Evaluating drought index using NDDI method on toposequence of the Western Lawu Mountain, Karanganyar Regency, Indonesia

Rahayu Rahayu*, Aktavia* Herawati*, *Sumani* Sumani*, Mujiyo* Mujiyo*, Ganjar* Herdiansyah*, Fitria Dewi* Qomariah

[1]Department of Soil Science, Faculty of Agriculture, Universitas Sebelas Maret, Surakarta, Indonesia

Abstract. Global climate change can potentially impact the agricultural sector through La Nina and El Niño phenomena such as increasing drought risk. Karanganyar Regency, Central Java, is categorized as an area with high drought vulnerability. This study aims to identify the level of drought using the Normalized Difference Drought Index (NDDI) method and analyze the influence of land characteristics on the drought index in the toposequence of the western slope of Mount Lawu. The study was conducted from August 2024 to March 2025 using an exploratory descriptive survey approach. Sampling points were determined through purposive sampling based on land map units in 4 zones of toposequence. The NDDI method utilizes the vegetation index (NDVI) and the wetness index (NDWI). The results show that severe drought occurs in areas with a topography of 200–400 masl and moderate drought occurs at 600–1000 masl with drought index values of 0.25 and 0.21 – 0.23, respectively. Statistical test results indicate that topography, slope gradient, and precipitation have a significant influence on the drought index. The highest drought index occurs in areas with a 0–15% slope and precipitation of 1,292.40 mm/year. The 5-year trend indicates that the drought index increases at the beginning of the dry season, which spans from July to August, and then decreases as the dry season comes to a close in September to November.

1 Introduction

Climate change refers to the condition of changing global climate patterns, caused by unpredictable weather conditions such as changes in rainfall and air temperature over a specific period. Climate change in Indonesia is influenced by its geographical location, as Indonesia is situated in a tropical monsoon climate zone, making it susceptible to El Niño and La Niña climate phenomena. This phenomena have a significant impact on the agricultural sector [1]. The western slopes of Mount Lawu in Karanganyar Regency, which have a diverse topography ranging from lowlands to highlands, are highly vulnerable to the impacts of climate change. Differences in topography and landform lead to variations in rainfall, soil type, and land-use patterns, which trigger vulnerability to natural disasters such as landslides, floods, droughts, forest fires, and strong winds.

* Corresponding author: aktavia_h@staff.uns.ac.id

© The Authors, published by EDP Sciences. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

Extreme drought is triggered by climate variability, which can have fatal consequences for the agricultural sector. Crops experience severe water stress, leading to stunted growth, wilting, and even plant death. Additionally, drought drastically reduces soil fertility, diminishing its capacity to retain water and nutrients, resulting in suboptimal land productivity. This naturally results in crop failure and loss, which ultimately leads to significant economic losses for farmers and the wider community [2].

Several previous studies have been conducted on drought index analysis using the Normalized Difference Drought Index (NDDI) method. In 2024, [3] conducted a drought analysis to determine the distribution of drought indices in Slogohimo District, Wonogiri Regency. The results obtained show that vegetation affects the drought index value; the lower the vegetation density, the higher the drought index. Other studies have reported that the diversity of land use significantly impacts drying conditions, while dryness can be reduced by controlling soil moisture. The high variability of vegetation or plantations will enhance this [4]. It is strongly agreed that the available water capacity in soil can be improved by increasing organic matter content [5]. In addition, the NDDI method is a recommended tool for analyzing drought index, which is vegetation cover and water fluctuations as important factors [6,7]. Overall, the NDDI is beneficial for predicting the drought index for the agricultural sector [8], formulating sustainable drought management strategies [9], and enabling effective watershed management strategies [6].

The western slope area of Mount Lawu is one example of rainfed agricultural land in Indonesia that is highly susceptible to drought. The sloping topography and limited surface water resources further increase the land's vulnerability in this area. Recent studies show that during the dry season, the water flow from springs used for irrigation decreases drastically, forcing farmers to implement strict water management systems and choose secondary crops that are more drought-resistant [10]. The resilience of the agricultural system in this mountainous region is highly dependent on local adaptation and community collaboration in effectively managing water resources. Farmers need up-to-date weather information, guidance on managing extreme weather risks, and more accurate weather predictions to face these challenges. Therefore, this research is very important for obtaining more precise information related to drought risk prediction and mitigation on the western slope of Lawu Mount. The objectives of this research are: (1) To determine the drought index using the NDDI method on the western slope of Lawu Mount; (2) To determine the pattern of the NDDI drought index over a five-year period; and (3) To determine the influence of land characteristics on the drought index.

2 Material And Methods

2.1 Research Area

This research was conducted on the west slope toposequence of Lawu Mount, located at coordinates 7°32’37”–7°34’23” LS serta 110°58’21”–111°9’39” BT (Fig. 1), which consists of 12 districts. The region has a tropical rainforest climate with four varying precipitation zones, ranging from approximately 1,292 mm to over 3,295 mm per year (Fig. 2), making some areas tend to be wetter while others are relatively drier. Sources of land diversity in this region include topography, slope gradient, land use, soil type, and rainfall. The topography is divided into 4 zones: 200 – 400, 400 – 600, 600 – 800, and 800 – 1000 meters above sea level (masl) (Fig. 2), with slope gradients of 0–15%, 15–30%, and over 30%. Most of the area is used as dry fields and seasonal agricultural land, especially on the mid-slope areas, while the steeper parts are generally managed more simply. The soil that develops in this area

is dominated by Andisols and Alfisols, whose parent material originates from the volcanic material of Lawu Mount.

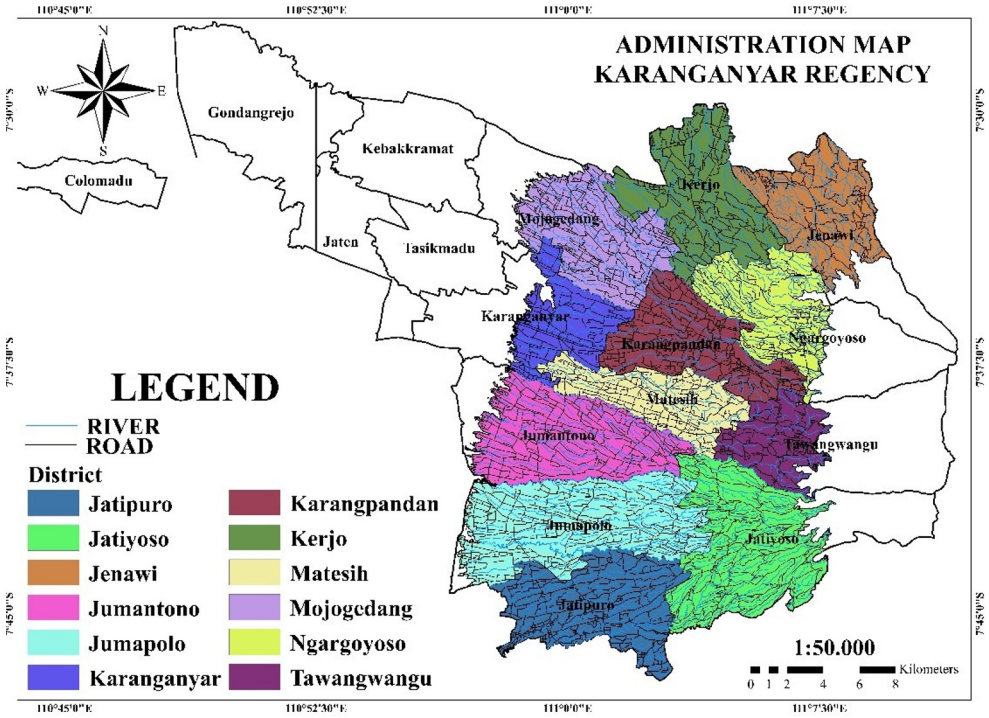


Fig. 1. Area of research

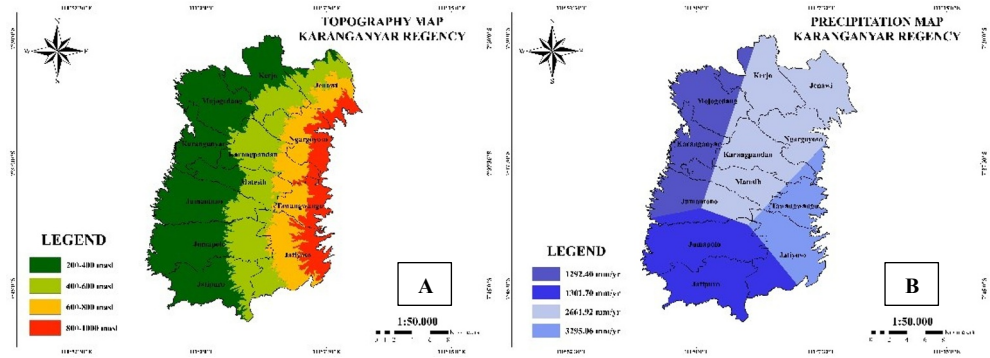


Fig. 2. Toposequence zones (A) and precipitation zones in the studied area (B)

The method used is descriptive-exploratory thru field surveys and image analysis using Landsat OLI 8. The research location is divided into several land map units (LMUs) to facilitate the characterization of each land area. The land map units were determined using purposive sampling based on the results of overlaying various land diversity source maps, resulting in 27 land map units representing the characteristics of each. The distribution of land map units in the research area can be seen in Figure 3, while the characteristics of each land map unit can be seen in Table 1.

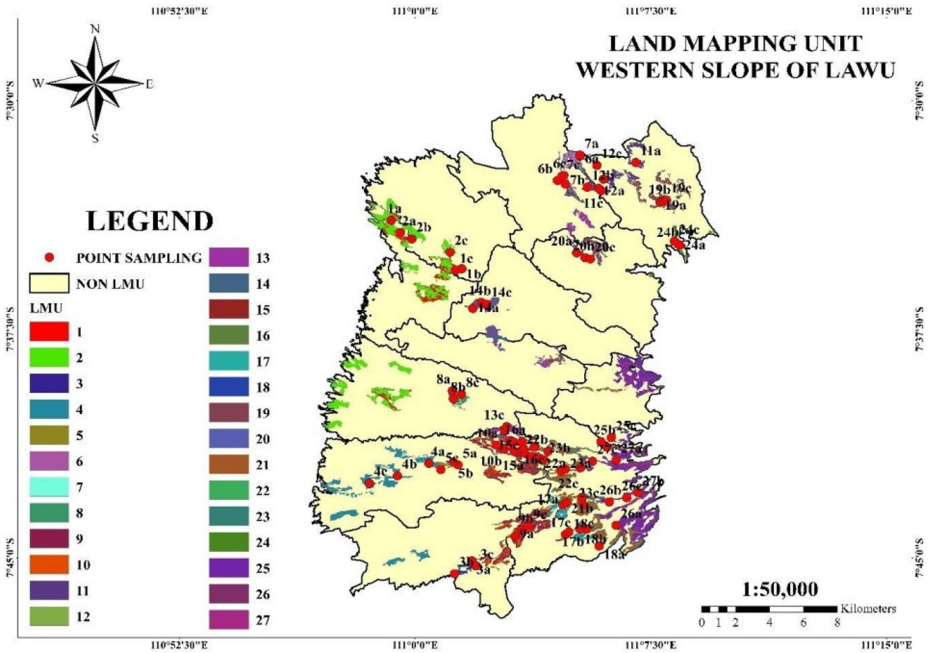


Fig. 3. The distribution of land map unit in research area

Table 1. The characteristics of each land map unit

LMU	Precipitation (mm yr^{-1})	Soil Type	Topography (masl)	Gradient Slope (%)
1	1,292.4	Alfisols	200 - 400	15-30
2	1,292.4	Alfisols	200 - 400	0-15
3	1,301.7	Alfisols	200 - 400	15-30
4	1,301.7	Alfisols	200 - 400	0-15
5	1,301.7	Andisols	200 - 400	0-15
6	2,661.92	Alfisols	200 - 400	15-30
7	2,661.92	Alfisols	200 - 400	0-15
8	2,661.92	Andisols	200 - 400	0-15
9	1,301.7	Andisols	400 - 600	15-30
10	1,301.7	Andisols	400 - 600	0-15
11	2,661.92	Alfisols	400 - 600	15-30
12	2,661.92	Alfisols	400 - 600	0-15
13	2,661.92	Andisols	400 - 600	15-30
14	2,661.92	Andisols	400 - 600	0-15
15	3,295.06	Andisols	400 - 600	15-30
16	3,295.06	Andisols	400 - 600	0-15
17	1,301.7	Andisols	600 - 800	15-30
18	1,301.7	Andisols	600 - 800	0-15
19	2,661.92	Andisols	600 - 800	15-30
20	2,661.92	Andisols	600 - 800	0-15
21	3,295.06	Andisols	600 - 800	15-30
22	3,295.06	Andisols	600 - 800	0-15
23	3,295.06	Andisols	600 - 800	>30
24	2,661.92	Andisols	800 - 1000	15-30
25	3,295.06	Andisols	800 - 1000	15-30
26	3,295.06	Andisols	800 - 1000	0-15
27	3,295.06	Andisols	800 - 1000	>30

2.2 Determining Drought Index Using NDDI

Drought analysis using the Normalized Difference Drought Index (NDDI) method is carried out in several stages. (1) Top of Atmosphere (ToA) radiometric correction and image cropping according to the research area boundary data, (2) NDVI calculation, (3) NDWI calculation, and (4) NDDI calculation. To determine the differences in drought indices over a five-year period, Landsat images were measured according to the desired year.

2.2.1 Radiometric Correction and Data Cropping

The Landsat 8 image acquisition was then radiometrically corrected and cropped. Radiometric correction aims to convert the initial digital number (DN) values into surface reflectance values, making the resulting data more representative of the actual conditions in the field. The radiometric correction process is a crucial step in satellite image processing to obtain high-quality scientific data, thus supporting the creation of accurate land cover maps [11]. After successful radiometric correction, the cropping stage is performed to cut the image area to match the research area boundaries. The correction results show a significant decrease in DN values due to their transformation to a reflectance scale. This change in value indicates that the correction successfully transformed the DN value into surface reflectance, making the data more accurate for analysis in subsequent stages. An example of the results of radiometric correction and data cropping can be seen in Figure 4.

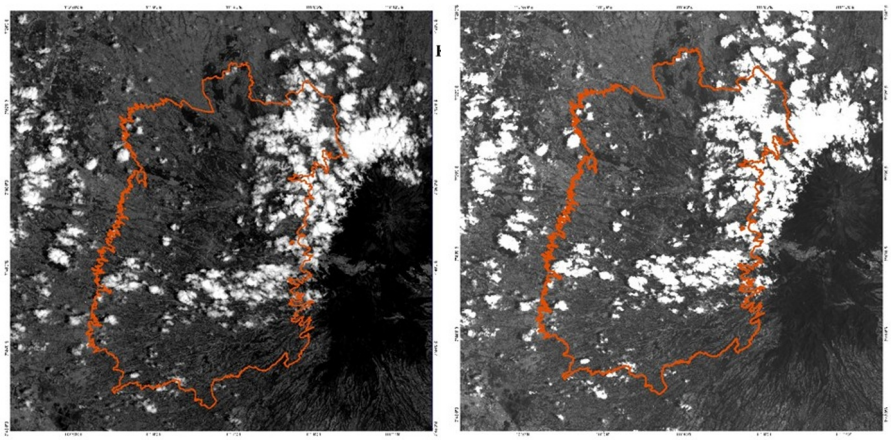


Fig. 4. Imagery data citra in October before (left) and after (right) radiometric correction

2.2.2 Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) describes the greenness or density of vegetation based on satellite image analysis by calculating the ratio of the difference between the NIR (4) and Red (5) bands to their sum (Equation 1). According to [9], low NDVI (approaching zero or negative) occurs due to reduced vegetation, characterized by a decrease in reflectance in both bands.

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad \text{[Equation 1]}$$

Where NIR is the near-infrared reflected band (band 5) and RED is red reflected band (band 4). The vegetation index results were then categorized based on Table 2. The NDVI scale is in the range from -0.861224 to 0.922975, whereas the scale gets closer to 1, indicating that

the area has a high population of vegetation. A lower scale indicates that the area has little to no vegetation. The changes in vegetation at five years are obtained with atmospheric correction.

Table 2. The classification of the Normalized Difference Vegetation Index (NDVI)

Scale of NDVI	Class/ Category
-0.861224 – 0.03	No Vegetation
0.03 - 0.15	Low vegetation
0.15 - 0.25	Slightly low vegetaton
0.25 – 0.35	Medium vegetation
0.35 – 0.922975	High vegetation

2.2.3 Normalized Difference Water Index (NDWI)

NDWI analysis is used to identify land moisture levels through satellite imagery by comparing the NIR (5) and SWIR (6) bands. The NIR band is more sensitive to reflective objects such as buildings, while the SWIR band is more sensitive to light-absorbing objects such as water [7]. The reflectance index varies from −1 to +1 and is utilized in the extraction of water bodies from satellite photos. The NDWI is derived from the surface reflectance of the NIR and SWIR bands of Landsat 7 and 8, as presented in Equation 2.

$$NDWI = \frac{(NIR-SWIR)}{NIR+SWIR} \text{.....[Equation 2]}$$

Whereas NIR is near-infrared reflected band (band 5) and SWIR is red reflected short band (band 6). The water index results were then categorized based on Table 3.

Table 3. The classification of the Normalized Difference Water Index (NDWI)

Nilai NDWI	Kategori
-0,732996 - 0	Non water bodies
0 - 0,33	Medium wetting
0,33 -1	High wetting

Source: [7]

2.2.4 Normalized Difference Drought Index (NDDI)

The Normalized Difference Drought Index (NDDI) was developed by [12], which is the main goal of establishing this index was to create a tool that effectively measures the behavior and severity of drought by integrating multiple indices to analyze the issue. The NDVI and NDWI indices were used for this purpose. The NDDI readings are measured on a scale from −1 to 1, with negative values indicating the presence of clouds or water, and positive values approaching 1 indicating severe drought conditions. The calculation of NDDI was presented in Equation 3. The drought index results were then categorized based on Table 4.

$$NDDI = \frac{(NDVI-NDWI)}{NDVI+NDWI} \text{ .....(Equation 3)}$$

Table 4. The classification of the Normalized Difference Drought Index (NDDI)

NDDI interval	Drought level
-0.05 - 0.01	Normal
- 0.15	Mild
0.15 - 0.25	Moderate
0.25 - 1	Severe
>1	Extreme

Source: [8]

NDVI, NDWI, and NDDI image analysis was conducted for four time periods: the rainy season (January), the transition to the dry season (May), the dry season (July), and the transition to the rainy season (September) over a five-year period from 2020 to 2024. A five-year range and four seasonal phases were chosen to capture more stable drought patterns, reduce annual condition bias, and more representatively illustrate drought change dynamics in each seasonal phase. The drought index was then statistically analyzed using ANOVA (Analysis of Variance) and the DMRT (Duncan Multiple Range Test) to determine the effect of sources of variation on the drought index.

3 Result And Discussion

3.1 Analisis Normalized Difference Vegetation Index (NDVI)

Monthly NDVI data over five years reveal significant changes throughout the year (Fig. 5). NDVI serves as an indicator for identifying land use changes from vegetation because its value varies spatially and temporally according to plant growth conditions [12].

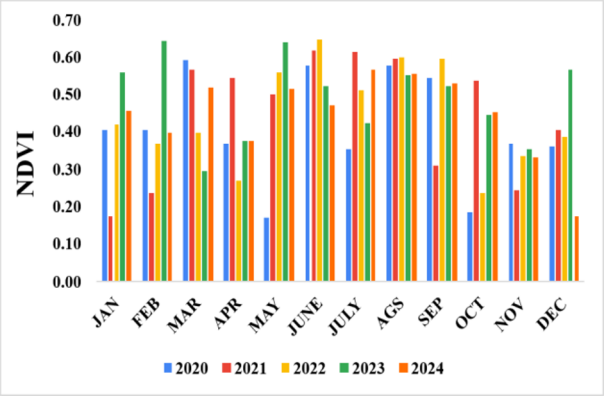


Fig. 5. The pattern of distribution of Normalized Difference Vegetation Index (NDVI) in each month and year

Monthly NDVI values range from 0.33 to 0.57, indicating moderate to relatively dense vegetation conditions. The highest values, ranging from 0.48 to 0.57, generally occur from June to September. The increase in NDVI during this period indicates more intensive vegetation activity, characterized by increased canopy density and the vegetation's ability to absorb light radiation. NDVI tends to be positive in vegetated areas, such as crops, shrubs, grass, and forests, and approaches zero or has negative values in non-vegetated areas. Therefore, the higher the NDVI, the higher the level of green vegetation cover. Conversely, lower NDVI values (0.33–0.38) are commonly observed from October to December, reflecting a decline in vegetation due to reduced water availability and the transition into the

beginning of the rainy season. When NDVI is low, the area has low vegetation density and water absorption capacity [1]. Year-over-year comparisons show variations between observation periods, with 2020 and 2021 having relatively higher NDVI values compared to 2023 and 2024 for most months. This could be related to differences in annual climate conditions, particularly rainfall distribution and land conditions, which also influence vegetation development.

3.2 Analisis Normalized Difference Water Index (NDWI)

The NDWI for the period 2020–2024 exhibits a fairly consistent seasonal fluctuation pattern (Fig. 6). The variation in values between years is attributed to annual climate conditions, particularly the distribution of rainfall and the level of soil moisture resistance in each year. Monthly NDWI values range from 0.18 to 0.30, reflecting variations in land surface moisture levels within the study area.

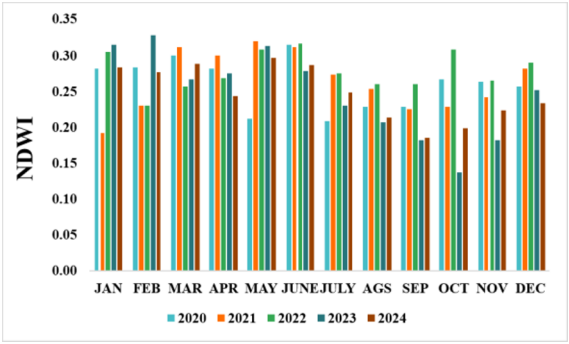


Fig. 6. The pattern of distribution of Normalized Difference Water Index (NDWI) in each month and year

The highest value, around 0.30, generally appears in May. This condition indicates that at the beginning of the transition season, the vegetation and soil surface are relatively wetter, which is related to the continued availability of water from the previous rainy season. High NDWI values indicate sufficient water or vegetation availability, while low NDWI values indicate areas without surface water content, such as residential land, open land, and unmanaged rice fields. Conversely, the lowest NDWI value, around 0.18, was most frequently observed in September, reflecting decreased land moisture due to higher evaporation intensity and limited water supply during the dry season. Low NDWI values are influenced by the conversion of forest land to agricultural or plantation land, as well as human activities, leading to a further reduction in water absorption areas, which also affects groundwater absorption.

3.3 Determining of Drought Index using NDDI Method

The NDDI drought index is calculated from a combination of NDVI and NDWI to describe land drought conditions (Fig 7). NDDI values fluctuate each month, with the highest drought in August (0.56) and the lowest in November (0.3). The graph pattern shows that NDDI began to increase in June and reached its peak in July–September, with a higher range of values compared to other months.

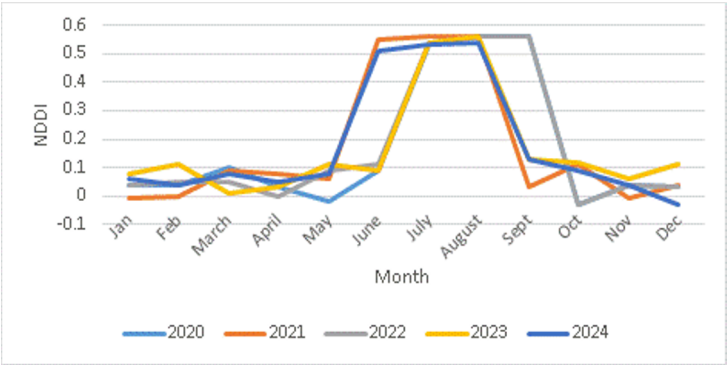
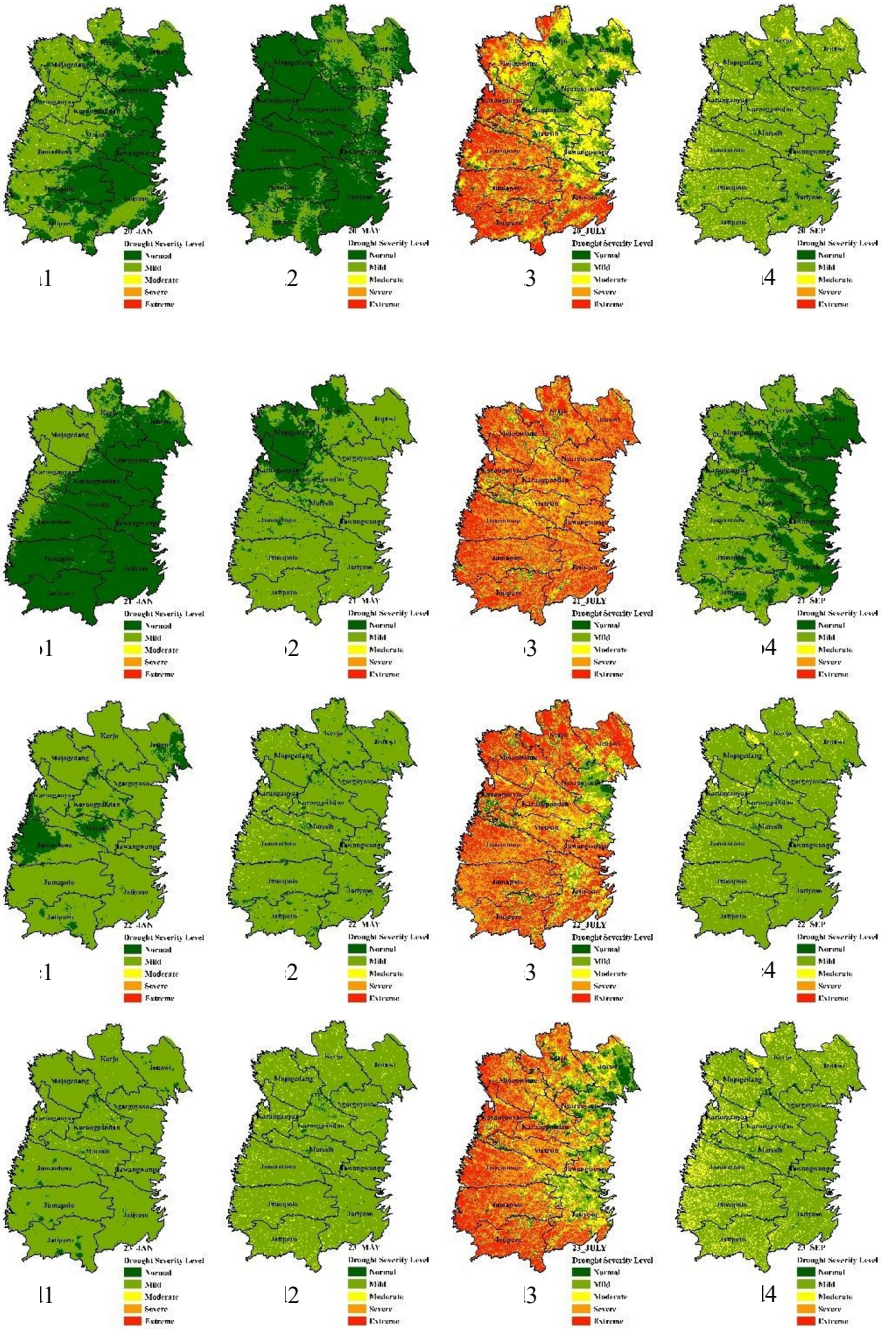


Fig. 7. The pattern of distribution of Normalized Difference Drought Index (NDDI) in each month and year

This increase reflects increasingly intense drought conditions, related to low rainfall and high evapotranspiration rates during the dry season. At this phase, the vegetation experiences greater water stress, leading to a decrease in the vegetation index, while the wetness index also shows a decline, resulting in a higher NDDI value. NDDI assumes that high drought index occurs when both the vegetation and wetness indices decrease, leading to drought in agricultural land. The drought index tends to increase during the dry season due to reduced rainfall and increased evapotranspiration [13]. Conversely, the lowest NDDI generally occurs from November to January, coinciding with the beginning of the rainy season and its peak. During this period, water availability increased and vegetation began to recover its physiological activity, resulting in NDDI values indicating wetter land conditions and a low risk of drought [3].

3.4 The Distribution of Drought Index in many years

The 2020–2024 NDDI visualization shows clear drought variations both monthly and annually, with patterns following the dynamics of the rainy season, transition period, and dry season (Fig. 8). The distribution of drought on the western slopes of Mount Lawu appears to be influenced by vegetation density, land cover conditions, and the availability of surface water, which varies greatly at each topography. Lowland areas generally have more open vegetation cover, making them more susceptible to soil moisture decline and increased surface temperatures, which trigger earlier droughts compared to zones at medium to high topography. During the rainy season (January), most areas with a topography of 200–600 meters above sea level (masl) exhibited mild drought conditions, whereas the 600–800 masl zone was relatively normal due to denser vegetation cover and better water accumulation. During the transition phase toward the dry season (May), an increase in the Normalized Difference Drought Index (NDDI) was observed, particularly in the 200–600 masl zone, which experienced rapid changes in land condition due to increased evapotranspiration and decreased precipitation. At a topography of 600–1000 masl, the drought that appeared was still in the mild category, indicating that this area has better water storage capacity compared to the lowlands.


20_JAN
20_MAY
20_JULY
20_SEP
21_JAN
21_MAY
21_JULY
21_SEP
22_JAN
22_MAY
22_JULY
22_SEP
23_JAN
23_MAY
23_JULY
23_SEP
Drought Severity Level
Normal
Mild
Moderate
Severe
Extreme

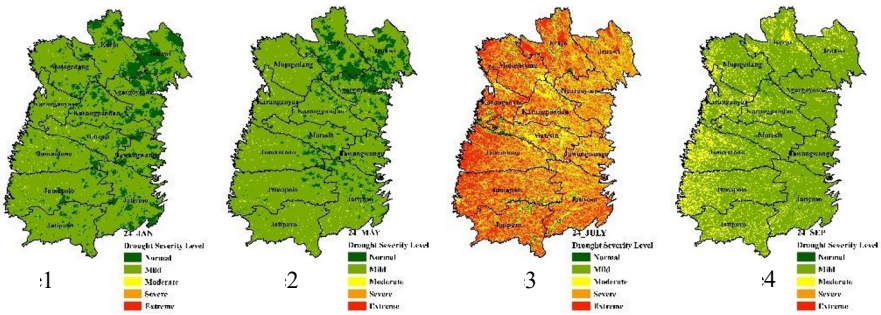


Fig. 8. Normalized Difference Drought Index of January, May, July, and September from 2020-2024
Notes: a= year of 2020; b= year of 2021; c= year of 2022; d= year of 2023; e= year of 2024; 1= January; 2= May; 3= July; 4 =September

The peak of the drought was seen in July, when areas 200–600 meters above sea level consistently fell into the moderate to high drought category. This condition reflects a combination of low rainfall supply, low groundwater storage capacity in dryland and rainfed areas, and high rates of water loss through evaporation. At an topography of 600–1000 meters above sea level, some areas also show increased drought, although the category is generally lower due to the presence of relatively denser vegetation and soil texture that allows for better water retention. As September approaches, marking the transition to the rainy season, the drought index is beginning to decrease to the mild category in most areas, reflecting increased humidity due to early season rains and reduced evapotranspiration pressure. Overall, the spatial and temporal patterns of NDDI over five years indicate that low-lying topography is more sensitive to drought and experiences changes in conditions more quickly than areas at higher elevations. This highlights the importance of topographic factors, soil characteristics, and vegetation cover in influencing land resilience to drought.

3.5 The effect of differences of land characteristics on Drought Index using NDDI Method

The study area exhibits diverse land characteristics, including topography, soil types, slope gradients, and precipitation patterns. To determine the influence of land characteristics on drought, ANOVA was performed with a significance level of 5% (p-value < 0.05). The ANOVA results (Table 5) indicate that topography, slope, and precipitation have a significant influence on the NDDI drought index.

Table 5. The effect of differences of land characteristics on the drought index (NDDI)

Land characteristic	***p-value****
Topography	**0.000**
Soil type	0.111
Slope	**0.039**
Precipitation	**0.005**

Note: *significance level at 5% (p<0.05)

The ANOVA results show that land characteristic factors such as topography, slope, and precipitation have a highly significant impact on the drought index, with p-values of 0.000, 0.0039, and 0.005, respectively. The sensitivity analysis results of drought to specific land characteristics are also influenced by the type of drought index used [14]. Land characteristics, such as topography and slope, can affect drought distribution through variations in temperature and precipitation patterns across different topographies; however, their influence is more detectable using NDVI. Further analysis was conducted regarding the

influence of land characteristic factors and the NDDI drought index using DMRT (Duncan's Multiple Range Test) at a significance level of 5%.

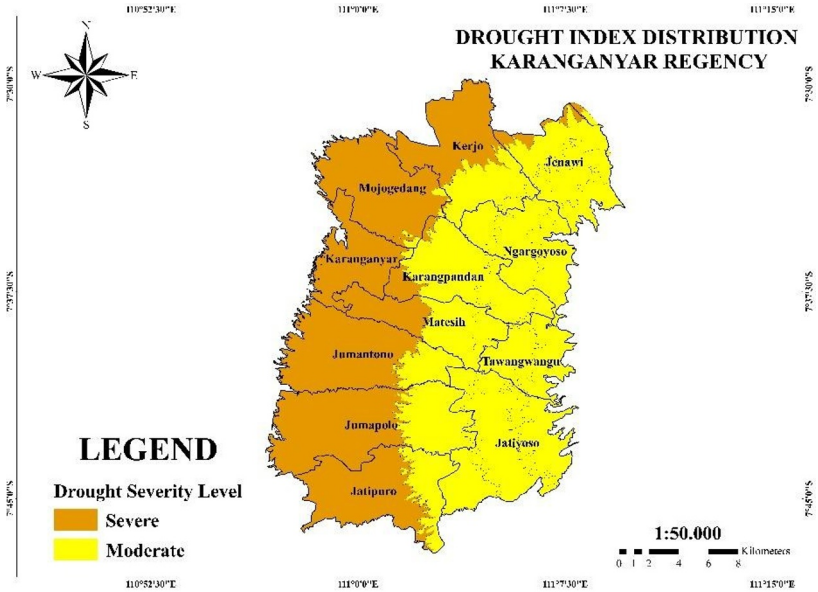


Fig. 9. The distribution of Normalized Difference Drought Index on toposequence in 2024

The distribution of the drought index across various topographies in 2024 revealed that low topography indicates vulnerability to drought, with severe levels occurring in areas with topography of 200–400 meters above sea level. Conversely, high topography indicates drought resistance, with a drought index class of moderate (Fig. 9). This is closely related to the density of vegetation in the area; the denser the vegetation, the higher the water storage capacity, making it more resistant to drought [9].

The analysis results show that the average NDDI drought index varies significantly between toposequences (Table 6). The toposequence range of 200-400 meters above sea level (masl) exhibits a high level of drought (0.2496a), as indicated by the drought index, which is significantly different from the topography range of 800-1,000 masl (0.2100c). The topography ranges of 400-600 masl (0.2296b) and 600-800 masl (0.2286b) indicate an average level of drought with a significant impact. This suggests that areas with lower topography are more likely to experience more intense droughts compared to regions with higher topography. NDDI has high sensitivity to changes in soil moisture and vegetation, making it a useful tool for monitoring drought in areas with diverse topographic characteristics [8]. High temperatures, strong solar radiation, and low soil moisture in the lowlands accelerate drought, especially during the dry season.

Table 6. The effect of toposequence on the drought index (NDDI)

Toposequence (masl)	NDDI
800-1.000	0.2100a
600-800	0.2286b
400-600	0.2296b
200-400	0.2496c

Note: The number that is followed by the same letters indicates no significant difference according to DMRT

Further tests were also conducted on the slope factor against the NDDI drought index at a 5% significance level. The analysis results (Table 7) show that the average NDDI drought index varies across slope groups. The 0-15% slope group shows a moderate average drought level (0.2400b), which is the most influential slope and significantly different from other slope groups.

Table 7. The effect of slope on the drought index (NDDI)

Slope (%)	NDDI
>30	0.2183a
15-30	0.2264a
0-15	0.2400b

Note: The number that is followed by the same letters indicates no significant difference according to DMRT

Higher NDDI on slopes of 0-15% indicates that areas with relatively flat or gentle slopes are more likely to experience more severe drought levels. On gentle or flat slopes, surface drainage tends to be slow, especially in clayey soils. During the rainy season, the infiltration rate is high; however, prolonged waterlogging can disrupt the aeration of plant roots. Slope gradients of 15-30% and >30% respectively, indicate drought indices with averages of 0.2264b and 0.2183b. That notation indicates that there is no significant difference between the two. NDDI on both slopes was lower compared to the 0-15% group, suggesting a less severe drought level on the gentle slope. Gentle slopes generally have better groundwater retention capacity, thus reducing the risk of drought. However, agricultural land, such as dry fields on gentle slopes, is actually vulnerable to drought because these conditions are considered less than ideal for water infiltration and have a higher open vegetation density. High slope gradients generally tend to increase surface run-off due to low infiltration of rainwater into the soil, as only a small amount of water can be absorbed through soil pores and rock crevices on the surface. Agricultural land prone to drought is typically found in areas with moderate to steep slopes, as very little water is absorbed into the soil. This low water availability is insufficient to meet crop water needs.

The analysis results of the influence of precipitation on the NDDI drought index show that precipitation of 1,292.40 mm per year has the highest impact, with an index of 0.2567a, indicating an average severe drought level (Table 8). This precipitation is significantly different from the area with of 3,295.06 mm per year, which results an index of 0.2233c. The NDDI, calculated from the ratio of NDVI and NDWI, is highly sensitive to changes in vegetation and soil water content, thereby more accurately reflecting surface drought conditions [12]. The precipitation is the most dominant factor influencing the level of drought in agricultural land [15]. The lower the precipitation, the higher the level of drought that occurs. Precipitation is a key parameter in determining water availability and drought potential; however, the limited spatial data from rainfall stations prevent a detailed depiction of drought distribution patterns [14].

Table 8. The effect of precipitation on the drought index (NDDI)

Precipitation (mm year$^{-1)}$	NDDI
1,292.40	0.2567c
1,301.70	0.2443b
2,661.92	0.2263a
3,295.06	0.2233a

Note: The number that is followed by the same letters indicates no significant difference according to DMRT

4 Conclusion

The research results indicate that the toposequence affects the drought index. In low-lying areas (200-600 masl), the level of drought ranges from moderate to severe, while in higher areas (600-1000 meters above sea level), the drought index is normal to mild. Based on monthly analysis, the NDDI drought index varies each month, with the highest value in August (0.56) and the lowest in November (0.03). Land characteristics such as precipitation and slope affect the drought index. The distribution of the drought index over 5 years (2020–2024) shows that the highest drought tends to occur in areas with a topography of 200-600 masl and a slope of 0–15%, with low vegetation density, especially during the dry season with precipitation of 1,292.40 mm/year. The 5-year trend indicates that the drought index increases at the onset of the dry season, which spans from July to August, and then declines as the dry season concludes in September to November.

References

1. H. M. Suud and D. E. Kusbianto, Exploring El Nino effects on agricultural area using Landsat images analysis: A case study in Bondowoso Regency, Indonesia. SAINS TANAH - Journal of Soil Science and Agroclimatology. **21**, 2 (2024). https://doi.org/10.20961/stjssa.v21i2.85190
2. S. N. Aripbilah and H. Suprapto, Analisis Kekeringan Di Kabupaten Sragen Dengan Metode Palmer, Thornthwaite, Dan Standardized Precipitation Index. Jurnal Sumber Daya Air. **17**, 2 (2021). https://doi.org/10.32679/jsda.v17i2.742
3. A. Herawati, M. Mujiyo, B. D. E. P. Nugroho, N. M. Istiqomah, V. Irmawati, K. Hasanah, T. Hardian, and A. Anggita, Drought potential index using Normalized Difference Drought Index (NDDI) method based on Geographical Information System (GIS) in Slogohimo, Wonogiri Indonesia. IOP Conference Series: Earth and Environmental Science. **1314**, 1 (2024). https://doi.org/10.1088/1755-1315/1314/1/012040
4. M. Mujiyo and R. Nurdianti, Agricultural Land Dryness Distribution Using the Normalized Difference Drought Index (NDDI) Algorithm on Landsat 8 Imagery in Eromoko , Indonesia. Environment and Natural Resources Journal. **21**, 2 (2023). https://doi.org/10.32526/ennrj/21/202200157
5. B. Minasny and A. Mcbratney, Limited effect of organic matter on soil available water capacity. European Journal of Soil Science. **69**, 1 (2017). https://doi.org/10.1111/ejss.12475
6. E. Davoodi, M. Soleimani-motlagh, and R. Chamanpira, Prediction of temporal and spatial variations of the NDDI drought index in the Khorramabad watershed using remote sensing. **2**, 2025 (2026). https://doi.org/10.22069/IJERR.2025.23327.1487
7. A. Ashok, H. P. Rani, and K. V Jayakumar, Monitoring of dynamic wetland changes using NDVI and NDWI based landsat imagery. Remote Sensing Applications: Society and Environment. **23**, (2021). https://doi.org/10.1016/j.rsase.2021.100547
8. F. Salas-martínez, O. A. Valdés-rodríguez, O. M. Palacios-wassenaar, A. Márquez-grajales, and L. D. Rodríguez-hernández, Methodological estimation to quantify drought intensity based on the NDDI index with Landsat 8 multispectral images in the central zone of the Gulf of Mexico. May (2023). https://doi.org/10.3389/feart.2023.1027483
9. G. B. Pamungkas, Analisis Kekeringan Berbasis Remote Sensing dengan Metode Normalized Difference Drought Index (NDDI) secara Multi-Years. **2**, 2 (2023)

10. S. Sumarwati, Traditional ecological knowledge on the slope of Mount Lawu, Indonesia: all about non-rice food security. Journal of Ethnic Foods. **9**, 1 (2022). https://doi.org/10.1186/s42779-022-00120-z
11. X. Pons, L. Pesquer, J. Cristóbal, and O. González-Guerrero, Automatic and improved radiometric correction of landsat imageryusing reference values from MODIS surface reflectance images. International Journal of Applied Earth Observation and Geoinformation. **33**, 1 (2014). https://doi.org/10.1016/j.jag.2014.06.002
12. Y. Gu, J. F. Brown, J. P. Verdin, and B. Wardlow, A five-year analysis of MODIS NDVI and NDWI for grassland drought assessment over the central Great Plains of the United States. Geophysical Research Letters. **34**, 6 (2007). https://doi.org/10.1029/2006GL029127
13. M. I. Pramestika, Y. R. Aisy, Y. S. D. Pamungkas, N. A. A. Zahra, M. A. H. P. Perdana, N. L. E. Utami, Y. Khoirurrizqi, and W. Widyatmanti, Exploring Spatial and Temporal Variations of Agricultural Drought in Roraya Watershed Using Normalized Difference Drought Index (NDDI). Jurnal Geografi. **22**, 2 (2024)
14. C. Jiang, C. Ma, S. Duan, X. Min, Y. Z. Zhang, D. Li, and X. Zhang, Monitoring of Agricultural Drought Based on Multi-Source Remote Sensing Data in Heilongjiang Province, China Chenfa. Journal of Integrative Agriculture Monitoring. (2025)
15. A. Handayani and H. Setiadi, Distribution of Drought on Agricultural Land in Palabuhanratu District Sukabumi Regency. Jurnal Geografi : Media Informasi Pengembangan Dan Profesi Kegeografian. **20**, 1 (2023). https://doi.org/10.15294/jg.v20i1.41285