Google Earth Engine and Artificial Intelligence

Subjects: Remote Sensing

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Remote sensing (RS) plays an important role gathering data in many critical domains (e.g., global climate change, risk assessment and vulnerability reduction of natural hazards, resilience of ecosystems, and urban planning). Retrieving, managing, and analyzing large amounts of RS imagery poses substantial challenges. Google Earth Engine (GEE) provides a scalable, cloud-based, geospatial retrieval and processing platform. GEE also provides access to the vast majority of freely available, public, multi-temporal RS data and offers free cloud-based computational power for geospatial data analysis. Artificial intelligence (AI) methods are a critical enabling technology to automating the interpretation of RS imagery, particularly on object-based domains, so the integration of AI methods into GEE represents a promising path towards operationalizing automated RS-based monitoring programs.

Keywords: Google Earth Engine (GEE) ; artificial intelligence (AI) ; machine learning ; deep learning ; computer vision ; remote sensing

1. Introduction and Motivation

Big data approaches have been making substantial changes in science and in society at large [1][2]. Geospatial big data, which are collected with ubiquitous location-aware sensors that are inherently geospatial [3], are a significant portion of big data. The size of such data is growing rapidly, by at least 20% per year [4]. The United Nations Initiative on Global Geospatial Information Management (UN-GGIM) estimated that 2.5 quintillion bytes of data (one quintillion bytes = 1000 petabytes (PB); 1 PB = 1000 Terabytes (TB)) are being generated every single day, a large portion of which is location-aware. About 25 PB of data are being generated per day at Google, a significant portion of which is spatio-temporal data [4]. This trend will accelerate even faster as the world becomes more mobile and as unoccupied aircraft systems (UAS) and satellite imagery are acquired more often and at higher resolutions [5]. Along with this exponential increase in geospatial big data, the need for cloud computing and high-performance computing for modeling, analyzing, and simulating geospatial contents is also rapidly increasing [4]. Geospatial big data have recently gained attention from researchers and practitioners in geographic information science (GIScience) and remote sensing (RS) [6]. Efficient collection, management, storage, analysis, and visualization of big data have become critical for the development of intelligent decision systems and provide unprecedented opportunities for business, science, and engineering [7]. Handling the 5 “Vs” (volume, variety, velocity, veracity, and value [8]) of big data is still a very challenging task. This is even more challenging for RS imagery due to its large volume (i.e., high resolution and multiple bands) and long timespan; geospatial big data pose significant challenges to conventional geographic information systems (GIS) as well as RS approaches and platforms [9][10][11][12][13].

Geospatial big data, especially RS big data, have posed substantial challenges due to their large volume, high spatial-temporal resolution, and complexity. One of the very promising and practical solutions for analyzing RS big data is Google Earth Engine (GEE). GEE is a scalable, cloud-based geospatial retrieval and processing platform. It also provides access to the vast majority of freely available, public, multi-temporal RS data and offers free cloud-based computational power for geospatial data analysis [14][15][16]. More specifically, GEE provides free access to a multi-PB archive of geospatial datasets spanning over 40 years of historical and current Earth observation (EO) imagery, including satellite imagery (e.g., Sentinel from the European Space Agency (ESA), Landsat from the United States Geological Survey (USGS), Moderate Resolution Imaging Spectroradiometer (MODIS) from the National Aeronautics and Space Administration (NASA)**,** the Cropland Data Layer (CDL) from the United States Department of Agriculture’s (USDA) and National Agricultural Statistics Service (NASS), and the National Agriculture Imagery Program (NAIP), also from the USDA)**,** airborne imagery, weather and climate datasets, as well as digital elevation models (DEMs) [14][16]. Those RS data can be efficiently imported and processed on the cloud platform, avoiding the need to download data to local computers for processing [17]. Along with computing and storage resources, GEE also supports many RS algorithms (e.g., image enhancement, image classification, and cloud masking), which are readily accessible and customizable and allow data processing and visualization at different scales through JavaScript or Python Application Program Interfaces (APIs) [14][16][18][19]. These capabilities reduce most of the time-consuming preprocessing steps needed in traditional RS approaches. The computational power of GEE along with its comprehensive data catalog and data processing methods make GEE an ideal platform for solving geospatial big data problems. GEE allows researchers and practitioners to focus on developing and solving their domain problems by making it easier to retrieve data and algorithms and to compute all in one place. For example, the Landsat archive on GEE is already preprocessed for atmospheric and topographic effects—this saves researchers and practitioners a substantial amount of time and effort in terms of downloading and preprocessing data [16]. GEE, with free planetary-scale geospatial big data (solved the data availability, data storage, and data preprocessing challenges) and free computing resources, facilitates computationally cumbersome geospatial big data analysis for researchers and practitioners with minimal local computing and storage resources. GEE, in the parlance of the RS Communication Model, reduces the number of channels required to construct an RS system, and therefore the time required to go from query to result [20]. Researchers from a wide range of fields are able to generate multiscale (local, national, regional, continental, and global scale) insights that would have been nearly impossible without the geospatial big data and computing capacity available in GEE [21].

GEE provides the free cloud-computing platform to tackle geospatial big data challenges, and recent substantial advances in artificial intelligence (AI) can and will further elevate the power of GEE. There are three AI's main subdisciplines: computer vision (CV), machine learning (ML) and its subdomain, deep learning (DL). These technologies are central to leveraging big data for applications in many domains and have achieved significant advances in a wide range of applications that have a high social impact, such as damage assessment and prediction of natural disasters (e.g., automatic flooding damage assessment [1] and wildfire prediction [22]) and healthcare [23][24][25]. Geospatial artificial intelligence (GeoAI) combines methods in spatial science (e.g., GIScience and RS), AI, data mining, and high-performance computing to extract meaningful knowledge from geospatial big data [26]. GeoAI stems from GIScience methods applied to RS data but has advanced the field of AI to solve geospatial-specific big data challenges and problems.

2. The State of the Art: GEE with AI

2.1. Crop Mapping

Crop mapping is the most-well-developed application using GEE and AI.

Creating country-level, crop-specific maps using RS data can be difficult because of the large amount of data involved. GEE provides data storage and online processing capabilities, greatly ameliorating the issues with downloading data and managing computing resources. Several algorithms were compared in [27] on GEE, CART, IKPamir, logistic regression, a MLP, NB, RF, and an SVM, for crop-type classification in Ukraine. The authors also used an ensemble NN but had to move off the GEE platform since NNs were not currently supported. It is often difficult to map croplands on a large scale using RS imagery because of a lack of ground-truth validation data. However, there are also problems relating to differing cultivation techniques and definitions of what makes up cropland. To address these issues, the authors in [28] collected large amounts of training points from Google Earth imagery and analyzed Landsat and DEM data to create a cropland data layer across Europe, the Middle East, and Russia. Accurate classification and mapping of crops is essential for supporting sustainable land management. A two-step approach for crop identification in the central region of Ukraine was developed in [29] by exploiting intra-annual variation of temporal signatures of remotely sensed observations (Sentinel-1 and Landsat images) and prior knowledge of crop calendars. Crop maps are often created using vegetation indices and field observation data. The authors in [30] argued that this may lead to datasets and ML models that can only predict in specific areas and not generalize up to larger areas (i.e., regions or countries) or to other time periods in the same area. They further argued that what is needed is a more generalized method that can take in information like weather and climate data or DEM data and scale up to field-level predictions or larger.

Agricultural expansion can cause harmful effects to ecosystems and their levels of biodiversity. Producing crop-type maps using RS imagery and ML is one way to help monitor agricultural expansion over large areas, and these maps in turn can help policymakers and land-use managers make more informed decisions about current and future land use. However, creating the maps themselves normally requires a lot of data and it is not a straightforward task to pick an ML model that will perform well with that data. There is also the concern that the predictions from that ML model will be uninterpretable, given that many ML and DL models are so-called "black boxes". To get around this issue, the authors in [31] trained a maximum likelihood model and a fuzzy-rules classifier to determine paddy rice distribution in Iran. Plants look very different in RS imagery depending on the type of imagery that you use, but also over the course of a plant's lifetime. This is especially true of crops like rice, so it is important to incorporate phenological information in order to be able to monitor it over time. Over a three-year time period, the authors in [32] were able to map paddy rice using Sentinel imagery by utilizing several different spectral indices and creating composites of different paddy rice growth periods. Continued agricultural expansion threatens many ecosystems around the globe with high levels of biodiversity. Being able to monitor agricultural expansion is one part in being able to make timely decisions related to water and soil health in addition to pollution levels caused by fertilizer use. Mapping croplands over a large scale with NNs and high-resolution RS imagery has resulted in highly accurate maps, but NNs are computationally expensive to train. A U-Net was used in [33] to map sugarcane in Thailand but used a lightweight NN as an encoder for the DL model to reduce computing costs. Sugarcane grows in rainy conditions in complex landscapes, making mapping it difficult. However, using phenology information can help identify sugarcane in high-resolution RS imagery as shown in [34]. The performance of ANN to CART, RF, and SVM models on GEE was compared for sugarcane mapping in China using Sentinel-2 imagery. Shade-grown coffee landscapes are critical to biodiversity in the forested tropics, but mapping it is difficult because of mountainous terrain, cloud cover, and spectral similarities to more traditional forested landscapes. Landsat, precipitation, and DEM data were used in [35] to map shade-grown coffee in Nicaragua using an RF model. Accuracy scores across different land class types (including shade-grown coffee) were high; a relative variable importance was also analyzed on what data contributed most to the RF model's performance. It is difficult to know beforehand the effect different datasets will have on producing LULC maps. It is therefore useful to compare the performance of a ML classifier on different datasets like Landsat and Sentinel imagery, so that future researchers know which datasets fit their application. The differences between Landsat and Sentinel imagery were explored in [36] for identifying cotton in China over the course of the plant's life cycle.

2.2. Land Cover Classification

LULC maps can help decision-makers and land managers make more informed decisions about the environment. Still, producing LULC maps with ML and RS data requires a lot of compute and labeled input training data. GEE currently offers free compute, so researchers can use the data that they are interested in without having to worry about hardware setup or compute time. The authors in [37] took advantage of this to create an LULC map in Northern Iran, predicting for water, rangelands, built-up areas, orchards, and other LULC classes. They used Landsat RS imagery, field observations, and historical datasets to train CART, RF, and SVM models. The SVM performed better than the CART and RF models, but perhaps more importantly the authors also ran a spatial uncertainty analysis to show each model's confidence level on the output maps. More research should include uncertainty incorporated into reporting metrics or on maps produced with ML to better convey a model's certainty to both citizens and decision-makers.

There are currently high data and computational costs of having to store RS data across different machines using different ML algorithms. There is an additional challenge in that most RS analyses depend on optical data, which is often obscured by clouds and shadows. In addition, most land cover maps have coarse resolution and do not often describe the same things as other maps (making them not directly comparable). These static maps need to be more accurate and updated frequently to be of real use, and cloud computing alongside data and algorithms being in one place has allowed both of these to become a reality. An RF model was used in [38] to determine land-use classes such as vegetation, croplands, and urban areas from Landsat imagery in Zambia.

In RS imagery, many different land-use types have similar spectral signatures or are very complex, making them difficult to be properly identified. Several different ML models available on GEE were trained in [39] with different combinations of input data to determine which were the most important in determining land-use types in Golden Gate Highland Park in China. Although RS and ML have allowed LULC analysis to become ever more accurate for general LULC classes, it is still challenging to correctly identify land subtypes. For example, while classifying vegetation to a high degree of accuracy has become more commonplace, identifying vegetation subtypes like shrubs or grassland is not as straightforward, especially in mixed-use areas. In addition, as is the case for many RS applications, it is challenging to know which types of input data will contribute to a given ML model's ability to learn these subtypes. Therefore, the authors in [40] set out to compare the contribution of SAR data and different indices (NDVI, EVI, SAVI, NDWI) derived from optical data on overall classifier performance. A land cover map of the whole African continent at 10 m resolution was generated in [41], using multiple data sources including Sentinel-2, Landsat-8, Global Human Settlement Layer (GHSL), Night Time Light (NTL) Data, SRTM, and MODIS Land Surface Temperature (LST). Different combinations of data sources were tried to determine the best data input configurations. Pixel-based classification methods often suffer from "salt-and-pepper" noise in their end predictions. Object-based classifiers can help alleviate this problem but are not commonly used because of their high compute overhead. While GEE does not have many object-based classifiers, it does provide free compute. To take advantage of this while comparing the performance of pixel-based and object-based classification methods, [42] produced LULC maps in Italy using Landsat, Planet, and Sentinel RS imagery. The authors compared the performance of RF and SVM models alone with that of the same models used in conjunction with the SNIC and gray-level co-occurrence matrix (GLCM) texture data. Their results showed that pixel-based methods worked better at lower resolutions (i.e., using

Landsat data), whereas object-based methods worked better for higher-resolution RS imagery. The best classifier was the RF model trained with SNIC and incorporating GLCM data. Still, the authors noted that ML models were heavily influenced by input data, feature engineering, the classes that you were trying to predict for, and the place being studied. Many studies evaluate ML methods and the effect that input data sources have on their performance. Not as much research is done into determining how data sampling strategies affect ML classifiers. The authors in [43] compared different data sampling strategies and their effects on how different ML classifiers performed on LULC tasks. A multi-seasonal sample set was collected in [44] for global land cover mapping in 2015 from Landsat 8 images. The concept of "stable classification" was used to approximately determine how much reduction in training sample and how much land cover change or image interpretation errors can be acceptable.

Mountain Land Cover (MLC) classification can be relatively challenging due to high spatial heterogeneity and the cloud contamination in optical satellite imagery over the mountainous areas. Distribution of Land Cover (LC) classes in these areas is mostly imbalanced. To date, three approaches have been proposed to address the class imbalance problem: (1) applying specific classification methods by focusing on the learning of minority classes, (2) assigning higher weights on minority classes by adjusting classifiers, and (3) rebalancing training datasets (e.g., oversampling and under-sampling techniques). A hybrid data-balancing method, called the Partial Random Over-Sampling and Random Under-Sampling (PROSRUS), was proposed in [45] to resolve the class imbalance issue. The class imbalance problem reduces classification accuracy for infrequent and rare LC classes. A new method was proposed in [46] by integrating random under-sampling of majority classes and an ensemble of Support Vector Machines, namely Random Under-sampling Ensemble of Support Vector Machines (RUESVMs). Rapid urban expansion puts pressure on local ecosystems and human well-being, so urban sustainability studies are increasingly turning to applications that process large amounts of geospatial data and model ecosystem services. Currently, it is not straightforward for urban or ecology scientists to use cloud-based platforms like GEE as their processing routines are more complicated than the many common mapping applications (i.e., classification) available on GEE. While determining ecosystem service values is complicated (many disciplines, many opinions, etc.), GEE was used in [47] to illustrate a processing workflow for how LULC classes can be used to compute more complex ecosystem service values.

2.3. Forest and Deforestation Monitoring

Forests provide many ecosystem services, from preventing soil erosion, regulating the hydrological cycle, and providing shelter for many plant and animal species. However, deforestation is occurring at a rate that is making it impossible for individual species to recover. As deforestation accelerates, there are cascading effects for entire ecosystems. In Brazil, agriculture, ranching, and land occupation is causing the vast forest of the Amazon to become fragmented. Still, it is difficult to monitor the changes through time due to cloud cover and the rate that new satellite imagery comes in every day. The authors in [48] showed how GEE can be used to overcome data storage and compute needs and analyze about 20 year's worth of Landsat data to determine forest cover changes. Land use maps can help inform policymakers and land-use managers but are often static and of coarse resolution. It would be more useful to create these maps in a repeatable manner, one in which code and data could be reused for making decisions based on up-to-date information. Sentinel-2 data were analyzed in [49] and several different ML classifiers were trained to distinguish between four different forest types in Italy during both summer and winter seasons. Monitoring tree species distribution is an important metric in monitoring overall forest health and in determining current carbon storage efforts. However, doing so is difficult without the use of high-resolution RS data, much of which is either private and inaccessible or too expensive to collect (in the case of LiDAR or UAS data). Recent research in environmental mapping applications uses DL and NN to identify tree species across large areas with minimal feature engineering, but NNs currently need large amounts of compute and labeled input data to train on. To classify tree species across a large area in China while fitting within compute restraints, an RF was trained on the GEE platform in [50] using optical and SAR imagery, DEM data, and field observations.

A participatory forest mapping methodology was developed and tested in [51] to map the extent and species composition of forest plantations in the Southern Highlands area of Tanzania. Collecting field observations of plant phenology can be time- and labor-intensive to repeatedly obtain. RS imagery can help continuously monitor phenology information because of its high spatial and temporal resolution. To create a forest type map in India using RS imagery and ML, the authors in [52] predicted for evergreen and deciduous forest types, as well as "non-forest" classes. Collecting, storing, and processing large amounts of RS imagery presents a barrier to doing research in the environmental and earth sciences. GEE provides data storage, compute, data processing, and ML algorithms on its platform. The researchers in [53] used GEE to map mangrove extent in Indonesia.

2.4. Vegetation Mapping

Accurate near real-time estimates of vegetation cover and biomass are critical to adaptive rangeland management. An approach was developed and tested in [54] to automate the mapping and quantification of vegetation cover and biomass using Landsat 7 and Landsat 8 imagery across the grazing season (i.e., changing phenological conditions). Annual percent land cover maps of plant functional types across rangeland ecosystems were produced to effectively and efficiently respond to pressing challenges facing conservation of biodiversity and ecosystem services. The authors in [55] utilized the historical Landsat satellite record, gridded meteorology, abiotic land surface data, and over 30,000 field plots within an RF model to predict per-pixel percent cover of annual forbs and grasses, perennial forbs and grasses, shrubs, and bare ground over the western United States from 1984 to 2017, at approximately 30 m resolution. Rangelands in the western United States are home to many different animal and plant species. They are ecologically diverse and have been traditionally monitored by taking and analyzing in situ measurements in different areas. However, continually collecting field observations can be time- and labor-intensive and land managers are often asked to make decisions about large areas with sparse field information. RS data can help monitor rangelands with a large spatial scope and a short return time, making them key to informing land management decisions in a timely manner. Using climate and field data alongside Landsat imagery and MODIS land-use maps, ML models used in [21] were able to predict for several important rangeland indicators like plant height, total vegetation and rock cover, as well as bare soil.

Invasive species can degrade ecosystems and harm biodiversity as well as soil and water quality. It is often difficult to monitor invasive species in coastal environments from optical RS imagery, though, because of frequent cloud cover. A specific invasive species in China was used in [56] as a case study for developing an ML pipeline that takes into account both cloud cover and phenological information. Invasive species can have harmful environmental effects as they disrupt ecosystem balances. Long-term datasets, like those of the grass *S. alterniflora*, are not always available, making them difficult to detect using RS methods. In order to produce a map of this invasive species, field data were collected and processed in [57] in addition to UAS imagery and optical RS data from several different platforms.

It is often difficult to detect changes in savanna landscapes due to their high heterogeneity in vegetation types, which makes it even harder to attribute change to natural or anthropogenic causes. This is especially problematic in areas like the Brazilian Cerrado where agricultural expansion is happening on a large scale. In order to clarify what changes have been happening there, over three decades worth of Landsat imagery was used in [58] to determine which areas have experienced vegetation change. Wetlands provide many ecosystem services and provide important habitats for several different plant and animal species. In order to make informed conservation and policy decisions, it is important not only to be able to map the current state of wetlands vegetation, but how that vegetation is changing over time. However, different sets of input data and ML methods used for change detection of wetland vegetation need to be evaluated more fully as choices made during preprocessing and hyperparameter tuning can affect the end result of an analysis. The authors in [59] used an adaptive stacking algorithm to train an ML classifier on optical, SAR, and DEM data to identify wetland vegetation.

2.5. Water Mapping and Water Quality Monitoring

Static surface water maps are often produced at the regional or national level, but do not show long-term trends resulting from seasonality or global warming's effects. In [60], the authors created a web portal using GEE as a backend alongside an expert system to identify bodies of water in Landsat imagery. RS has been widely used to map and monitor surface water. In [61], the authors used all available Landsat images to study surface water dynamics in Oklahoma from 1984 to 2015. The authors in [61] found significant inter-annual variations in the number of surface water bodies and surface water areas. They also found that both the number of surface water bodies and surface water areas had a positive relationship with precipitation and a negative relationship with temperature.

Floods and heavy precipitation events often occur at times of heavy cloud cover, making optical imagery not well-suited to water mapping or flood monitoring during those times. Traditionally, ground-based gauges are used to monitor water level and stream flow, but only work at specific points, limiting their utility during large-scale flood events. SAR imagery, however, is often used in water mapping or flood monitoring analyses because of its ability to see through clouds and work over large spatial scales. This is especially important for monsoonal regions like Southeast Asia where intense rains can lead to flood conditions. However, SAR imagery is also susceptible to classification errors when flooding occurs under tree cover or looks like concrete/pavement in urban areas, so preprocessing steps should be carefully considered. The authors in [62] analyzed to what degree different preprocessing steps affect the output water maps using both SAR and DEM data and two variations of Otsu's thresholding algorithm. Glacial lake outburst floods (GLOF) are one of the serious natural hazards in the Himalayan region. To reduce the potential risks of GLOF, the information about the location and spatial distribution of glacial lakes is critical. In [63], the authors used Landsat 8 images available on GEE to map glacial lakes in the Tibet Plateau region. Their results revealed that climate warming played a major role in glacial lake changes.

Categorizing urban water resources faces two main challenges. First, it is often difficult to distinguish between water and things like asphalt or shadows in urban settings using RS imagery. Second, the distribution of water resources has changed alongside the accelerating impacts of climate change, making up-to-date, temporally aware water monitoring difficult. GEE provides free data storage, datasets, and compute, but as of yet high-accuracy DL models like NNs are not available on the platform. In [64], the authors compared the performance of MNDWI and an RF to that of a multi-scale CNN (MSCNN) and showed that the DL method was the most accurate (with less false classifications) for identifying urban water resources in several Chinese cities. While DL receives a lot of attention in water mapping research, these models still require a lot of input data and large amounts of compute to train them. However, as compute becomes publicly available in cloud-based platforms like GEE, obtaining large amounts of labeled training data remains a key bottleneck to using DL models. One way to make the data labeling process less time- and resource-intensive was illustrated in [65], where the authors used current water maps and a segmentation algorithm to automatically collect data labels from Sentinel-1 imagery.

Optical imagery used in surface water mapping analyses is often occluded by clouds, and many common methods used to map surface water confuse snow, ice, rock, and shadows as water. DeepWaterMapv2 was released in [66] and aimed to address these false positive misclassifications.

ML models have achieved high levels of accuracy in identifying water bodies in RS imagery. However, the models often misclassify soil, rock, clouds, ice, and shadow as water and often rely on cloud-free, optical RS imagery, which is not always available. The authors in [67] used masking, filtering, and segmentation algorithms to identify bodies of water in Sri Lanka in complex, mountainous environments. It is challenging to repeatedly produce up-to-date, accurate surface water maps over large areas. Water bodies change their shape and overall distribution through time, and humans use water in ways that look dissimilar to natural water bodies in RS imagery. Most studies to date focus on one type of water body (lakes, rivers, etc.) or create a binary classification mask giving little to no detail on various water body classification types. To explore the potential to distinguish between surface water body subtypes, [68] used slope, shape, phenology, and flooding information as input to an RF model to predict for lakes, reservoirs, rivers, wetlands, rice fields, and agricultural ponds.

2.6. Wetland Mapping

Wetland serves as the globally biggest carbon pool, and thus has important ecological service functions (e.g., water conservation, regulation, and maintenance of species diversity) [69][70][71]. Global climate change and human activities have posed dramatic challenges in the past few decades to wetland ecosystems, and wetland mapping is essential to conserve and manage terrestrial ecosystems [72]. RS makes investigating large wetland systems and monitoring their change over time possible [73].

Wetlands are highly dynamic landscapes, often making past efforts to map them out-of-date. This is especially true at the regional or national level, where it is often difficult to monitor wetlands at scale due to their remote location and large spatial scale. While there are efforts to monitor wetlands in Canada at the sub-regional and -province level, this is mostly through governmental efforts to produce static maps. Cloud computing on GEE was utilized in [74] to create an open-source, reproducible map of wetland occurrence probability using LiDAR and RS data for the entire area of Alberta. Mapping subtypes of wetlands is difficult because while they look similar in RS imagery, they are diverse environments that cover a wide area. The same is true for classifying peatlands, a subtype of wetlands, which cover large geographic areas in complex patterns. This is problematic because peatlands, like wetlands, provide critical habitats that promote biodiversity while also being a global carbon sink. Past studies have shown that while optical data are useful for peatland mapping, it is often occluded by clouds or other atmospheric conditions. SAR data, on the other hand, can detect bodies of water and vegetation at any time of day or night, but are prone to being noisy due to surface moisture content and roughness. The authors in [75] demonstrated that by combining SAR, optical, and LiDAR data on the GEE platform, a BRT model was able to predict peatland occurrence across Alberta province with relatively high accuracy at high resolution.

Large, inundated wetlands can be effectively mapped using RS imagery. Small wetlands or wetlands that are inundated only part of the time are much more difficult to identify. Yet, it is more important to do so now than ever given that wetlands are rapidly being converted for agricultural use or are drying up due to climate-induced drying. Monitoring wetlands at large scales is possible, however, with the help of automated techniques like ML. For example, NAIP imagery and LiDAR derived DEM data were used in [76] to detect wetlands across the northern United States using unsupervised classification on the GEE platform. Being able to identify wetlands in RS imagery is the first step towards monitoring their health or decline in a new climate regime, and to make policy choices based on this information. To this end, spatially high-resolution sensors like LiDAR or data products like NAIP can help researchers identify wetlands in RS imagery but are not collected often enough to map wetlands at a fine temporal resolution. This is problematic because wetlands are dynamic ecosystems; they can be both wet and dry over the course of the same season. To get around this limitation, Sentinel-1 and 2 imagery were combined in [77] with aerial photographs and field data to map the spatial variation of wetlands in portions of the United States over time. Environmental problems are often associated with land-use changes, but these changes are not solely linked to urban expansion. Land use change also negatively affects areas like coastal wetlands, which are not monitored as regularly. The possibility of using GEE to map coastal wetlands in Indonesia was explored in [78] by comparing all of the different classifiers on the platform and how they perform with Landsat, digital elevation, and Haralick texture data. The authors showed that in all cases, ML models did much better at binary than multi-class classification.

Tidal flats, often referred to as coastal non-vegetated areas, are dynamic ecosystems, both due to their natural rhythms of water advance and retreat, but also due to anthropogenic change and rising sea levels. It is difficult to monitor tidal flats without the use of multi-temporal, high-resolution RS imagery because of how they change through time. With Landsat 8 and high-resolution Google Earth imagery, an RF model was used in [79] on GEE to classify tidal flat types and their distribution in China. The authors reported very high classification rates across tidal flat classes. However, the authors detailed that satellites like Landsat did not fully capture tidal ranges. Coastal wetlands are usually composed of coastal vegetation areas and tidal flats. Coastal tidal flats are natural transitions from terrestrial ecosystems to ocean ecosystems and are vulnerable to anthropogenic activities and natural disturbances such as sea-level rise, land reclamation, and aquaculture. Many existing global land cover data products have a wetland layer, but do not explicitly differentiate coastal vegetation area and coastal tidal flats (no specific layer for coastal tidal flats).

2.7. Infrastructure and Building Detection, Urbanization Monitoring

Materials like parking lots, roads, and buildings (i.e., concrete, asphalt) can be classified as “impervious surfaces” in RS analyses and are often indicative of human development and urban extent. Impervious surfaces change the hydrological cycle and produce heat effects, affecting overall ecosystem health and well-being. To monitor these materials, researchers have tried using night-time lights to estimate their extent, but this process leads to overestimates as light scatters. To investigate how best to identify impervious materials in RS imagery regardless of cloud cover, the authors in [80] combined nighttime light, DEM, and SAR data and an RF model on GEE. Their resulting maps were more accurate than commonly used maps like GlobeLand30. The authors in [81] put forward a new scheme to conduct long-term monitoring of impervious−relevant land disturbances using Landsat archives.

While greenhouses are used to grow food and help ensure food security, their proliferation can have environmental consequences. Previous attempts to classify greenhouses from RS imagery as part of LULC research have focused on small-scale proof-of-concept applications and have not emphasized identifying the structures in complex terrain types. To explore the possibility of identifying greenhouses in RS imagery over a large area in China, an ensemble ML model was designed in [82] to distinguish them from water, forest, farmland, and construction sites. Urban green spaces have a multitude of benefits, such as regulating urban climate, improving air quality, and reducing stormwater. RS has proven useful for studying the landscape structure of urban green spaces. The authors in [83] assessed the impact of urban form on the landscape structure of urban green spaces in 262 cities in China. The results revealed that cities with a high road density tended to have a smaller area of urban green spaces and be more fragmented. In contrast, cities with complex terrains tended to have more fragmented urban green spaces.

2.8. Wildfires and Burned Area

Traditional wildfire mapping field surveys and digitization efforts are time-consuming and hard to reproduce over time. Burned area indices can be created to monitor post-fire landscapes and their subsequent recovery, but their thresholds are not dynamic and so perform differently in different locations. Sentinel-2 data was used in [84], along with two different burn areas and LULC maps to train different ML classifiers (k-nearest neighbor (KNN), RF, SVM) to map wildfire damage in Australia. As the planet warms, forest fires are increasing in occurrence and severity. This has negative consequences for ecosystems, biodiversity, and human health. To estimate the damage caused by forest fires and their subsequent recovery rates, RS imagery is needed to monitor forests and burn scars over large areas. However, to date, most fire products are created with coarse RS imagery, making regional and local fire monitoring difficult. To determine the impact of using higher-resolution RS data products, how Landsat and Sentinel optical imagery affected an ML model’s performance in burn area classification was compared in [85].

Burned area maps showing where wildfires have occurred are important in being able to analyze global wildfire trends. However, many burned area maps derived from RS imagery are from the MODIS platform. The 250 m spatial resolution of products like FireCCI51 leave out a lot of detail, so the authors in [86] used CBERS, Gaofen, and Landsat imagery to create a 30 m burned-area dataset for 2015. However, the authors noted that their method had difficulty recognizing burned areas from recently plowed fields in agricultural areas, so crop-type masks should be used to remove potential false positives. Additionally, Landsat data was used for both the data collection and validation stage. Thus, the authors were not able to assess the suitability of using Landsat imagery for data collection purposes despite their high accuracy rates. Later on, [87] adapted the exact same processing steps on GEE to produce a burned area map for the year 2005, illustrating how sharing and storing code on GEE makes it easy to re-run analyses or adapt them for new use cases.

Satellite-derived spectral indices such as the relativized burn ratio (RBR) allow fire severity maps to be produced across multiple fires and broad spatial extents. In order to better interpret the fire severity in terms of on-the-ground fire effects compared to non-standardized spectral indices, [88] produced a map of composite burn index (CBI), a frequently used field-based measure of fire severity.

2.9. Heavy Industry and Pollution Monitoring

Mining can lead to lots of environmental degradation during the actual mining process itself, but often continues to do so if mines are not properly reclaimed after the mine is no longer active. Field techniques for monitoring environmental damage operate on a limited spatial and temporal scale, failing to fully capture what is happening. RS can help monitor ecological changes during mining and ensure that mining companies clean up after mining has stopped during the reclamation process. A mapping study was performed in [89] for mining areas in the Brazilian Amazon using Sentinel-2A images and the CART classifier in GEE. To monitor mining disturbances at a coalfield in Mongolia, the LandTrendr algorithm was used in [90] to analyze Landsat data. The authors designed a fast, efficient method on the GEE platform to monitor surface mining operations and show that only 26% of promised reclamation was undertaken at the Shengli Coalfield. Heavy industry projects like mining normally require reclamation after the fact to ensure that local ecosystems can heal and regenerate. Monitoring sites that have undergone mining is made much easier with RS imagery because they are often large, spatially distributed ecological disturbances. This is especially the case for underground mining projects where subsidence occurs but is difficult to track without an aerial view. Landsat imagery and the LandTrendr algorithm were utilized in [91] to monitor water accumulation in subsidence areas of past mining in China. Mining is economically important because of the many jobs and resultant materials it provides but is associated with various environmental and health risks. One such danger comes from the failure of tailings dams, which store water with toxic levels of waste solids. Even though these failures can cause significant damage to the environment, human health, and infrastructure, there is not a global database containing active tailings dams. This in turn can make it easier for illegal mines to operate as legal mining operations with tailings dams are not heavily monitored. In order to keep track of mines and dams in Brazil, two different CNNs were used in [92] to first classify potential mining sites and then to classify perceived/potential environmental risk.

2.10. Climate and Meteorology

Accurate satellite-derived albedo estimations are needed to parameterize and in turn to validate climate simulation models. MODIS satellite observations from 2000 to 2015 were analyzed in [93] using GEE to derive global snow-free land surface albedo estimations and trends at a 500 m resolution. A method was presented in [94] to obtain high-resolution sea surface salinity (SSS) and temperature (SST) by using Sentinel-2 Level 1-C Top of Atmosphere reflectance data. The consistency between Tropical Rainfall Measuring Mission (TRMM) multi-satellite precipitation and monthly gauged precipitation has been confirmed worldwide. A downscaling framework (from 25 km to 1 km) was proposed in [95] for TRMM precipitation products by integrating GEE and Google Colaboratory (Colab).

Urbanization has changed the urban landscape and resulted in increasing land surface temperature (LST). In [96], the authors investigated the impacts of landscape changes on LST intensity (LSTI) in a tropical mountain city in Sri Lanka. There are several ongoing attempts to classify cities around the world based on various characteristics like urban canopy cover, total built-up area, neighborhood sizes, and urban heat island effects (for example, see Urban Atlas, World Urban Database Access and Portal Tools (WUDAPT)). These datasets can help planners and policymakers make more informed decisions as they consider implementing sustainability measures in their respective cities. However, these types of spatial datasets often rely on surveying methods that need to be continually updated. A cloud-based workflow was implemented in [97] and compared to the traditional method of using SAGA GIS for producing local climate zone city maps based on data like WUDAPT.

2.11. Disaster Management

RS imagery has long been used to monitor community recovery after natural disasters. Decision makers can use RS imagery and analyses to redirect resources during the recovery process. Even so, many studies focused on disaster recovery use VHR imagery that increases data storage and compute needs. To explore the suitability of GEE for disaster recovery, the authors in [98] used an RF model trained on Landsat imagery to do change detection on pre- and post-disaster areas in the Philippines. Building detections in post-disaster scenes are a valuable resource for timely assessing damages in disaster management. Using RGB images as input, an automatic building detection method was proposed in [99] to find buildings and their irregularities in pre- and post-disaster (sub-) meter resolution images.

Landslides are a major natural hazard in mountainous regions. Traditionally, landslide mapping heavily relies on field surveys and visual interpretation of satellite imagery. A new method was proposed in [100] for mapping landslides in Nepal using RF on GEE. Many agricultural landscapes have incorporated surface drainage systems to stop fields from flooding during heavy precipitation and runoff. These underground drainage networks have caused flood forecasting to become harder to do since it is more difficult to track water in space and time, as drainage networks are not always well mapped. The authors in [101] created surface drainage maps through running an RF model on the GEE platform, by analyzing vegetation, thermal, moisture, and climate datasets, along with surface drainage records.

2.12. Soil

Many authors come to GEE curious to test out the new cloud computing platform for their domain-specific application. GEE provides freely available compute and data to interested researchers, which they then use to explore the strengths and limitations of GEE. An early soil mapping study was performed in [102] on GEE in 2015. Collecting field samples for soil mapping can be time- and labor-intensive and can be bound to small areas given their costs. These data collections also need to be repeated, representing a barrier to presenting up-to-date information that covers large spatial areas to decision-makers. To address these issues, the authors in [103] used field observations, DEM data, and Landsat imagery on GEE to map different soil types and soil attributes across a large region in Brazil.

2.13. Cloud Detection and Masking

Cloud detection is a well-studied task and GEE has several cloud detection/masking algorithms available on its platform. However, some of them have shown to be unstable leading to considerable under- or overestimation. To explore how CV algorithms and ML models can be used together on GEE, [104] combined the existing Cloud-Score algorithm with an SVM to detect clouds in imagery ranging from Amazon tropical forests, Hainan Island, and Sri Lanka. Fmask is the most commonly used method but has limited use in mountainous regions where terrain and shadows can be confused for clouds or when sudden changes in the Earth’s surface occur in time-series imagery. A convolutional neural network (CNN) called DeepGEE-CD was built in [105] to detect clouds in RS imagery directly on the GEE platform. Cloud screening may be cast as an unsupervised change detection problem in the temporal domain. A cloud screening method based on detecting abrupt changes along the time dimension was introduced in [106], assuming that image time series follow smooth variations over land (background) and abrupt changes are mainly due to the presence of clouds.

2.14. Wildlife and Animal Studies

UAS (i.e., drones) are able to collect high-quality data over large aggregations of wildlife, as they offer an attractive opportunity for improving methods and increasing cost effectiveness of monitoring wildlife populations. The authors in [107] explored the use of UAS for identifying Ny. darlingi breeding sites with high-resolution imagery (~0.02 m/pixel) and their multispectral profile in Amazonian Peru. Land use changes such as deforestation, irrigation, wetland modification and road construction, may drive infectious disease outbreaks and interfere with their transmission dynamics. Accurate classification of Ny. darlingi -positive and -negative water bodies would increase the impact of targeted mosquito control on aquatic life stages. Researchers in [108] developed a semi-automated framework for monitoring large complex wildlife aggregations using drone-acquired imagery over four large and complex waterbird colonies.

The success of conservation and mitigation management strategies may greatly depend on the knowledge of the temporal and spatial patterns of roadkill risk, and its relationship with key environmental drivers. The authors in [109] used a set of freely available environmental variables, namely habitat information from RS observations and climatic information from weather stations, to assess and predict the roadkill risk.

2.15. Archaeology

Utilizing RS imagery for anthropological studies can be difficult because of a lack of financial resources, technical training, or compute needed to analyze large RS datasets. More specific to searching for mounded sites and scattered materials that would indicate past human habitation in RS imagery, it is difficult to pair legacy field data with RS imagery. When archaeologists look for potsherds, either in the field or at development sites, the standard practice is to form walking surveys to detect evidence of prior human settlement. This usually involves a large group of people walking in parallel lines over a given area, documenting what they find along the way. This process involves a lot of upfront personnel costs. The authors in [110] demonstrated the potential role of GEE in the future of archaeological research through two case studies. The authors in [111] used drone imagery and GEE to detect potsherds in the field in the hopes of speeding up this process. In [112], the authors utilized optical and SAR data on GEE to create a classifier capable of outputting a likelihood that there is a mounded site in a given region of the Cholistan Desert in Pakistan.

2.16. Coastline Monitoring

Observing and quantifying the changing position of the shorelines is critical to present-day coastal management and future coastal planning. The authors in [113] presented an automated method to extract shorelines from Landsat and Sentinel satellite imagery. The authors in [114] evaluated the capability of satellite RS to resolve at differing temporal scales the variability and trends in sandy shoreline positions. In [115], the authors proposed a method to map continuous changes in coastlines and tidal flats in the Zhoushan Archipelago during 1985–2017, using Landsat images on the GEE platform.

2.17. Bathymetric Mapping

Mapping bathymetry across large areas is a difficult problem. This is in part because high-resolution aerial radar data, which produces some of the best bathymetry maps, are expensive to collect and only cover small areas. Researchers in [116] paired field observations of coastal depths with RS imagery to train multiple linear regression models that can then predict in areas where no depth information is available. Without accurate bathymetry information, ships risk getting stranded in shallow water areas around the globe. Typically, ships equipped with sonar and planes that have airborne LiDAR are used to get water depth measurements. However, sonar is not suitable for shallow water measurements and airborne LiDAR is expensive to get. Moreover, there are very few bathymetry datasets that have a global reach. The authors in [117] used airborne LiDAR, sonar, and Landsat data to estimate bathymetry in Japan, Puerto Rico, the USA, and Vanuatu using an RF model.

2.18. Ice and Snow

Global warming is putting pressure on Arctic ice and snow cover as the Arctic is heating up much more rapidly than the rest of the planet. In Alaska, changes in perennial snow cover have wide-ranging implications from changing hydrology and vegetation patterns, altering the local topology through more frequent freeze-thaw cycles, and by disrupting the ability of subsistence hunters in the region to find food. The authors in [118] used a CART model to track the changes in the cryosphere in Alaska. The duration and seasonality of lake ice is sensitive to local environmental changes such as wind, air temperature, and snow accumulation. Lake ice phenology (LIP, ice breakup and freeze-up dates and ice duration) is a particularly robust proxy for climate variability.

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