



# Google Earth Engine: empowering developing countries with large-scale geospatial data analysis—a comprehensive review

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## Abstract

Google Earth Engine (GEE) serves as a versatile platform for processing and visualising geospatial datasets, with its primary aim being to provide an open platform for planetary-scale geospatial analysis. Over time, GEE has proven itself as a valuable and robust tool, offering access to a wide array of imagery within a single consolidated system. Its cloud computing environment and computational power eradicate the need to store, process and analyse vast amount of satellite imagery on local computers. GEE has the potential to address some of the challenges associated with earth observation and geospatial applications, particularly in developing countries. Its development has lessened the reliance on high-speed processors and extensive storage capacities. Moreover, GEE presents users with a unique opportunity to conduct analyses with minimal financial investment and equipment requirements. The platform has showcased its capability to perform spatial and temporal analyses on global-scale data at significantly accelerated computational speed, rendering it an attractive tool for the scientific community, offering both versatility and accessibility. Its application spread across various sectors including crop inventory, vegetation mapping and monitoring, land cover mapping, disaster management, hydrological studies, urban planning and management, wetland conservation and management, climate change analysis and forestry analysis. For researchers in developing countries, who often grapple with challenges related to data accessibility, funding for computer hardware and software and resource limitations, GEE opens up new avenues. However, despite its potential, the utilization of GEE in developing countries has fallen short of expectations. Therefore, it is crucial for developing countries to fully leverage this platform to accelerate their sustainable development.

**Keywords** Crop inventory · Disaster management · Hydrology · Climate change · Forestry application · Urban planning and management

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## Introduction

The Google Earth Engine (GEE) is a cloud computing platform designed to store and process massive datasets, often reaching petabyte scale, for analysis and decision-making purposes (Kumar and Mutanga 2018). It houses a large collection of global time-series satellite imagery, including historical earth imagery dating back over 40 years, all stored in a public data repository (Gorelick et al. 2017). These images become readily available for global-scale data mining following ingestion on a daily basis. The main advantage of GEE lies in its elimination of the need to download and process raw imagery locally; instead, all processing occurs seamlessly in the cloud (Yang et al. 2022). This feature is particularly valuable as it obviates the users to possess the latest machines or software. Consequently, scientists lacking access to resources in less developed and developing

countries are afforded equal opportunity to conduct investigations compared to their counterparts in developed countries (Mutanga and Kumar 2019). Although satellite images need not be downloaded, thereby proving advantageous in areas with slow internet connectivity, GEE still necessitates an online connection (Kumar and Mutanga 2018). Similarly, while researchers may not solely rely on specialised remote sensing software such as Environment for Visualizing Images (ENVI) and Earth Resources Data Analysis System (ERDAS) Imagine, they may find them necessary for certain capabilities not available on GEE, such as object-based image analysis. Thus, the GEE web platform broadens the horizons for large-scale earth observation studies in resource-poor developing countries (Gorelick et al. 2017; Kumar and Mutanga 2018).

Data are sourced from several government-supported archives such as the Land Process Distributed Active Archive Center (LPDAAC), the USGS and the ESA Copernicus Open Access Hub, with the repository updated regularly (Kussul et al. 2015; Ma et al. 2015a, b). The fusion of data from various sensors can yield more accurate information, overcoming the limitation of individual sensors, which proves convenient for users. The existing dataset encompasses the entire Landsat series, the Moderate Resolution Imaging Spectrometer (MODIS); the National Oceanographic and Atmospheric Administration Advanced Very High-Resolution Radiometer (NOAA AVHRR); Sentinel 1, 2 and 3 and the Advanced Land Observing Satellite (ALOS) (Kumar and Mutanga 2018). Users can delve into this extensive data repository for change detection, trend mapping and resource quantification on the Earth's surface like never before (Mutanga and Kumar 2019). The Landsat dataset stands out as the most popular, constituting a significant portion of the GEE dataset, with data ranging from the past to the most recent Landsat series available for download and use. Most images have been pre-processed, with cloud removal and mosaicking carried out by previous users to streamline analysis; however, raw imagery is also available, adding value beyond cloud-removed mosaics (Kumar and Mutanga 2018). Similarly, several datasets have been pre-processed to transform raw digital numbers into top-of-atmosphere reflectance and even surface reflectance, eliminating the need for specialised software to correct for solar and atmospheric effects. Additionally, atmospheric and meteorological data are available within the GEE. Ready-to-use computed products such as Enhanced Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI) are also available in GEE (Kumar and Mutanga 2018).

Processing long-term global remote sensing data on a continuous basis necessitates substantial storage capacity and efficient processing capabilities. GEE is a unique tool that can efficiently process enormous amounts of geospatial data, for example, hundreds of satellite photos, each

containing tens of terabytes of data, and generate large-scale maps (Kussul et al. 2015; Ma et al. 2015a, b; Gorelick et al. 2017; Ghaffarian et al. 2020; Amani et al. 2020a; Brown et al. 2022). GEE leverages Google's computational infrastructure to align data analysis, greatly improving processing efficiency and enabling large-scale, multi-temporal studies on a global scale (Kraaijenbrink et al. 2017; Robinson et al. 2017; Yu et al. 2017; He et al. 2018). Users have the flexibility to upload additional datasets and choose whether to share their uploaded data and generated scripts with others. Moreover, GEE offers Application Programming Interfaces (APIs) that allow two apps to communicate with each other and other tools to assist with large-scale data analysis. The user-friendly front-end makes it an ideal platform for interactive data exploration and algorithm creation (Gorelick et al. 2017). GEE analysis output can be exported in various forms, such as map tiles, tables, videos and images in GeoTIFF or TFRecord format, or a new Earth Engine asset to a user's Google Drive account or Google Cloud Storage (GCS). GCS is a paid service that requires the creation of a project, billing for the project and the setup of a storage bucket (Kumar and Mutanga 2018).

Users have the capability to build and run custom algorithms through the programming interface, with the analysis being parallelized across multiple processors, thus significantly speeds up the processing time. This permits for the execution of continental-scale studies with relative ease, a feat unattainable through traditional desktop computing (Gorelick et al. 2017). For example, a study analysing global forest cover variations between the 2000 and 2012 was completed in 100 h on GEE, processing 654,178 Landsat 7 scenes with a spatial resolution of 30 m, totalling 707 terabytes of data. In contrast, the same analysis would have taken over 1,000,000 h on a desktop computer (Kumar and Mutanga 2018). Regardless of geographical location, the availability of a diverse time-series dataset and cutting-edge data processing algorithms accessible via GEE, either directly or through shared resources from fellow users, increases our capacity to manage and analyse Earth observation data for informed decision-making. GEE fosters collaborative knowledge sharing by enabling users to upload their raster and vector datasets and freely share scripts with others (Kumar and Mutanga 2018). Additionally, the platform offers data request forums and troubleshooting platforms, enhancing data accessibility and providing processing assistance at user fingertips.

GEE offers several options for temporal analysis, each tailored to different needs and methodologies. These include continuous change detection and classification (CCDC), exponentially weighted moving average change detection (EWMACD) and Landsat-based trend identification (LandTrendr) (Kennedy et al. 2010; Zhu and Woodcock 2014; Brooks et al. 2014). LandTrendr is a sophisticated

program designed to detect spectral changes at pixel level using Landsat data (Shelestov et al. 2017). CCDC utilizes harmonic functions to detect significant fluctuations in temporal data, while EWMACD constructs a model based on training data and then compares the model to real data points using Shewhart X-bar charts and an exponentially weighed moving average. These methods offer diverse approaches to temporal analysis, enabling users to choose the most suitable technique for their specific research objectives within the GEE platform.

Despite its numerous advantages, the utilization of GEE remains low in developing countries, while developed countries have efficiently harnessed its capabilities across diverse sectors. This is largely attributed to factors such as limited awareness of the GEE platform and its capabilities, lack of basic technical skills and support, absence of partnerships and collaboration and challenges related to infrastructure and internet connectivity in developing countries. As a result, the potential of GEE for rapid large-scale geospatial analysis has yet to be fully realized in these regions. This review highlights the wide-ranging applications of GEE in sectors such as vegetation mapping, land cover and land use mapping, forestry analysis, urban planning, climate change analysis, wetland conservation, crop yield estimation, disaster management and hydrological studies. In addition, we have proposed several interventions to enhance the utilization of GEE in developing countries. These interventions include capacity building initiatives to enhance technical skills, technical assistance programs to provide support and guidance, awareness campaigns to promote GEE's benefits, partnerships with other institutions to foster collaboration and tailored support for specific sectors or regions to address unique challenges and are crucial for overcoming barriers to adoption and maximizing the benefits of this powerful platform for sustainable development. Overall, implementing these interventions developing countries can harness the full potential of GEE to address pressing challenges and drive sustainable development.

## Present status of GEE utilization

Kumar and Mutanga (2018) investigated the country-wise usage pattern of GEE since its inception. They discovered that the usage of GEE was more skewed in technologically advanced countries like the USA, compared to countries in Asia, Africa and the Middle East. Institutions in less developed countries often do not effectively utilize this resource due to various reasons, including limited global cooperation, insufficient training and technical support, lack of technical skills for data processing, linguistic barriers (most important root cause), limited funding, inadequate infrastructure facilities, slow internet connections, limited access to

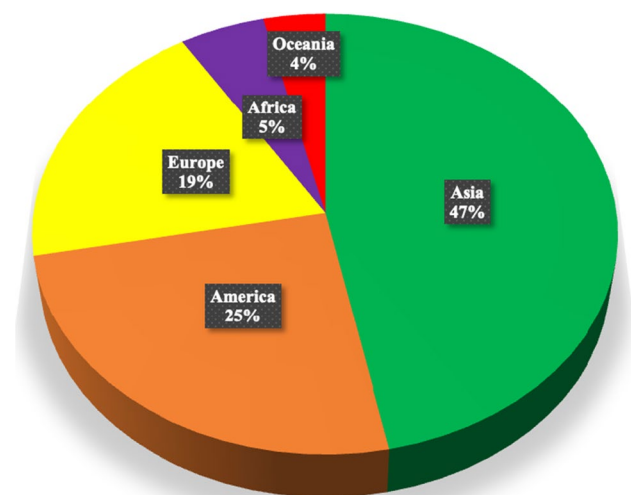
laboratory equipment, political legitimacy issues, restricted or no accessibility to data and limited research opportunities. Many researchers may not be aware that adopting GEE eliminates the need to download datasets. While GEE's methods are simpler and more understandable, its application may remain elusive until a proper graphical user interface (GUI) is developed, like those found in ERDAS Imagine or ENVI. Consequently, the potential of the GEE platform is not fully appreciated in developing countries.

On the contrary, GEE scripts have the potential to be transformed into web apps with graphical user interface, thereby enhancing usability and portability. In less developed countries, there is a lack of awareness and weak data exchange networks (Velastegui-Montoya et al. 2023). Furthermore, most scientists working in the application field lack a programming background. Despite the availability of big data processing engines, the cost of data collection remains a significant challenge, particularly when the required data is not within the GEE dataset (Dube et al. 2016). Regarding the sector-wise usage of GEE, studies in the natural resources mapping and management domain, particularly in the forest and vegetation category, accounted a significant portion, followed by agriculture, hydrology, land use and land cover (LULC), urban studies, natural disaster, atmosphere and climate research, image processing and pedosphere (Kumar and Mutanga 2018).

## A comparison of GEE usage in developed and undeveloped countries

GEE is a powerful geospatial analysis platform, fundamentally transforming the way we study and understand our planet. Its accessibility and versatility render it an invaluable tool for researchers, scientists, policymakers and environmentalists across the globe. However, the utilization and impact of GEE can significantly diverge between developed and undeveloped countries, owing to differences in resources, infrastructure and priorities. Globally, GEE is employed by 125 countries. A continent-wise examination of the number of published publications unveils that Asia, closely followed by the American continent, has the highest volume of articles (Fig. 1). On both a global scale and within the Asian region, China emerges as the frontrunner in terms of publication numbers. Conversely, within the American continent, the USA holds the top position in publication output, closely trailed by Brazil (Velastegui-Montoya et al. 2023).

In developed countries, access to high-quality geospatial data is plentiful. These countries often boast well-established satellite programs, advanced remote sensing capabilities and extensive data-sharing agreements. Researchers in developed countries leverage GEE to analyse vast datasets with



**Fig. 1** Continent wise GEE publication

ease, to monitor land use changes, study climate patterns, manage natural resources and make data-driven decisions. Conversely, less developed countries may lack the resources and infrastructure necessary to collect and maintain extensive Earth observation datasets. Access to high-resolution satellite imagery is limited, and data are not updated regularly (Perera and Tateishi 1995). This limitation restricts the range and precision of analyses that can be conducted using GEE in these regions. Moreover, limited internet connectivity and computer hardware further hinders access and utilization. While developed countries have greater access to data and infrastructure, they harness GEE to monitor environmental quality, sustainable agriculture and disaster management. Undeveloped countries face hurdles related to data access, infrastructure and financial resources (Kumar and Mutanga 2018), but they can still derive benefit from GEE by leveraging international partnerships and initiatives. Bridging the technology gap and promoting knowledge sharing are essential steps in ensuring that GEE's transformative potential benefits all countries, regardless of their development status.

### Assets and liabilities of GEE

The major advantage of GEE is the availability of corrected data, such as ortho-rectified, atmospherically corrected and calibrated top of atmosphere Landsat data in addition to raw data (Çolak et al. 2019). GEE simplifies the complex pre-processing of SAR (Synthetic Aperture Radar) data by providing pre-processed, analysis-ready SAR datasets, a feature particularly beneficial for new users (Di Tullio et al. 2018). Moreover, GEE has the capacity to handle petabytes of remote sensing data across extensive geographic scales and

longer time periods (Ravanelli et al. 2018). The functionalities of GEE cater to the requirements of typical scientific project, with the complexities of parallel computing seamlessly concealed through processes automation (Ravanelli et al. 2018). With its formidable processing capabilities, the cloud-based platform enables the computation of multiple ensemble rules to improve classification accuracy. However, GEE does have certain limitations hindering its widespread utilization. These limitations include a restricted number of spatial functions, including Gaussian and Laplacian filters, edge detection methods (e.g. Sobel, Roberts and Canny), line detection using the Hough Transform and morphological operators (e.g. dilation and erosion) due to parallel processing. Additionally, GEE lacks support for certain features such as frequency-domain techniques (e.g. FFT and Wavelet), hierarchical algorithms (e.g. hierarchical clustering), graph-based methods (e.g. graphcut), geometric descriptors (e.g. Haar, SIFT, SURF) and physical-based models (e.g. radiative transfer models). Furthermore, the storage of complex SAR phase data is incompatible with GEE tiling principle, thereby limiting the application of Polarimetric SAR and Interferometric SAR, which heavily rely on phase information (Amani et al. 2020a).

Other deficiency of GEE includes challenges in creating new tools, as it demands an understanding of all GEE algorithms and their functionality (Amani et al. 2020a). Additionally, there is a limited choice of classification and regression techniques available within GEE, and currently, there is no efficient and accurate segmentation algorithm available within the platform (Amani et al. 2019a). Increasing the number of training samples or input features is a common method to enhance the classification accuracy. However, under GEE's classification methods, users are constrained to using only a limited number of samples or features (Amani et al. 2019b). Due to computational constraints, GEE cannot effectively conduct complex machine/deep learning algorithms requiring large training datasets or longer training times (DeLancey et al. 2019). Users frequently confront time-consuming process when trying to download processed data midway through their workflow for additional analysis in a third-party software environment. This is often due to large map sizes and internet speed limitations (Amani et al. 2020b). The various assets and liabilities of GEE are presented in Table 1.

### Application of GEE in different sectors with special reference to agriculture

GEE has evolved as a formidable tool with diverse applications spanning various domains (Fig. 2). Within the agriculture domain, GEE's applications are manifold. It facilitates plantation mapping and monitoring, phenology-based

**Table 1** Advantage and disadvantage of GEE over ArcGIS and QGIS

GEE	ArcGIS	QGIS
<p>Cloud-based computing</p>	<p>ArcGIS offers cloud-based solutions, but still requires local installations for desktop use, which can be resource-intensive</p>	<p>QGIS is a desktop-based software, which relies on users' local computing resources for data processing and analysis</p>
<p>Easy to share scripts and codes</p>	<p>Does not require codes and sharing</p>	
<p>Vast geospatial datasets</p>		
<p>GEE provides access to a wide range of satellite imagery, environmental datasets and other geospatial data sources, seamlessly integrated into the platform. Real-time data ingested daily basis. Quick filtering and sorting of data</p>	<p>ArcGIS relies on users to acquire and manage their own datasets, which can be time-consuming and resource-intensive</p>	<p>QGIS provides users with the flexibility to work with various data formats and sources; accessing and managing large geospatial datasets may require additional storage and processing resources</p>
<p>Most of the data available in GEE is already pre-processed and corrected. Many derived products like NDVI are readily available</p>	<p>Pre-processing and correction of new data takes a long time. Continental-scale analysis will be highly resource intensive and tedious</p>	
<p>Scalability</p>		
<p>GEE is designed for large-scale analysis, enabling users to process and analyse massive datasets efficiently. Its cloud-based architecture enables parallel processing and distributed computing, facilitating complex spatial and temporal analyses at scale with reduced analysis time and quick visualization of output</p>	<p>ArcGIS and QGIS may encounter performance limitations when dealing with large datasets or complex analyses, particularly in desktop environments with limited computing resources</p>	
<p>Open access</p>		
<p>GEE offers free access to its platform for academic and research purposes, making it an attractive option for users with limited budgets. This democratizes access to geospatial data and analysis tools</p>	<p>ArcGIS provides various licensing options</p>	
<p>Need to purchase software licenses which is costly for individuals or organizations</p>		<p>QGIS is open-source software and freely available for download; users may still incur costs associated with data acquisition, storage and processing</p>
<p>Integration with Google products</p>		
<p>GEE seamlessly integrates with other Google products and services, such as Google Earth and Google Maps, enhancing its usability and interoperability. This integration enables users to leverage additional functionalities and data sources within the Google ecosystem, streamlining workflows and enhancing productivity</p>	<p>ArcGIS and QGIS also offer integration with other systems but may not have the same level of seamless integration with external services as GEE</p>	
<p>Learning curve</p>		
<p>GEE has a steep learning curve, especially for users who are not familiar with coding or remote sensing concepts. Users may need to invest time in learning JavaScript or Python programming languages</p>	<p>ArcGIS and QGIS provide a more user-friendly graphical user interface (GUI), which may be easier for users with limited programming experience</p>	

**Table 1** (continued)

GEE	ArcGIS	QGIS
Writing codes requires knowledge of server-side, and debugging is relatively challenging	Does not require knowledge of server-side and debugging is relatively easy	
Limited flexibility		
While GEE provides a wide range of analysis capabilities, it may not offer the same level of flexibility and customization as other software packages that allow users to develop their own algorithms. Developing new tools for image analysis is very complex	ArcGIS and QGIS allow users to develop and integrate custom algorithms and plugins, providing greater flexibility to tailor analyses to specific requirements	
Data availability and quality		
The availability and quality of certain datasets may vary, limiting its suitability for specific applications. Users may encounter limitations in accessing certain datasets or may need to validate the accuracy of available data	ArcGIS and QGIS allow users to work with a wide range of data formats and sources, giving them more control over data selection and quality assurance	
Users can upload data to the servers up to 250 GBs and download results anytime	No need to upload data, but still require bigger storage and processing infrastructure	
Complex SAR (Synthetic Aperture Radar) amplitude and phase are not stored	User can store complex SAR amplitude and phase locally at their computers	
Training machine/deep learning algorithms is limited to 100 MB of data	There is no size limitation for ML/DL algorithms	
Internet dependency		
GEE requires a stable internet connection for data access and analysis. Users in areas with poor connectivity may face challenges in accessing the platform and performing analyses	ArcGIS and QGIS allowing users to work offline and access data stored locally on their computers. This offline capability makes QGIS more suitable for users operating in remote or disconnected environments	
Privacy and security concerns		
Since GEE operates on Google's cloud infrastructure, users may have concerns about the privacy and security of their data, especially sensitive or proprietary information. Users need to ensure compliance with data privacy regulations and consider data security measures	ArcGIS and QGIS allow users to maintain greater control over their data and privacy, as data is stored and processed locally on users' computers	



**Fig. 2** Application of GEE in various sectors

classification, farmland and crop area mapping (Jin et al. 2019), crop condition monitoring, crop yield estimation, irrigation mapping, as well as flood and drought mapping, and their impact assessment (Pandey et al. 2022). Its versatility extends beyond agriculture (He et al. 2018), to encompass forestry, vegetation monitoring (Tsai et al. 2018), grassland surveillance (Parente and Ferreira 2018), mangrove mapping (Diniz et al. 2019), land use and land cover analysis, risk and disaster management (Liu et al. 2018), urban planning, surface temperature assessment (Ermiida et al. 2020), climate change, forest fire tracking (Parks et al. 2018), hydrology, surface water mapping (Souza et al. 2019), assessment of built-up areas and mining, among others.

### Crop inventory

Differentiating between various crops typically necessitates images captured at different stages during the growth cycle of the crops. Vegetation indices (VIs) derived from satellite data have extensive applications in ecological research, ecosystem modelling and land surface monitoring. Nevertheless, satellite remote sensing datasets inherently contain noise due to factors such as cloud cover, air pollution, data processing issues and device malfunction. Most readily available NDVI products that address these complications are of coarse resolution. Accessing high-resolution NDVI datasets and producing them pose several technological and methodological challenges. Additionally, the existing cropland maps face challenges due to imprecise geo-location of individual farms caused by their coarse-resolution ( $\geq 250$  m), leading to uncertainties in calculated cropland areas from such products. Furthermore, large-scale, high-resolution crop mapping encounters complexities in

processing a large amount of heterogeneous high-resolution satellite imagery, acquired by various sensors, commonly known as the “Big Data” problem (Shelestov et al. 2017). The use of GEE solves these challenges in handling and processing big data and has proven to be more efficient in terms of cost, time, computation and automation (Amani et al. 2020b). Wang et al (2019) successfully created crop-type maps with over 80% accuracy without relying on in-season field data. They achieved this using Fourier transform coefficients of Landsat time series within the GEE platform.

GEE-based near real-time rice area mapping has emerged as a robust method across Southeast Asia, achieving an impressive accuracy of 96.5% and a kappa coefficient of 0.92 when compared to field survey data. This approach presents a valuable alternative to time-consuming and costly field surveys. In Tanzania and Kenya, practical applications of GEE yielded correct classification of cropland/non-cropland with an accuracy of 85%. Similarly, the maize/non-maize classifier achieved an accuracy of 79% and 63% in Tanzania and Kenya, respectively (Jin et al. 2019). Among different classification models, support vector machine (SVM) and artificial neural networks (ANN) demonstrated superior performance compared to random forest (RF) and C5.0 models (Minasny et al. 2019). Amani et al (2020b) utilized the GEE cloud computing platform along with an ANN algorithm and Sentinel-1 and Sentinel-2 images to produce object-based Annual Space-Based Crop Inventory (ACI) maps for Canada for 2018. The developed ACI map exhibited an overall accuracy and a Kappa coefficient of 77% and 0.74, respectively. Additionally, the average Producer Accuracy (PA) and User Accuracy (UA) for the 17 cropland classes were 79% and 77%, respectively. Gumma et al. (2020) developed a high spatial resolution (30 m or better) cropland map of South Asia for the year 2015 using Landsat satellite images and machine learning algorithms (MLA) on the GEE cloud computing platform. The developed map achieved producer’s, user’s and overall accuracy of 89.9%, 95.3% and 88.7% respectively. Shelestov et al. (2017) tested the efficiency of the GEE platform by executing complex workflows involving multi-temporal satellite images (e.g. Landsat-8 and Sentinel-2) to produce a high-resolution (30 m) crop classification map for country-level analysis. Results from the study demonstrated the efficiency of GEE through cloud-based parallel processing and the accessibility of pre-processed data. Notably, the study revealed that a neural network-based approach exhibited superior classification accuracy compared to other classifiers available in GEE, including SVM, decision tree and RF algorithms. Bağcı et al. (2023) employed an innovative DL methodology, specifically a Deep Transformer Encoder, to autonomously identify corn and cotton crops in Diyarbakir, Turkey, using satellite image indices from Sentinel-1 and Landsat-8. The findings revealed impressive accuracy rates of 85%, 95% and

87.5% for the Sentinel-1 dataset, Landsat-8 dataset and the combined Sentinel-1 and Landsat-8 datasets, respectively.

## Vegetation mapping and monitoring

Biophysical measures such as the Leaf Area Index (LAI), Fraction Vegetation Cover (FVC) and Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) play a crucial role in vegetation monitoring (Huete et al. 2002; Fensholt 2004). These measures provide valuable insight into vegetation health and coverage. LAI quantifies the amount of green vegetation that absorbs or scatters solar radiation, aiding in the assessment of plant canopy density. Conversely, FVC partitions the contributions of soil and vegetation, assisting in the distinguishing between bare ground and vegetated areas. FAPAR, a key vegetation indicator, is linked to ecosystem production and provides insights on the efficiency of plants in utilizing solar energy for photosynthesis (Putzenlechner et al. 2022). Remote sensing data can be utilized to estimate these critical variables, which have applications across various fields including ecology, meteorology and agriculture. GEE offers a range of vegetation indices, simplifying the process of conducting vegetation-related research efficiently and quickly (Tsai et al. 2018). Consequently, GEE has been extensively employed in tasks such as vegetation mapping and monitoring, forest mapping, tracking deforestation and forest expansion, assessing forest health, monitoring pasture and evaluating rangeland conditions (Parks et al. 2018). Its capabilities have significantly advanced research and management in these ecological and agricultural domains.

GEE leverages cloud computing and remote sensing data to implement a near real-time approach for vegetation assessment (Poortinga et al. 2018). One of the key tools in this endeavour is the Moderate Resolution Imaging Spectroradiometer (MODIS) Enhanced Vegetation Index (EVI) product, which effectively reduces canopy background variations while maintaining sensitivity in densely vegetated areas (Huete et al. 2002). To address the impact of smoke and sub-pixel thin clouds in the atmosphere, the blue band of remote sensing data is utilised atmospheric correction. EcoDash is a web-based tool that harnesses the EVI data from MODIS products obtained from both Terra and Aqua sensors to map vegetation on a planetary scale. This approach facilitates the global monitoring of vegetation, enabling the detection of both improvement and degradation using satellite imagery and cloud computing. It offers a cost-effective and efficient solution for land managers and environmental practitioners involved in land management and monitoring (Poortinga et al. 2018). In contrast, traditional approaches to such monitoring can be prohibitively expensive in terms of both time and resources.

Goldblatt et al. (2017) demonstrated the effectiveness of GEE classification using low-spectral but high-spatial resolution input data from WorldView, surpassing the classification results obtained from Landsat 30-m resolution data with complete spectral information. This approach highlights the advantage of high spatial resolution input data in detecting sparse vegetation, as well as distinguishing the space between trees, seasonal shrubs and grasses. Achieving accuracy in vegetation and land use mapping using remote sensing images can be challenging, particularly in regions with persistent cloud cover and rugged topography. GEE, as an open-source image analysis pipeline, offers a reliable method for monitoring forest cover and land use pattern in hilly, forested areas prone to cloud cover (Tsai et al. 2018). The utilization of spectral vegetation index (SVI) products and shade/illumination normalisation procedures contributes to significantly higher mapping accuracies compared to non-normalized spectral bands. He et al. (2018) used cloud computing platform to compute spectral vegetation indices from multi-seasonal Landsat data. Furthermore, the increasing use of drones is gradually replacing many labour-intensive and complex agricultural practices and is expected to play an increasingly significant role in the future (Vijayakumar et al. 2021a). GEE has the potential to facilitate the implementation of precision agriculture in developing countries by enabling the fusion of images with diverse temporal and spatial resolutions, including both drone and satellite imagery, along with varying degrees of spectral quality (Moltó 2022). The GEE's rapid processing capabilities further enhance its suitability for such applications.

## Land cover mapping

In the modern era, a plethora of satellites regularly provide free high spatial resolution data, opening up new opportunities for the regular creation of high-resolution land use and land cover maps (LULC) over vast territory (Roy et al. 2014). A prime example of this is the development of a LULC map for Chinese protected areas, which leverages time series data from GEE along with novel algorithms designed to address challenges like cloud cover and terrain effects. The GEE platform has played a pivotal role in facilitating the development of algorithms such as SimpleCloudScore, F-Mask and ACCA (Automated Cloud-Cover Assessment), which are instrumental in cloud removal from satellite images. Tu et al. (2020) successfully created a 10-m resolution land cover map for Guangdong Province, China, by integrating multi-source remote sensing data from Sentinel-1, Sentinel-2 and Luojia-1 within the GEE platform. The resulting map boasted an overall accuracy and Kappa coefficient of 86.1% and 0.84 respectively. Notably, their research found that RF models outperformed SVM, minimum distance (MD) and classification and regression tree (CART) models in terms



of performance. Lin et al. (2020) monitored LULC changes spanning from 1990 to 2019 on Haitan Island, China, using GEE. Their investigation unveiled notable transformations. The cultivated area and water area experienced a decline of 13.63% and 0.95%, respectively, while forest coverage and built-up land surged by 30.94% and 16.20% within the study area over the same period. The predominant processes driving these changes included reforestation, reduction in cultivated land and expansion of built-up areas on Haitan Island. Across the entire continent of Africa, cropland and non-cropland areas were surveyed using a combination of 10-day Sentinel data and 16-day Landsat TM data. For cropland, the overall accuracy reached 94%, with producer's accuracy at 85.9% and user's accuracy at 68.5% (Xiong et al. 2017). In the context of smallholder farmland mapping in southern Mali, ensemble classifiers and high spatial resolution data from Worldview 2 were employed. The ensemble approach, combining various spatial and spectral variables from multispectral Worldview-2 images, field data and five machine learning classifiers, enhanced the overall accuracy (75.9%) by 4.65% compared to the best individual classifier. Interestingly, the study found that adding more classifiers did not lead to continuous improvements in classification results (Aguilar et al. 2018).

Abdollahi et al. (2023) harnessed the power of GEE to generate high-fidelity land cover maps of metropolitan Melbourne for the year 2020, leveraging a combination of Landsat-8 multitemporal data, spectral indices and topographic components. Their investigation unearthed compelling insights: employing the SVM approach yielded an impressive overall accuracy (OA) and kappa accuracy of 88.47% and 85.34%, respectively. Notably, the application of a postprocessing technique resulted in substantial enhancements in both OA and kappa coefficient, with values increasing to 92.90% and 90.99%, respectively. Wahap and Shafri (2020) conducted land cover monitoring over Klang Valley, Malaysia, utilizing multiple machine learning algorithms (MLA) and Landsat composites from three different years (1988–2003–2018) available on the GEE cloud platform. Among the classification algorithms, CART showed the best accuracy, achieving 94.7%, 97.7% and 96.5% in 1988, 2003 and 2018 respectively, outperforming RF and SVM. A study on the land cover changes in Singapore used Landsat, Moderate Resolution Imaging Spectro-radiometer and GlobCover imagery available in GEE. The findings indicated that land reclamation and forest cover changes in Singapore were primarily driven by monsoon cycles affecting Southeast Asia, rather than anthropogenic factors (Sidhu et al. 2018). In the Tigris-Euphrates basin, LULC was mapped at a 30-m resolution using 1184 Landsat-8 scenes available on the GEE platform. Temporal changes were accounted for by creating six 2-month interval composite layers for the target year 2019, using the spectral and thermal bands of

Landsat-8. Image segmentation was performed using simple non-iterative clustering (SNIC) techniques and the RF algorithm. The resulting LULC map displayed a reasonable overall accuracy of 91.7%, with the highest user's accuracy observed in water and wetland classes and the lowest in rain fed crop and rangeland. Producer's accuracy was highest in water and barren areas and the lowest in garden and rangeland (Shafizadeh-Moghadam et al. 2021). A land-cover map of San Salvador basin in Uruguay was generated using GEE. The map displayed good agreement with past agriculture census data and revealed the transformation of grassland to cropland in the period 1990–2018 (Hastings et al. 2020). This demonstrates the utility of GEE in tracking and analysing land cover changes over time.

### Disaster management and earth sciences

Measuring the progress of post-disaster recovery and comprehending its various elements and influencing factors is a complex process. Governments and disaster planners rely on accurate information to formulate effective solutions for rebuilding affected areas and restoring normalcy. Natural catastrophe mapping often requires rapid processing, and while GEE may have some delay in making photos available, it remains a valuable platform for such application (Ghaffarian et al. 2020). Users can upload their own photographs to the platform and employ GEE processing capacity to obtain timely deliverables. Droughts can have devastating impacts on surface water availability. GEE's access to vegetation indices and climate data allows for the early detection and monitoring of drought conditions (Sazib et al. 2018; Ejaz et al. 2023). Globally, the GEE platform is being used to monitor drought occurrences by utilizing soil moisture content as an indicator. The model has been successfully tested in Ethiopia and South Africa (Kibret et al. 2020). The cloud-based engine enables the integration of global soil moisture datasets and web-based processing tools, facilitating the estimation of drought duration and intensity (Sazib et al. 2018). Ghaffarian et al. (2020) used GEE to evaluate the 3-year recovery process in the aftermath of Typhoon Haiyan in Leyte, Philippines, in 2013. The land cover maps generated using GEE showed accuracies exceeding 88%, and the analysis of selected land cover changes revealed that most municipalities had returned to their pre-disaster conditions after 3 years. GEE enables real-time flood monitoring using satellite imagery and rainfall data (Pandey et al. 2022). This information is valuable for flood preparedness and response. Nghia et al. (2022) used Sentinel-1 SAR data within GEE for flood mapping and monitoring in the downstream provinces of the Mekong River. The results revealed a gradual shift in flooding patterns in the downstream provinces of the Mekong Delta. Pandey et al. (2022) used Sentinel-1A SAR data in the GEE platform, to estimate the composite

area of flood inundation in the Ganga–Brahmaputra basin during the monsoon season from July to September. Their estimates showed 25,889 km<sup>2</sup> in Bangladesh, 20,837 km<sup>2</sup> in Bihar, 17,307 km<sup>2</sup> in West Bengal and 13,460 km<sup>2</sup> in Assam were inundated by floods. In recent years, drones have been increasingly used to collect high-resolution images immediately after natural calamities like cyclones, floods, droughts and heat waves (Vijaya Kumar et al. 2020). The images collected by drones can be rapidly processed in GEE with minimal human intervention, enhancing the speed and efficiency of disaster response efforts.

### Crop yield estimation

Accurate yield estimations on the regional level, in advance, utilizing satellite remote sensing, are imperative to ensure food security. Through the GEE, users can assess geographic yield variability at field scales, thus gaining a more comprehensive understanding of yield variability even at the state level (Gao et al. 2019). Jaafar and Mourad (2021) integrated Landsat data, gridded weather data and global soil datasets available in GEE to predict crop yields at a 30-m resolution. Their operational model, Global Yield Mapper in Earth Engine (GYMEE), has the potential to estimate potato, wheat and corn yields with a relative error of  $\pm 6\%$ . GYMEE also facilitates the estimation of evapotranspiration (ET) at a global scale, contributing to a better understanding of water use efficiency by crops. Jin et al. (2019) combined Sentinel-1 and Sentinel-2 imagery within the GEE platform to generate a country map of maize production areas and yields for Kenya and Tanzania in 2017 at 10-m resolution. This mapping task is particularly challenging due to the diverse small-holder farming landscapes and year-round cloud cover in East Africa. The maize/non-maize classifier achieved an accuracy of 79% in Tanzania and 63% in Kenya. Furthermore, they also developed a scalable crop yield mapper (SCYM) to predict maize yield, which captured approximately 50% of the yield variation at the district level in Western Kenya compared to ground-based crop cut measurement. He et al. (2018) used the GEE platform to merge MODIS and Landsat satellite data to estimate Gross Primary Productivity of seven crops in Montana, USA, from 2008 to 2015 at 30-m spatial resolution. The predicted annual crop output findings were in strong agreement with country-level crop production data provided by the US Department of Agriculture, exhibiting a high correlation ( $r=0.96$ ,  $p 0.05$ ). Moreover, the performance of predicted crop yields at a finer scale was also significant ( $r=0.42$ ,  $p 0.05$ ). Rice, a major food crop cultivated during rainy season (*kharif*), presents challenges for optical remote sensing due to cloud cover (Vijayakumar et al. 2022). Microwave remote sensing offers a solution by penetrating cloud cover and provide more accurate information during the rainy season, albeit involving complex

processing. The GEE platform offers users a convenient means to work with microwave remote sensing data, simplifying the associated processing tasks. Additionally, microwave remote sensing data from the European Space Agency are now available free of cost, making it a valuable resource for agriculture applications.

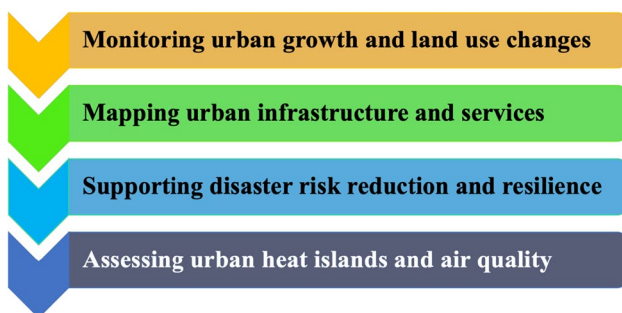
### Hydrological studies

Water, a precious and finite resource, plays a vital role in sustaining life, ecosystems, agriculture and industrial activities. Effective assessment and management of water resource are crucial to ensure their sustainable use and availability for present and future generations. In recent years, the advent of remote sensing and geospatial technologies has revolutionized the monitoring and management of water resources. GEE has emerged as a powerful tool for water resource management and various hydrological studies (Condeça et al. 2022). Analysing satellite images to gauge the quantity and quality of water sources has become a common practice, facilitating improved spatial planning and informed decision-making (Lin et al. 2020). Monitoring surface water resources through GEE has been particularly successful when water indices are employed as a methodology. These indices help track changes in water bodies over time and provide valuable information for water management (Mashala et al. 2023). GEE supports the integration of climate data, terrain information and land cover data to develop hydrological models. These models predict surface water availability, including streamflow (inflow, outflow) and water volume in reservoirs (Jain et al. 2021). Hydrological models can be calibrated using historical data and used to estimate future reservoir volumes. One notable development in this field is the work of Condeça et al. (2022) who devised a methodology for the precise determination of reservoir volumes using satellite images, water indices and GEE. This innovative approach automates the calculation of flooded water surface areas and stored water volumes in lakes, tanks and ponds. By automating the mapping of surface water bodies using satellite imagery, this methodology enables large-scale monitoring of water resources, which is crucial for effective water resource management and conservation efforts (Souza et al. 2019; Sreekanth et al. 2021). GEE's vast repository of satellite imagery enables the creation of time-series analysis to track changes in water levels and estimate reservoir volumes (Sreekanth et al. 2021). GEE can incorporate altimetry data from satellites like Jason-3 and Sentinel-3. Altimetry data provides precise measurements of water levels in large bodies of water, enhancing volume estimation accuracy. In Diyarbakir province, Turkey, Acar (2020) utilized Sentinel-1 SAR images to detect unregistered electric distribution transformers (EDT) in agricultural fields. This was achieved

through the application of MLA, including Extreme Learning Machine (ELM), K-nearest Neighbour (K-NN), Naive Bayes Algorithm (NBA) and SVM. The ELM technique yielded the most promising results, successfully detecting unregistered EDTs with a mean accuracy of 85.47%. Similarly, Acar et al. (2023) identified illegal substations in the agricultural fields of the southeast Anatolian region, Turkey, using Landsat-8 OLI images and MLA. They employed the LSTM (long short-term memory) method, a recurrent neural network model and the Logit-Boost method for automatic recognition of substations. The Logit-Boost method achieved an average accuracy of 88.89%, while the LSTM method achieved an average accuracy of 84.21%. Despite the remarkable processing capabilities offered by cloud computing, only a handful of studies have ventured to harness this technology in sub-Saharan African countries, particularly in rural catchments (Mashala et al. 2023).

## Urban planning and management

Urban areas are dynamic and complex environments characterized by rapid population growth, infrastructure development and land use changes (Lin et al. 2020). In this context, GEE offers unprecedented opportunities for enhancing urban planning and management (Fig. 3). By leveraging GEE capabilities, stakeholders can effectively monitor the expansion of urban areas, identify patterns of development and assess the impact of urbanization on natural ecosystems (Liang et al. 2020; Mashala et al. 2023). This information is crucial for understanding the drivers of urban growth, forecasting future trends and guiding land use planning and zoning decisions to promote sustainable development. Additionally, GEE facilitates a comprehensive understanding of the evolving dynamics within urban landscapes, enabling the identification of sustainable development pathways and the formulation of pragmatic strategies to address the intricate challenges confronting cities (Zelal and Dervisoglu 2023). Another important application of GEE in urban areas is mapping infrastructure and services, such as roads,



**Fig. 3** Urban planning and management with GEE

buildings, parks and utilities at high spatial resolution (Table 2). By utilizing this capability, planners and policymakers can pinpoint areas with infrastructure deficiency, prioritize investment in public services and improve accessibility and mobility for urban residents (Mashala et al. 2023). Moreover, GEE supports the analysis of urban heat islands and air quality by integrating satellite-derived data with meteorological models and ground-based measurements. It can map surface temperatures, identify heat island hotspots and assess the impact of urbanization on local climate patterns. Additionally, GEE aids in the monitoring of air quality indicators such as particulate matter, nitrogen dioxide and ozone concentrations, providing insights into the health impacts of air pollution on urban populations (Ghasempour et al. 2021). This information can inform urban planning and design strategies to mitigate heat island effects, reduce air pollution and enhance the liveability of cities.

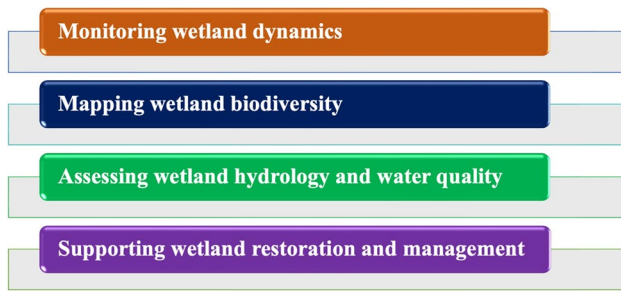
## Wetland conservation and management

Wetlands are among the most biologically diverse and productive ecosystems on Earth, providing a wide range of ecosystem services such as water purification, flood control and carbon sequestration (Gardner and Finlayson 2018; Xu et al. 2019). However, they are also among the most threatened ecosystems, facing degradation and loss due to factors such as urbanization, agriculture and climate change (Dixon et al. 2016). Leveraging GEE, user can identify wetland habitats, biodiversity hotspot, map land cover types, detect changes in wetland ecosystems due to human activities or natural processes and pinpoint priority areas for conservation within wetland ecosystems (Fig. 4) (Pham et al. 2023). Furthermore, GEE facilitates the monitoring of invasive species, habitat fragmentation and other threats to wetland biodiversity, enabling timely interventions to mitigate their impacts (Xu et al. 2019; Qu et al. 2023). This information is crucial for assessing the health and resilience of wetlands and informing conservation efforts (Moukrim et al. 2023). Additionally, GEE can monitor changes in wetland hydrological regimes, track water flow patterns and assess the impact of human activities such as water abstraction and land drainage on wetland ecosystems (Zhang et al. 2023). GEE supports the monitoring of water quality indicators such as turbidity, nutrient concentrations and algal blooms, providing insights into the health of wetland ecosystems and informing management decisions related to water resource management and pollution control (Kavzoglu and Goral 2022; Kwong et al. 2022; Kislik et al. 2022).

Mahdianpari et al. (2018) harnessed high-resolution Sentinel 1 and 2 satellite data to develop an extensive wetland inventory map of Newfoundland province, Canada. Their investigation unveiled that employing an object-based

**Table 2** GEE application in urban planning and management

Aim/objective	Datasets	Study area	Output of the study	Reference
Create a user-friendly GEE application for ecologists to seamlessly conduct ecological modeling, including the estimation of ecosystem services and modeling urban growth sustainability	Landsat time-series images (2005–2016)	Hohhot City, Inner Mongolia	Incorporated Ecosystem Service Value (ESV) into GEE for urban sustainability	Liang et al. (2020)
Estimation of spatiotemporal density of nitrogen dioxide (NO <sub>2</sub> ) and sulfur dioxide (SO <sub>2</sub> ) products and aerosol optical depth (AOD) during the first wave of the COVID-19 (January 2019 to September 2020)	TROPOMI for NO <sub>2</sub> and SO <sub>2</sub> , MODIS for AOD	Istanbul, Turkey	Significant decrease in NO <sub>2</sub> and AOD, while SO <sub>2</sub> remained unchanged. GEE effectively evaluates spatiotemporal air quality	Ghasempour et al. (2021)
Determination of urban areas in GEE platform using spectral indices (eight urban spectral indices and three vegetation indices)	Sentinel 2 MSI image in the GEE platform	Esenyurt, Istanbul	Green areas rapidly diminish due to escalating population and urbanization. The Band Ratio for Built-up Area (BRBA) yielded the highest accuracy of 91%. All three vegetation indices outperformed urban indices, with the NDVI achieving the highest accuracy at 95%	Zelal and Dervisoglu (2023)
Assessing the dynamics of LULC using 31 years data. The Top of Atmosphere (TOA) reflectance values for each spectral band within the GEE database were used in this study	Landsat 5 and Landsat 8 platforms offer 7 and 13 spectral bands respectively, each with a 30-m spatial resolution	Letaba watershed, South Africa	Water bodies, bare surfaces, natural forest and grassland exhibit annual declines of 4%, 2%, 3% and 3% respectively. Conversely, shrub lands, plantations and built-up areas experience annual increases of 41%, 24% and 47% respectively. These changes reflect population-driven shifts, underscoring the need for adaptive strategies	Mashala et al. (2023)

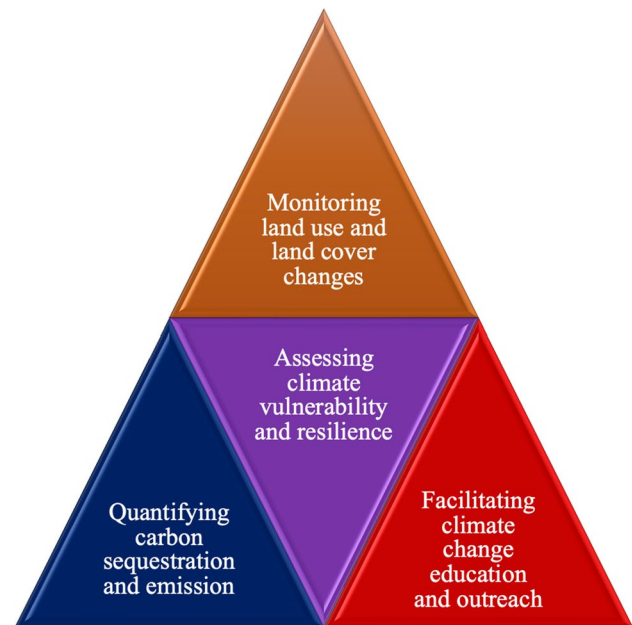


**Fig. 4** Wetland conservation and management through GEE

approach yielded superior results compared to pixel-based classification when delineating wetlands within the GEE platform, achieving an accuracy of 70% and 90% for all wetland and non-wetland classes, respectively. Despite the higher precision observed in classifying wetland types using multi-year optical data compared to Synthetic Aperture Radar (SAR), the amalgamation of both data sets notably enhanced overall accuracy levels. Similarly, Moukrim et al. (2023) created a water transition map covering the period from 1984 to 2019 to examine the spatiotemporal evolution of Dayet Aoua lake. Their findings revealed that recent changes in climate and land use in the lake's surroundings have affected the dynamics and recovery capacity of Dayet Aoua. Thus, GEE plays a crucial role in supporting wetland restoration and management efforts by providing tools for spatial planning, decision support and stakeholder engagement. The platform enables stakeholders to visualize and analyze geospatial data, model ecosystem dynamics and simulate the impact of management interventions such as habitat restoration, water flow restoration and invasive species control.

## Climate change analysis

Climate change poses one of the most pressing challenges of our time, with far-reaching impacts on ecosystems, economies and societies worldwide. Developing countries, often more vulnerable to the effects of climate change due to limited resources and infrastructure, require effective tools and resources to understand and mitigate its impacts (Vijayakumar et al. 2021b). GEE offers unprecedented opportunities for advancing climate change research, monitoring and adaptation efforts (Fig. 5). By harnessing its capabilities, researchers, policymakers and communities can better understand the drivers and impacts of climate change, develop effective mitigation and adaptation strategies and work towards a more sustainable and resilient future. One of the key applications of GEE in climate change studies is monitoring land use and land cover changes (Lin et al. 2020;



**Fig. 5** GEE for climate change analysis

Mashala et al. 2023). By leveraging machine learning (ML) algorithms and image processing techniques, researchers can analyze these images to track changes in land use patterns such as deforestation, urbanization and agricultural expansion (Arévalo et al. 2020; Kafy et al. 2023). This information is crucial for assessing the impact of human activities on ecosystems and understanding their contribution to climate change. GEE enables researchers to estimate carbon stocks in forests, grasslands and other vegetation types by combining satellite data with ground-based measurements and ecosystem models (Venkatappa et al. 2021; Kafy et al. 2023). This information used to monitor deforestation rates assesses the effectiveness of conservation efforts and supports climate change mitigation strategies such as REDD+ (Reducing Emissions from Deforestation and Forest Degradation). Moreover, GEE facilitates the analysis of greenhouse gas emissions from various sources such as deforestation, agriculture and industrial activities, providing valuable insights for policymakers and stakeholders (Roopsind et al. 2019).

GEE also supports the assessment of climate vulnerability and resilience at local, regional and global scales. By integrating climate models, remote sensing data and socioeconomic indicators, researchers can identify areas that are most susceptible to climate impacts such as sea-level rise, droughts and extreme weather events (Venkatappa et al. 2021). This information is essential for prioritizing adaptation measures, improving disaster preparedness and building resilient communities (Vijayakumar et al. 2021b). For example, between 2015 and 2019, droughts affected approximately 9.42 million hectares of cropland,

while floods impacted 3.72 million hectares in Southeast Asia. Over the same period, an estimated total loss of 20.64 million tons of crop production was recorded. Analysis of 40 years of data (from 1980 to 2019) in GEE revealed that rain fed crops in Thailand, Cambodia and Myanmar were significantly impacted by droughts, whereas Indonesia, the Philippines and Malaysia were more vulnerable to floods (Venkatappa et al. 2021). Additionally, GEE enables the monitoring of environmental changes over time, allowing for the evaluation of adaptation strategies and the identification of best practices. Based on aggregated time series of NDVI, temperature and rainfall data, Workie and Debella (2018) found that the onset of the growing season has shifted to an earlier time, and the duration of the growing season has increased in Ethiopia over the last 14 years. Adjusting crop growing periods is crucial for maximizing the use of summer rainfall in agriculture. However, realizing the full potential of GEE requires collaboration, capacity building and continued innovation to address emerging challenges and leverage new opportunities in the fight against climate change. The application of GEE for climate change analysis remains largely untapped in developing countries, despite its immense potential to support adaptation and mitigation efforts in these regions. By leveraging GEE's capabilities, developing countries can enhance their understanding of climate change impacts, strengthen their resilience to climate-related hazards and contribute to global efforts to address this urgent challenge.

## Forestry application

Forests in developing countries face significant threats, including deforestation, degradation and unsustainable land use practices. Addressing these obstacles necessitates the implementation of efficient monitoring and management strategies. GEE has emerged as a valuable asset in confronting the intricate hurdles linked with forest ecosystems globally (Fig. 6). One of the primary applications of GEE in forestry is the utilization of satellite imagery for monitoring forest cover and land use changes (Arévalo et al. 2020; Kafy et al. 2023). It allows researchers and land managers to track forest dynamics over time (Table 3). By analysing multi-temporal satellite imagery, GEE enables the detection of

deforestation, forest degradation and reforestation activities with high spatial and temporal resolution (Lin et al. 2020; Kombate et al. 2022). Jena and Pradhan (2019) investigated the impact of tin mining activity, settlements and illegal logging on forest dynamics in Belitung Island, Indonesia, using a combination of Landsat ETM, MODIS global land cover and Hansen global forest change datasets within the GEE platform. The study revealed a progressive decline in forest cover from 2012 to 2017, coinciding with a significant expansion of active tin mining areas, agricultural land and human settlements (Jena and Pradhan 2019). GEE facilitates the creation of accurate forest maps and inventories. By employing ML algorithms and classification models, GEE enables automated forest mapping, species identification and estimation of forest biomass (Lasaponara et al. 2022). These capabilities are invaluable for forestry professionals in assessing forest resources, planning sustainable land use practices and monitoring the effectiveness of conservation initiatives (Kafy et al. 2023).

GEE by leveraging satellite data identifies active fire hotspots and track fire progression. By integrating weather data, terrain information and historical fire patterns, GEE enhances early warning systems and supports timely fire management strategies, thereby mitigating the impacts of wildfires on forests and adjacent communities (Luu et al. 2024). It also facilitates the estimation of forest carbon stocks and fluxes. By analysing vegetation indices, canopy structure and biomass distribution, GEE enables the quantification of carbon sequestration rates and the assessment of forest carbon dynamics (Kafy et al. 2023). This information is vital for policymakers, conservation organizations and carbon offset initiatives seeking to enhance forest conservation and climate resilience. GEE supports biodiversity conservation efforts by habitat mapping, species distribution modeling and landscape connectivity analysis. By integrating satellite imagery with ecological data, GEE enables the identification of critical habitats, migration corridors and biodiversity hotspots (Crego et al. 2022). This knowledge aids conservation practitioners in prioritizing conservation actions, identifying areas of high conservation value and monitoring habitat changes over time. The forest application of GEE remains largely untapped in developing countries, despite its immense potential to support forest monitoring, management and conservation efforts. By leveraging GEE's



Fig. 6 GEE application in forestry

**Table 3** GEE applications in forestry

Aim	Region/country	Datasets	Significant finding	Reference
Monitor forest cover change from 2000 to 2016	Indonesia	Landsat-based forest cover	Interannual variations in forest area were observed, with the most significant changes occurred in 2011 and then in 2015	Fadli et al. (2019)
Detect small LULC changes in fire-disturbed environment	Italian peninsula (Campania, Basilicata, Calabria, Toscana, Umbria and Lazio)	Sentinel-2 NDVI time series data	LR, MLA and RF classifiers effectively identified and classified various changes such as woodland felling, construction of paths and roads and conversion from wooded areas to cultivated fields, achieving an overall accuracy of 0.86	Lasaponara et al. (2022)
Measuring the influence of LULC changes between 1996 and 2021 on the capacity of carbon storage within forest ecosystems	Chittagong Hill Tracts	Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model combined with GEE	The decline in green cover by 21% led to an annual average decrease in carbon sequestration of 21.65 million metric tons. The built-up areas increased by 388%, resulting in the replacement of 37% of the previous green cover and water bodies	Kafy et al. (2023)
Multi-hazard (floods and wildfires) exposure estimation using MLA and GEE	Quang Nam province, Vietnam	Flood: Historical flood events, and Sentinel 1 Wildfire locations: AQUA, J1, SUOMI and TERRA	The RD susceptibility models attained accuracies of 0.882 for floods and 0.884 for wildfires, respectively	Luu et al. (2024)
Develop a workflow using GEE for creation of species distribution models (SDM), to accurately estimate habitat suitability for various species	The developed spatial processing module (SPM) can be used across the world	Multi-petabyte catalog of raster products	The developed SPM allows users to harness GEE's rapid performance without requiring significant computing infrastructure. It supports complex analyses by integrating thousands of satellite images to model habitat suitability at a high spatial resolution	Crego et al. (2022)
LULC and forest-cover dynamics in Togo between 1985 and 2020	Landsat 5, 7 and 8 images with the RF algorithm	Landsat images and supervised classification	The forest area decreased from 49.9% in 1985 to 23.8% in 2020, with an annual deforestation rate of 2.11% and 422.15 km <sup>2</sup> per year. This decline is mainly due to agriculture expansion, savannahs and urbanization	Kombate et al. (2022)

capabilities, developing countries can enhance their capacity to address forest-related challenges and contribute to sustainable development and environmental stewardship. While GEE offers tremendous potential for forestry applications, several challenges remain to be addressed. These include data interoperability, algorithm validation and capacity building for end-users in developing countries.

## Interventions to realize GEE potential in developing countries

Realizing the potential of GEE in developing countries requires a combination of interventions aimed at addressing technological, institutional and capacity-related challenges. The key interventions that can help unlock GEE's potential in these regions are presented in Fig. 7. *Infrastructure development*: enhance access to reliable internet connectivity and computing resources, including hardware and software, to facilitate the use of GEE in remote areas of developing countries. *Capacity building*: provide training programs, workshops and educational resources to build technical capacity among local researchers and practitioners in remote sensing, geospatial analysis and GEE usage. *Localization of tools and resources*: adapt GEE tools, applications and educational materials to local contexts, languages and specific needs of developing countries to ensure relevance and usability. *Partnerships and collaboration*: foster partnerships and collaboration among governments, non-governmental organizations (NGOs), academic institutions and the private sector to

share knowledge, resources and expertise in leveraging GEE for various applications. *Awareness and advocacy*: raise awareness about the potential benefits of GEE for addressing environmental and societal challenges in developing countries through advocacy campaigns, outreach activities and knowledge-sharing platforms.

*Policy support*: develop supportive policies, regulations and frameworks that facilitate the use of GEE for environmental monitoring, natural resource management, disaster response and climate change adaptation in developing countries. *Financial support*: provide financial support and incentives, including grants, funding opportunities and subsidies, to encourage investment in GEE infrastructure, capacity building and research initiatives in developing countries. *Customized solutions*: tailor GEE applications and solutions to address specific challenges faced by developing countries, such as deforestation, water scarcity, agricultural productivity and urbanization, to maximize impact and effectiveness. *Community engagement*: engage local communities, indigenous groups and marginalized populations in the design, implementation and monitoring of GEE projects to ensure inclusivity, equity and sustainability. *Monitoring and evaluation*: establish monitoring and evaluation mechanisms to assess the impact, effectiveness and sustainability of GEE interventions in achieving desired outcomes and informing future decision-making processes. By implementing these interventions in a coordinated and collaborative manner, developing countries could harness the full potential of GEE to address pressing environmental, social and economic challenges and contribute to sustainable development and resilience building at local, national and global scales.



Fig. 7 Interventions to realize GEE potential in developing countries

## Conclusion

Satellite imaging has emerged as an indispensable source for accurate mapping and information, yet the burgeoning volume and variety of remote sensing data present challenges in effectively extracting relevant information. Processing multiple satellite images captured by different sensors to create high-resolution maps for large areas requires efficient and precise data processing tools. GEE stands out as a geo-big data platform hosted in the cloud that adeptly addresses these challenges. GEE effectively handles massive amounts of data, a significant bottleneck for researchers working with satellite imagery. It provides access to open-access remote sensing datasets, and a variety of algorithms, including cloud masking functions and classifiers, facilitates tasks such as compiling country-wide farmland inventories. The cloud-based GEE platform offers seamless access to a wealth of freely available satellite imagery. Additionally, GEE supports pixel-based classification for crop mapping, making it a versatile tool for researchers. A key advantage



of GEE is its user-friendly approach, allowing users to share code snippets and eliminating the need for deep knowledge of programming languages like JavaScript or Python. Furthermore, the platform boasts a thriving online community, making it accessible to a wide range of users.

GEE's extensive collection of pre-processed data layers, filtered to remove cloud cover and converted to various useful formats like top-of-atmosphere reflectance and surface reflectance, further enhances its usability. Particularly, for researchers in underdeveloped and developing countries, grappling with the massive volume of satellite data and conducting large-scale geographical analyses can be daunting due to infrastructure and technological limitations. GEE has proven to be a valuable and affordable resource for these researchers, levelling the playing field and enabling them to overcome major obstacles associated with geospatial analysis. While GEE has shown its capacity to analyze and derive meaningful results from massive global datasets and automate algorithms for operational use, it is important for more researchers in developing countries to fully harness its potential for their own projects and studies. GEE represents an opportunity for these researchers to access powerful geospatial analysis tools and contribute to the advancement of scientific knowledge and sustainable development.

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## Declarations

**Conflict of interest** The authors declare no competing interests.

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