrates the potential to identify a single plant species in a diverse forest, which could contribute to more effective ecological and sustainable forest management.

B. ML Applications Contributing Indirectly to SDGs

EO data provide continuous temporal information about the Earth and its ecosystem. This information can be processed using ML tools to achieve the SDGs. However, EO data involve a large variety of sensors/modalities and may require preprocessing before it can be analyzed. For instance, the presence of clouds degrades the quality of the optical satellite images. One particular type of high-altitude cloud found in the troposphere and stratosphere is the cirrus cloud. A separate study [3] discusses the issue of cirrus clouds causing distortion in RS images captured by the Landsat-8 Operational Land Imager (OLI). This study highlights the presence of residual parallax due to the OLI's focal plane design, leading to misalignments between the visible bands and the cirrus detection band (Band 9). To address this, this work proposes a technique called cirrus band-to-band registration (CB2BR). The gradient-based technique corrects these misalignments, improving the accuracy of cirrus removal in RS tasks. The results presented in [3] demonstrate that CB2BR effectively eliminates artifacts caused by cirrus displacement, resulting in more accurate ship detection.

Quantum computing and ML have recently been used to analyze EO data. They offer potential improvements in runtime and better learning capacity. As a first step of quantum ML for EO application, Sebastianelli et al. [4] provide guidelines for hyperparameter tuning of hybrid quantum CNN (QCNN) for land cover classification. The proposed approach performed competitively and converged much faster than the existing CNN models. The experimental results demonstrate that the desired system complexity and accuracy can be achieved by carefully tuning the hyperparameters of QCNN, rather than by increasing the number of qubits.

II. Challenges and Future Directions

The articles featured in this special stream showcase the diverse ways in which EO data, when combined with ML technologies, contribute to the attainment of SDGs. These innovative applications span from delineating agricultural fields (SDG 2) to mapping urban public areas (SDG 11). Furthermore, the introduction of comprehensive benchmark datasets like AI4SmallFarms, alongside the launch of the Earth Observation database (EOD)[1] [13], has facilitated access to these useful datasets. However, several open challenges still need to be addressed [14]. The ML models on EO data need to be more easily interpretable and explainable by human operators. The black-box-like architecture of most existing machine/deep learning models can have serious implications, especially if these models are to be used for society applications. The explainability of these ML models can provide crucial information to the end users (government and non-government agencies) overseeing the achievements of SDGs [14]. Additionally to the explainability of ML models, there is a need to quantify the uncertainty in data and/or model. Estimating uncertainty would further provide confidence to the end user regarding the model's output [14].

There is also a need to improve the community reuse of EO data and models. While there exist analysis ready data (ARD) pipelines to reduce the overhead cost of preprocessing of cross-modal/cross-sensor/cross-provider EO data, they do not follow the findable, accessible, interoperable, reusable (FAIR)

[1] https://eod-grss-ieee.com/home

guiding principles to enhance the reusability of the data. The FAIR principles incorporate four principles: findability, accessibility, interoperability, and reusability for scholarly data that include conventional data, tools, and algorithms. Recently, the best practices of ARD principles were integrated with FAIR principles to enable broader community access and reuse of EO data and algorithms [15]. The adaptation of FAIR principles with ARD essentials in the decision support systems targeting SDGs would further enhance the reuse of EO data and ML algorithms contributing toward SDGs.

The SDGs concern diverse domains such as agriculture, urban management, and policy. This interdisciplinary approach requires domain expertise and better coordination with various stakeholders [16].

Most of the existing ML approaches on EO data for SDGs focus on a particular geographical region. While these location-specific models can capture the SDGs targets and indicators for a particular region, these models need to be further adapted to analyze the EO data of another region. The EO data with rich spatial and temporal information provide an opportunity to monitor the entire planet and its ecosystem at a global scale. Recent advancements in machine/deep learning could be utilized to create a global monitoring tool that offers a comprehensive overview of SDG targets and indicators [14].

UJJWAL VERMA
Manipal Institute of Technology Bengaluru
Manipal Academy of Higher Education
Udupi 576104, India
e-mail: ujjwal.verma@manipal.edu

DALTON LUNGA
Oak Ridge National Laboratory
Oak Ridge, TN 37831-6324 USA
e-mail: lungadd@ornl.gov

RONNY HÄNSCH
DLR
82234 Weßling, Germany
e-mail: ronny.haensch@dlr.de

CLAUDIO PERSELLO
Faculty ITC
University of Twente
7522 NH Enschede, The Netherlands
e-mail: c.persello@utwente.nl

SILVIA LIBERATA ULLO
Department of Engineering
University of Sannio
82100 Benevento, Italy
e-mail: ullo@unisannio.it

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