



Application of Google Earth Engine for Agriculture Drought Monitoring in East Lombok

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ABSTRACT

In tropical regions such as East Lombok Regency, where food production is highly dependent on rainfall, drought poses a major threat to the agricultural sector. This study aims to monitor drought patterns over time using Google Earth Engine (GEE). Vegetation indices, including the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Normalized Difference Drought Index (NDDI), were derived from Landsat 8 satellite imagery. The analysis revealed that during the dry season, particularly in August and September, the southern region—especially Jerowaru Sub-district—experienced severe drought conditions. The western parts, including Sambelia, Pringgabaya, and Suela Sub-districts, were also significantly affected, with the most impacted areas being rain-fed rice fields, corn plantations, and mixed horticultural crops. Temporal trend analysis indicated an increasing drought intensity in the later years of observation. The resulting information can support decision-making in drought risk mitigation and sustainable water resource management. By integrating satellite-based drought assessment with agricultural planning, this approach can strengthen food security and promote adaptive agricultural practices in drought-prone regions such as East Lombok Regency.

Keywords: Drought, Google Earth Engine, NDVI, NDWI, NDDI

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1. Introduction

Drought is one of the natural disasters that significantly impacts the agricultural sector, especially in areas heavily reliant on rainfall for sustaining food production. In East Lombok Regency, Indonesia, drought phenomena frequently occur, leading to substantial economic losses and threatening community food security (Gorelick et al., 2017; UN-SPIDER, n.d.). Therefore, effective drought monitoring is crucial to identify potential risks and plan appropriate mitigation strategies. Satellite-based remote sensing technology has proven to be an effective tool for monitoring vegetation conditions and detecting drought, utilizing various vegetation indices that provide vital information on plant health and soil conditions (Rismayatika & Rahman, 2020; Du et al., 2018).

One such cloud computing platform is Google Earth Engine (GEE), which is specifically designed for analyzing massive amounts of geographical data. Researchers may do complicated studies using GEE's access to a large collection of satellite images and powerful processing algorithms, rather than downloading data locally (Tamiminia et al., 2020). These indices the

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Normalized Difference Vegetation Index (NDVI), the Vegetation Condition Index (VCI), the Temperature Condition Index (TCI), and the Vegetation Health Index (VHI) are crucial for agricultural drought monitoring, and researchers can compute them using GEE (Thilagaraj et al., 2021). In addition to helping to identify when drought is about to begin, these indexes also track how severe it is and how it affects crop yields.

In this study, the application of GEE for agricultural drought monitoring in East Lombok Regency will focus on utilizing MODIS satellite data to calculate these indices. Previous research has shown that using VHI as a vegetation health indicator is highly effective in identifying drought conditions in various regions, including areas with uneven rainfall distribution (Ejaz et al., 2023; Sazib et al., 2018). By integrating climate data with satellite imagery, GEE facilitates in-depth spatio-temporal analyses of drought impacts on agricultural lands in the region.

One of the key advantages of using GEE is its capability to perform real-time analyses and produce mapping outputs that policymakers and farmers can utilize to make informed decisions based on up-to-date information. Through this approach, it is expected to enhance responses to drought conditions and improve strategies for water resource and agricultural management in East Lombok Regency (Kumar & Mutanga, 2018; Rahman et al., 2024). This study aims to provide a comprehensive overview of how GEE can be implemented in the local context to enhance food security through improved drought monitoring.

To better understand the link between vegetation indicators and soil moisture conditions, this project will investigate techniques for estimating NDVI, VCI, TCI, and VHI using GEE. The findings will then be compared with meteorological data. Research in this area has shown promise in improving food security in East Lombok Regency via the use of technological drought monitoring systems (Funk et al., 2015; Kilic et al., 2022). Through the use of cutting-edge technology, our aim is to provide stakeholders with precise and prompt data pertaining to the effects of the drought and the essential steps to alleviate them.

The main objectives of this research are to monitor drought patterns over time using Google Earth Engine (GEE), then evaluate temporal trends in drought intensity. Finally, provide spatial information to support drought risk mitigation and sustainable water resource management. Improving agricultural resilience and food security in drought-prone regions of East Lombok.

2. Method

2.1. Research Area

The region under investigation is the East Lombok Regency of West Nusa Tenggara Province. Located in central Lombok, East Lombok Regency has borders with Central Lombok and West Lombok Regencies to the west, the Flores Sea to the north, and the Indian Ocean to the south. To the east, it faces the Alas Strait. With a total size of 1,230.76 km², East Lombok Regency is made up of 21 sub-districts, 15 urban settlements, and 239 rural villages (Wikipedia).

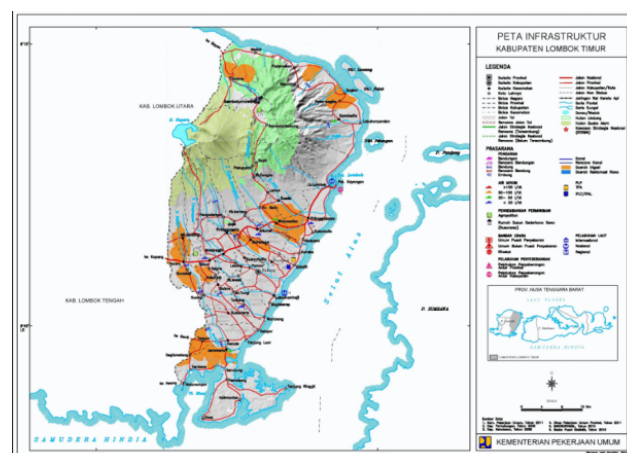


Figure 1. Map of the research area in East Lombok Regency.

2.2. Data Collection

This study uses both non-spatial and spatial data. The non-spatial data used are rice productivity data for East Lombok Regency from 2020 to 2024. The spatial data used are Landsat 8 TOA images from path 116 and row 66 during the months of June, July, August, and September from 2020 to 2024. From May to September, the dry season, was used to determine the picture collection timeframe. Google Earth Engine is the platform that this research was conducted on. The picture data used in this investigation is shown in with all of its parameters in Table 1.

Table 1. The acquisition dates of landsat images with cloud cover less than 30%.

Year	Month			
	June	July	August	September
2020	15	1, 17	2, 18	3, 19
2021	2	4, 20	5, 21	6, 22
2022	5, 21	23	8, 24	9, 25
2023	8, 24	10, 26	11, 27	12, 28
2024	10, 26	12	13,29	14,30

3. Results and Discussion

Drought poses a significant threat to agricultural productivity in tropical regions such as East Lombok Regency, where rainfall plays a central role in food production. Monitoring drought patterns over time is crucial for developing responsive strategies to ensure food security and sustainable land use. In this context, the use of remote sensing technologies, particularly the Google Earth Engine (GEE) platform, offers a powerful and efficient means of assessing drought conditions across both space and time. This study leverages satellite-derived vegetation indices—including the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Normalized Difference Drought Index (NDDI)—based on Landsat 8 imagery to evaluate drought severity. The following section outlines the methodological steps taken to process and analyze the data, forming the basis for the subsequent interpretation of spatial and temporal drought trends in East Lombok.

Included in the data processing for this research are operations such as cloud masking, vegetation index calculation, and NDDI calculation, as well as picture filtering. Google Earth Engine is used to process the data. Satellite images and vector data are examples of Big Geospatial Data that may be processed and stored using Google Earth Engine, a cloud computing platform (Gorelick et al., 2017). According to Tamminia et al. (2020), the GEE platform is equipped with petabyte-scale satellite images, huge computing resources, a high-level API, and machine learning techniques that researchers may use to handle vast geo-big data for different remote sensing applications. Agricultural, earth science, disaster management, land cover, and vegetation monitoring are some of the areas that may benefit from GEE-assisted analysis (Mutanga & Kumar, 2019).

Picture filtering, cloud masking, and vegetation index computation are all carried out using GEE in this research. Drought index parameters may be determined using Top of Atmosphere data (Rismayatika et al., 2020). The picture acquisitions utilized (June - September 2020–2024), the bands utilized (visible light, NIR, and SWIR), and the image metadata with cloud cover (less than 30%) are all filtered by the image processing pipeline. By merging several satellite photos, cloud masking may eliminate cloud cover from the final product. Determining vegetation indices is the final stage. We utilize the Normalized Difference Vegetation Index (NDVI) to measure the amount of greenery and the Normalized Difference Water Index (NDWI) to measure the amount of moisture in the vegetation. In Equations 1 and 2, you may find the NDVI and NDWI formulae.

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (1)$$

$$NDWI = \frac{NIR - SWIR1}{NIR + SWIR1} \quad (2)$$

Landsat 8 TOA's short-wave infrared (SWIR) band is located in band 7, visible light (red) is located in band 4, and near-infrared (NIR) is located in band 5. Rouse (1974) created the Normalized Difference Vegetation Index (NDVI) to measure the degree of verdantness and photosynthetic activity in plants. The saturation of the vegetation canopy, as well as its biophysical attributes including absorbed photosynthetically active radiation, efficiency, and plant production, may be monitored with relative ease using this indicator. At the same time, one way to find out how much water plants have is to utilize the Normalized Difference Water Index (NDWI). When comparing green canopies to dry ones, NDWI is quite sensitive to changes in the water content of plants (Gao, 1996). A drought index is built from these two metrics.

The NDDI, or Normalized Difference Drought Index, is the drought index that is used. In order to determine the severity of drought in a given region, NDDI integrates data from vegetation and water indicators (Stancalie et al., 2014). A number between -1 and 1 is the NDDI index. When the NDVI and NDWI readings are close to 1, it indicates that the item or region is very dry. In areas where the NDVI and NDWI values are high, the drought level is lower when the value is closer to -1 (Du et al., 2018). Classification of NDDI values is necessary for the identification of regions prone to drought. The NDDI values for different degrees of drought are classified according to (Renza et al., 2010) in Table 2. To see the NDDI formula, go to **Equation 3**.

$$NDDI = \frac{NDVI - NDWI}{NDVI + NDWI} \quad (3)$$

Table 2. Classification of drought levels based on NDDI.

NDDI Value	Drought Level
-0.05 - ≤0.01	Normal
0.01 - ≤0.15	Normal Drought
0.15 - ≤0.25	Moderate Drought
0.25 - ≤1	Severe Drought
>1	Extreme Drought

Table 2 presents the classification of drought levels based on the Normalized Difference Drought Index (NDDI) values. The NDDI was used to categorize the severity of drought conditions across the study area. Values ranging from -0.05 to ≤0.01 indicate normal conditions with sufficient vegetation moisture. An NDDI between 0.01 and ≤0.15 represents a normal drought, suggesting mild water stress in vegetation. The moderate drought category, with NDDI values between 0.15 and ≤0.25, reflects increasing dryness and reduced vegetation health. When NDDI values range from 0.25 to ≤1, the area experiences severe drought, indicating significant water shortages and vegetation stress. Finally, NDDI values greater than 1 correspond to extreme drought conditions, where vegetation moisture is critically low and drought impact is at its highest intensity.

The analysis conducted in this study includes descriptive, spatial, and temporal analysis. Spatial-descriptive analysis is used to analyze the distribution of drought levels in the study area. Meanwhile, temporal analysis is used to analyze the drought level patterns from 2020 to 2024 in East Lombok Regency.

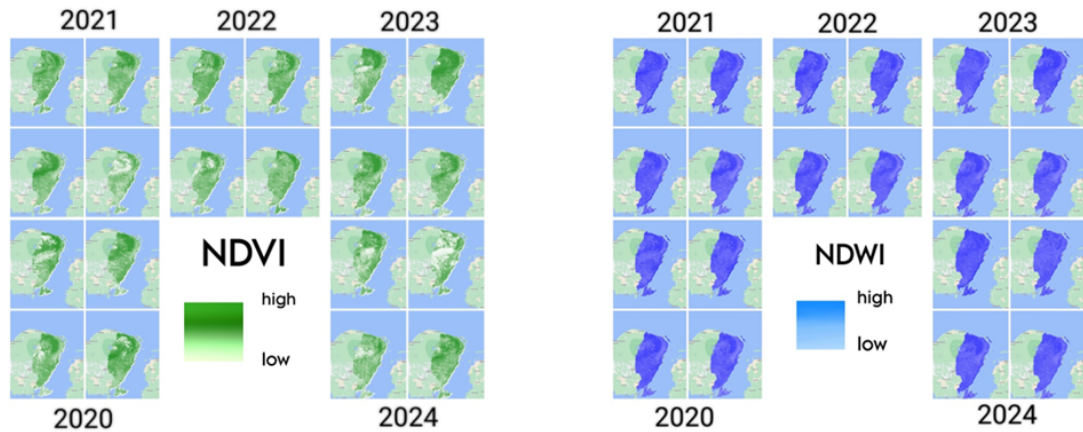


Figure 2. NDVI & NDWI Results Map

Google Earth Engine successfully processed the NDVI vegetation index and NDWI moisture index data in a multitemporal manner from June to September of 2020-2024. Based on **Figure 2**, high NDVI values indicate a high density and greenness of vegetation on paddy fields. Meanwhile, high NDWI values indicate the water content in the paddy fields. From 2021 to 2024, high NDVI values were observed in the irrigated paddy fields located in the northern part of East Lombok. From 2020 to 2024, high NDWI values were also found in the northern part of East Lombok Regency, where most of the land is irrigated paddy fields.

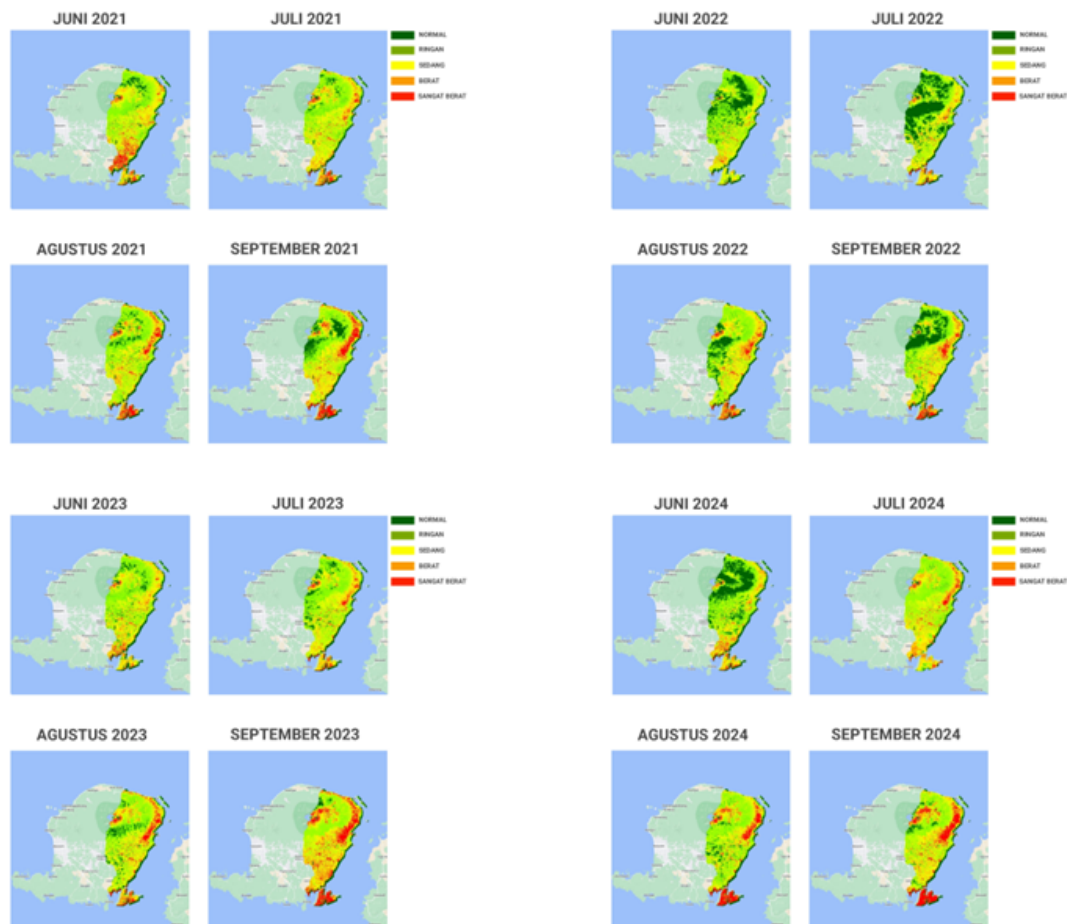


Figure 3. NDDI Results Map

The southern portion of East Lombok Regency had a severe drought in September 2020. In August and September of both 2021 and 2022, the southern portion of East Lombok Regency had a severe drought. In September of 2023, there was a severe drought in the western and southern regions. Southern and western regions had a severe drought in August and September of 2024.

As seen in Figure 3, the NDDI processing results are visible. From 2020 to 2024, the southern section of the research area—specifically, the coastline Jerowaru Sub-district—was under an extremely severe drought. The moderate-severe drought class was predominantly found in the western part of the study area, including the paddy fields in the Sambelia, Pringgabaya, and Suela Sub-districts. Rainwater falls into these paddy fields. Northern and western regions of the research area experience drought to a greater extent than the rest. The trend in the extent of drought in paddy fields in Central Lombok Regency can be seen in Figure 3.

Table 3. NDVI, NDWI, and NDDI Value

	NDVI	NDWI	NDDI
Jun-20	0.414968	0.254675	-1.6907
Jul-20	0.407237	0.258127	-9.35903
Aug-20	0.473124	0.260007	-0.06475
Sep-20	0.436294	0.208835	0.049735
Jun-21	0.487968	0.274943	0.141202
Jul-21	0.48108	0.262585	0.023793
Aug-21	0.474253	0.250286	-0.90747
Sep-21	0.413491	0.196254	2.55151
Jun-22	0.45038	0.300208	-0.0052
Jul-22	0.306552	0.219793	5.864711
Aug-22	0.439264	0.233739	-0.82308
Sep-22	0.39337	0.219013	-0.20556
Jun-23	0.465206	0.275879	0.113783
Jul-23	0.478707	0.266847	8.955312
Aug-23	0.459607	0.240096	-0.10352
Sep-23	0.47022	0.188189	0.507814
Jun-24	0.331376	0.226736	-12.0202
Jul-24	0.523947	0.26493	0.230741
Aug-24	0.466093	0.242063	7.581156
Sep-24	0.445885	0.194412	0.508665

Based on Table 3, it can be seen that the drought levels in East Lombok Regency from 2020 to 2024 were predominantly observed during the peak of the dry season, from July to September. In 2021, severe drought occurred in September. In 2022, extreme drought occurred in July. In 2023, extreme drought also occurred in July. Meanwhile, in 2024, extreme drought occurred in August.

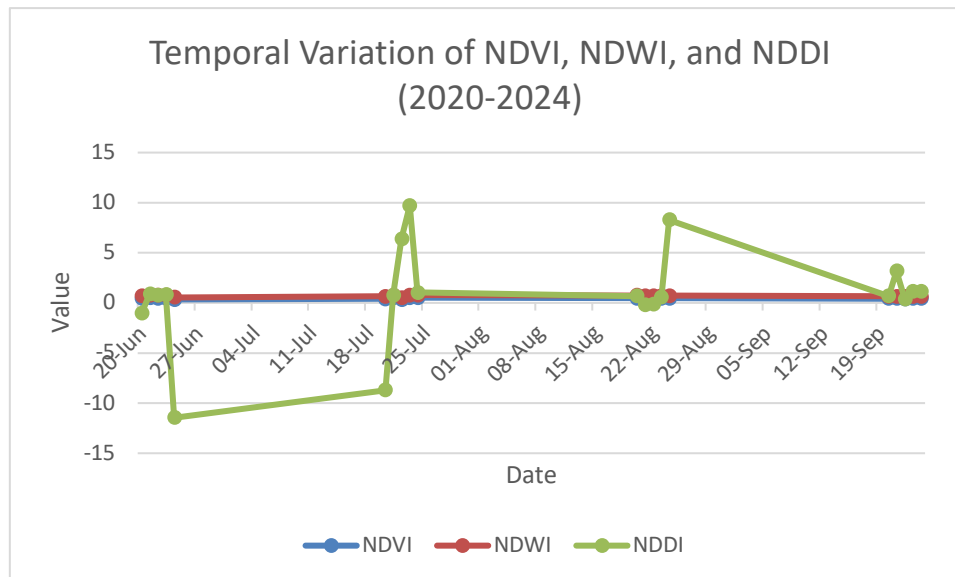


Figure 4. Temporal Variation of NDVI, NDWI, and NDDI (2020-2024)

The chart clearly shows seasonal fluctuations in vegetation and water indices, with NDDI values rising during the dry months (particularly July–September), indicating higher drought intensity. Conversely, NDVI and NDWI tend to increase during wetter periods, reflecting healthier vegetation and higher moisture availability.

4. Conclusion

Google Earth Engine is capable of providing spatial data for NDVI and NDWI for temporal drought analysis from 2020 to 2024. Agricultural drought in paddy fields in East Lombok Regency shows that extreme drought dominated from July to September in the Jerowaru Sub-district. Meanwhile, moderate drought was mostly located in the western part of the study area, specifically in the irrigated paddy fields of the Sambelia, Pringgabaya, and Suela Sub-districts. The findings of this study hold significant implications for agricultural planning and management. By integrating GEE-based drought monitoring into local agricultural decision-making, regional authorities can optimize irrigation scheduling, enhance water resource allocation, and plan crop rotation systems that are resilient to seasonal water shortages. Moreover, the spatial identification of drought-prone areas allows for targeted mitigation strategies, such as promoting drought-tolerant crop varieties and developing early warning systems.

For future research, integrating satellite-based drought indices with ground-based meteorological and soil moisture data would improve accuracy and reliability in drought assessment. Further studies could also explore machine learning models within the GEE platform to enhance predictive drought mapping. These advancements would contribute to a more comprehensive understanding of drought impacts, supporting sustainable agricultural practices and long-term food security in drought-vulnerable regions like East Lombok Regency.

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