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## Mapping Drought Severity Based on Sentinel-2 Harmonized Data Using Google Earth Engine

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### ABSTRAK

Kekeringan merupakan salah satu bencana hidrometeorologi yang berdampak signifikan terhadap ekosistem dan keberlanjutan pemanfaatan lahan, khususnya di wilayah tropis lembab yang selama ini dianggap relatif resilien. Penelitian ini bertujuan untuk menganalisis tingkat kekeringan di Kabupaten Konawe Selatan menggunakan Normalized Difference Drought Index (NDDI) tahun 2024 dengan penginderaan jauh melalui platform Google Earth Engine. Analisis hubungan antar-variabel juga dilakukan dengan pendekatan statistik korelasi terhadap Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Land Surface Temperature (LST), dan precipitation. Analisis NDDI mengindikasikan bahwa kelas kekeringan sedang mendominasi hingga 35,93% wilayah, sedangkan kekeringan rendah hanya mencakup 27,99%. Korelasi antara NDDI dengan NDVI, NDWI, LST, dan presipitasi relatif lemah ( $R^2 < 0,3$ ), yang mengindikasikan bahwa kekeringan tidak hanya dipengaruhi oleh curah hujan, tetapi merupakan fenomena multidimensional. Hasil penelitian ini dapat dimanfaatkan untuk perencanaan mitigasi dan adaptasi kekeringan, pengelolaan sumber daya air dan lahan, serta sebagai informasi public yang dapat meminimalkan terkait risiko dampak kekeringan.

**Kata Kunci:** kekeringan; Normalized Difference Drought Index; Google Earth Engine; Konawe Selatan; Sentinel-2 Harmonized.

### ABSTRACT

Drought is a hydrometeorological disaster that significantly impacts ecosystems and the sustainability of land use, particularly in humid tropical regions that have long been considered relatively resilient. This study aims to analyze the level of drought in Konawe Selatan Regency using the 2024 Normalized Difference Drought Index (NDDI) with remote sensing via the Google Earth Engine platform. Inter-variable relationships were also analyzed using a statistical correlation approach to the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Land Surface Temperature (LST), and precipitation. The NDDI analysis indicates that moderate drought dominates up to 35.93% of the area, while low drought only covers 27.99%. The correlation between the NDDI and NDVI, NDWI, LST, and precipitation is relatively weak ( $R^2 < 0.3$ ), indicating that drought is not solely influenced by rainfall but is a multidimensional phenomenon. The results of this study can be used for drought mitigation and adaptation planning, water and land resource management, and as public information that can minimize the risk of drought impacts.

**Keywords:** drought; Normalized Difference Drought Index; Google Earth Engine; Konawe Selatan; Sentinel-2 Harmonized.

## INTRODUCTION

Indonesia's location on the equator makes the region vulnerable to hydrometeorological disasters. Hydrometeorological disasters can be caused by weather and climate (Musliyadi and Samsuddin, 2021). These disasters can include floods, landslides, strong winds, and drought. Global warming and climate change are closely related to weather, making it difficult to predict. This situation results in extreme weather, which can lead to hydrometeorological disasters. One of the most common hydrometeorological disasters is drought. Droughts have caused numerous problems in meeting water needs for households, agriculture, and the industrial sector.

According to the National Disaster Management Agency (2024), drought is a high-risk disaster, with approximately 341 districts/cities at high risk across Indonesia. Droughts were recorded to have occurred 5.13% of the time in Southeast Sulawesi Province from 1999 to 2019 (BNPB, 2021). Konawe Selatan Regency occupies the area with the widest range of drought hazards based on meteorological factors and the soil's water retention capacity (BNPB, 2021). This situation indicates that Konawe Selatan Regency is threatened by drought with a recurring pattern every year. Given this situation, a more comprehensive approach is needed in drought mitigation efforts to minimize its impact on the community.

Rapid technological developments have facilitated natural disaster mitigation efforts, such as drought, through remote sensing technology. Remote sensing allows for object identification without direct physical contact. This is because remote sensing involves collecting information about an object or phenomenon remotely, using sensors that record the interaction of energy (such as light, heat, or radio waves) with the object through satellite imagery. Satellite imagery has been widely adopted for natural disaster mitigation needs. In this context, cloud-based monitoring platforms have become increasingly important to accelerate the processing and analysis of satellite data.

Cloud-based geospatial data monitoring platforms such as Google Earth Engine (GEE) can be used to calculate and present raw and processed data (Pham and Tran, 2020) for hydrometeorological disaster identification.

Many satellites are freely available, and image processing is straightforward through GEE. Studies in Bangladesh have demonstrated that Landsat 5 and Landsat 8 satellite imagery have been utilized to analyze the impacts of disasters and land-use change on food security and adaptation efforts in the region (Parven et al., 2022). Landsat 7 and Landsat 8 satellite imagery have also been utilized in studies of Iraqi rivers to analyze drought there (Albarakat et al., 2022). A study of the Idriss 1 Dam in northeastern Morocco utilized a combination of Landsat 8 and Sentinel 2 to monitor the severity and frequency of drought risk with high precision (Benzougagh et al., 2022). These findings demonstrate that satellite imagery can provide valuable spatial insights for understanding disaster patterns, including drought.

Drought severity can be mapped using a combination of NIR, Red, and SWIR bands on Landsat-8 and Sentinel-2 sensors, known as the Normalized Difference Drought Index (NDDI) (Nepal et al., 2021). Its broad spatial coverage allows it to be used in drought mapping in various countries, including Indonesia. However, each sensor has limitations, making data integration increasingly relevant for generating more detailed information.

Although Sentinel-2 data, particularly the Harmonized Landsat-8 and Sentinel-2 (HLS) products, have significant potential for drought monitoring due to their relatively high spatial resolution and revisit frequency, their use in specific drought studies remains very limited. HLS products have been widely utilized in vegetation and agricultural monitoring, such as phenology analysis and biocharacteristic indices, but direct applications for drought mapping are still rare, especially in Indonesia (Nguyen et al., 2020; Varghese et al., 2021).

Although several studies have explored the potential of Sentinel-2 in the context of drought, such as a comprehensive review by Varghese et al. (2021) that evaluated Sentinel-2's application to measuring soil moisture, evapotranspiration, and vegetation response, limitations remain in their direct application to drought analysis (Varghese et al., 2021). Furthermore, integration of Sentinel-2 with Landsat-8 (through data fusion and HLS products) has been conducted for vegetation analysis and land monitoring (e.g., using ESRCNN or Google Earth Engine approaches),

but rarely explicitly addresses drought. This highlights the wide scope of research opportunities, particularly in tropical regions like Indonesia.

The need for medium to medium resolution imagery data with consistent temporal coverage is crucial to support local drought mitigation and adaptation. Combinations such as MODIS and Landsat have limitations, both in terms of resolution and temporal continuity. Sentinel-2 offers a better alternative, but the limited duration of medium-to high-resolution time series and temporal and spatial gaps in Landsat time series still pose obstacles for local or regional-scale drought analysis applications (Li et al., 2025).

This significant gap between potential and actual results reflects a significant research gap. Further exploration of how the Harmonized Sentinel-2 product can be optimized to produce accurate drought indices would add substantial value to climate adaptation and drought risk mitigation efforts, particularly in vulnerable areas.

This study aims to map drought levels using the NDDI algorithm in Konawe Selatan Regency. The results are expected to provide more accurate spatial information on the distribution and severity of drought, thereby providing a basis for local governments and stakeholders to formulate more effective

mitigation, adaptation, and water resource management strategies in drought-prone areas.

## RESEARCH METHOD

### Research Type

This research uses quantitative research with a descriptive and analytical approach. This type of research illustrates that this research uses numerical data that can be measured and analyzed statistically to understand the drought phenomenon. This research focuses on describing drought characteristics such as severity, spatial distribution, and influencing factors.

### Study Area and Period

This research was conducted in June 2025 in Konawe Selatan Regency. The study area covers 423,282.03 ha. Astronomically, the regency is located between latitudes  $3^{\circ}58'56''\text{S}$  and  $4^{\circ}31'52''\text{S}$ , and longitudes  $121^{\circ}58'\text{E}$  and  $123^{\circ}16'\text{E}$  (Figure 1). This area comprises 25 sub-districts, each with 336 villages. The study area has an altitude of up to 953 masl. The topography was generally varies, including flat, sloping, and steep areas, especially in protected forest areas such as Wolasi. This region has lowlands on the coast and highlands in the central and southern parts. The study area experiences high rainfall, with an average of temperature  $26.73^{\circ}\text{C}$  and humidity of 85.75%.

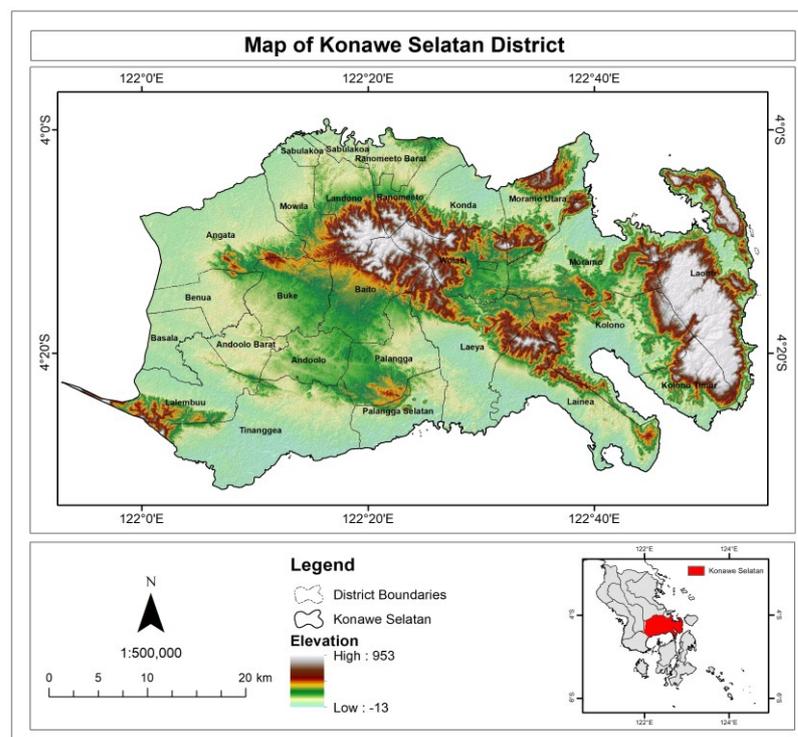


Figure 1. Map of Research Location (Digital Elevation Model, 2025)

## Types and Sources of Data

This study used spatial data sourced from secondary sources and obtained through various open-access platforms. All data were downloaded and extracted using GEE as the basis for spatial data processing.

The data types in this study were categorized into primary data and secondary data, also referred to as causal factor data. Sentinel-2 Harmonized data from 2024 were used as the primary source for vegetation analysis using the NDDI approach. Sentinel-2 has a spatial resolution of 10 meters, which is relevant for calculating vegetation indices. The Sentinel-2 Harmonized dataset is available through the GEE platform under the collection name Copernicus/S2\_Harmonized.

Landsat 8 OLI/TIRS satellite imagery from 2024 and WorldClim Version 2.1 from 1970-2000 were used as the causal factor database. Landsat 8 data were used to derive Land Surface Temperature (LST) information, which is assumed to influence drought dynamics. The spatial resolution of this data is 30 meters, with the collection available in GEE under the collection name Landsat/LC08/C02/T1 for the Landsat 8 OLI/TIRS satellite. Global climate data from WorldClim is used to identify long-term rainfall patterns that are predisposing factors for drought. The WorldClim dataset has a spatial resolution of 30 arc-seconds (~1 km), with the main variables being temperature, rainfall, radiation, and humidity. WorldClim data can be downloaded from the official website <https://www.worldclim.org> and is also available in GEE through the WorldClim/V1/Bio collection.

## Data Collection Technique

The data collection technique in this study was conducted using a remote sensing approach, utilizing available secondary data accessible through GEE. The first step was to define the study area boundaries using administrative data from Konawe Selatan Regency, which then served as the basis for clipping the entire dataset to simplify the computational process (Gorelick et al., 2017).

The satellite data was then filtered based on the study period, specifically the dry season from July to November, so that only images that matched the study's temporal range were used. This determination was adjusted to reflect

the average rainfall pattern in Indonesia over three decades (BMKG, 2021).

Pre-processing included applying cloud masking and cloud shading to the optical data to minimize noise, and adjusting the coordinate projection system to ensure uniform spatial referencing across all datasets. Relevant variables were then extracted from each dataset, such as spectral channels for calculating the drought index, thermal channels for surface temperature, and climate parameters for rainfall. The final stage is to integrate all extraction results into a spatial database, then export them in raster or table format so that they can be further analyzed spatially and statistically (Amani et al., 2020).

## Data Analysis Technique

### 1. Normalized Difference Vegetation Index

The NDVI algorithm is used to determine the NDVI value and distribution in Konawe Selatan Regency. NDVI data is one of the main components in calculating drought severity using the NDDI. NDVI calculation is important because the value and distribution of the vegetation index can represent vegetation cover and density, which are crucial in maintaining ecosystem balance (Xiong and Wang, 2022). The vegetation index was extracted from Sentinel-2 Harmonized data using a subtraction technique from the Red Band (Band 4) and the Near-Infrared Band (Band 8). The wavelength of the Red band is 664.5 nm, while the NIR band is 835.1 nm. The NDVI value was calculated using the following equation (Lillesand et al., 2015).

$$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R}$$

Variable Definitions:

$\rho_{NIR}$  : spectral reflectance band near-infrared (band 5)

$\rho_R$  : spectral reflectance band red (band 4)

NDVI values range from -1 to 1. Values closer to 1 indicate high vegetation density, while values closer to -1 indicate non-vegetation. Non-vegetated areas generally represent built-up areas, open areas, and water bodies (Aldiansyah et al., 2021, 2024). Areas with high vegetation density generally have a positive correlation with groundwater

availability (Lazo et al., 2019), making these locations less susceptible to drought.

## 2. Normalized Difference Water Index

The NDWI algorithm is also a component in determining the level of drought in a region. The NDWI index can identify the presence of open water features by utilizing the NIR and SWIR bands (McFeeters, 1996). NDWI calculations were also performed using Sentinel-2 Harmonized imagery, specifically from the NIR/Band 8 band (835.1 nm) and SWIR/Band 11 band (1613.7 nm). NDWI values were calculated using the following equation (Paniagua et al., 2020).

$$NDWI = \frac{\rho_{NIR} - \rho_{SWIR}}{\rho_{NIR} + \rho_{SWIR}}$$

Variable Definitions:

- $\rho_{NIR}$  : spectral reflectance band near-infrared (band 5)  
 $\rho_{SWIR}$  : spectral reflectance band SWIR (band 11)

The NDWI ranges from -1 to 1. An NDWI value >0 indicates a water area. A value <0 indicates a non-water area (Rismayatika et al., 2020). This suggests that areas with positive values tend to be better protected from drought due to their well-watered environment.

## 3. Normalized Difference Drought Index

The NDDI algorithm is used to map drought severity. The NDDI is an index with good sensitivity to drought (Zheng et al., 2021). Therefore, this index incorporates other indices such as NDVI and NDWI, which are quite sensitive to the presence of vegetation and water in an area (Tavazohi and Nadoushan, 2018). The results of the previous NDVI and NDWI calculations are then reformulated into the NDDI index. The equation is shown below (Charat et al., 2009).

$$NDDI = \frac{NDVI - NDWI}{NDVI + NDWI}$$

Variable Definitions:

- $NDVI$  : Normalized Difference Vegetation Index  
 $NDWI$  : Normalized Difference Water Index

The drought severity level from the NDDI results was then classified into five

classes, namely very low (<-2), low (-2 – 0.7), moderate (0.7 – 1.25), high (1.25 – 3), and very high (>3) (Nepal et al., 2021).

## 4. Land Surface Temperature

The LST data derived from Landsat-8 imagery was further analyzed to identify correlations with NDDI values. This analysis aimed to assess the extent to which increasing surface temperatures could affect the level of vegetation dryness in the study area. The LST calculations were performed using Landsat-8 imagery, using Band 10 Thermal Infrared I/TIRS I (10.60–11.19 nm) and Band 11 TIRS II (11.50–12.51 nm). The LST values were calculated using the following equation (Artis and Carnahan, 1982).

$$LST = \frac{BT}{\left[1 + \left(\frac{\lambda \times BT}{a}\right) \ln(e)\right]}$$

Variable Definitions:

- $BT$  : brightness temperature of TOA (°K)  
 $\lambda$  : wavelength of emitted radiance (0.00115)  
 $a$  : the constant obtained from  $h \cdot c / \sigma$  (1,4388  $\mu\text{mK}$ )  
 $e$  : land surface emissivity

## 5. Precipitation

Precipitation data from WorldClim were used to analyze long-term climate patterns and then correlated with NDDI values. This analysis was conducted to determine the role of rainfall variability in influencing drought dynamics, as detected through the NDDI index. Annual precipitation was calculated by summing rainfall for each month using the following equation.

$$P_{annual} = \sum_{i=1}^{12} P_i$$

Variable Definitions:

- $P_{annual}$  : total annual rainfall  
 $P_i$  : rainfall in month  $i$

## 6. Correlation Analysis

The analysis of relationships between variables was conducted using a statistical correlation approach based on point sampling of raster data. The first step was spatial sampling of the raster data extracted from NDDI, NDVI, LST, and Precipitation. A total

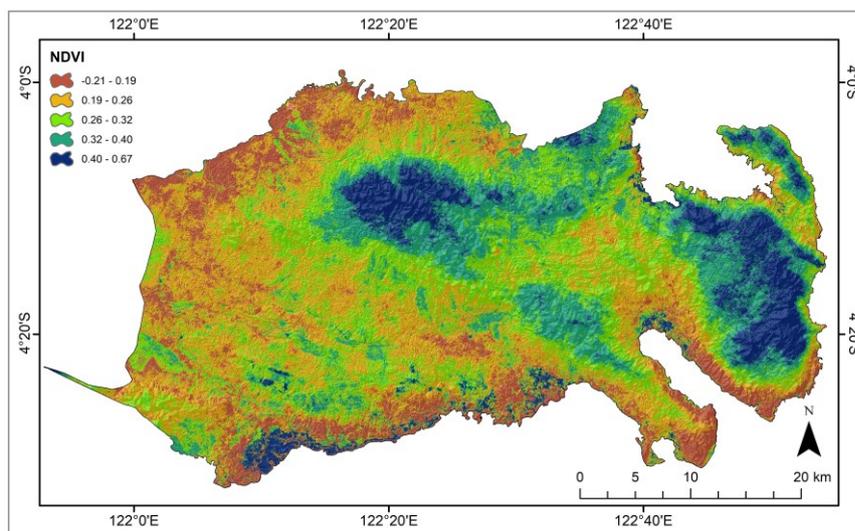
of 1,528 sample points were selected evenly across the study area using the sampling tool in ArcGIS Desktop. The values of each raster at each sample location were extracted, resulting in an attribute table containing pairs of NDDI–NDVI, NDDI–NDWI, NDDI–LST, and NDDI–Precipitation values.

The extracted data was then exported to tabular format (.csv) and further processed using Microsoft Excel. The correlation analysis was conducted using a simple linear regression method, with NDDI as the independent variable (X), while NDVI, NDWI, LST, and Precipitation were the dependent variables (Y). The relationships between variables were visualized in the form of a scatter plot, with the regression equation and coefficient of determination ( $R^2$ ) to assess the strength of the relationship. The significance of the relationships was further evaluated to

determine the reliability of the correlation results.

## RESULT

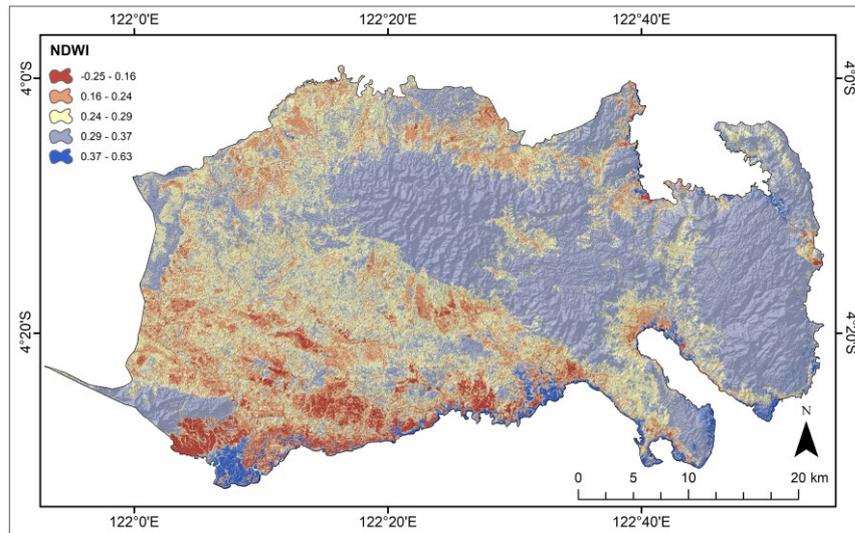
Drought monitoring can be used by the government, NGOs, and the community to support accurate decision-making in managing water and land resources. It also helps in developing mitigation and adaptation measures, as well as disseminating information about potential risks and community responses. The NDVI algorithm represents the level of greenness, density, and condition of vegetation in a region. The NDVI values in this study were obtained from the Red and NIR bands and used for drought analysis. The NDVI analysis ranged from -0.21 to 0.67, which were then grouped into five categories using the natural breaks method. The NDVI classification results are shown in Figure 2.



**Figure 2.** Normalized Difference Vegetation Index of Konawe Selatan Regency 2024

Based on Figure 2 shows that the lowest NDVI values are distributed throughout almost the entire region, except for the northeast coast, where distribution is limited to settlements, open land, fish ponds, and water bodies. Meanwhile, high NDVI values are found in mountainous areas in the east and central regions, as well as in the mangrove areas on the south side. Based on area, the highest NDVI class was shown by the 0.32–0.40 class, covering 131,702.72 ha (31.11%), followed by the 0.26–0.32 class, covering 109,263.65 ha (25.81%), the 0.19–0.26 class, covering 81,526.95 ha (19.26%), the 0.40–0.67 class, covering 57,187.70 ha (13.51%), and the -0.21–0.19 class, covering 43,601.01 ha (10.30%).

The NDWI algorithm is known to correlate strongly with vegetation water content. NDWI values in this study were obtained from the NIR and SWIR bands. NIR reflectivity is closely related to the total dry matter of leaf biomass, not the vegetation water content. SWIR also represents vegetation water content. Therefore, SWIR is largely determined by the amount of vegetation water in the electromagnetic spectrum. This makes NDWI suitable for monitoring drought levels in a region. The NDWI analysis in this study ranged from -0.25 to 0.63, which were then grouped into five categories using the natural breaks (Jenks) method. The NDWI classification results are shown in Figure 3.

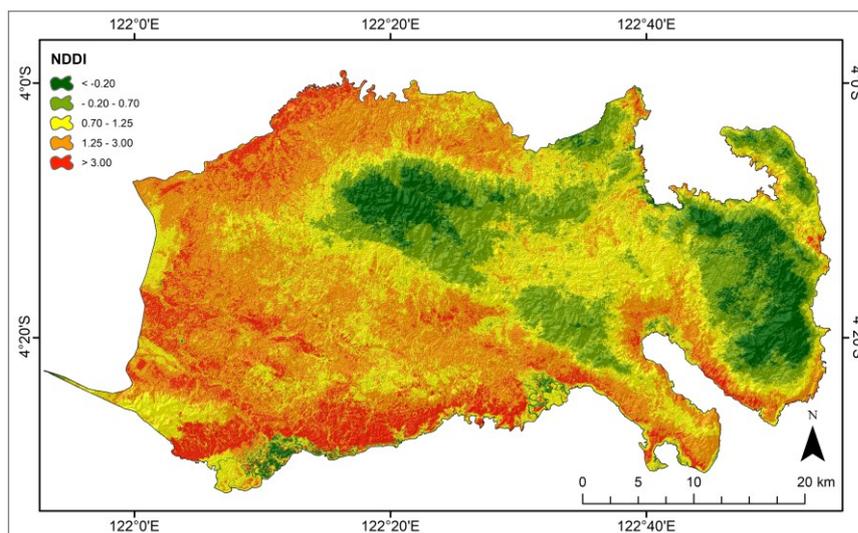


**Figure 3.** Normalized Difference Water Index of Konawe Selatan Regency 2024

Based on Figure 3 shows that the lowest NDWI values stretch from the south to the southwest. Low NDWI values indicate low surface water content. These values are generally identified as residential areas, open land, or rice fields. Meanwhile, high NDWI values stretch from the southeast coast to the southwest, where this area falls within the mangrove area. Based on area, the highest NDWI class is shown by the 0.29–0.37 class, covering 213,576.00 ha (50.46%), followed by the 0.24–0.29 class, covering 118,450.83 ha

(27.98%), the 0.16–0.24 class, covering 63,168.42 ha (14.92%), the -0.25–0.16 class, covering 18,572.95 ha (14.92%), and the 0.37–0.63 class, covering 9,513.83 ha (2.25%).

After obtaining the NDVI and NDWI, a drought analysis using the NDDI was conducted to determine the drought severity in Konawe Selatan Regency. The NDDI calculation results were classified into five drought severity classes: very low, low, moderate, high, and very high. The NDDI classification results are shown in Figure 4.



**Figure 4.** Normalized Difference Drought Index of Konawe Selatan Regency 2024

Based on Figure 4, the most prevalent drought class in Konawe Selatan Regency is high, covering an area of 152,064.98 ha, equivalent to 35.93% of the total area. The second most widespread drought class is moderate, covering 118,472.42 ha (27.99%).

High to moderate drought classes are dominant in sloping-flat morphological areas where settlements and plantations are concentrated. Impermeable surfaces, rapid drainage, and exposed garden soils cause rapid soil moisture depletion, leading to earlier groundwater

levels during the dry season.

Areas with low drought levels are distributed across mountainous and coastal areas. This indicates that both regions have good vegetation cover, resulting in abundant springs. Konawe Selatan features mountains with karst morphology, although not all areas are dominated by karst landforms. Karst is a type of rock that readily dissolves in water, such as limestone, which forms landscapes with distinctive features such as caves, underground rivers, and sinkholes. Its impact on springs and drought is quite significant. Karst areas tend to have high water infiltration capacity, allowing rainwater to quickly infiltrate the soil and form underground rivers.

This study also examined the relationship between variables using 1,528 sample points. The correlation between NDDI and NDVI showed a relatively strong positive relationship with an  $R^2$  value of 0.5162 (Figure 5a). This means that variations in drought, as represented by the NDDI, can explain approximately 51% of the change in the green vegetation index. This phenomenon is quite interesting because increasing drought should decrease green vegetation cover. However, this positive pattern is common in areas dominated by plantations or cultivated vegetation that remain green despite increasing levels of drought, for example, due to additional irrigation or the more tolerant nature of perennial crops to water deficits. In other words, this positive correlation can be interpreted as an indication of drought-resistant vegetation or land management factors that mitigate the direct impact of drought on vegetation.

The correlation between NDDI and LST shows a positive relationship, but with a weak determination value ( $R^2 = 0.152$ ) (Figure 5b). This indicates that increasing dryness tends to be in line with rising land surface temperatures, but the contribution of NDDI explains only a small portion of the variation in LST. This is common, as surface temperature is strongly influenced by other factors, such as land cover type, vegetation density, surface material, and daily solar radiation intensity. Although the relationship is weak, this positive trend is consistent with the theory that drier soil and vegetation conditions, lower evapotranspiration capacity, make it easier for surface temperatures to rise.

The correlation between the NDDI and NDWI shows a negative relationship with an  $R^2$

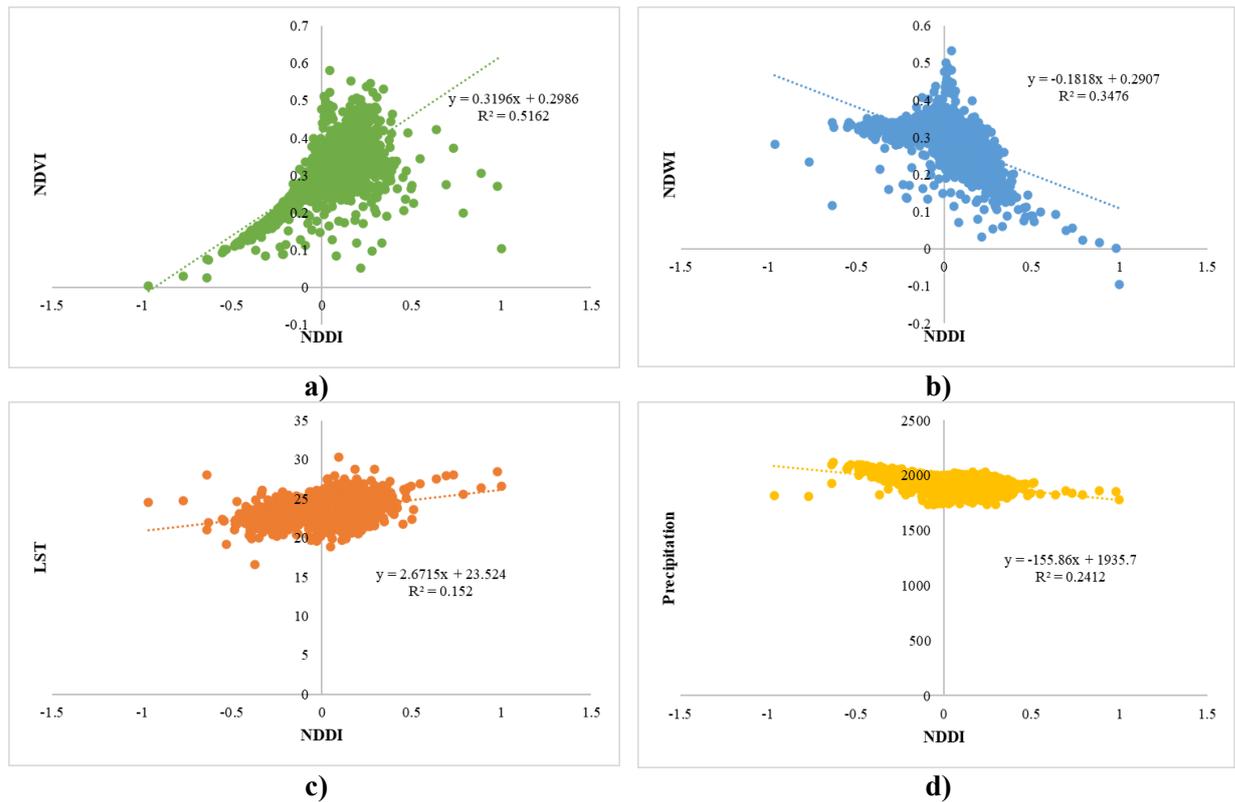
of 0.3476 (Figure 5c). This means that the higher the drought value, the lower the vegetation water content, as indicated by the NDWI. This relationship is quite consistent because drought directly reduces leaf water content and vegetation moisture. This negative correlation demonstrates that the NDDI is quite sensitive in detecting changes in vegetation moisture conditions in the field, although approximately 65% of the NDWI variation is influenced by other factors, such as differences in vegetation type, plant age, or land cover heterogeneity. Methodologically, this negative relationship is a common pattern in drought index studies.

The relationship between the NDDI and precipitation shows a negative correlation with an  $R^2$  of 0.2412 (Figure 5d). Increasing drought is accompanied by a decrease in rainfall, which logically indicates a correlation. However, the relatively low determination value indicates that drought is not solely determined by rainfall, but also by other factors such as soil water retention capacity, morphological conditions, and vegetation cover, which influence evapotranspiration. Thus, while these results align with the basic concept that precipitation deficits trigger drought, the weak relationship confirms that the NDDI captures a more complex drought signal than simply a function of rainfall.

The relationship between the NDDI and precipitation shows a negative correlation with an  $R^2$  of 0.2412. Increasing drought is accompanied by a decrease in rainfall, which logically suggests a relationship. However, the relatively low determination value indicates that drought is determined not only by rainfall but also by other factors such as soil water retention capacity, morphological conditions, and vegetation cover, which influence evapotranspiration. Thus, while these results align with the basic concept that precipitation deficits trigger drought, the weak relationship confirms that the NDDI captures a more complex drought signal than simply a function of rainfall.

## DISCUSSION

The ideal condition of a region with a healthy ecosystem is characterized by high vegetation density, balanced water distribution, and low levels of drought. Such an ecosystem supports environmental sustainability, microclimate stability, and optimal land



**Figure 5.** The relationship between NDDI with a) NDVI, b) NDWI, c) LST, and d) Precipitation

productivity. However, vegetation index analysis results indicate variations in vegetation density in Konawe Selatan Regency. Some areas fall into the very low to low NDVI category, with NDVI values ranging from -0.45 to 0.29, while others maintain dense vegetation at 0.45–0.66. This condition reflects the degradation of vegetation cover in some areas. Previous studies have confirmed that vegetation degradation is generally triggered by land use change, increased anthropogenic pressure, and regional climate dynamics (Wable et al., 2020; Adepoju et al., 2019). However, this study emphasizes that the spatial distribution of low NDVI in Konawe Selatan is quite significant and indicates the presence of degradation hotspots. Therefore, these findings are important as a basis for sustainable vegetation management to minimize drought risk and maintain ecosystem stability. Ideally, the balance of groundwater availability can be maintained through adequate vegetation cover, ensuring a stable hydrological cycle. In reality, the results of the water index analysis show significant differences in soil moisture availability in Konawe Selatan Regency. Most areas have NDWI values in the negative range, indicating low water content, while areas with high moisture are relatively limited. Previous

studies have shown that the NDWI is sensitive to moisture fluctuations and can be used as an indicator of hydrological drought (Gao, 1996; Xu, 2006). However, this study found that the soil moisture imbalance in Konawe Selatan is more complex, with the central inland region tending to be drier while the coastal areas are relatively wetter. This is important because the uneven spatial distribution of the NDWI can indicate the vulnerability of inland areas to water crises, which has implications for food security and sustainable land use.

Normatively, areas with adequate water reserves, high vegetation density, and stable rainfall are less susceptible to drought risk. However, the NDDI analysis results indicate that Konawe Selatan is still predominantly in the moderate to high drought category. The largest area falls within the moderate drought category, with values ranging from 0.16 to 0.24, covering nearly 35.93% of the area, while the very low drought category only covers 27.99%. This finding is consistent with the research of Salas-Martínez et al. (2023), which found the NDDI to be effective in mapping spatial drought conditions in semi-humid areas. However, what distinguishes this study is the identification of a dominant moderate drought category in Konawe Selatan, indicating

environmental stress influenced not only by rainfall but also by vegetation degradation and limited soil moisture. This situation underscores the need for a more comprehensive spatial-based mitigation strategy to prevent long-term ecological vulnerability.

The relationship between vegetation indices, humidity, surface temperature, and rainfall should ideally exhibit a linear and significant balance. However, the correlation analysis in this study indicates a weak relationship between the NDDI and other variables, such as NDVI ( $R^2 = 0.152$ ) and rainfall ( $R^2 = 0.242$ ). This fact indicates that drought in Konawe Selatan is not solely determined by rainfall, but also by other factors such as vegetation cover degradation, land use changes, and surface temperature dynamics. Previous research has shown that drought is a multidimensional phenomenon that cannot be explained by a single climate variable (Vicente-Serrano et al., 2010; Zargar et al., 2011). The emerging research gap is that most studies still focus on rainfall as the primary variable, while this study highlights the complex interactions between NDVI, NDWI, LST, and precipitation in determining the drought index. The importance of this finding is that it provides a new perspective that drought mitigation strategies need to simultaneously integrate aspects of vegetation, moisture, and climate dynamics to produce more adaptive environmental management policies.

This study has several methodological and technical limitations that require careful consideration when interpreting the results. First, the primary data used comes from medium-resolution Sentinel-2 Harmonized imagery. While this imagery is quite reliable for mapping vegetation and soil moisture at a regional scale, its limited spatial resolution prevents accurate detection of micro-details, such as differences in moisture at the plot or local community level. Second, this study was not spatio-temporal in nature, but rather was conducted for a single year. This limitation prevents the results from describing inter-annual drought dynamics, even though climate fluctuations and seasonal variability play a crucial role in explaining drought patterns.

Third, in processing the drought index, this study used a median filter for the July–November period, a period climatologically categorized as the dry season. This approach is effective in representing annual drought

extremes, but it potentially overlooks intra-seasonal variations that could provide a more detailed picture of the onset, peak, and end phases of drought. Fourth, land surface temperature was analyzed using a median filter approach for a full year. This simplifies the temporal variation in temperature, which is inherently fluctuating daily and monthly, so the dynamics of extreme heat that impact evapotranspiration are not fully reflected.

Fifth, the climate variables used are limited to global WorldClim rainfall data with a specific spatial resolution. Although this dataset is widely used in climate studies, its use does not fully represent local rainfall variability due to limitations in spatial interpolation, particularly in humid tropical regions with high topographic heterogeneity, such as Konawe Selatan. Furthermore, the simple linear correlation analysis approach used in this study does not fully capture the non-linear nature of the relationship between vegetation, humidity, temperature, and precipitation.

These limitations highlight the need for further research using data with higher spatial and temporal resolution, integrating multiple sources of local climate data, and applying more complex spatial analysis methods, including machine learning and dynamic hydrological modeling. Therefore, future studies are expected to provide a more accurate and comprehensive picture of drought dynamics in tropical regions.

The results of this study have important implications for natural resource management in Indonesia. As a country with a high dependence on the agricultural and plantation sectors, the risk of drought in areas like Konawe Selatan could set a precedent for other regions with similar characteristics in eastern Indonesia. The resulting NDVI, NDWI, and NDDI-based mapping provides spatial information that can be used for spatial planning, disaster mitigation, and strengthening national food security policies. Furthermore, this research highlights the urgency of integrating vegetation management, water conservation, and climate change mitigation into sustainable development policies. Therefore, this research supports the national agenda of strengthening the implementation of the National Action Plan for the Environment and Forestry (RAN-API) and the Ministry of Environment and Forestry's programs, which emphasize the importance of ecosystem

conservation at the regional level.

Globally, this research contributes to understanding drought risk in humid tropical regions, which are increasingly vulnerable to climate change. Most drought research still focuses on semi-arid and arid regions, while humid tropical regions are often viewed as more resilient. However, this research demonstrates that humid tropical regions like Konawe Selatan also face significant drought risks due to vegetation degradation and soil moisture imbalances. These findings expand the global literature on ecological vulnerability in tropical zones and support the achievement of the Sustainable Development Goals (SDGs), particularly Goal 13 on climate action and Goal 15 on terrestrial ecosystems. Therefore, this research is not only relevant to Indonesia but also provides an empirical contribution to the global discourse on drought adaptation and mitigation in the era of climate change.

## CONCLUSION

This study shows that vegetation conditions, soil moisture, and drought levels in Konawe Selatan Regency in 2024 exhibit significant spatial variation. The vegetation index indicates that some areas still have moderate to high vegetation density, but many areas are experiencing degradation with low NDVI values. The moisture index shows an uneven distribution, with inland areas tending to be drier than coastal areas. The drought index analysis indicates a dominance of moderate to high drought levels, indicating that most areas remain vulnerable to water deficits and ecosystem degradation.

The correlation analysis between NDDI and NDVI, NDWI, LST, and precipitation shows a relatively weak relationship, with a low determination value. These findings indicate that drought in Konawe Selatan is not solely influenced by a single factor such as rainfall, but rather is a multidimensional phenomenon influenced by complex interactions between vegetation conditions, soil moisture, and climate dynamics.

Thus, this study emphasizes the need for drought mitigation efforts through an integrated approach that integrates vegetation management, water resource conservation, and adaptation to climate change. Practically, the results of this study can inform spatial planning, food security policies, and environmental management strategies at the

regional and national levels. Furthermore, these findings contribute to the global literature by demonstrating that humid tropical regions like Konawe Selatan are vulnerable to drought due to a combination of biophysical and climatic factors, thus requiring serious attention within a climate change adaptation framework.

## RECOMMENDATION

Based on the research findings, several recommendations can be used as a reference for further research and for policymakers. First, future research is recommended to use remote sensing data with higher spatial and temporal resolution and integrate multi-sensor data to depict the dynamics of vegetation, soil moisture, and drought in greater detail. Second, the analysis should be expanded spatio-temporally to include both annual and seasonal periods to more comprehensively identify patterns of drought fluctuations over time.

Third, the methodological approach can be improved by applying non-linear statistical models, machine learning, or dynamic hydrological modeling to uncover more complex relationships between biophysical and climate variables. Fourth, the use of local climate data at a more detailed scale, such as measurements from regional climatology stations, will increase the accuracy of the results compared to relying solely on global datasets.

Furthermore, in a policy context, the results of this study should be utilized to strengthen spatially based drought mitigation strategies integrated with national programs, such as the RAN-API and the Climate Village Program (ProKlim). The integration of vegetation and drought index data with spatial planning and food security policies also needs to be improved. At the global level, further research is expected to compare drought phenomena in humid tropical regions with semi-arid or arid ecosystems, thereby strengthening scientific contributions to the global literature on climate change adaptation.

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