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Review of Geospatial Analysis using Google Earth Engine

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ABSTRACT

This research showcases the capabilities of Google Earth Engine (GEE) in geospatial analysis of various spectral indices, demonstrating its potential in understanding environmental phenomena. GEE's accessibility and ease of use make it an ideal platform for exploring spectral indices such as NDVI, LST,EVI (Enhanced Vegetation Index),SAVI (Soil Adjusted Vegetation Index),MSAVI (Modified Soil Adjusted Vegetation Index),MSAVI (Modified Soil Adjusted Vegetation Index),NDBI (Normalized Difference Built-up Index),SIF (Solar-Induced Fluorescence),CVI (Chlorophyll Vegetation Index),CWSI (Crop Water Stress Index),GNDVI (Global Normalized Difference Vegetation Index), and SUHI (Surface Urban Heat Island). Additionally, GEE is used to predict soil variation and identify patterns of crop-limiting factors using airborne multispectral images. The normalized difference vegetation index (NDVI) is calculated from aerial spectral images, indicating areas of crop growth and revealing spatial patterns of soil variability. Landsat satellite images are used to derive thermal indices based on Land Surface Temperature (LST), highlighting high LST values in urban and industrial areas. GEE will optimize the SAVI parameter value to minimize soil effects. This study presents a new approach to enhance soil information in urban/suburban environments using remote sensing technologies. The proposed method, called Ratio Normalized Difference Soil Index (RNDSI), combines spectral signatures of soil, impervious surface areas, and vegetation to identify soil covers. The results show that RNDSI is effective in separating soil from other land cover types and can be used as an input to Land Use Land Cover Change (LULCC) models. Additionally, the study compares the sensitivity of various vegetation indices (NDVI, SAVI, TSAVI, MSAVI, and GEMI) to soil background effects.

Keywords: Google Earth Engine (GEE), Spectral indices, Geo-spatial analysis, Remote sensing, Earth observation, Vegetation monitoring, NDVI (Normalized Difference Vegetation Index), EVI (Enhanced Vegetation Index), NDWI (Normalized Difference Water Index), MNDWI (Modified Normalized Difference Water Index)

INTRODUCTION

Google Earth Engine (GEE) has revolutionized remote sensing analysis, providing a powerful platform for processing vast amounts of geospatial data. This research delves into the application of GEE in exploring a diverse range of spectral indices, offering valuable insights into environmental phenomena. By harnessing the capabilities of GEE, we can efficiently analyze key indices such as NDVI, LST, EVI, SAVI, MSAVI, NDBI, SIF, CVI, CWSI, GNDVI, and SUHI, shedding light on vegetation health, land surface temperature, soil moisture, and urban heat island effects.

Furthermore, GEE enables us to predict soil variability and identify crop-limiting factors through the analysis of airborne multispectral images. The normalized difference vegetation index (NDVI) derived from these images serves as a powerful tool for assessing crop growth and delineating spatial patterns of soil properties. Additionally, Landsat satellite imagery allows for the calculation of thermal indices based on Land Surface Temperature (LST), highlighting areas prone to urban heat island effects.

This research also introduces a novel approach to enhance soil information extraction in urban and suburban environments. By combining the spectral signatures of soil, impervious surfaces, and vegetation, the Ratio Normalized Difference Soil Index (RNDSI) offers a robust method for identifying soil covers. This innovative technique has the potential to significantly improve land use land cover change (LULCC) modeling and urban planning.

Remote sensing, coupled with advanced image processing techniques, has emerged as a vital tool for monitoring Earth's dynamic processes. Google Earth Engine (GEE) provides a user- friendly and scalable platform for conducting comprehensive geospatial analysis. This research leverages the power of GEE to explore a wide array of spectral indices, enabling us to gain valuable insights into various environmental parameters.

By analyzing spectral indices such as NDVI, EVI, and SAVI, we can assess vegetation health, monitor crop growth, and detect changes in land cover. Additionally, thermal indices derived from LST data, as obtained from Landsat imagery, allow us to identify urban heat island effects and assess their impact on local climate and human well-being.

To address the challenges associated with soil variability, this research proposes a novel approach, the Ratio Normalized Difference Soil Index (RNDSI). This index effectively separates soil from other land cover types, providing valuable information for LULCC modeling and urban planning.

By comparing the sensitivity of different vegetation indices to soil background effects, we can optimize their application and improve the accuracy of remote sensing-based assessments.

OBJECTIVES

1. To study about various spectral indices (such as vegetation indices, soil indices, water indices, land surface temperature indices) of Google earth Engine of geospatial analysis
2. To collect the different journals of the spectral indices.
3. By studying these journals we can know the improvement of land cover classification and extraction of built-up areas.

LITERATURE SURVEY

1. **Akhona Madasa et al** examines the paper **"**Application of geospatial indices for mapping land cover/use change detection in a mining area**"** which shows that advent of big data has revolutionized the field of civil engineering, particularly in remote sensing applications. The term "big data" emerged in the mid-1990s and gained popularity in 2006. Big data is characterized by three dimensions: volume, variety, and velocity. Remote sensing big data has transformed our understanding and interaction with the planet. The growth of geospatial data has led to the development of new technologies and platforms for processing and analyzing large datasets. Cloud computing platforms, such as Amazon Web Services, Google Cloud Platform, Microsoft Azure, and IBM Cloud, have emerged as essential tools for handling big data.

The applications of GEE in environmental monitoring are vast. Researchers have utilized the platform for various studies, including land cover classification, crop monitoring, disaster response, and climate change analysis. GEE's ability to process large datasets and provide scalable computing resources has made it an essential tool for environmental monitoring. This review aims to provide a comprehensive overview of the applications of GEE in environmental monitoring. The study analyzes various publications that have utilized GEE for remote sensing big data processing. The review categorizes the publications based on their application, dataset, algorithms, and methods.

The findings of the review highlight the versatility and scalability of GEE in environmental monitoring. The platform's ability to process large datasets and provide accurate results has made it an essential tool for researchers and practitioners. The review also identifies areas for future research, including the development of new algorithms and methods for processing remote sensing big data.

Overall, this review demonstrates the potential of GEE in revolutionizing environmental monitoring. The platform's capabilities and applications make it an essential tool for researchers, practitioners, and policymakers working in the field of environmental monitoring.

The methodology employed in this review paper involved a comprehensive literature search to identify relevant publications that utilized Google Earth Engine (GEE) for remote sensing big data processing. The search was limited to peer-reviewed articles and conference papers published in English, and was conducted using databases such as Google Scholar, Scopus, Web of Science, and IEEE Xplore. The search terms used included combinations of "Google Earth Engine", "GEE", "remote sensing", "big data", "environmental monitoring", and "Earth observation". A standardized checklist was used to assess the quality of the included publications, evaluating their clarity, relevance, and validity. The results of the included publications were synthesized and summarized using a narrative meta-analysis approach, to identify the most successful and reliable datasets and algorithms for environmental monitoring at large scale.

2. **Halfia Tamiminia et all** examines the paper **"**Google Earth Engine for geo-big data applications: A meta-analysis and systematic review" which shows the paper that introduces the concept of "big data" in the context of geospatial data, highlighting its volume, variety, and velocity. It emphasizes the challenges associated with processing and analyzing such large datasets. Cloud computing platforms, particularly Google Earth Engine (GEE), have emerged as powerful tools to address these challenges.

GEE is a cloud-based platform that provides access to a vast amount of remote sensing imagery and other geospatial data. It offers powerful computing capabilities, enabling users to perform complex analyses without requiring significant computational resources. By leveraging its capabilities and addressing its limitations, GEE can continue to revolutionize the field of remote sensing and contribute to sustainable development. A systematic review and meta- analysis were conducted on 349 relevant journal articles focusing on the use of Google Earth Engine (GEE) for environmental monitoring.

The study extracted data on various parameters, including datasets, algorithms, study regions, disciplines, and specific applications, to gain insights into GEE's large-scale environmental applications. The publications were categorized and analyzed to identify trends, popular methods, and the reliability of different datasets and algorithms. This approach aimed to uncover patterns in the use of GEE across disciplines, geographic extents, and resolutions, as well as to evaluate the effectiveness of various methods and datasets for environmental monitoring tasks.

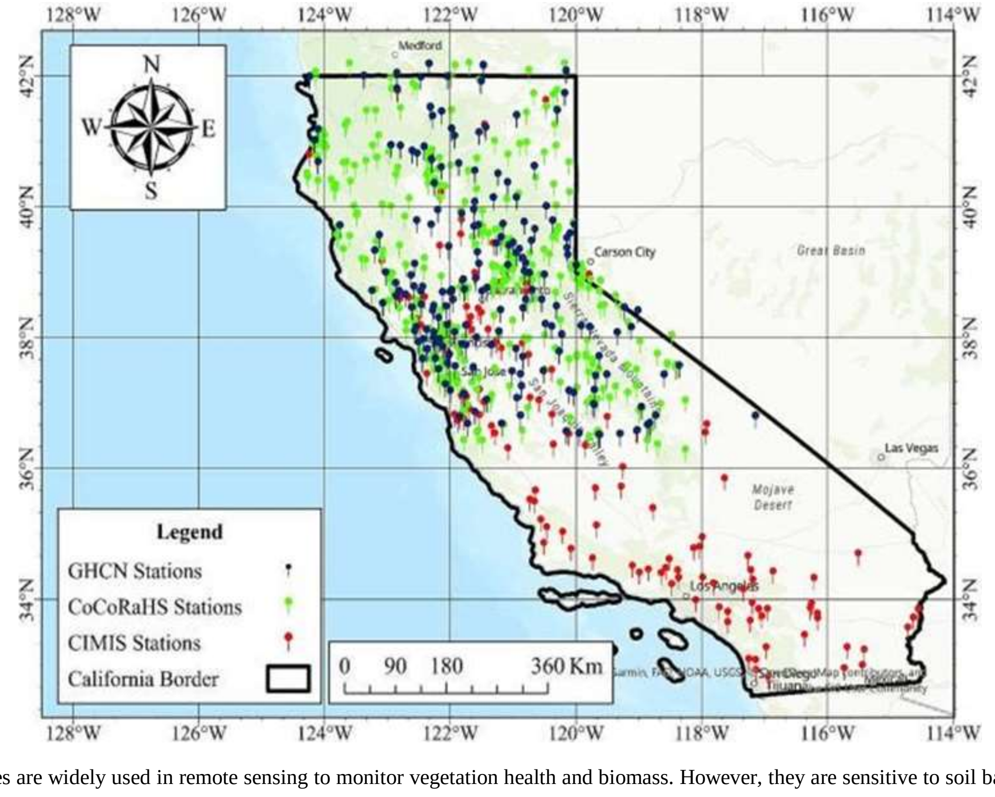
3. **Yingbing Deng et all** examines the paper RNDSI: A ratio normalized difference soil index for remote sensing of urban/suburban environments

Land use land cover change (LULCC) is a critical aspect of urban planning and environmental management. Bare soil is a vital component of LULCC, but its identification using remote sensing technologies is challenging due to its complex physical and chemical compositions. This study aims to develop a new index, called the Ratio Normalized Difference Soil Index (RNDSI), to enhance soil information in urban/suburban environments. The study area consists of two counties in Wisconsin, USA. Landsat Thematic Mapper (TM) imagery was used to develop the RNDSI. Stratified random sampling was used to select samples of soil, impervious surfaces, and vegetation. The normalized difference soil index (NDSI) was calculated using the combination of TM bands 7 and 2. The RNDSI was developed by dividing the NDSI by the first component of the tasseled cap transformation (TC1). The RNDSI was able to separate soil from impervious surfaces and vegetation more effectively than other indices such as the biophysical composition index (BCI) and the enhanced built-up and bareness index (EBBI). The RNDSI values for soil were clustered in the range of 0.1 to 0.4, while impervious surfaces and vegetation had lower RNDSI values.

The RNDSI is a promising tool for enhancing soil information in urban/suburban environments. The complexity of soil properties and their dependency on various factors make it challenging to develop soil indices. The RNDSI has the potential to be used as an input to LULCC models. Further research is needed to validate the RNDSI and explore its applications in urban planning and environmental management.

This study focuses on Milwaukee and Waukesha counties in Wisconsin, USA, characterized by urban and suburban land use patterns. Landsat Thematic Mapper (TM) imagery, with a spatial resolution of 30 meters, was utilized for data collection approach was employed to select 200 random samples categorized into soil, impervious surfaces, and vegetation. Spectral analysis of the samples was performed using ENVI software, focusing on their reflective properties in the visible and near-infrared regions. The normalized difference soil index (NDSI) was calculated using TM bands 7 and 2, and the ratio normalized difference soil index (RNDSI) was developed by dividing the NDSI by the first component of the tasseled cap transformation (TC1). Validation of the RNDSI involved field data, including soil type, moisture content, and vegetation cover. Comparative analysis assessed the RNDSI's performance against other indices, such as the biophysical composition index (BCI) and the enhanced built-up and bareness index (EBBI), based on their ability to distinguish soil from impervious surfaces and vegetation.

4. **Genevieve Rondeaux et all** examines the paper **"**Optimization of Soil-Adjusted Vegetation Indices" which shows that this study focuses on testing and comparing the sensitivity of various vegetation indices to soil background effects. The normalized difference vegetation index (NDVI), soil-adjusted vegetation index (SAVI), transformed soil-adjusted vegetation index (TSAVI), modified soil-adjusted vegetation index (MSAVI), and global environment monitoring index (GEMI) were simulated using the SAIL model for a range of soil reflectances. The results show that the SAVI family of indices with the form VI = (NIR - R) / (NIR + R + X) is optimized when X = 0.16. The MSAVI performed best in minimizing soil effects.



Vegetation indices are widely used in remote sensing to monitor vegetation health and biomass. However, they are sensitive to soil background effects, which can lead to inaccurate results. This study aims to optimize soil-adjusted vegetation indices to minimize soil effects. The SAIL model was used to simulate various vegetation indices for a range of soil reflectances. The sensitivity of each index to soil effects was tested and compared.

The MSAVI performed best in minimizing soil effects, followed by the TSAVI and SAVI. The NDVI was most sensitive to soil effects. The methodology employed in this study involved selecting two counties in Wisconsin, USA (Milwaukee and Waukesha) as the study area, characterized by urban and suburban land use patterns. Landsat Thematic Mapper (TM) imagery was used, with a spatial resolution of 30 meters, acquired for the summer season. Stratified random sampling was applied, selecting 200 random samples divided into three categories: soil, impervious surfaces, and vegetation. Spectral analysis was conducted using ENVI software, focusing on the reflective properties of the samples in the visible and near- infrared regions.

The normalized difference soil index (NDSI) was calculated using TM bands 7 and 2, and the RNDSI was developed by dividing the NDSI by the first component of the tasseled cap transformation (TC1). The RNDSI was validated using field data, including soil type, moisture content, and vegetation cover, and compared with other indices (BCI and EBBI) to separate soil from impervious surfaces and vegetation. Finally, accuracy assessment was conducted using statistical analysis and visual inspection of the index images.

5. **Noel Gorelick et all** examines the paper "Google Earth Engine: Planetary-scale geospatial analysis for everyone" which shows the Earth Engine consists of a multi-petabyte analysis- ready data catalog, a high-performance computation service, and an interactive development environment. The data catalog houses a large repository of publicly available geospatial datasets, including satellite and aerial imaging systems, environmental variables, and socio- economic datasets. The computation service is based on a large parallel processing system that automatically subdivides and distributes computations.

The Earth Engine system is built on top of a collection of enabling technologies, including the Borg cluster management system, Bigtable and Spanner distributed databases, and the FlumeJava framework for parallel pipeline execution. The system architecture is designed to efficiently distribute complex computations across many machines. Earth Engine is being used across a wide variety of disciplines, including global forest change, global surface water change, crop yield estimation, and urban mapping. The platform has been integrated into a number of third-party applications, including analyzing species habitat ranges, monitoring climate, and assessing land use change. While Earth Engine provides a powerful platform for planetary-scale geospatial analysis, there are still several challenges and limitations. These include scaling challenges, computational model mismatch, client/server programming model, and advancing the state of the art. To address these challenges, the Earth Engine team is working on integrating deep learning techniques, facilitating easy access to other scalable infrastructures, and improving the user experience.

Google Earth Engine is a powerful platform for planetary-scale geospatial analysis. It provides a large catalog of publicly available geospatial datasets, a high-performance computation service, and an interactive development environment. While there are still several challenges and limitations, the Earth Engine team is working to address these issues and advance the state of the art in geospatial analysis.

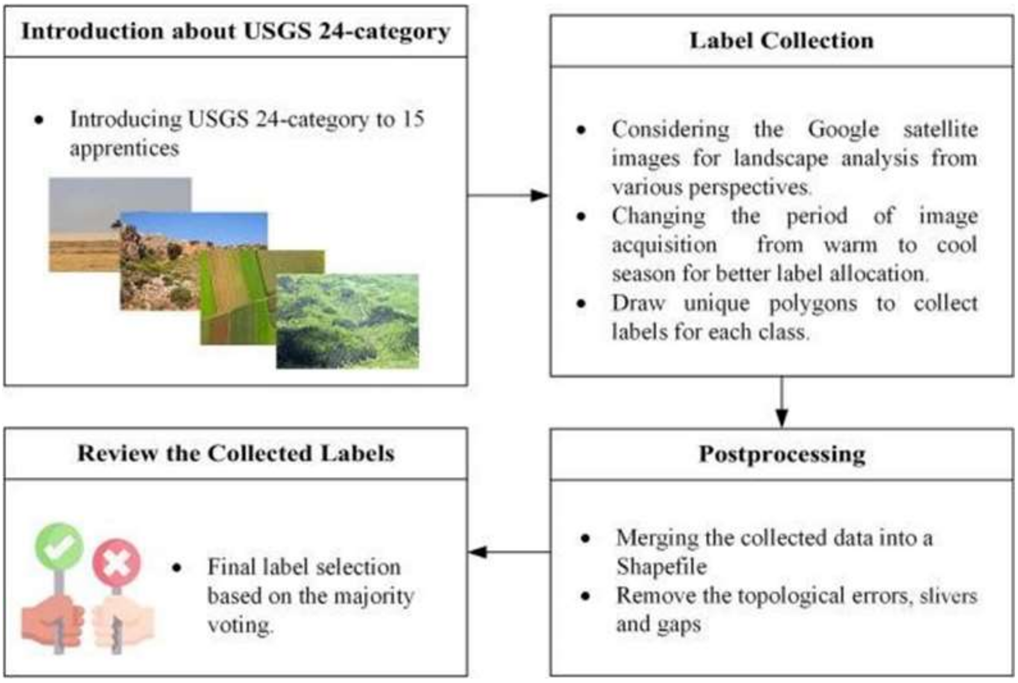
6. **Joachim Etouna et all** examines the paper "Assessment of Land Degradation Status and Its Impact and Semi-Arid Areas by Correlating Spectral and Principal Component Analysis" shows that the document discusses land degradation in arid and semi-arid areas, focusing on assessing degradation using spectral indices and principal component analysis (PCA). Land degradation in arid and semi-arid regions significantly affects soil health and ecosystem productivity, driven by both natural and human-induced factors. The study examines these processes in the Far North region of Cameroon, leveraging satellite imagery (Landsat 8 OLI) and spectral analysis to evaluate the extent and severity of degradation. Several indices were utilized, including the Modified Soil Adjusted Vegetation Index (MSAVI2), Normalized Difference Bare Soil Index (NDBSI), Texture Index (NDTeI), and others, along with PCA to synthesize data. The results highlight six classes of land degradation, from "severe" to "close to nil," mapped across the region. Severe degradation, covering approximately 3,139 km², was attributed primarily to vegetation loss and topsoil grain size changes. High degradation areas, spanning 6,763 km², were influenced by bareness and roughness, whereas moderate degradation (8,341km²) was linked to roughness and sand spread. The study reveals that encrusting, sand spread, and rough lithology contribute to lower levels of degradation.

A novel weighted sum method integrated the indices into a composite degradation model, which showed a strong correlation with SPC1R-NIR-SWIR1-SWIR2, achieving a high determination coefficient ($R^2 = 0.9999$). This model enabled precise mapping of degradation hotspots and facilitated decision-making for land rehabilitation. Furthermore, overlaying population density data identified priority areas for governmental intervention, such as th eDiamaré and Mayo-Danay departments, where human activity exacerbates degradation risks.The study underscores the importance of remote sensing and GIS tools in monitoring land degradation and planning mitigation strategies. Recommendations include incorporating topographical variables in varied terrains, using portable spectroradiometers for field validation, and addressing biases caused by settlement structures. The research concludes that integrating spectral indices with PCA provides an effective framework for detecting and addressing land degradation, especially in vulnerable arid and semi-arid ecosystems.

Satellite imagery from the Landsat 8 OLI sensor was acquired for January 2015, coinciding with the dry season to ensure minimal vegetation interference. Seven scenes were downloaded, representing various bands of the electromagnetic spectrum, with spatial resolutions of 15–30 meters. Preprocessing included radiometric calibration, atmospheric correction, and image mosaicking. A wavelet resolution merge technique was applied to combine multispectral and panchromatic data for enhanced readability.The degradation map classified the study area into six degradation levels: severe, high, moderate, low, very low, and close to nil. The SPC1R- NIR-SWIR1-SWIR2 index strongly correlated with severe degradation areas, dominated by barren land and coarse soil textures. Further analysis integrated population density, revealing high-risk zones where degradation intersects with dense human settlements. The study's primary limitation was its exclusion of slope data due to the region's relatively flat topography. Future research should incorporate portable spectroradiometers for precise field validation and mitigate potential biases from settlement structures.

7. **Sukanya Ghosh et all** examines the paper "Google earth engine based computational system for the earth and environment monitoring applications during the COVID-19 pandemic using thresholding technique on SAR datasets" which shows the SAR imagery, particularly from Sentinel-1, was processed on GEE to detect water inundation during flood events in the Ganga- Brahmaputra plains. The study utilized pre- and post-flood data to delineate water and non- water regions through a histogram-based thresholding method, Otsu's algorithm. This approach is validated with Sentinel-2 optical images and Google Earth imagery, ensuring accuracy through comparison with real-world data. The paper underscores the advantages of GEE, such as its cloud-based infrastructure, pre- processed datasets, and ability to analyze large-scale Earth observations without hardwar dependencies. The automated methodology enables efficient, high-resolution flood

monitoring, assisting in emergency response and decision- making during disasters. However, limitations like computational restrictions for complex machine learning algorithms in GEE are acknowledged.

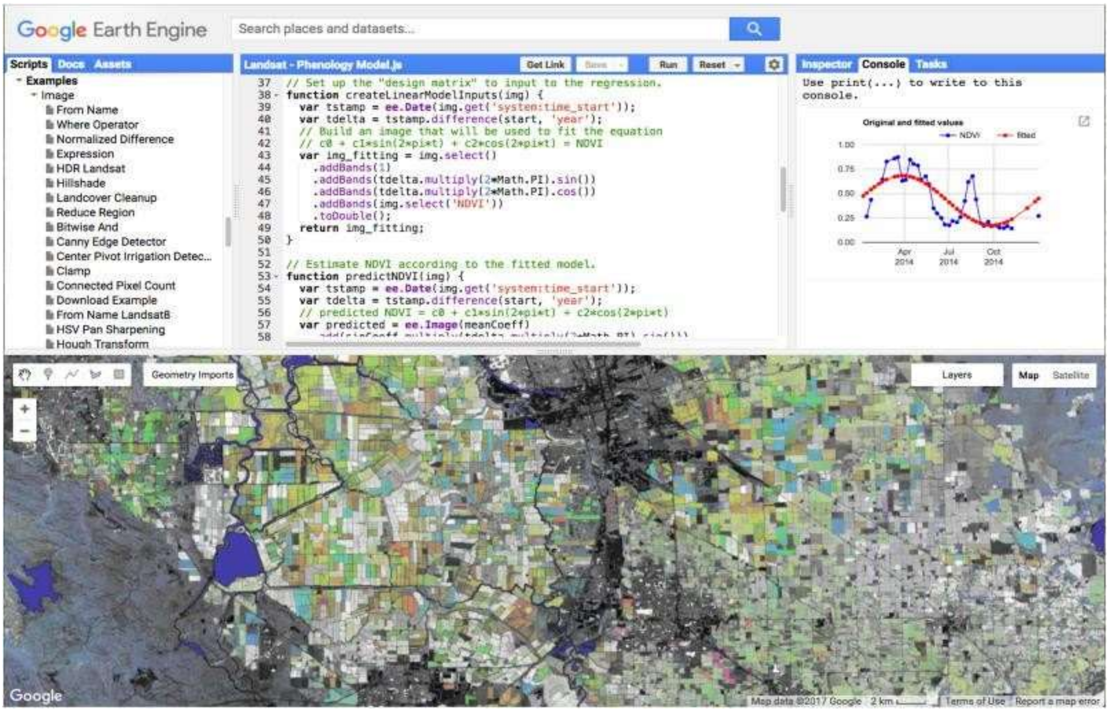


The data preprocessing stage begins with the acquisition of Sentinel-1 SAR imagery, selected for its all-weather and day-and-night capabilities, making it highly suitable for flood monitoring during the constraints of the COVID-19 pandemic. Images were carefully chosen to represent both pre-flood and post-flood scenarios in the Ganga-Brahmaputra plains, a region prone to significant inundation events. GEE's cloud-based platform facilitated the integration and processing of these large datasets, eliminating the need for high-end local computational infrastructure. The results obtained from SAR-based classification were validated using Sentinel-2 optical imagery and high-resolution data from Google Earth. Sentinel-2 data, with its multispectral bands, provided an independent and detailed reference for cross-verification. Additionally, Google Earth imagery was used for visual comparison, further strengthening the reliability of the automated methodology. This multi-source validation process confirmed the accuracy of the flood inundation maps and highlighted the effectiveness of combining SAR data with advanced computational techniques.

One of the key strengths of the proposed approach lies in its implementation within the GEE environment. GEE’s pre-processed datasets and scalable infrastructure allowed for seamless analysis of large-scale Earth observations. The automation of the workflow significantly reduced manual intervention and expedited the generation of flood inundation maps, making it particularly valuable for real-time monitoring and emergency response. Moreover, the use of cloud-based resources eliminated hardware dependencies, enabling researchers to conduct large-scale analyses with minimal local computational requirements.

8. **K.R.Remitha et all** examines the paper "Dynamic change analysis of water spread region and its impact assessment using spectral indices of remotely sensed data" which shows that the paper focuses on evaluating the spatial and temporal changes in water spread regions in Coimbatore, Tamil Nadu, India. The research employs remote sensing techniques using satellite imagery from Landsat 5 and Landsat 9 over 32 years (1990–2022) to study the dynamics of 11 lakes. Key indices like the Normalized Difference Water Index (NDWI), Normalized Difference Vegetation Index (NDVI), and Normalized Difference Built-up Index (NDBI) are used to assess these changes.

The NDWI is employed for precise identification of water bodies, utilizing the reflectance properties of green and near-infrared (NIR) bands. NDVI evaluates vegetation health around water bodies, indicating changes in agricultural practices.NDBI detects urban development around the lakes, signifying human encroachment and its mitigation over time. There was a significant increase in the total water spread area from 13.01 hectares in 1990 to 435.17 hectares in 2022. This expansion reflects improved maintenance and rehabilitation measures such as desilting and runoff management initiated by the government and NGOs. Mixed results were observe.



Some lakes showed an increase in vegetation due to agricultural activities, while others exhibited a decline, attributed to urban encroachments. NDBI Trends An initial increase in urbanization (1990–2000) was curtailed in later years through efforts to reduce encroachment. This highlights the effectiveness of urban planning and environmental conservation measures. The increase in water spread supports groundwater recharge and recreational activities like boating, benefiting the local climate and community well-being.water resource planning for sustainable development. Regular maintenance and policy interventions are critical to managing urban water bodies. The study employs a comprehensive methodology to evaluate the spatial and temporal changes in water spread regions of Coimbatore, Tamil Nadu, India, utilizing remote sensing and geospatial techniques. The research integrates satellite imagery from Landsat 5 and Landsat 9, covering a 32-year period from 1990 to 2022. The methodology begins with the acquisition of multi-temporal satellite data, which is pre-processed to correct for atmospheric and radiometric distortions. This ensures consistency and reliability in the datasets, enabling precise analysis of land use and land cover changes around the selected water bodies.

The temporal data analysis reveals significant variations in the water spread area of the lakes, showing an increase from 13.01 hectares in 1990 to 435.17 hectares in 2022. This expansionis attributed to governmental and non-governmental initiatives such as desilting, runoff management, and lake rehabilitation programs. The NDVI results indicate mixed trends, with some lakes exhibiting an increase in vegetation cover due to agricultural activities, while others show a decline linked to urban encroachment. The NDBI results demonstrate an initial surge in urbanization during the 1990s, followed by a stabilization and slight decline in later years due to regulatory interventions and urban planning efforts aimed at conserving water bodies.

9. **Nanki Sidhu et all** examines the paper "Using Google Earth Engine to detect land cover change: Singapore as a use case" which shows that the Land use and land cover play a pivotal role in regulating the Earth's surface heat balance. Vegetated areas, through transpiration and shading, have been shown to reduce surface temperature significantly. Urbanization, characterized by impervious surfaces, often contributes to the Urban Heat Island (UHI) effect, where urban areas exhibit higher temperatures than surrounding rural regions (Oke, 1982). Zhou et al. (2014) demonstrated spatial patterns and drivers of UHIs in China's major cities, highlighting the role of vegetation and water bodies in mitigating urban heat.

Remote sensing has become an indispensable tool in environmental monitoring. Studies such as Weng et al. (2004) utilized Landsat data to estimate the relationship between LST and vegetation indices like NDVI (Normalized Difference Vegetation Index). Their findings emphasized the inverse correlation between vegetation abundance and LST. Similarly, Xu (2006) modified the Normalized Difference Water Index (NDWI) to enhance the detection of water bodies, which are critical in cooling the surrounding environment.Satellite-derived indices such as NDVI, NDWI, NDBI (Normalized Difference Built-up Index), and BI (Brightness Index) have been widely used to understand land cover characteristics and their thermal properties. For example, Rogan and Chen (2004) explored how these indices can monitor changes in land cover over time, facilitating better understanding of their impact on LST. Xiao et al. (2008) studied LST variations in Beijing, revealing that urban built-up areas correlated positively with higher temperatures, while vegetative and water-dominated regions showed cooling effects.

Long-term analysis of LST trends provides insights into the impact of climate change and anthropogenic activities. Studies employing Landsat data over extended periods (e.g., 15–20 years) have revealed significant temperature changes linked to urban expansion and deforestation (Zhou et al., 2014). These temporal analyses underline the importance of sustainable land management practices to mitigate temperature rise in vulnerable regions.

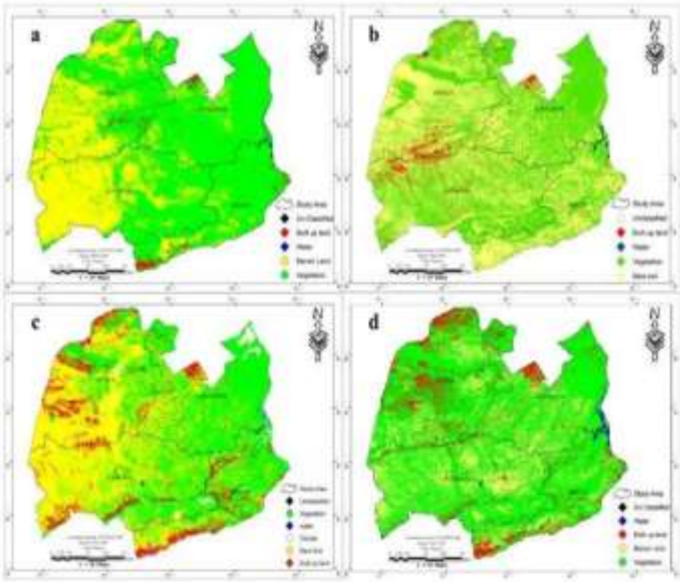


Image a: This image likely represents the earliest time point. It shows significant vegetation cover, some barren land, and a small area of built-up land.

Image b: This image indicates a noticeable increase in built-up land compared to image a. It suggests urbanization and development are occurring in the area.

Image c: The land cover in image c appears to be experiencing a shift toward more barren land, possibly indicating deforestation, soil erosion, or desertification.

Image d: Image d showcases a continued increase in built-up land and a significant decrease in vegetation cover compared to previous images. This signifies continued development and urbanization in the area.

Overall Interpretation:

The images illustrate a trend of increasing urbanization and a decreasing amount of vegetation cover. This suggests a clear pattern of land use change in the area.

Temperature among different land use land cover (LULC) classes and investigate relationship between normalized satellite indices and land surface temperature (LST) in arid Potohar region. Used Landsat 7 (ETM+) and 8 (OLI & TIRS) satellite data from 2000-2015 Applied geospatial To analyze spatio-temporal trends in techniques to analyze temperature trends Generated normalized satellite indices (NDVI, NDWI, NDSI, NDBI, BI) Conducted regression analysis to find relationships between indices and LST. Software Matlab 2015 Erdas 2016 ENVI ArcGIS SPSS. Demonstrated significance of land use/land cover in determining surface heat balance Proved that increase in vegetative areas and water bodies can reduce overall surface temperature Validated effectiveness of RS & GIS techniques for analyzing earth's surface.

10. **Aqil Tariq et all** examines the paper “Land surface temperature relation with normalized satellite indices for the estimation of spatio-temporal trends in temperature among various land use land cover classes of an arid Potohar region using Landsat data” which shows that the urbanization is a leading driver of land cover changes, resulting in higher surface temperatures, commonly referred to as the Urban Heat Island (UHI) effect. Oke (1982) laid the foundation for understanding the energy dynamics contributing to UHIs, which are exacerbated by the replacement of natural vegetation with impervious surfaces. Studies such as Zhou et al. (2014) further emphasized the critical role of green spaces in mitigating urban heat, suggesting that increasing urban vegetation can significantly enhance thermal comfort in industrialized regions.

Thermal indices derived from satellite data, such as the Normalized Difference Vegetation Index (NDVI) and LST, are widely used to analyze temperature variability in urban areas. Weng et al. (2004) employed Landsat data to explore the relationship between NDVI and LST, finding an inverse correlation between vegetation abundance and surface temperatures. The integration of such indices with spatial autocorrelation methods, like Moran’s I, has improved the understanding of spatial patterns and interactions of urban heat islands (Moran, 1950). Bivariate Moran’s is a robust statistical method for identifying spatial autocorrelation, particularly in urban studies. By linking LST with vegetation indices, researchers can assess the spatial interdependence of urban heat patterns and land cover changes. Xiao et al. (2008) applied this approach to quantify the spatial variability of urban temperatures, demonstrating its effectiveness in identifying high-risk areas. To investigate different remote sensing thermal indices and their impact on land surface temperature (LST) in an urbanized and industrialized city in Southeast Brazil. Used Landsat satellite images to derive thermal indices based on LST. Conducted supervised classification for land use and land cover changes. Analyzed NDVI and LST spatial variability. Applied bivariate Moran’s I for spatial autocorrelation analysis. GIS software for spatial analysis. Remote sensing tools for LST and NDVI calculations.Statistical software for data analysis (e.g., GeoDA). Confirmed the relationship between urbanization, land cover, and surface temperature. Recommended increasing urban vegetation to mitigate heat island effects and improve thermal comfort.

11. **J.I.Lizaso et all** examines the paper "Using the normalized difference vegetation index and a crop simulation model to predict soil spatial variability" which shows that the spatial crop models are essential tools in precision agriculture, as they account for the spatial variability of environmental and management factors affecting crop growth. Jones et al. (2003) highlighted the importance of models like DSSAT (Decision Support System for Agrotechnology Transfer) in precision agriculture. DSSAT integrates climate, soil, and crop management data to simulate crop yield and identify factors limiting productivity. The CERES-Maize model, part of DSSAT, is widely used for simulating maize growth and yield under various environmental and management scenarios (Tsuji et al., 1998).

Remote sensing has revolutionized agriculture by providing timely and accurate spatial data for monitoring crop health and productivity. Studies by Moran et al. (1997) demonstrated how remotely sensed data could be integrated with crop models to assess spatial variability in yield and identify environmental stressors. Vegetation indices, such as the Normalized Difference Vegetation Index (NDVI), are commonly used to monitor crop canopy health and biophysical characteristics, including leaf area index (LAI) and biomass (Clevers, 1989).

Spectral data derived from remote sensing platforms are valuable for analyzing biophysical crop parameters, such as LAI, chlorophyll content, and canopy structure. Hatfield et al. (2008) emphasized the potential of spectral reflectance data in assessing crop growth and health. These relationships help identify stress factors, including water shortages, nutrient deficiencies, and pest infestations, enabling timely management decisions.Spatially distributed patterns of pests and diseases are critical factors affecting crop productivity. Yang et al. (2009) explored the use of remote sensing data in pest and disease management, demonstrating its role in detecting early outbreaks and guiding site-specific pesticide applications. Integrating spatial crop models with pest and disease monitoring systems enhances the precision and effectiveness of control measures.

12. **Dr. Nagi Mohammed et all** examines the paper "Positional Accurcy Testing Of Google Earth" which shows that the Google Earth is widely used in geospatial studies for obtaining location and elevation data. Studies have assessed its horizontal and vertical accuracy in various regions. Potere (2008) highlighted that Google Earth's spatial accuracy depends on data sources, image resolution, and processing methods. According to Ibrahim et al. (2011), Google Earth coordinates provide satisfactory accuracy for general mapping purposes but are less reliable for precise engineering or cadastral surveys.

The horizontal accuracy of Google Earth has been evaluated in urban and rural settings. For instance, Giannopoulos et al. (2015) compared Google Earth coordinates with those obtained from GPS, finding horizontal Root Mean Square Error (RMSE) values between 1.5m and 5.0m, depending on the terrain and urban density. Vertical accuracy assessments, such as those conducted by Zandbergen (2008), revealed RMSE values ranging from 1.7m to 9.0m, influenced by the quality of the digital elevation model (DEM) used by Google Earth.

Google Earth's accuracy has been deemed acceptable for medium- and small-scale mapping. Scholars like Mohammadi et al. (2013) have utilized it for creating preliminary contour maps and conducting site investigations. Its cost-effectiveness and global coverage make it a valuable tool for resource-constrained projects. However, its limitations in precision mapping necessitate cross-verification with high-accuracy GPS or surveying equipment.

Global Positioning System (GPS) receivers with Real-Time Kinematic (RTK) correction provide high-precision spatial data, often used as a benchmark for validating the accuracy of tools like Google Earth. According to Leick (2004), RTK GPS can achieve sub-meter accuracy for both horizontal and vertical measurements, making it an essential tool for studies requiring precise geolocation. Studies comparing Google Earth data with RTK GPS, such as by Yilmaz et al. (2015), confirm Google Earth's adequacy for non-critical applications but highlight its limitations for engineering-grade accuracy.

To estimate and evaluate Google Earth's horizontal and vertical accuracy in Khartoum State. Selected 16 points in Khartoum town Used Trimble 1800 surveying GPS receiver with RTK technique Compared Google Earth coordinates with GPS coordinates Computed Root Mean Square Error (RMSE) Conducted measurements in both September and October 2012. Software Google Earth GPS processing software Trimble GPS equipment. ***:*** Google Earth provides acceptable accuracy for medium and small scale mapping Horizontal accuracy: 1.80m Vertical accuracy: 1.73m Suitable for preliminary studies and investigations Can be used for producing contour maps at 1:50,000 scale and smaller.

13. **Thanan Rodrigues et all** examines the paper "Impact of urban and industrial features on land surface temperature" which shows that the paper urban growth and land cover changes significantly affect environmental sustainability, especially in rapidly urbanizing regions like Singapore. According to Seto et al. (2011), monitoring urban sprawl is essential for understanding its impact on ecosystems and urban planning. Landsat and MODIS data have been widely used in such studies due to their medium spatial resolution and temporal coverage, which provide valuable insights into urban and vegetation dynamics (Zhu et al., 2019). Enhanced Vegetation Index (EVI) is frequently employed as a reliable vegetation metric for analyzing land cover changes, particularly in urban areas where vegetation is sparse (Huete et al., 2002).

Enhanced Vegetation Index (EVI) for Land Cover Change Detectior.EVI has been recognized as a key index for monitoring vegetation in urban and industrial regions. Studies by Huete et al. (2002) showed that EVI is more effective than NDVI in areas with high biomass or atmospheric noise, such as urban-industrial zones. Temporal EVI signatures, when analyzed in time series, allow researchers to detect seasonal trends and long-term vegetation changes, as demonstrated by Jiang et al. (2008).

PROBLEM STATEMENT

The increasing frequency and severity of flood events, particularly in vulnerable regions like the Ganga-Brahmaputra plains, necessitate timely and accurate flood monitoring systems. Traditional ground-based methods and optical satellite imagery are often limited by weather conditions, cloud cover, and the need for extensive computational resources, particularly during emergencies like the COVID-19 pandemic when access to physical resources and mobility are constrained.

The challenge lies in developing a robust, automated, and accessible solution for real-time flood mapping that can overcome these limitations. Specifically, there is a need for a system that leverages advanced computational tools, processes large datasets efficiently, and provides accurate results in a timely manner to aid disaster response and management efforts.

This study aims to address these challenges by utilizing Synthetic Aperture Radar (SAR) data, known for its weather-independent capabilities, and implementing a thresholding technique (Otsu's algorithm) within the Google Earth Engine (GEE) platform. The objective is to develop a scalable, cloud-based computational system for accurate and real-time flood monitoring with minimal manual intervention and hardware dependency

The rapid urbanization and agricultural expansion in Coimbatore, Tamil Nadu, India, have significantly altered the natural landscape over the past three decades, leading to notable changes in water spread regions. Despite the implementation of rehabilitation and conservation measures, the interplay between water body dynamics, vegetation changes, and urban encroachment remains insufficiently understood. There is a lack of comprehensive studies employing advanced geospatial techniques to quantify and assess the spatial and temporal changes in water spread regions and their surrounding landscapes.

This research seeks to address these gaps by analyzing the dynamic changes in water bodies using multi-temporal satellite data from 1990 to 2022 and evaluating the associated impacts on vegetation and urban development. The study aims to use spectral indices—NDWI, NDVI, and NDBI—to assess water spread changes, vegetation health, and urbanization trends, providing insights into the effectiveness of conservation efforts and identifying areas requiring further intervention for sustainable water resource management.

CONCLUSION

In conclusion, Google Earth Engine (GEE) has revolutionized the field of geo-spatial analysis by providing a powerful platform for the analysis of various spectral indices. The platform's user-friendly interface and cloud-based infrastructure have also made it accessible to a wide range of users, from students to professionals.Some of the key applications of GEE in geo- spatial analysis of spectral indices include .Land cover classification and change detection: GEE's machine learning algorithms and high-resolution imagery enable accurate classification and monitoring of land cover changes.Crop monitoring and yield prediction: GEE's spectral indices and machine learning algorithms allow for accurate crop monitoring and yield prediction. Disaster response and recovery GEE's high-resolution imagery and change detection capabilities enable rapid damage assessment and response.Climate change research GEE's long-term data record and machine learning algorithms enable research on climate change impacts and mitigation strategies.Natural resource management GEE's spectral indices and machine learning algorithms enable monitoring and management of natural resources such as forests and water resources.Broader Implications and Future Directions Google Earth Engine continues to reshape how geospatial data is utilized for planetary-scale challenges. The studies highlighted emphasize the need for further integration of GEE with emerging technologies like machine learning and artificial intelligence, which can enhance the accuracy and applicability of spectral indices. Additionally, there is potential for expanding GEE’s role in policy formulation, disaster response, and climate change mitigation by providing timely and actionable insights.

In conclusion, GEE has emerged as a cornerstone of modern geospatial analysis, empowering researchers to address critical environmental and societal issues with unprecedented scale and efficiency. Its ability to integrate diverse datasets, streamline analyses, and generate actionable results has solidified its position as a transformative tool in the field. As technology and datasets continue to evolve, the applications of GEE are expected to grow, further enriching the field of geospatial science and its contributions to sustainable development.

REFERENCES

1. Abadi et al., 2016

M. Abadi, A. Agarwal, P. Barham, E. Brevdo, Z. Chen, C. Citro, G.S. Corrado, *et al.*

Tensorflow: Large-scale Machine Learning on Heterogeneous Distributed Systems. arXiv preprint arXiv:1603.04467 (2016)

2. Barroso et al., 2013

L.A. Barroso, J. Clidaras, U. Hölzle

The datacenter as a computer: an introduction to the design of warehouse-scale machines

Synth. Lect. Comput. Archit., 8 (3) (2013), pp. 1-154

3. Câmara et al., 2000

G. Câmara, R. Souza, B. Pedrosa, L. Vinhas, A.M.V. Monteiro, Paiva, *et al.*

TerraLib: technology in support of GIS innovation. Proc. II Brazilian Symposium on GeoInformatics

GeoInfo2000, 2 (2000), pp. 1-8

4. Chambers et al., 2010

C. Chambers, A. Raniwala, F. Perry, S. Adams, R.R. Henry, R. Bradshaw, N. Weizenbaum

FlumeJava: easy, efficient data-parallel pipelines ACM SIGPLAN Not., 45 (6) (2010), pp. 363-375

5. Chang et al., 2008

F. Chang, J. Dean, S. Ghemawat, W.C. Hsieh, D.A. Wallach, M. Burrows, T. Chandra, *et al.*

Bigtable: a distributed storage system for structured data ACM Trans. Comput. Syst., 26 (2) (2008), p. 4

View in ScopusGoogle Scholar

6. Climate Engine, 2016 Climate Engine

Desert Research Institute, University of Idaho http://climateengine.org (2016)

(accessed July 2016)

7. Collect Earth, 2016 Collect Earth

United Nations Food and Agriculture Organization http://www.openforis.org/tools/collect-earth.html (2016)

(accessed July 2016)

8. Coltin et al., 2016

B. Coltin, S. McMichael, T. Smith, T. Fong Automatic boosted flood mapping from satellite data Int. J. Remote Sens., 37 (5) (2016), pp. 993-1015

CrossrefView in ScopusGoogle Scholar

9. Copernicus Data Access Policy, 2016

Copernicus Data Access Policy http://www.copernicus.eu/main/data-access (2016)

(accessed June 30, 2016)

10. Corbett et al., 2013

J.C. Corbett, J. Dean, M. Epstein, A. Fikes, C. Frost, J.J. Furman, S. Ghemawat, *et al.*

Spanner: Google's globally distributed database ACM Trans. Comput. Syst., 31 (3) (2013), p. 8 (TOCS)

View in ScopusGoogle Scholar

11. Cossu et al., 2010

R. Cossu, M. Petitdidier, J. Linford, V. Badoux, L. Fusco, B. Gotab, L. Hluchy, *et al.*

A roadmap for a dedicated earth science grid platform Earth Sci. Inf., 3 (3) (2010)

Google Scholar

12. Dong et al., 2016

J. Dong, X. Xiao, M.A. Menarguez, G. Zhang, Y. Qin, D. Thau, C. Biradar, B. Moore

Mapping paddy rice planting area in northeastern Asia with Landsat 8 images, phenology-based algorithm and Google Earth Engine

Remote Sens. Environ, 185 (2016), pp. 142-154

View PDFView articleView in ScopusGoogle Scholar

13. Fikes, 2010

A. Fikes

Storage Architecture and Challenges http://goo.gl/pF6kmz (2010)

(accessed June 30, 2016) Google Scholar