GOOGLE EARTH ENGINE (GEE): INTEGRATING VEGETATION INDICES FOR AGRICULTURAL AND FOREST MONITORING

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ABSTRACT

Google Earth Engine (GEE) provides a fast, scalable, and cost-effective cloud computing platform for sustainable agriculture and effective forest management. This study uses the GEE cloud platform and Copernicus Sentinel-2 data for timely and accurate vegetation monitoring, crop health assessment, and canopy dynamics tracking. Traditional field monitoring methods are time-consuming and limited in spatial coverage. To address this, we processed Sentinel-2 multispectral imagery to generate cloud-free composite images and calculated ten key vegetation indices, including NDVI, EVI, NDMI, and others (GNDVI, NDWI, NDRE, RENDVI, SAVI, MSAVI, and NDMSI). The results demonstrate that integrating Earth observation technologies with cloud computing enhances data-driven agricultural and environmental decision-making with high spatial and temporal precision.

INTRODUCTION

Investigating the conditions of vegetation, agriculture and forest is a fundamental requirement to ensure food security, monitor ecosystem health, and effectively govern natural resources. For decades, satellite imageries have been used in calculating the various indices that served as a powerful tool to assess crop type, forest canopy health, moisture and vegetation conditions across vas landscapes. Therefore, indices derived mathematically from spectral reflectance value simplify the biophysical parameters, enabling efficient classification and monitoring of land cover types. Traditional field-based monitoring approaches are often time-consuming, costly and limited in spatial coverage, making it difficult to track large areas or detect rapid changes. To address the challenge, this study uses the high-resolution capabilities of the Copernicus sentinel-2 mission and the efficient, scalable processing power of the Google Earth Engine (GEE) cloud platform. This integration provides a fast and cost-effective framework to monitor agricultural and forest vegetation dynamics with high.

The Sentinel-2 mission, part of the European Union's Copernicus Program, provides high-resolution multispectral images of 13 spectral bands that ranges from visible to shortwave infrared wavelengths. The key characteristics of Sentinel-2 images specifically their fine spatial resolution (10-60 m), high temporal resolution (a 5-day revisit time with two satellites), and free data availability has immense potential for the monitoring of agriculture and vegetation. This characteristic enables the wide range of indices calculation that are useful for the understanding of vegetation and moisture with high spatial and temporal accuracy and precision (Ivanova et al., 2023). Google Earth Engine is a cloud-based geospatial platform, has transformed remote sensing data processing much easier. GEE provides efficient computational capacities and visualization in a large scale for multi-spectral temporal satellite datasets without effort for local computing resources (Amani et al., 2020). This paper focuses on the calculation, analysis and mapping of ten key agricultural and vegetation related indices such as NDVI, NDMI, NDWI, etc., derived from Sentinel-2 satellite imagery using Google Earth Engine platform. The main objective of this study is to demonstrate which indices are utilized in agriculture and Forest monitoring highlighting their significance for data-driven decision-making in sustainable land management.

METHODOLOGY

In this study, multispectral images from Sentinel-2 were used as the primary input data which is processed in the Google Earth Engine (GEE) platform to compute vegetation, agriculture, and forest canopy conditions. Each index was computed using its respective standard mathematical equation which is composed of relevant spectral bands. Cloud masking and shadow masking using Scene Classification Layer (SCL) was applied prior to compositing to ensure high-quality, cloud-free imagery.

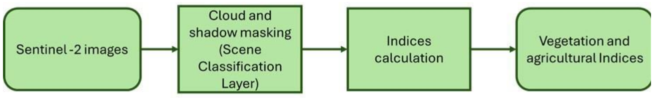

Figure 1: Methodology framework

INDICES OVERVIEW

Each vegetation index captures a specific aspect of vegetation or forest canopy characteristics. Below is a summary of the key indices applied in this study.

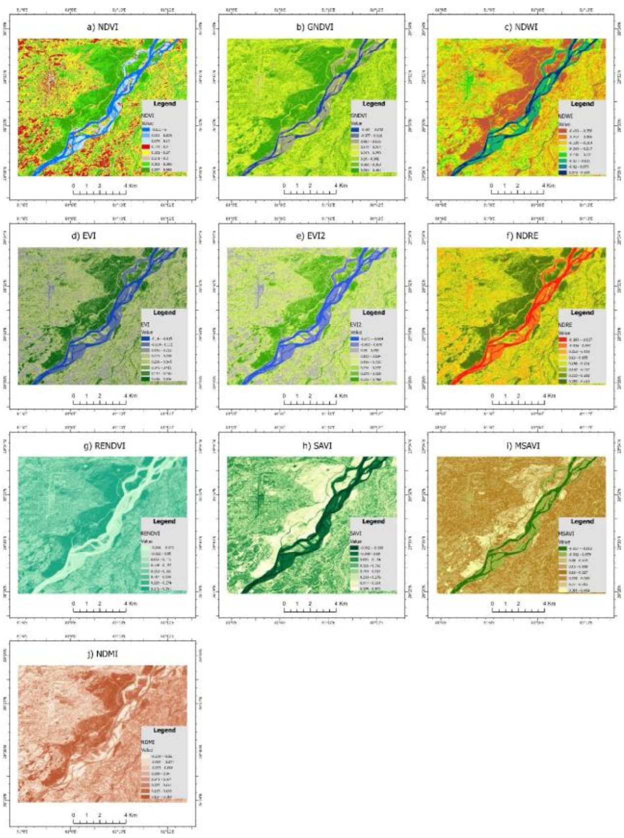

Figure 2: Spatial Distribution of Ten Vegetation Indices Calculated from Sentinel-2 Imagery: (a) NDVI, (b) GNDVI, (c) NDWI, (d) EVI, (e) EVI2, (f) NDRE, (g) RENDVI, (h) SAVI, (i) MSAVI, and (j) NDMI.

1. NDVI (Normalized Difference Vegetation Index)

NDVI as shown in figure 2 (a) is an index of vegetation greenness and photosynthetic action which is suitable for estimating vigor throughout the crop or forest canopy cycle based on how plants reflect specific electromagnetic spectrum ranges. It is a simple arithmetical indicator (Demirel et al., 2010) which is linked to Photo-synthetically Active Radiation (PAR) and measures the ability of leaves and gives amount of the vegetation cover on the land surface over wide areas. This index shows a positive correlation with photosynthetic activity, vegetation cover, biomass, and Leaf Area Index (LAI). The NDVI algorithm is computed by measuring the difference between near-infrared reflectance and red-light absorption. The function used is

$$\mathrm{NDVI} = \frac{B_8 - B_4}{B_8 + B_4}$$

Where, B_8 is NIR band and B_4 is red band.
NDVI standards range from -1 to 1 which corresponds as follows.

Table 1: NDVI Value

Water Body	-1-0
Bare Soil, Rock, Sand and Snow	0-0.2
Shrub and Grassland	0.2-0.4
Sparse and Unhealthy Forest	0.4-0.6
Dense and Healthy Forest	0.6-1

2. GNDVI (Green Normalized Difference Vegetation Index)

GNDVI as shown in figure 2 (b) is an index for estimating photo synthetic activity and is commonly used to determine water and nitrogen uptake into the plant canopy. It is applicable for both agriculture crops and forest vegetation. It is a modification of NDVI in which the green band replaces the red band to enhance sensitivity to chlorophyll concentration and canopy stress. It shows strong correlation with nitrogen content and plant biomass (Gitelson et al., 1996). The formula of GNDVI is

GNDVI= (B8-B3)/(B8+B3)

Where, B_8 is NIR band and B_3 is Green band. Since GNDVI uses the green wavelength, it is less prone to saturation in dense vegetation compared to NDVI and can detect subtle changes in plant health, especially under water or nutrient stress (Ciganda et al., 2009). GNDVI standard ranges from -1 to 1 which corresponds as follows.

Table 2: GNDVI Value

-1 to 0	water bodies, snow, or bare soil, where no green vegetation is present
0.1 to 0.5	sparse, stressed, or moderate vegetation
0.5 to 1	healthy, dense vegetation with high chlorophyll content, vigorous growth, and strong photosynthetic activity

3. NDWI (Normalized Difference Water Index)
NDWI as shown in figure 2 (c) is an index used for evaluating vegetation liquid water contents and detecting water bodies in both agriculture and forest landscapes. NDWI is useful for evaluating reflectance from vegetation canopies that have similar scattering properties, but slightly different liquid water absorption due to canopy water content (Gao, 1996). As a result, NDWI is sensitive to changes in the liquid water content of vegetation canopies and open water areas. The index is measured using the green and near-infrared bands of satellite images. The formula for NDWI is:

$$\mathrm{NDWI} = \frac{B_3 - B_8}{B_3 + B_8}$$

Where, B_8 is NIR band and B_3 is green band. NDWI standard ranges from -1 to 1, where the positive value indicate open water body and the negative values represent soil, vegetation and built-up areas.

Table 3: NDWI Value

-1 to -0.3	Drought , non- aqueous surfaces
-0.3 to 0	Moderate drought, non aqueous surfaces
0 to 0.2	Flooding, humidity
0.2 to 1	Water surface

4. EVI (Enhanced Vegetation Index)
EVI as shown in figure 2 (d) is an optimized vegetation index designed to enhance the vegetation signal with improved sensitivity in high biomass regions such as dense forest and croplands. The EVI is more responsive to canopy structural variations, including leaf area index (LAI), canopy type, plant physiognomy, and canopy architecture. The formula to calculate it is:

$$\mathrm{EVI} = 2.5 \times \frac{B_8 - B_4}{B_8 + 6B_4 - 7.5B_2 + 1}$$

Where, B_8 is NIR band, B_4 is Red band, and B2 is Blue band.
EVI standard ranges from -1 to 1 with healthy vegetation generally around 0.2 to 0.8.

Table 4: EVI Value

-1 to 0.1	Water, bare soil
0.1 to 0.4	Grasslands, cropland
0.4 to 1	Dense vegetation

5. EVI2 (2 – bands Enhanced Vegetation Index)
EVI2 as shown in figure 2 (e) is a simplified version of the original EVI, designed for sensors that do not have the blue band. It eliminates the need for the blue band while still maintaining sensitivity to vegetation greenness, especially in high biomass regions. The formula to calculate EVI 2 is:

$$\mathrm{EVI2} = 2.5 \times \frac{B_8 - B_4}{B_8 + 2.5B_4 + 1}$$

Where, B_8 is NIR band, and B_4 is Red band.
The value ranges from -1 to 1 where lower value indicate the water, bare soil and higher value indicate dense vegetation.

Table 5: EVI2 Value

-1 to 0.1	Water, bare soil
0.1 to 0.4	Grasslands, cropland
0.4 to 11	Dense vegetation

6. NDRE (Normalized Difference Red Edge)

NDRE as shown in figure 2 (f) is an index that analyse whether images obtained from multi-spectral image sensors contain healthy vegetation or not (Barnes et al., 2000). It does this by measuring the amount of chlorophyll in a plant. The best timing to apply NDRE is mid-to-late growing season when the plants are mature and ready to be harvested. It is represented by a certain value calculated using a combination of a Near-InfraRed (NIR) band and the RedEdge range between visible Red and NIR. The NDRE formula is:

$$\mathrm{NDRE} = \frac{B_8 - B_5}{B_8 + B_5}$$

Where, B_8 is NIR band and B_5 is Red Edge band. NDRE standard ranges from -1 to 1 which corresponds as follows.

Table 6: NDRE Value

-1 to 0.2	Bare soil or developing crop
0.2 to 0.4	Unhealthy crop or immature crop
0.4 to 1	Healthy, mature , ripening crops.

7. RENDVI (Red Edge Normalized Difference Vegetation Index)

RENDVI as shown in figure 2 (g) is an index that estimate stem water potential and monitor plant health. It's like the Normalized Difference Vegetation Index (NDVI) but utilizes the red-edge region of the spectrum for calculation, which is more sensitive to subtle changes in chlorophyll content and plant stress (Evangelides & Nobajas, 2020). It measures the difference between the reflectance of the red-edge band and the near-infrared band, normalized by their sum. This allows for a more robust assessment of vegetation health, especially in situations where traditional NDVI might be affected by factors like soil background or shading. The formula is

$$\mathrm{RENDVI} = \frac{B_7 - B_5}{B_7 + B_5}$$

Where, B_7 is Red Edge band (783 mm) and B_5 is Red Edge band (703 mm).
The NDVIre value ranges from -1 to 1, with values close to 1 indicate dense vegetation and values close to 0 indicate bare soil or other non-vegetated areas. RENDVI improves sensitivity to subtle changes in plant or forest canopy health by using the red-edge region.

8. SAVI (Soil Adjusted Vegetation Index)

SAVI as shown in figure 2 (h) is an index designed to monitor vegetation in regions where soil brightness significantly affects vegetation signals (A. R. Huete, 1988). This index is typically used in sparse or arid areas. It enhances the accuracy of vegetation analysis by minimizing the soil background influence. Through these capabilities, it makes SAVI a preferred index in early-stage crop monitoring, dry land ecosystems, and construction site vegetation studies. It modifies the NDVI formula by introducing a soil brightness correction factor (L), commonly set to 0.5.
The formula is:

$$\mathrm{SAVI} = \frac{(B_8 - B_4)(1 + L)}{B_8 + B_4 + L}$$

$$\mathrm{SAVI} = \frac{1.5\,(B_8 - B_4)}{B_8 + B_4 + 0.5}$$

Where, B_8 is NIR band (842 mm) and B_4 is Red band, L is the soil brightness correction.
SAVI ranges from -1 to 1 where low value of SAVI corresponds to water, bare surfaces, while high values indicate healthy vegetation. SAVI minimizes soil background effects, making it valuable in semi-arid farmlands and sparse forest regions.

Table 7: SAVI Value

Less than 0	Water, bare surfaces
0 to 0.2	Soil dominated areas
0.2 to 0.5	Moderate vegetation cover
Greater than 0.5	Dense/healthy vegetation

9. MSAVI (Modified Soil Adjusted Vegetation Index)

MSAVI as shown in figure 2 (i) is an index designed to substitute Normalized difference vegetation index (NDVI) and NDRE where they fail to provide accurate data due to low vegetation or a lack of chlorophyll in the plants. During the stages of germination and leaf development, there is a lot of bare soil between the seed lings. NDVI and NDRE both interpret this as poor vegetation. Here is where MSAVI comes to aid. "SA" stands for "soil-adjusted," revealing the key aspect of this vegetation index. It reduces the effect of the soil on the calculation of vegetation density in the field. MSAVI further reduces soil influence and is especially useful for monitoring early-stage crop growth or sparse forest regeneration.

The formula for calculating MSAVI is:

$$\mathrm{MSAVI} = \frac{2B_8 + 1 - \sqrt{(2B_8+1)^2 - 8(B_8 - B_4)}}{2}$$

Where B_8 is NIR band and B_4 is Red band.
MSAVI ranges from -1 to 1 were,

Table 8: MSAVI value

-1 to 0.2	Bare Soil
0.2 to 0.4	Seed Germination Stage
0.4 to 0.6	Leaf Development Stage

10. NDMI (Normalized Difference Moisture Index)

NDMI as shown in figure 2 (j) is an index that assess vegetation water content and monitor water stress in crops. It determines vegetation water content by combining near infrared and short-wave infrared reflectance. The formula to calculate NDMI is:

$$\mathrm{NDMI} = \frac{B_8 - B_{11}}{B_8 + B_{11}}$$

Where, B_8 is NIR band (842 nm) and B_{11} is Shortwave Infrared band (1610 nm).

The value ranges from -1 to 1 where higher value indicate healthy, well-watered vegetation while lower value suggest dryness or drought stress.

Table 9: NDMI Value

-1 to -0.8	Bare soil
-0.8 to -0.2	Sparse canopy cover, wet
-0.2 to 0.4	Average canopy cover, low water stress
0.4 to 1	Full canopy cover, no drought stress

The current study presents a possible way for monitoring vegetation and agriculture, but it is subject to several limitations that influence the generalizability and interpretation of the results.

Lack of Ground Truth Data: The most significant limitation is the absence of in situ (field-based) validation data. The field data can be collected from the field using Kobo Toolbox including spatial as well as other associated attributes (Bade et al., 2025). The study relies solely on satellite spectral reflectance values and mathematical derivations.

Sensitivity to external factors: Cloud masking has long been the traditional approach to cleaning optical satellite imagery, employing techniques like removing contaminated pixels. While effective for single-scene analysis, this method creates a data gap that severely limits the upscaling of the methodology for large area continuous monitoring. Over the decades, several advanced techniques for cloud filling or gap filling have been developed to synthesize missing data. By applied cloud filing methodology that used the present and future information, to reconstruct missing pixels for generating monsoon composite images.

Future studies can apply similar techniques by integrating cloud-optical imagery from the Landsat series to reconstruct the missing data and develop a fully cloud-free image to monitor vegetation health. However, a crucial step in this process is that Landsat data (typically 30m resolution) should be downscaled to match the 10-meter spatial resolution of the Sentinel-2 imagery while filling the clouds to maintain consistency and precision in the final product.

Scalability of threshold: The threshold used to classify values are often specific to the study area's climate and vegetation types. These thresholds are difficult to generalize globally; future research should calibrate the thresholds. This can be achieved by using machine learning algorithms with GEE to create dynamics and adaptive classification models that learn site-specific spectral signature from reliable training data rather than relying on static, predefined numeric cutoffs.

CONCLUSION

The study illustrated the effectiveness of the usability of Sentinel-2 multispectral imagery and the Google Earth Engine (GEE) platform for monitoring agricultural and vegetation conditions through various spectral indices. The integration of spatially distributed satellite data and cloud-based calculations provides effective and efficient processing and visualization of major vegetation and agricultural indices. The calculated indices can provide valuable insight into crop mapping, moisture status, agricultural and vegetation dynamics, that ultimately supports data-driven monitoring and management of vegetation and agriculture. The presented approach in this study supports the scalable and replicable framework that can be applied to local conditions to the global monitoring to enhance the sustainability in land and resources management practices.

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