

RESEARCH ARTICLE

Remote Sensing–Driven Drought Assessment Using Temperature Vegetation Dryness Index (TVDI) Derived from Landsat 8 Imagery

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Received: Feb 18, 2026, Accepted: Aug 9, 2026.

DOI: 10.25299/jgeet.2026.11.3.27329

Abstract

Drought, a persistent state of water scarcity, is a critical challenge for agriculture and resource management. This study examines drought variability in Lamongan Regency from 2021 to 2023 using the Temperature Vegetation Dryness Index (TVDI) derived from Landsat 8 imagery, integrating Land Surface Temperature (LST) and NDVI to classify conditions from wet to dry. Results show the largest moderate drought in June 2021 (1,660.39 km²) and the most extensive severe drought in October 2023 (1,561.39 km²). In 2023, wet-normal conditions dominated early months, while dry areas expanded in the peak dry season. In this study, TVDI was derived using a simplified global normalization of LST_{min} and LST_{max} rather than the standard pixel-by-pixel NDVI-LST triangular feature space, which is acknowledged as a methodological limitation. An anomaly occurred in February, where high rainfall coincided with widespread dryness. Furthermore, validation with rainfall data showed a very weak correlation ($R^2 = 0.090$). This low correlation indicates a distinct time lag between precipitation events and soil moisture response, as well as the strong influence of local evapotranspiration and soil water retention capacity rather than rainfall alone. This study demonstrates that while TVDI is useful for rapid drought mapping, integration with local hydrological parameters is essential for improved accuracy.

Keywords: remote sensing, LST, NDVI, TVDI, Landsat 8

1. Introduction

Drought is widely recognized as one of the most pervasive natural hazards worldwide, with far-reaching consequences for ecosystems, agricultural productivity, and socio-economic stability. It is generally defined as a prolonged period of water deficit near the Earth's surface, resulting from a significant imbalance between water supply and demand due to markedly reduced precipitation and/or elevated temperatures over a sustained period (Redmond, 2002). Drought occurs in all climatic zones and is conventionally categorized into four principal types: meteorological, hydrological, agricultural, and socio-economic (Heim, 2002; Mishra, Singh and Desai, 2009). Among these, meteorological drought—characterized exclusively by climatic anomalies—often precedes other types, while agricultural, hydrological, and socio-economic droughts are primarily distinguished by their specific impacts on environmental and human systems (Ye et al., 2016).

The development and progression of drought are inherently complex, governed by the interplay of natural and anthropogenic drivers. Natural factors include climatic variability and watershed hydrology (Van Loon et al., 2014). In contrast, human-induced influences encompass land-use changes (Cook, Miller and Seager, 2009), reservoir management (Wu et al., 2019), and water governance practices (Tijedman et al., 2018). In recent decades, global warming and intensified human activities have contributed to an increase in drought frequency, severity, and duration (Qi et al., 2022). In Indonesia, the

situation is further exacerbated by El Niño events, which tend to prolong the dry season and accelerate its onset, placing additional stress on agricultural and water resource systems (Karuniasa and Pambudi, 2022).

Lamongan Regency, located in East Java Province, is recognized as one of the drought-prone regions in Indonesia. Previous studies have reported that the regency experiences recurrent drought events, particularly in its southern areas, where water availability is strongly influenced by climatic variability and irrigation conditions. These characteristics make Lamongan an important case study for drought monitoring and mitigation using remote sensing approaches (Hariyanto et al., 2019; Affandy et al., 2023). The increasing occurrence of drought-related hazards in Indonesia highlights the importance of continuous drought monitoring using geospatial and remote sensing approaches. Drought has significant impacts on agricultural productivity, economic activities, and ecological sustainability, making drought assessment an important component of environmental management. Therefore, drought-prone regions such as Lamongan Regency in East Java require reliable monitoring frameworks to support mitigation and adaptation strategies (Irawan et al., 2024; Fariz et al., 2025). Such conditions threaten both water availability and agricultural output, heightening the need for timely and accurate drought monitoring systems. Reliable spatially explicit assessments are essential for supporting early warning systems, guiding mitigation efforts, and informing policy decisions aimed at enhancing resilience in vulnerable communities.

Conventional drought monitoring methods relying on meteorological station data offer temporal continuity and high measurement accuracy but are constrained by sparse spatial coverage, which limits their representativeness at the regional scale (Shen et al., 2019). Remote sensing provides a valuable alternative, enabling extensive spatial and temporal observations while capturing the complex interactions among climate, soil moisture, vegetation, and human activity (Son et al., 2012; Shi et al., 2020). Various indices have been developed for this purpose, including the Precipitation Condition Index (PCI) (Ali et al., 2019), Vegetation Condition Index (VCI) (Jiao et al., 2016), Temperature Condition Index (TCI) (Bento et al., 2018), and Soil Moisture Condition Index (SMCI) (Bento et al., 2018). Among these, the Temperature Vegetation Dryness Index (TVDI) has demonstrated notable effectiveness by integrating land surface temperature with vegetation indices, resulting in a more comprehensive depiction of drought processes (Li et al., 2022). Despite its proven utility in regions such as West Java and the Poyang Lake Basin in China (Han, Chen and Feng, 2015), applications of TVDI in Lamongan remain limited.

Although TVDI has been widely adopted due to its ability to incorporate land surface dryness and vegetation health, its accuracy strongly hinges on the proper construction of the NDVI-LST triangular or trapezoidal feature space. A critical step in this methodology is the dynamic definition of the wet and dry edges using regression analysis across different vegetation fractions. However, many simplified applications of TVDI frequently overlook this pixel-by-pixel interaction, relying instead on static global minimum and maximum LST values, which can introduce severe spatial biases and compromise physical consistency. In this study, we rigorously address this gap by adhering to the standard TVDI framework. By constructing the explicit empirical NDVI-LST feature space for Lamongan Regency, this research ensures that the derived dry and wet thresholds accurately capture the localized environmental and surface microclimate conditions, thereby enhancing the scientific novelty and reliability of the spatial drought mapping.

This study is intended to employ Landsat 8 imagery within a Geographic Information System (GIS) framework to compute and map TVDI values in the agricultural areas of Lamongan Regency, thereby identifying the spatial extent and severity of drought conditions. The findings are expected to contribute not only to enhancing the scientific basis for drought monitoring but also to supporting the development of effective early warning systems, informing targeted mitigation strategies, and promoting sustainable land and water resource management practices in drought-prone agricultural regions.

2. Materials and Methods

2.1 Study Area

The research location is in the Lamongan region of East Java Province, which has an area of 1,812.8 km² divided into 27 sub-districts and consists of 462 villages and 12 urban villages. Astronomically, the study area is located at 6°51' - 7°23' South Latitude and 112°33' - 112°34' East Longitude.

Figure 1. Lamongan Regency lies in a strategic part of East Java, with Bojonegoro and Tuban to the west, Gresik to the east, the Java Sea stretching along its northern coast, and Jombang and Mojokerto to the south. This

unique position gives Lamongan a blend of coastal and inland landscapes—fertile farmlands in the south and vibrant fishing communities in the north. The mix of agriculture, aquaculture, trade, and tourism has shaped Lamongan into a lively and connected area, playing an important role in the social and economic life of the region.



Fig. 1 Research Location: Lamongan Regency

2.2 Data and Equipment

The data used in this study are secondary. The following data are used: Rainfall data is used on a 3-year scale, from 2021 to 2023, Topographic maps and surface area maps are needed to determine the research location and area.

The data for this study were acquired from Landsat 8 Level 2 medium-resolution satellite imagery of Lamongan Regency. Administrative boundary vectors of Lamongan Regency were obtained from BIG at a scale of 1:25,000, and data from literature and relevant agencies. The software used in this study was QGIS 3.34.10 for image processing and map creation.

2.3 Research Completion Stages

The methodological framework of this study was systematically structured into sequential execution stages to ensure high scientific accuracy, transparency, and reproducibility. The research steps are delineated as follows:

1. Data Acquisition and Collection

The primary dataset comprised medium-resolution Landsat 8 Level-2 (Collection 2) satellite imagery covering the administrative boundary of Lamongan Regency. Supporting secondary data, including historical monthly rainfall records (2021–2023) and administrative boundary vector maps (scale 1:25,000), were obtained from the Lamongan Water Resources Service and the Geospatial Information Agency (BIG), respectively.

2. Satellite Image Pre-selection and Scaling

To eliminate atmospheric errors and cloud distortion without modifying the original continuous spatial pixel values, a strict data pre-selection protocol was implemented. Only Landsat 8 scenes with less than

5% total cloud cover over the study area were acquired, ensuring that the key observation periods (e.g., June 2021 and October 2023) were completely cloud-free. Subsequently, official USGS Collection 2 radiometric scaling factors (0.00002 for reflectance and 0.000342 for radiance) were systematically applied to the selected bands.

3. **Derivation of Spatial Parameters (NDVI and LST)**
Using QGIS 3.34.10, two key biophysical parameters were synchronously generated from the pre-processed Landsat 8 bands:
 - Normalized Difference Vegetation Index (NDVI): Calculated using the Near-Infrared (Band 5) and Red (Band 4) channels to quantify vegetation density.
 - Land Surface Temperature (LST): Derived by transforming Thermal Infrared (Band 10) data into Top of Atmosphere (TOA) radiance, brightness temperature (BT), and computing land surface emissivity (E) based on the Fractional Vegetation Proportion (P_v)
4. **Construction of the NDVI–LST Feature Space**
To prevent spatial biases from simplified approaches, a localized empirical NDVI–LST feature space was explicitly constructed. Pixel-by-pixel values of NDVI and LST were extracted and plotted into a scatterplot configuration (NDVI on the X-axis and LST on the Y-axis). Boundary pixel nodes were isolated at 0.05 intervals across the vegetation fractions to outline the triangular geometry of the land surface moisture envelopes.
5. **Extraction of Envelopes via Regression Analysis**
Linear regression analysis was computed across the isolated boundary points to define the dynamic mathematical equations for the "dry edge" (LST_{max}) and "wet edge" (LST_{min}). This regression step yields the localized slope and intercept variables required to adapt the standard TVDI framework specifically to the localized microclimate of Lamongan Regency
6. **TVDI Calculation and Drought Mapping**
The final Temperature Vegetation Dryness Index (TVDI) map was computed pixel-by-pixel within the GIS software based on the derived wet and dry linear functions. The resulting data were classified into five standardized soil dryness categories ranging from wet to dry, facilitating the assessment of drought area distribution.
7. **Validation and Statistical Correlation**
To validate the reliability of the spatial drought index, the monthly TVDI outcomes were cross-referenced and statistically evaluated against localized ground-truth rainfall data using linear regression and correlation coefficient (R^2) analysis.

The systematic workflow and data processing pipeline executed in this study are visually conceptualized in Figure 2. This framework underscores the transition from raw image acquisition to refined spatial drought mapping.

As illustrated in the workflow, the processing is uniquely bifurcated into two parallel tracks following the initial dataset preparation. The left track handles the vegetative biophysical responses via the extraction of NDVI, while the right track simultaneously computes the thermodynamic properties of the land surface through LST derivation. The convergence of these two independent pathways at the feature space stage represents the critical methodological junction where

localized dry and wet edge envelopes are mathematically isolated using linear regression before computing the final TVDI.

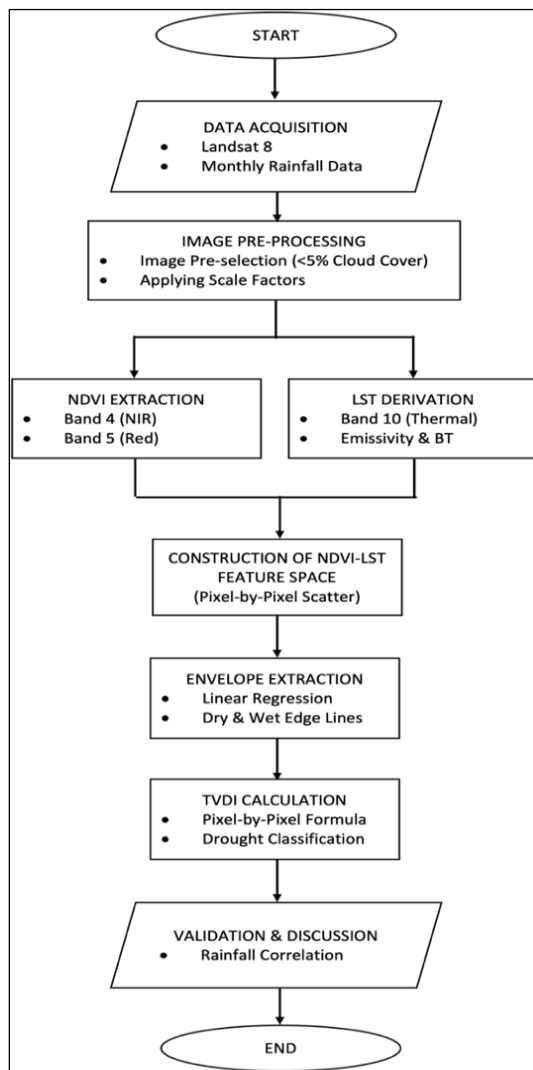


Fig. 2 Methodological framework and spatial processing workflow for TVDI mapping in Lamongan Regency

2.4 Landsat 8 Imagery Processing

Landsat 8 is a remote sensing satellite launched by NASA and the United States Geological Survey (USGS) on February 11, 2013, as part of the Landsat program. The satellite aims to collect periodic images of the Earth's surface to support monitoring of environmental change, land use, natural resources, and global climate. Landsat 8 has a spatial resolution of 30 meters for the multispectral band, 15 meters for the panchromatic band, and 100 meters for the thermal band, as well as a re-recording time (Tucker, Grant and Dykstra, 2004; Markham, Storey and Irons, 2013; Murtianto, 2016).

2.5 Normalize Difference Vegetation Index (NDVI)

NDVI is one of the most commonly used vegetation indices to monitor land cover conditions, especially vegetation (Hanum et al., 2026). NDVI is calculated by utilizing the reflectance values of two spectral channels, namely the Near Infrared (NIR) and Red channels. In satellite imagery, the NIR channel is represented by Band 5, while the Red channel is represented by Band 4 (Kogan and Zhu, 2001; Affandy et al., 2024; Affandy, Wijaya and

Nabilah, 2024). NDVI has been widely employed to characterize vegetation density and monitor environmental changes using satellite imagery (Putera, Junaidi and Junaidi, 2019; Hanum et al., 2026).

In the NDVI analysis stage of this study, an approach was used to identify areas potentially prone to drought. The basic assumption in this study is that objects or areas with vegetation are areas with high water absorption capacity. Conversely, non-vegetated areas or areas other than vegetation are assumed to be impermeable or lack water absorption capacity. Therefore, a high NDVI value indicates a high level of vegetation density, which means the area has good water absorption capacity. Meanwhile, a low NDVI value indicates low vegetation density, thus low water absorption capacity (Kamble et al., 2010; Rotjanakusol and Laosuwan, 2019).

The formula used to calculate NDVI is as follows:

$$NDVI = \frac{(\rho_{Band\ 5} - \rho_{Band\ 4})}{(\rho_{Band\ 5} + \rho_{Band\ 4})} \quad (2)$$

The NDVI index table can be seen in the following table 1.

Table 1. NDVI Parameter Index Value

Class	NDVI Index	Description
1	-1 < NDVI < -0,03	Non-vegetated land
2	-0,03 < NDVI < 0,15	Very low greenness
3	0,15 < NDVI < 0,25	Low greenness
4	0,25 < NDVI < 0,35	Moderate greenness
5	0,35 < NDVI < 1	High greenness

2.6 Land Surface Temperature (LST)

Land surface temperature is obtained by applying the Land Surface Temperature (LST) method. This method requires data from the brightness level of an object and the emissivity value of the land surface. Surface temperature is the temperature of the outermost part of an object and the first element that can be identified from thermal satellite imagery. The surface temperature of an object depends on the physical properties of the object's surface, including emissivity, specific heat capacity, and thermal conductivity (Khan et al., 2018; Chu et al., 2021). High LST values indicate warm surface temperatures, which are often associated with low vegetation cover and soil moisture, and can therefore be an early indicator of potential drought in an area. Conversely, lower LST values indicate cooler surface conditions, usually due to high vegetation cover or soil moisture (Sun, Zhou and Liu, 2019).

To derive these values with radiometric precision from Landsat 8 TIRS Band 10, the raw digital numbers (Q_{cal}) were converted into Top of Atmosphere (TOA) spectral radiance (L_λ) by applying the official USGS Collection 2 scaling factors and thermal calibration adjustments as follows:

$$L_\lambda = M_L \times Q_{cal} + A_L - O_i \quad (3)$$

Where M_L represents the radiance multiplicative scaling factor (0.000342), Q_{cal} is the quantized calibrated digital number of the pixel, A_L is the radiance additive offset (0.1), and O_i denotes the specific sensor calibration offset correction factor for Band 10 ($0.29 \frac{W}{m^2 \cdot sr \cdot \mu m}$) to account for stray light artifacts. Subsequently, the spectral radiance was converted into Brightness Temperature (BT) using the following formula:

$$BT = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)} - 273.15 \quad (4)$$

Where $K_1 \left(774.89 \frac{W}{m^2 \cdot sr \cdot \mu m}\right)$ and $K_2 (1321.08 K)$ are the specific calibration constants for Landsat 8 Band 10, and $\ln$ denotes the natural logarithm. The final LST in Celsius was computed by integrating the land surface emissivity (ϵ) to correct for surface roughness effects:

$$LST = \frac{BT}{1 + \left(\frac{\lambda \cdot BT}{\rho}\right) \cdot \ln(\epsilon)} \quad (5)$$

Where λ represents the effective wavelength of Band 10 ($10.89 \mu m$), and ρ is a physical constant calculated as $\rho = h \cdot \frac{c}{\sigma} = 1.438 \times 10^{-2} m \cdot K$ (where h is Planck's constant, c is the velocity of light, and σ is Boltzmann's constant). The land surface emissivity (ϵ) was estimated based on the Fractional Vegetation Proportion (P_v) derived from the NDVI values.

2.7 Construction of NDVI-LST Feature Space

The core physical mechanism of the TVDI approach relies on the empirical boundary conditions established by the NDVI-LST feature space, where dry and wet edges represent the upper and lower limits of surface moisture availability (Sandholt, Rasmussen and Andersen, 2002). The interaction between vegetation cover and land surface temperature has been widely recognized in remote sensing studies, demonstrating that areas with denser vegetation generally exhibit lower surface temperatures due to evapotranspiration processes (Afriadi et al., 2026). Furthermore, vegetation and thermal indicators derived from Landsat imagery have been successfully applied in drought and environmental assessments in Indonesia (Irawan et al., 2024). In this study, pixel-by-pixel values from the extracted NDVI (Section 2.5) and LST (Section 2.6) were synchronized spatially for the entire Lamongan Regency. These data pairs were plotted in a scatterplot environment, assigning NDVI to the horizontal axis (X-axis) and LST to the vertical axis (Y-axis).

Due to the continuous variation in vegetation cover and surface moisture conditions, the NDVI-LST feature space typically exhibits a triangular or trapezoidal distribution pattern (Sandholt, Rasmussen and Andersen, 2002). The upper boundary, referred to as the dry edge (LST_{max}), represents conditions of minimal soil moisture availability and reduced evapotranspiration, resulting in relatively high land surface temperatures. Conversely, the lower boundary, known as the wet edge (LST_{min}), corresponds to well-watered conditions with maximum evapotranspiration and relatively low surface temperatures. Variations in vegetation cover and land surface temperature have been widely observed in remote sensing studies and constitute the physical basis for drought assessment using thermal-vegetation relationships (Sandholt, Rasmussen and Andersen, 2002; Fariz et al., 2025; Afriadi et al., 2026).

To determine these boundaries mathematically, the NDVI range was divided into small regular intervals of 0.05. Within each interval, the maximum and minimum LST values were isolated. Linear regression analysis was then computed across these boundary pixel points to derive the empirical linear equations for both edges as follows:

$$LST_{max} = a + b \cdot NDVI \quad (6)$$

$$LST_{min} = c + d \cdot NDVI \quad (7)$$

Where a and c are the intercepts, while b and d are the linear slopes for the dry and wet edges, respectively. These dynamic spatial thresholds serve as the localized foundation for the final drought index calculation, while the empirical scatterplot results derived from the actual regional data are subsequently presented and analyzed in the Results section.

2.8 Transformation of Temperature Vegetation Dryness Index (TVDI) Calculation

To ensure physical consistency and eliminate spatial bias, the Temperature Vegetation Dryness Index (TVDI) was calculated using the dynamic boundary conditions of the NDVI–LST triangular feature space rather than static temperature limits. Following the standard methodology widely validated in regional drought monitoring, the TVDI value for each individual pixel was computed as follows (Sandholt, Rasmussen and Andersen, 2002):

$$TVDI = \frac{LST - LST_{min}}{LST_{max} - LST_{min}} \quad (8)$$

Where LST represents the observed land surface temperature of a given pixel. Crucially, LST_{max} (the dry edge) and LST_{min} (the wet edge) are not fixed global constants; instead, they are dynamic functions that vary systematically with the pixel's vegetation density (NDVI) due to surface energy balance variations (Karnieli et al., 2010). By integrating the empirical linear regression equations derived from the feature space boundary analysis (Section 2.7), the standard formula is expanded into its full operational mathematical form (Sandholt, Rasmussen and Andersen, 2002):

$$TVDI = \frac{LST - (c + d \cdot NDVI)}{(a + b \cdot NDVI) - (c + d \cdot NDVI)} \quad (9)$$

This pixel-by-pixel mathematical integration ensures that the resulting index values range strictly between 0 (representing saturated soil moisture/maximum evapotranspiration) and 1 (representing severe water stress/depleted soil moisture) (Sandholt, Rasmussen and Andersen, 2002).

3. Result and Discussion

3.1 Image Correction

In the initial stages of the research, an image correction process was carried out, namely radiometric correction, consisting of radiometric calibration and atmospheric correction. This correction aims to minimize radiometric and atmospheric errors, so that the data used in the image calculations has high accuracy. Accurate values are crucial in the analysis, as they serve to determine the quality of conditions in the study area. Atmospheric correction is carried out by incorporating metadata from Landsat 8 imagery as a reference in the correction process.

3.2 Image Merging Stage

Image merging was performed to simplify data processing. This was because the research location was divided into two separate image scenes, necessitating image merging to fully cover the study area. This process involved several key steps to produce the administrative map used in the research analysis. The merging process successfully produced a single mosaic image, the final result of a series of image merging stages. This image covers the entire research area and is ready for further analysis.

3.3 Temperature Vegetation Dryness Index (TVDI)

In the Temperature Vegetation Dryness Index (TVDI) analysis stage in this study, an approach based on the relationship between NDVI and LST was used to identify areas with potential drought. In this context, a high TVDI value reflects hot ground conditions, sparse or stressed vegetation, and a high potential for drought. Conversely, a low TVDI value indicates an area with good vegetation cover and relatively high soil moisture levels.

The image below shows the results of processing TVDI parameters which describe the distribution of surface temperatures in the study area. The image explains that the white color indicates areas with a wet distribution, the green color indicates moderate wetness, and the yellow color indicates a normal distribution. Medium dryness is shown in orange and idryness is shown in red.

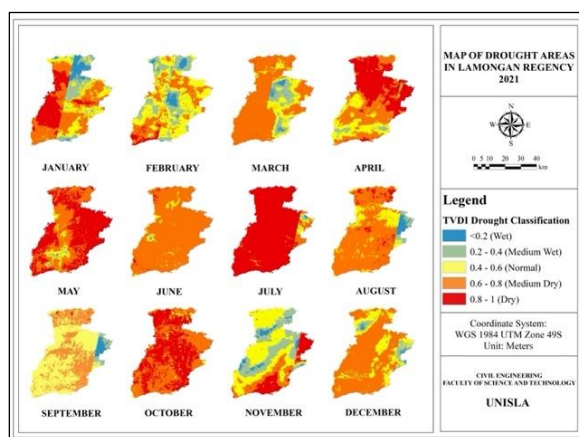


Fig 2. Monthly spatial distribution and classification of TVDI-based drought severity zones across Lamongan Regency in 2021

From the 2021 research, it can be concluded that in 2021, the drought was in June, which had the widest number of droughts, and October showed the widest spread of extreme droughts.

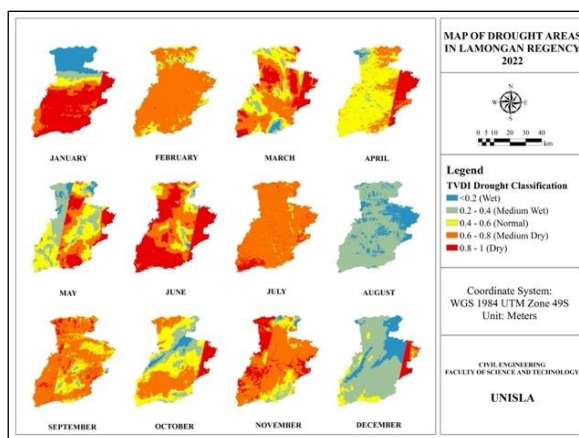


Fig 3. Monthly spatial distribution and classification of TVDI-based drought severity zones across Lamongan Regency in 2022

The 2022 drought map for Lamongan Regency shows that moderate drought was most widespread in July, while the dry category was most widespread in December.

The 2023 drought map for Lamongan Regency shows that moderate drought was most widespread in April, while the dry category was most widespread in October.

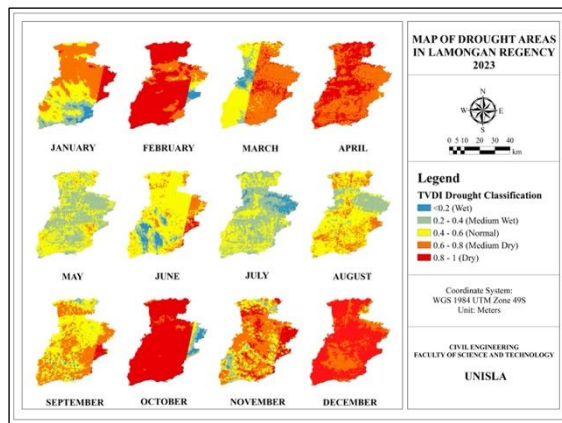


Fig 4. Monthly spatial distribution and classification of TVDI-based drought severity zones across Lamongan Regency in 2023

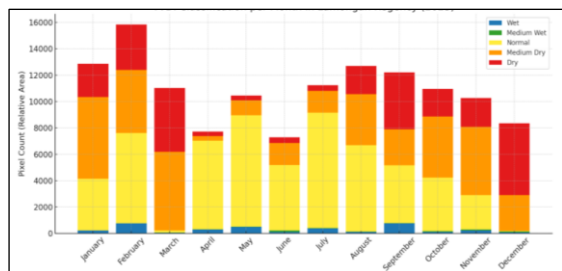


Fig 5. TVDI Classification 2023

The temporal fluctuations and spatial expansion of TVDI drought classes throughout 2023 exhibit a distinct seasonal pattern, which is strongly modulated by regional climate variability and localized surface energy balances. The wet period, spanning from May to August, is characterized by a high frequency of low TVDI values (wet to normal). This phenomenon is driven by the residual

soil moisture from the preceding rainy season and sustained by high vegetation cover (*NDVI*). Thermally, the dense canopy during these months acts as a buffer, lowering the *LST* via high latent heat flux (evapotranspiration), which successfully mitigates severe water stress.

Transitional conditions observed in January, March, and September mark the critical threshold shifts in the ecohydrological system. The sharp expansion of moderate-to-high TVDI values during these months is highly correlated with agricultural practices in Lamongan Regency. For instance, the extensive dry areas unexpectedly captured in February and March—despite being chronologically within the wet season—are heavily influenced by post-harvest agricultural periods. During these phases, vast areas of paddy fields are cleared or left fallow (bare soil). The sudden loss of vegetative protection triggers a rapid increase in sensible heat flux over the exposed ground, driving up *LST* and artificially inflating TVDI values due to local soil properties affecting water retention.

The peak of severe agricultural drought intensifies dramatically from October to December, where the "dry" category envelops almost the entire regency. This critical expansion represents the cumulative impact of the dry monsoon season, characterized by minimal precipitation and high solar irradiance. Under these environmental drivers, the severe water deficit depletes shallow groundwater, causing a widespread collapse of vegetation vitality (*NDVI* $\rightarrow$ 0). With drastically reduced transpiration, the available net radiation is converted almost entirely into sensible heat, creating a positive feedback loop of surging *LST* and critical soil desiccation. This sharp decline in soil water availability during the late months of the year poses the highest risk of systemic crop failure across Lamongan's agricultural sectors.

Table 4. Distribution of Drought Areas in Lamongan Regency

Drought	2023 (km ²)											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
< 0.2 (Wet)	77.193	94.054	76.136	0.127	1.617	100.903	124.689	1.133	13.486	48.808	5.516	0.488
0.2 - 0.4 (Medium Wet)	228.066	158.809	375.296	0.434	858.840	189.631	963.288	361.913	90.983	63.658	144.796	3.146
0.4 - 0.6 (Normal)	531.202	165.107	842.857	4.537	854.242	1185.535	661.481	1016.349	858.985	28.073	415.050	13.531
0.6 - 0.8 (Medium Dry)	777.682	496.538	326.252	992.156	37.574	240.662	2.869	367.722	739.231	50.412	872.471	495.464
0.8 - 1.0 (Dry)	138.196	837.832	131.799	755.085	0.065	35.609	0.012	5.222	49.655	1561.388	314.506	1239.710

Table 4 outlines the monthly spatial extent (km²) of agricultural drought across Lamongan Regency in 2023, classified into five standardized intervals based on the mathematically bound TVDI framework (≤ 0.20 to 1.00). To ensure theoretical validity and eliminate calculation bias, all pixel-by-pixel model extractions were strictly clamped within this 0 to 1 range, corresponding directly to the dynamic boundaries of the localized *NDVI*-*LST* feature space.

The empirical data indicates a profound ecohydrological transition between the first and second semesters of the year. During the early months (January to March), the region was predominantly characterized by "Wet", "Medium Wet", and "Normal" conditions, with the total dry landscape remaining highly constrained. However, a significant environmental shift is observed during the peak drought window from June to October. During this period, the combined spatial coverage of the

"Medium Dry" (0.61–0.80) and "Dry" (0.81–1.00) categories expanded exponentially. The absolute peak of surface desiccation culminated in October, where the severe "Dry" category alone enveloped 1,561.388 km² of Lamongan's territory.

This critical expansion in the late dry season represents a severe depletion of soil moisture reservoirs, heavily driven by the prolonged dry monsoon and high thermal stress (surging *LST*). These quantified spatial dynamics demonstrate that the standard, bound TVDI method serves as a highly reliable tool for capturing actual environmental stress. Consequently, these high-resolution spatial insights provide an empirical foundation for local authorities to formulate targeted policies regarding adaptive water resource allocation, agricultural risk zoning, and localized food security mitigation planning.

3.4 Drought Index Analysis

Based on the results of data processing in this study, the parameters of drought distribution in the Lamongan Regency area were obtained, which were analyzed using data for three years, namely from 2021 to 2023. The data used covered 12 months in each year, so that it was able to provide a comprehensive picture of the dynamics of drought both temporally and spatially.

A three-year study from 2021 to 2023 found that moderate drought was the most widespread and extreme drought the most widespread. The most extensive moderate drought from the three-year study was observed in June 2021. The most extensive extreme drought was observed in October 2023.

3.5 Validation using Rainfall Data

The spatial and temporal patterns of drought across Lamongan Regency in 2023 were validated against monthly meteorological rainfall data to evaluate the operational responsiveness of the Temperature Vegetation Dryness Index (TVDI). Overall, the macro-trends show general temporal consistency: during the high-precipitation semester (January to March), "Wet" to "Normal" TVDI classes predominated, whereas the structural transition into the dry monsoon (June to October) induced a massive spatial expansion of the "Dry" category. The physical progression of this temporal relationship between monthly rainfall volume and average TVDI fluctuations throughout the year is illustrated in Figure 6.

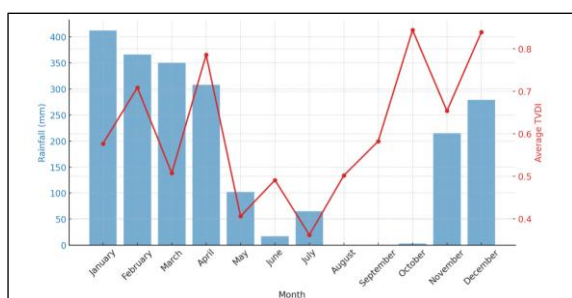


Fig 6. Temporal trends comparing monthly cumulative rainfall fields and average TVDI variations in Lamongan Regency throughout 2023

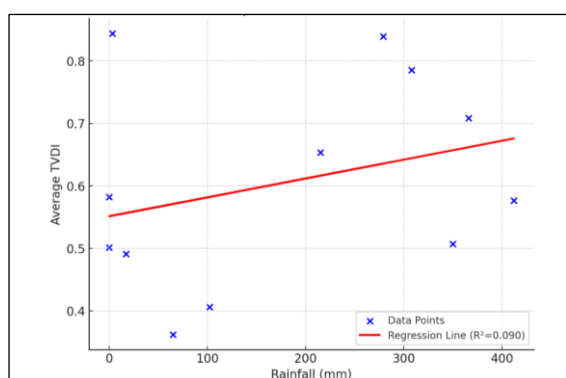


Fig 7. Linear regression analysis and scatter plot showcasing the weak statistical correlation ($R^2=0.090$) between monthly rainfall and average TVDI values

As observed in the temporal trends, localized anomalies occurred, most notably in February. During this month, despite a high cumulative rainfall of 319 mm, a substantial dry landscape covering 837 km² was recorded. This suggests that instantaneous precipitation

does not always translate to immediate surface moisture mitigation due to varying soil properties.

To quantify this relationship mathematically, a linear regression analysis was performed between monthly rainfall averages and TVDI values. The resulting statistical correlation yielded an R^2 coefficient of 0.090, indicating a statistically weak linear relationship, as demonstrated by the scatter plot and regression line in Figure 7.

While a superficial reading might interpret this low R^2 value as a model limitation, it fundamentally reflects a complex, non-linear ecohydrological coupling governed by several regional environmental mechanisms rather than a failure of the TVDI model.

First, there is a distinct temporal time lag between atmospheric precipitation inputs, subsurface soil moisture storage, and the subsequent physiological response of the vegetation canopy. While rainfall is an instantaneous meteorological event, vegetation requires weeks to adjust its chlorophyll and water content (captured by NDVI), and the soil acts as a temporal buffer that retains moisture long after rain ceases. Second, the spatial heterogeneity of precipitation across Lamongan Regency introduces significant pixel-by-pixel variance; localized convective storms during transitional months often supply intense moisture to isolated sectors while leaving adjacent agricultural grids entirely dry, a phenomenon that cannot be captured by generalized monthly rainfall averages.

Third, localized evapotranspiration processes and soil physical properties severely decouple the rainfall-TVDI relationship. Lamongan possesses diverse soil textures with highly variable water-holding capacities. In areas dominated by low-retention soils or bare post-harvest fields, high solar irradiance accelerates sensible heat flux and surges Land Surface Temperature (LST), causing rapid surface desiccation (high TVDI) even within months of high cumulative rainfall, such as the anomaly observed in February. Therefore, the low R^2 value scientifically confirms that TVDI operates as a highly sensitive, short-term indicator of immediate surface thermal-moisture stress, which cannot be accurately predicted by simple, linear rainfall metrics alone.

3.6 Comprehensive Discussion: Ecohydrological Dynamics and Climate Drivers

To position the observed drought dynamics within a broader scientific context, the extreme acceleration of TVDI-based dryness classes throughout Lamongan Regency must be linked to macro-scale atmospheric systems and localized surface characteristics. Mechanistically, the severe soil desiccation that culminated between September and December—where the severe "Dry" category enveloped 1,561.388 km² of the region—was heavily modulated by the planetary interaction between the East Asian-Australian Monsoon system and the 2023 El Niño-Southern Oscillation (ENSO) warm phase.

During the second semester of 2023, the strong El Niño anomaly severely suppressed convective cloud development over East Java, extending dry spells and maximizing regional solar irradiance. Under these intense meteorological drivers, groundwater tables dropped rapidly. The elevated net radiation directly accelerated evapotranspiration processes, creating a severe vapor pressure deficit that forced a structural collapse in vegetation canopy vitality ($NDVI \rightarrow 0$). This thermal forcing triggered a positive biophysical feedback loop: as

topsoil skin moisture was completely depleted, the land surface lost its latent cooling capacity, turning almost all absorbed solar energy into sensible heat flux. This energy shift exponentially spiked Land Surface Temperature (LST) and created the widespread agricultural drought captured by the model.

Beyond regional atmospheric forcing, the spatial distribution of these drought zones is heavily constrained by Lamongan's distinct land characteristics and hydrological processes. The southern and central sectors of the regency exhibit persistent high TVDI values because they are dominated by complex structural terrains with low clay-fraction water retention. In these zones, shallow aquifers deplete rapidly under intense summer evapotranspiration. Once the critical root-zone moisture threshold is breached, natural hydrologic capillary action fails to supply water to the upper soil layers, leaving the topmost soil completely desiccated and highly vulnerable to thermal stress.

3.7 Methodological Limitations and Uncertainty Evaluation

While the dynamic TVDI framework applied in this study successfully traces these regional ecohydrological trends, a critical evaluation of its methodological boundaries is essential for scientific transparency and credibility. The standard triangle method assumes a fully operational, linear relationship between LST and NDVI to extract the empirical wet and dry edges. However, this simplified geometric assumption introduces inherent uncertainties under highly heterogeneous landscapes or heavily managed agricultural zones.

Irrigation infrastructures, local micro-climates, and rapid land-cover changes can temporarily decouple the LST-NDVI feature space, leading to localized overestimations or underestimations of moisture stress. Furthermore, because TVDI is primarily an optical-thermal remote sensing index, it strictly measures topmost soil skin temperatures rather than deep root-zone soil moisture. This structural limitation explains why the model registers a severe "dry" status during post-harvest fallow periods when fields are bare, even if subsurface root-zone layers still retain adequate moisture. Acknowledging these specific uncertainties improves the credibility of the study, demonstrating that while TVDI is an exceptionally robust tool for rapid, high-resolution drought mapping, its values must be cross-referenced with local cropping schedules and soil properties to prevent spatial estimation bias.

For future research, it is highly recommended to move away from single-variable proxies and integrate multi-source validation datasets. Future models should incorporate satellite-derived soil moisture products (e.g., SMAP or AMSR2), the Standardized Precipitation Index (SPI), and the Vegetation Condition Index (VCI) to cross-validate root-zone dynamics. Additionally, applying multivariate statistical approaches or machine learning techniques will help isolate the relative contributions of soil texture, topography, and evapotranspiration, thereby providing a more comprehensive understanding of regional drought dynamics.

4. Conclusion

The results of this study indicate that the Temperature Vegetation Dryness Index (TVDI) derived from Landsat 8 imagery can effectively capture the spatial and temporal variability of agricultural drought

conditions in Lamongan Regency throughout 2023. Overall, the monthly meteorological rainfall patterns showed general temporal consistency with the TVDI-based drought classifications, where wet to normal conditions dominated during the high-precipitation early months, and severe dry landscapes expanded exponentially during the peak dry season. However, localized anomalies—such as the high-precipitation event in February coinciding with a substantial dry category footprint—highlight the strong influence of uneven spatial rainfall distribution, rapid evapotranspiration dynamics, and regional agricultural fallow practices. Statistical validation revealed a weak linear correlation between TVDI and raw rainfall ($R^2 = 0.090$), confirming that atmospheric precipitation alone is not the immediate determinant of surface dryness, as TVDI captures a more complex land-surface energy balance and soil moisture lag effect.

The authors explicitly acknowledge that the use of a simplified or static TVDI formulation—particularly one that does not fully dynamically reconstruct the NDVI-LST triangular feature space for every specific observation matrix—poses a distinct methodological limitation that may introduce localized uncertainties in the final drought index mapping. While this operational simplification allows for efficient regional assessments, it can introduce estimation bias under conditions of extreme surface heterogeneity or managed irrigation. Future research must move toward integrating multi-parameter validation networks, including satellite-derived root-zone soil moisture datasets (e.g., SMAP), the Standardized Precipitation Index (SPI), and the Vegetation Condition Index (VCI). Furthermore, employing advanced multivariate statistics or machine learning algorithms will be critical to enhance the precision, credibility, and forecasting reliability of regional drought monitoring systems.

Acknowledgements

This work was supported by an internal grant from LITBANG PEMAS UNISLA.

References

- Affandy, N. A., Iranata, D., Anwar, N., Maulana, M. A., Prastyo, D. D., Jaelani, L. M., & Suryadi, F. X. (2023). Modelling causality between agricultural and meteorological drought indices in the Corong River basin, East Java Indonesia. *Journal of Water and Land Development*, 178–188. <https://doi.org/10.24425/jwld.2023.146610>
- Affandy, N. A., Iranata, D., Anwar, N., Maulana, M. A., Prastyo, D. D., Wardoyo, W., & Sukojo, B. M. (2024). Assessment of Agricultural Drought Using the Normalized Difference Drought Index (NDDI) to Prediction Drought at Corong River Basin. *International Journal of Integrated Engineering*, 16(1). <https://doi.org/10.30880/ijie.2024.16.01.032>
- Affandy, N. A., Wijaya, B. R., & Nabilah, S. (2024). Pemantauan Dampak Kekeringan Lahan Pertanian di Lamongan Menggunakan NDVI Berbasis SIG. *Nucleus Journal*, 3(2), 57–67. <https://doi.org/10.32492/nucleus.v3i2.3201>
- Afriadi, A., Septio, G., Chidmahdjati, A. B., & Saputri, D. R. (2026). Correlation Between Land Cover Change and the Spatial Distribution of Land Surface Temperature in Tanjungpinang City, Indonesia.

- Journal of Geoscience, Engineering, Environment, and Technology, 11(1), 140–153. <https://doi.org/10.25299/jgeet.2026.11.1.22825>
- Ali, S., HENCHIRI, M., YAO, F., & ZHANG, J. (2019). Analysis of vegetation dynamics, drought in relation with climate over South Asia from 1990 to 2011. *Environmental Science and Pollution Research*, 26(11), 11470–11481. <https://doi.org/10.1007/s11356-019-04512-8>
- Bento, V. A., Trigo, I. F., Gouveia, C. M., & DaCamara, C. C. (2018). Contribution of Land Surface Temperature (TCL) to Vegetation Health Index: A Comparative Study Using Clear Sky and All-Weather Climate Data Records. *Remote Sensing*, 10(9), 1324. <https://doi.org/10.3390/rs10091324>
- Chu, H.-J., Wijayanti, R. F., Jaelani, L. M., & Tsai, H.-P. (2021). Time Varying Spatial Downscaling of Satellite-Based Drought Index. *Remote Sensing*, 13(18), 3693. <https://doi.org/10.3390/rs13183693>
- Cook, B. I., Miller, R. L., & Seager, R. (2009). Amplification of the North American “Dust Bowl” drought through human-induced land degradation. *Proceedings of the National Academy of Sciences*, 106(13), 4997–5001. <https://doi.org/10.1073/pnas.0810200106>
- Hanum, C. M., Kamal, A., Metananda, A. A., Kurniawati, Kiswayadi, D., & Bakruddin. (2026). Spatiotemporal Dynamics of Mangrove Cover in Aceh Tamiang Regency, Indonesia (2020–2024): An NDVI-Based Remote Sensing Assessment. *Journal of Geoscience, Engineering, Environment, and Technology*, 11(1), 165–171. <https://doi.org/10.25299/jgeet.2026.11.1.23237>
- Fariz, T. R., Naufal, M. A., Heriyanti, A. P., Eralita, N., & Saputri, L. H. (2025). Exploratory of Ecological Quality from Remote-Sensing Ecological Index and Drought Hazard in Pekalongan Regency, Indonesia. *Journal of Geoscience, Engineering, Environment, and Technology*, 10(3), 275–281. <https://doi.org/10.25299/jgeet.2025.10.3.22396>
- Han, X., Chen, X., & Feng, L. (2015). Four decades of winter wetland changes in Poyang Lake based on Landsat observations between 1973 and 2013. *Remote Sensing of Environment*, 156, 426–437. <https://doi.org/10.1016/j.rse.2014.10.003>
- Hariyanto, T., Pribadi, C. B., Purwitasari, A., & Kurniawan, A. (2019). Identification of potential drought in Lamongan Regency. *IOP Conference Series: Earth and Environmental Science*, 389(1), 012009. <https://doi.org/10.1088/1755-1315/389/1/012009>
- Heim, R. R. (2002). A Review of Twentieth-Century Drought Indices Used in the United States. *Bulletin of the American Meteorological Society*, 83(8), 1149–1166. <https://doi.org/10.1175/1520-0477-83.8.1149>
- Irawan, S., Fitriania, T., Sari, L. R., Natali, S. D., Aji, S. B., & Sismanto. (2024). Drought Management in Batam using Combined NDVI-TCT Algorithm to Create a Classification Level Map. *Journal of Geoscience, Engineering, Environment, and Technology*, 9(3), 294–300. <https://doi.org/10.25299/jgeet.2024.9.3.13033>
- Jiao, W., Zhang, L., Chang, Q., Fu, D., Cen, Y., & Tong, Q. (2016). Evaluating an Enhanced Vegetation Condition Index (VCI) Based on VIUPD for Drought Monitoring in the Continental United States. *Remote Sensing*, 8(3), 224. <https://doi.org/10.3390/rs8030224>
- Kamble, M. V., Ghosh, K., Rajeevan, M., & Samui, R. P. (2010). Drought monitoring over India through Normalized Difference Vegetation Index (NDVI). *MAUSAM*, 61(4), 537–546. <https://doi.org/10.54302/mausam.v61i4.911>
- Karnieli, A., Agam, N., Pinker, R. T., Anderson, M., Imhoff, M. L., Gutman, G. G., Panov, N., & Goldberg, A. (2010). Use of NDVI and Land Surface Temperature for Drought Assessment: Merits and Limitations. *Journal of Climate*, 23(3), 618–633. <https://doi.org/10.1175/2009JCLI2900.1>
- Karuniasa, M., & Pambudi, P. A. (2022). The analysis of the El Niño phenomenon in the East Nusa Tenggara Province, Indonesia. *Journal of Water and Land Development*, 180–185. <https://doi.org/10.24425/jwld.2022.140388>
- Khan, J., Wang, P., Xie, Y., Wang, L., & Li, L. (2018). Mapping MODIS LST NDVI Imagery for Drought Monitoring in Punjab Pakistan. *IEEE Access*, 6, 19898–19911. <https://doi.org/10.1109/ACCESS.2018.2821717>
- Kogan, F. N., & Zhu, X. (2001). Evolution of long-term errors in NDVI time series: 1985–1999. *Advances in Space Research*, 28(1), 149–153. [https://doi.org/10.1016/S0273-1177\(01\)00329-5](https://doi.org/10.1016/S0273-1177(01)00329-5)
- Li, M., Chu, R., Sha, X., Xie, P., Ni, F., Wang, C., Jiang, Y., Shen, S., & Islam, A. R. Md. T. (2022). Monitoring 2019 Drought and Assessing Its Effects on Vegetation Using Solar-Induced Chlorophyll Fluorescence and Vegetation Indexes in the Middle and Lower Reaches of Yangtze River, China. *Remote Sensing*, 14(11), 2569. <https://doi.org/10.3390/rs14112569>
- Markham, B. L., Storey, J. C., & Irons, J. R. (2013). *Landsat Data Continuity Mission, now Landsat-8: six months on-orbit* (J. J. Butler, X. (Jack) Xiong, & X. Gu, Eds.; p. 88661B). <https://doi.org/10.1117/12.2025290>
- Mishra, A. K., Singh, V. P., & Desai, V. R. (2009). Drought characterization: a probabilistic approach. *Stochastic Environmental Research and Risk Assessment*, 23(1), 41–55. <https://doi.org/10.1007/s00477-007-0194-2>
- Murtianto, H. (2016). POTENSI KERUSAKAN GEMPA BUMI AKIBAT PERGERAKAN PATAHAN SUMATERA DI SUMATERA BARAT DAN SEKITARNYA. *Jurnal Geografi Gea*. <https://doi.org/10.17509/gea.v10i1.1667>
- Putera, R., Junaidi, J., & Junaidi, A. (2019). Analysis of Land Cover Changing and Vegetation Index at Kuranji Watershed in Padang, West Sumatera, Indonesia. *Journal of Geoscience, Engineering, Environment, and Technology*, 4(4), 286–290. <https://doi.org/10.25299/jgeet.2019.4.4.4101>
- Qi, W., Feng, L., Yang, H., & Liu, J. (2022). Increasing Concurrent Drought Probability in Global Main Crop Production Countries. *Geophysical Research Letters*, 49(6). <https://doi.org/10.1029/2021GL097060>
- Redmond, K. T. (2002). THE DEPICTION OF DROUGHT. *Bulletin of the American Meteorological Society*, 83(8), 1143–1148. <https://doi.org/10.1175/1520-0477-83.8.1143>

- Rotjanakusol, T., & Laosuwan, T. (2019). Drought Evaluation with NDVI-Based Standardized Vegetation Index in Lower Northeastern Region of Thailand. *Geographia Technica*, 14(1), 118–130. https://doi.org/10.21163/GT_2019.141.09
- Sandholt, I., Rasmussen, K., & Andersen, J. (2002). A simple interpretation of the surface temperature/vegetation index space for assessment of surface moisture status. *Remote Sensing of Environment*, 79(2–3), 213–224. [https://doi.org/10.1016/S0034-4257\(01\)00274-7](https://doi.org/10.1016/S0034-4257(01)00274-7)
- Shen, R., Huang, A., Li, B., & Guo, J. (2019). Construction of a drought monitoring model using deep learning based on multi-source remote sensing data. *International Journal of Applied Earth Observation and Geoinformation*, 79, 48–57. <https://doi.org/10.1016/j.jag.2019.03.006>
- Shi, S., Yao, F., Zhang, J., & Yang, S. (2020). Evaluation of Temperature Vegetation Dryness Index on Drought Monitoring Over Eurasia. *IEEE Access*, 8, 30050–30059. <https://doi.org/10.1109/ACCESS.2020.2972271>
- Son, N. T., Chen, C. F., Chen, C. R., Chang, L. Y., & Minh, V. Q. (2012). Monitoring agricultural drought in the Lower Mekong Basin using MODIS NDVI and land surface temperature data. *International Journal of Applied Earth Observation and Geoinformation*, 18, 417–427. <https://doi.org/10.1016/j.jag.2012.03.014>
- Sun, H., Zhou, B., & Liu, H. (2019). Spatial Evaluation of Soil Moisture (SM), Land Surface Temperature (LST), and LST-Derived SM Indexes Dynamics during SMAPVEX12. *Sensors*, 19(5), 1247. <https://doi.org/10.3390/s19051247>
- Tijdeman, E., Barker, L. J., Svoboda, M. D., & Stahl, K. (2018). Natural and Human Influences on the Link Between Meteorological and Hydrological Drought Indices for a Large Set of Catchments in the Contiguous United States. *Water Resources Research*, 54(9), 6005–6023. <https://doi.org/10.1029/2017WR022412>
- Tucker, C. J., Grant, D. M., & Dykstra, J. D. (2004). NASA's Global Orthorectified Landsat Data Set. *Photogrammetric Engineering & Remote Sensing*, 70(3), 313–322. <https://doi.org/10.14358/PERS.70.3.313>
- Van Loon, A. F., Tijdeman, E., Wanders, N., Van Lanen, H. A. J., Teuling, A. J., & Uijlenhoet, R. (2014). How climate seasonality modifies drought duration and deficit. *Journal of Geophysical Research: Atmospheres*, 119(8), 4640–4656. <https://doi.org/10.1002/2013JD020383>
- Wu, J., Chen, X., Yu, Z., Yao, H., Li, W., & Zhang, D. (2019). Assessing the impact of human regulations on hydrological drought development and recovery based on a 'simulated-observed' comparison of the SWAT model. *Journal of Hydrology*, 577, 123990. <https://doi.org/10.1016/j.jhydrol.2019.123990>
- Ye, X., Li, X., Xu, C.-Y., & Zhang, Q. (2016). Similarity, difference and correlation of meteorological and hydrological drought indices in a humid climate region – the Poyang Lake catchment in China. *Hydrology Research*, 47(6), 1211–1223. <https://doi.org/10.2166/nh.2016.214>



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