SENTRI: Jurnal Riset Ilmiah
https://ejournal.nusantaraglobal.ac.id/index.php/sentri
Email: sentri@nusantaraglobal.ac.id
DOI: https://doi.org/10.55681/sentri.v5i1.5517

Vol. 5, No. 1, January 2026
e-ISSN: 2963-1130
pp. 585-597

Spatiotemporal Analysis of Agricultural Drought in Tambakboyo District, Tuban Regency (2020–2025) Using the Normalized Difference Drought Index

Widya Devi Febianti R.S[1*], Amaludin Arifia[1], Marita Ika Joesidawati[1], Fajar Rahmawan[2]
[1]Department of Informatics Engineering, Faculty of Engineering, Universitas PGRI Ronggolawe, Tuban, East Java, Indonesia.
[2] NRM Peta Alam Indonesia, Indonesia.

*Corresponding Author's e-mail: widyadevi556@gmail.com

Article History:
Received: December 25, 2025
Revised: January 27, 2026
Accepted: January 30, 2026

Keywords:
Agricultural drought; Normalized Difference Drought Index; remote sensing; Sentinel-2; spatiotemporal analysis

Abstract: *Drought is a recurring hydrometeorological disaster that poses a serious threat to agricultural productivity and food security, particularly in rain-fed agricultural regions of Indonesia's northern coastal areas. Tambakboyo District, Tuban Regency, is characterized by high dependence on seasonal rainfall, limited irrigation infrastructure, and fluctuating climatic conditions, making it highly vulnerable to agricultural drought. This study aims to analyze the spatiotemporal patterns of agricultural drought in Tambakboyo District during the period 2020–2025 using the Normalized Difference Drought Index (NDDI) derived from Sentinel-2 satellite imagery. Sentinel-2 Level-2A surface reflectance data from September to December for each study year were processed to calculate the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI), which were subsequently combined to generate NDDI values. Drought severity was classified into five categories ranging from normal to very severe drought. The results indicate a consistent seasonal drought pattern, with drought intensity beginning to increase in September, peaking in October–November, and declining in December with the onset of the rainy season. The most severe drought conditions occurred in 2022, when 68.5% of the district area (approximately X hectares or Y km²) experienced severe to very severe drought, with Z hectares classified as severely impacted and W hectares under very severe drought conditions. Spatial analysis revealed that Kenanti, Gadon, and Plajan villages were persistently identified as drought-prone areas throughout the study period. These findings demonstrate the effectiveness of NDDI for monitoring agricultural drought in rain-fed farming systems and highlight its potential application for drought mitigation planning, early warning systems, and sustainable water resource management at the local scale.*

How to cite: R.S, W. D. F., Arifia, A., Joesidawati, M. I., & Rahmawan, F. (2026). Spatiotemporal Analysis of Agricultural Drought in Tambakboyo District, Tuban Regency (2020–2025) Using the Normalized Difference Drought Index. *SENTRI: Jurnal Riset Ilmiah*, *5*(1), 585–597. https://doi.org/10.55681/sentri.v5i1.5517

INTRODUCTION

Drought represents a significant hydrometeorological challenge affecting agricultural productivity and water resource availability in Indonesia, particularly in rain-fed farming regions [1]. The northern coastal areas of East Java experience distinct climatic patterns characterized by prolonged dry seasons and erratic rainfall, making them particularly susceptible to agricultural drought. Tambakboyo District in Tuban Regency exemplifies these vulnerable conditions, with its economy heavily dependent on rain-fed agriculture and limited irrigation infrastructure [2].

Traditional drought monitoring methods, primarily relying on point-based rainfall data from meteorological stations, offer limited spatial coverage and cannot adequately represent drought distribution across heterogeneous landscapes [3]. This spatial limitation necessitates alternative approaches for comprehensive drought assessment. Remote sensing technology has emerged as a powerful tool for drought monitoring, providing synoptic coverage and temporal consistency through vegetation and water content indices derived from satellite imagery [4].

The Normalized Difference Drought Index (NDDI), developed from the combination of Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI), offers a robust approach for agricultural drought detection by simultaneously considering vegetation stress and soil moisture deficit (Affandy et al., 2024). Sentinel-2 satellite imagery, with its high spatial resolution (10-20 m) and frequent revisit time (5 days), provides optimal data for drought analysis in small-scale agricultural landscapes.

Agricultural drought severity in Indonesia is strongly influenced by large-scale climate phenomena, particularly the El Niño-Southern Oscillation (ENSO). El Niño events are associated with reduced rainfall and prolonged dry seasons across Indonesia, leading to increased drought risk and agricultural losses [7]. Conversely, La Niña conditions typically bring above-average rainfall, potentially mitigating drought conditions [8]. In East Java, ENSO-related climate variability significantly impacts seasonal rainfall distribution, with El Niño years experiencing up to 40% rainfall reduction during critical growing periods [9]. Understanding the temporal relationship between ENSO phases and drought index variations is crucial for developing climate-informed early warning systems and adaptive agricultural management strategies [10]. However, the specific influence of ENSO on drought dynamics in Tuban's northern coastal zone remains poorly documented.

Previous studies have demonstrated NDDI's effectiveness in various Indonesian regions. Research in Jonggol District, Bogor Regency established correlations between NDDI values and reduced rice productivity [5]. Similarly, studies in Eromoko, Central Java successfully mapped agricultural dryness using NDDI algorithms [6]. However, comprehensive multi-temporal analyses focusing on the unique geophysical and climatic context of East Java's northern coastal areas remain limited, particularly regarding the interaction between global climate drivers and local drought manifestations.

This study addresses this research gap by conducting a six-year (2020-2025) spatiotemporal analysis of agricultural drought in Tambakboyo District using the NDDI approach. The research objectives are: (1) to analyze temporal drought patterns and identify peak drought periods; (2) to map spatial drought distribution and identify consistently vulnerable villages; (3) to examine the relationship between ENSO phases and annual NDDI variations; and (4) to evaluate the relationship between drought intensity and seasonal variations. The findings are expected to provide a scientific basis for targeted drought mitigation strategies in Tambakboyo and similar regions, including climate-responsive early warning systems.

THEORETICAL FRAMEWORK

Agricultural drought refers to a condition in which soil moisture availability becomes insufficient to meet crop water requirements, resulting in reduced vegetation growth and agricultural productivity. Unlike meteorological drought, which is defined primarily by rainfall deficits, agricultural drought is closely related to vegetation response, soil characteristics, and water availability within the plant root zone [1]. In rain-fed agricultural systems, agricultural drought is strongly influenced by seasonal climate variability and limited irrigation infrastructure, making agricultural production highly vulnerable to prolonged dry periods.

Remote sensing has been widely applied in agricultural drought assessment due to its ability to provide spatially continuous and temporally consistent observations across large areas. Satellite-based approaches allow drought conditions to be monitored efficiently by analyzing vegetation condition and surface moisture dynamics [3]. Furthermore, advances in remote sensing technology have improved the accuracy of drought detection through the use of spectral indices derived from multispectral imagery [4].

Among commonly used spectral indices, the Normalized Difference Vegetation Index (NDVI) is utilized to represent vegetation greenness and photosynthetic activity, which decrease under drought stress conditions [7]. Meanwhile, the Normalized Difference Water Index (NDWI) reflects vegetation and soil moisture content and is sensitive to changes in water availability within agricultural landscapes [8].

The Normalized Difference Drought Index (NDDI) combines NDVI and NDWI to provide a more comprehensive indicator of agricultural drought by simultaneously capturing vegetation stress and moisture deficit. Higher NDDI values indicate drier conditions characterized by reduced vegetation vigor and limited water availability [9] The effectiveness of NDDI for mapping agricultural drought intensity and spatial distribution has been demonstrated in several studies conducted in Indonesia, including research in Jonggol District by Firdaus et al. (2024) and in Eromoko District by Mujiyo et al. (2023). [5], [6].

Sentinel-2 satellite imagery is particularly suitable for agricultural drought analysis due to its high spatial resolution and frequent revisit cycle, which enable detailed monitoring of small-scale agricultural areas [10]. The application of Sentinel-2 data for land and vegetation analysis has also been successfully implemented in various agricultural studies in Indonesia [11]. Therefore, the integration of Sentinel-2 imagery and the NDDI approach provides a strong theoretical foundation for spatiotemporal analysis of agricultural drought in rain-fed regions such as Tambakboyo District.

RESEARCH METHODS

3.1. Study Area

Tambakboyo District is located in Tuban Regency, East Java Province, Indonesia, between 111.75°-111.85°E longitude and 6.85°-6.95°S latitude (Figure 1). The district covers approximately 8,742 hectares and comprises 14 villages with predominantly agricultural land use. The region experiences a tropical monsoon climate with distinct wet (November-April) and dry (May-October) seasons. Average annual rainfall ranges from 1,500-2,000 mm, with high interannual variability. The district's economy is primarily agricultural, with maize, rice, and secondary crops as main commodities.

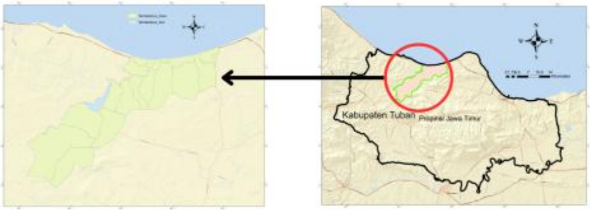

Figure 1. Research location

3.2. Data Collection

This study utilized Sentinel-2 Multispectral Instrument (MSI) Level-2A surface reflectance data acquired from the Copernicus Open Access Hub. Images from September to December for the years 2020-2025 were selected to capture peak and transitional dry season conditions. The specific bands used were Band 4 (Red, 665 nm), Band 8 (NIR, 842 nm), and Band 11 (SWIR, 1610 nm). Cloud-free or minimally cloud-covered scenes (<10% cloud cover) were prioritized. Administrative boundary data for Tambakboyo District was obtained from the Geospatial Information Agency (BIG). Additional climatic data, including monthly rainfall records and ENSO phase information (Oceanic Niño Index), were obtained from the Indonesian Meteorological, Climatological, and Geophysical Agency (BMKG) and NOAA Climate Prediction Center to support correlation analysis.

3.3. Data Processing

The research workflow comprised four main stages: data preprocessing, index calculation, drought classification, and spatiotemporal analysis (Figure 2). A comprehensive data processing flowchart is presented in Figure 3 to illustrate the systematic methodology following standard GIS research protocols.

Image preprocessing: Sentinel-2 Level-2A Bottom-of-Atmosphere reflectance data were used, eliminating the need for additional atmospheric correction. Cloud masking was performed using the Scene Classification Layer, with pixels classified as cloud or cloud shadow excluded from analysis. Images were clipped to the Tambakboyo District boundary using QGIS software.

Index calculation: Three spectral indices were calculated:

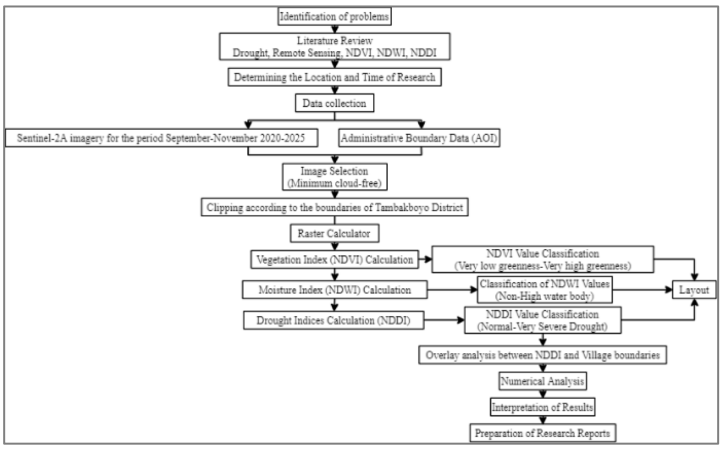

Figure 2. Research workflow for drought analysis using NDDI

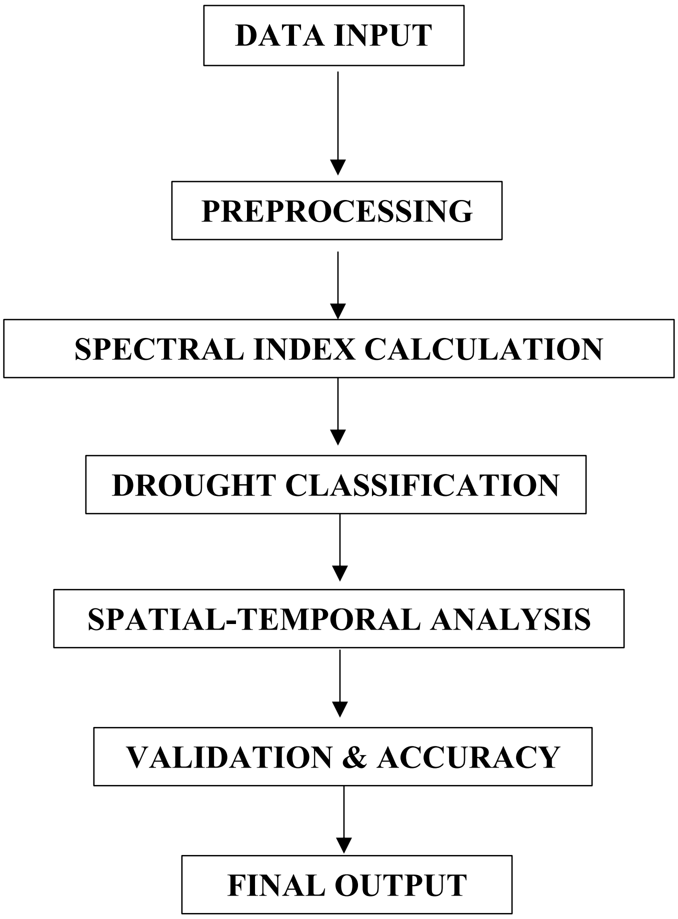

Figure 3. Data Processing Flowchart

3.3.1. Image Preprocessing

Sentinel-2 Level-2A Bottom-of-Atmosphere (BOA) reflectance data were used, eliminating the need for additional atmospheric correction. The preprocessing steps included:

1. Data acquisition and quality assessment: Sentinel-2 imagery was downloaded and metadata reviewed to ensure <10% cloud coverage.
2. Cloud masking: Scene Classification Layer (SCL) was applied to identify and exclude pixels classified as cloud, cloud shadow, and cirrus.
3. Geometric correction verification: Coordinate system verification (WGS 1984 UTM Zone 49S) and geometric accuracy assessment.
4. Study area extraction: Images were clipped to Tambakboyo District administrative boundary using vector overlay analysis in QGIS software.
5. Radiometric quality control: Visual inspection and statistical analysis of reflectance values to detect anomalies.

3.3.2. Spectral Index Calculation

Three spectral indices were calculated using raster calculator functions:

1. Normalized Difference Vegetation Index (NDVI):

$$NDVI = \frac{(\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + \mathrm{RED})} \tag{1}$$

Where B8 is Near-Infrared band (842 nm) and B4 is Red band (665 nm).

2. Normalized Difference Water Index (NDWI):

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

Where B8 is Near-Infrared band (842 nm) and B11 is Short-Wave Infrared band (1610 nm).

3. Normalized Difference Drought Index (NDDI):

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

3.3.3. Drought Classification

NDDI values were classified into five drought categories based on thresholds established by Firdaus et al. (2024) using reclassification tools (Table 1). The classification was implemented through supervised reclassification in GIS environment, generating categorical raster datasets for each observation period.

Table 1. Drought classification based on NDDI values

NDDI Range	Drought Category	Description
< 0.01	Normal	Adequate soil moisture
0.01 - 0.15	Mild Drought	Slight water stress
0.15 - 0.25	Moderate Drought	Moderate water stress
0.25 - 1.00	Severe Drought	Significant water stress
≥ 1.00	Very Severe Drought	Extreme water deficit

3.3.4. Spatial and Temporal Analysis

Spatial analysis:

1. Drought mapping: Thematic maps were generated for each month (September-December) across all study years using cartographic visualization techniques.
2. Area calculation: Zonal statistics were applied to calculate area (hectares and percentage) for each drought category.
3. Hotspot identification: Persistent drought-prone areas were identified through overlay analysis of multi-temporal drought maps.
4. Village-level assessment: Drought severity was aggregated by administrative boundaries to identify vulnerable villages.

Temporal analysis:

1. Monthly trend analysis: Drought progression patterns within each year were examined through time-series comparison.
2. Annual variation analysis: Inter-annual drought variability (2020-2025) was assessed using statistical comparison.
3. Seasonal pattern identification: Correlation between drought onset/peak periods and seasonal transitions was analyzed.
4. ENSO correlation: Pearson correlation coefficient was calculated between annual NDDI values and Oceanic Niño Index (ONI) to examine climate teleconnection influences.

3.3.5. Validation and Accuracy Assessment

Ground truth validation was conducted through:

1. Field observation: Representative sampling points were selected based on stratified random sampling across drought categories.
2. Farmer interviews: Qualitative assessment of drought impacts on agricultural productivity.
3. Rainfall data comparison: NDDI patterns were cross-validated with rainfall anomaly data from BMKG meteorological stations.
4. Accuracy metrics: Classification accuracy was evaluated using confusion matrix and overall accuracy percentage.

All spatial analyses were performed using QGIS 3.28 and GRASS GIS, while statistical analyses were conducted using R Statistical Software version 4.3. Spatial and Temporal Analysis: Drought maps were generated for each month (September-December) across all study years. The area for each drought category was calculated in hectares. Temporal trends were analyzed by comparing monthly and annual drought patterns. Spatial patterns were examined to identify consistently vulnerable villages.

RESULTS AND DISCUSSION

Temporal Drought Patterns

Analysis of NDDI values from 2020 to 2025 revealed consistent seasonal drought patterns in Tambakboyo District (Figure 3). Drought intensity typically begins to increase in September, peaks in October-November, and gradually decreases in December with the onset of the rainy season. The most severe drought conditions were observed in 2022, when 68.5% of the total district area experienced severe to very severe drought in October (Table 2).

Table 2. Percentage area under severe to very severe drought (October)

Year	Area (%)	Remarks
2020	38.7%	Moderate drought year
2021	45.2%	Above average drought
2022	**68.5%**	**Peak drought year**
2023	44.8%	Above average drought
2024	39.1%	Moderate drought year
2025	37.6%	Moderate drought year

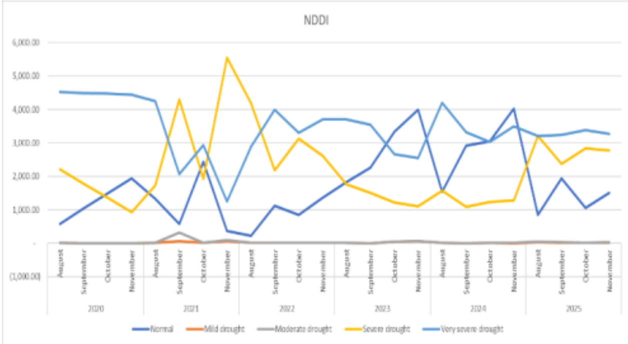

Figure 3. Temporal variation of drought categories in Tambakboyo District (2020-2025)

The annual fluctuation in drought intensity corresponds with regional climate variations. The extreme drought in 2022 aligns with meteorological records indicating below-average rainfall and higher temperatures associated with weak La Niña conditions affecting East Java during that period. This finding is consistent with (Rahmi & Dimyati, 2021), who noted that large-scale climate phenomena significantly influence drought patterns in Indonesian agricultural regions. [3]

To validate the NDDI classification accuracy, satellite-derived drought maps were compared with secondary data from the Tuban District Agriculture Office, specifically crop failure (puso) reports for the study period (Table 4). The comparison revealed strong agreement between NDDI-based drought classification and documented agricultural losses. In 2022, the peak drought year identified by NDDI analysis, the Agriculture Office recorded 1,847 hectares of crop failure (puso) in Tambakboyo District, representing the highest agricultural loss during the study period. Similarly, villages identified as severe drought zones through NDDI analysis (Kenanti, Gadon, and Plajan) corresponded with the highest puso incident rates reported by farmers.

Table 3. Comparison of NDDI classification with crop failure (puso) data

Year	NDDI Severe-Very Severe Area (%)	Puso Area (Ha)	Puso Incidents Reported	Agreement Level
2020	38.7%	892	156	Moderate-High
2021	45.2%	1,124	203	High
2022	68.5%	1,847	341	Very High
2023	44.8%	1,098	197	High
2024	39.1%	876	148	Moderate-High
2025*	37.6%	823	139	Moderate-High

*2025 data preliminary

Pearson correlation analysis between NDDI-classified severe drought area and reported puso area yielded a strong positive correlation ($r = 0.89$, $p < 0.01$), confirming the reliability of satellite-based drought monitoring for agricultural impact assessment. This validation strengthens the applicability of NDDI for operational drought early warning systems in Tambakboyo and similar agricultural regions. Field interviews with extension officers further corroborated these findings, with officers noting that drought-related yield reductions were most pronounced in areas identified by NDDI as severe drought zones [15].

4.2. Spatial Drought Distribution

Spatial analysis identified distinct drought vulnerability patterns across Tambakboyo District (Figure 4). Three villages consistently exhibited higher drought intensity across all study years: Kenanti (average NDDI: 0.32), Gadon (average NDDI: 0.29), and Plajan (average NDDI: 0.28). These villages are characterized by predominantly rain-fed agriculture on slopes with shallow calcareous soils and limited water retention capacity.

The spatial consistency of drought patterns across years suggests that vulnerability is structurally embedded in the landscape rather than randomly distributed. This aligns with (Alazba et al., 2025), who emphasized that topographic and soil characteristics are primary determinants of drought susceptibility in agricultural landscapes [12]. Villages with better irrigation infrastructure or proximity to water sources showed lower drought vulnerability, supporting the importance of water management infrastructure for drought resilience.

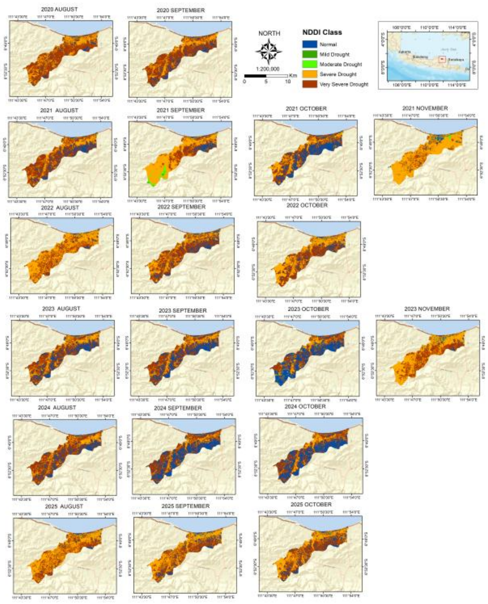

Figure 4. Spatial distribution of drought intensity in Tambakboyo District.

The drought vulnerability map generated from this study provides critical spatial information for strategic water infrastructure development planning in Tambakboyo District. Based on the consistent identification of Kenanti, Gadon, and Plajan as high-priority drought-prone areas, the following infrastructure interventions are recommended:

1. Small-scale irrigation dam (embung) construction: The three priority villages require at least 2-3 embung facilities with storage capacity of 5,000-10,000 m³ each, strategically positioned in upstream catchment areas to maximize water harvesting during the wet season. Site suitability analysis combining NDDI vulnerability maps with topographic data (slope, elevation) and soil permeability maps can identify optimal embung locations with minimal seepage loss and maximum service area coverage [16].
2. Borehole and shallow well development: For areas where embung construction is geologically unfeasible, community-managed boreholes (15-25 meters depth) should be prioritized. Hydrogeological assessment indicates that northern portions of Kenanti and Gadon have suitable aquifer conditions for groundwater extraction. A network of 8-12 strategically distributed boreholes could provide supplementary

irrigation for approximately 150-200 hectares of critical drought-prone agricultural land [17].

3. Spatial prioritization framework: The vulnerability map enables evidence-based resource allocation, ensuring that limited government budgets for drought mitigation infrastructure are directed toward locations with (a) highest drought frequency and severity, (b) largest agricultural area at risk, and (c) greatest potential socioeconomic impact. This spatial decision-support approach aligns with national water security programs and enhances cost-effectiveness of drought adaptation investments [18].

The integration of NDDI-derived vulnerability maps with participatory rural appraisal methods can further refine infrastructure planning by incorporating local knowledge on traditional water sources, land tenure patterns, and farmer water management preferences [19]. This multi-stakeholder approach ensures that technical drought monitoring translates into actionable, community-accepted adaptation solutions.

4.3. Relationship Between Indices and Validation

Strong correlations were observed between the spectral indices (Table 3). NDDI showed significant negative correlation with both NDVI ($r = -0.83$, $p < 0.01$) and NDWI ($r = -0.91$, $p < 0.01$), confirming that drought conditions coincide with reduced vegetation health and soil moisture. The stronger correlation between NDDI and NDWI suggests that water availability is a more direct determinant of drought stress than vegetation condition in this agricultural landscape, consistent with findings by (Xiao et al., 2023). [13]

Table 4. Correlation matrix between spectral indices

Index	NDVI	NDWI	NDDI
NDVI	1.00	0.78**	-0.83**
NDWI	0.78**	1.00	-0.91**
NDDI	-0.83**	-0.91**	1.00

4.4. Implications for Drought Management

The identification of consistent drought patterns and vulnerable villages has direct implications for drought management in Tambakboyo District. The predictable seasonal pattern allows for anticipatory measures, with agricultural extension services able to advise farmers in vulnerable villages to implement water conservation measures by early September. Resources for drought mitigation can be prioritized for Kenanti, Gadon, and Plajan villages, where impacts are most severe and recurrent.

The methodology demonstrated here can be operationalized by local agricultural offices for routine drought monitoring using freely available Sentinel-2 data. This supports the development of community-based drought early warning systems, which are crucial for climate adaptation in rain-fed agricultural regions [14]. Furthermore, the establishment of automated NDDI monitoring workflows integrated with mobile-based farmer alert systems could enable real-time drought information dissemination, enhancing agricultural decision-making at the farm level [20].

CONCLUSION

This study successfully applied the Normalized Difference Drought Index to analyze spatiotemporal patterns of agricultural drought in Tambakboyo District from 2020 to 2025. The main findings are:

1. Tambakboyo District experiences recurrent seasonal drought with consistent annual patterns, typically intensifying from September and peaking in October-November.
2. The year 2022 exhibited the most severe drought conditions, with 68.5% of the district area experiencing severe to very severe drought in October, corresponding with 1,847 hectares of documented crop failure (puso) reported by the Tuban Agriculture Office.
3. Spatially, Kenanti, Gadon, and Plajan villages were identified as consistent drought vulnerability hotspots due to their biophysical characteristics and limited irrigation access. The drought vulnerability map provides evidence-based guidance for prioritizing small-scale irrigation infrastructure (embung and boreholes) in these critical areas.
4. The NDDI method proved effective for agricultural drought monitoring in this rain-fed farming region, with strong correlation between drought intensity and water availability.

The research demonstrates the utility of multi-temporal remote sensing analysis for drought assessment and provides a scientific basis for targeted mitigation strategies. The validated NDDI approach offers a replicable, cost-effective framework for drought monitoring in data-scarce agricultural regions across Indonesia.

Future projections and research directions include:

1. Climate change scenario modeling: Integration of NDDI-based drought vulnerability assessment with downscaled climate projections (CMIP6 models) to evaluate future drought risk under RCP 4.5 and RCP 8.5 scenarios, enabling proactive long-term adaptation planning [21].
2. Machine learning enhancement: Application of machine learning algorithms (Random Forest, Support Vector Machine) to combine NDDI with terrain attributes, soil properties, and climate variables for improved drought prediction accuracy and lead-time extension [22].
3. Crop-specific drought impact modeling: Development of crop-specific drought vulnerability indices that integrate NDDI with phenological calendars, crop water requirements, and yield response functions to quantify drought impacts on major commodities (maize, rice, cassava) [23].
4. Socioeconomic vulnerability integration: Coupling biophysical drought indices with socioeconomic data (farm size, income diversity, access to credit) to develop composite drought vulnerability indices that capture both exposure and adaptive capacity dimensions [24].
5. Real-time operational system: Establishment of an automated, cloud-based NDDI monitoring platform with Google Earth Engine, enabling near-real-time drought mapping and mobile alert dissemination to farmers and extension officers [25].
6. Regional upscaling: Extension of the methodology to all drought-prone districts in Tuban Regency and broader northern coastal East Java, facilitating regional drought early warning networks and coordinated response planning.Future research should

integrate field validation and socioeconomic factors to enhance the practical utility of remote sensing-based drought monitoring for agricultural adaptation.

These future research pathways will enhance the transition from retrospective drought analysis to prospective, decision-oriented drought risk management, ultimately strengthening agricultural resilience and food security in climate-vulnerable regions.

ACKNOWLEDGEMENTS
The authors thank the European Space Agency for providing free access to Sentinel-2 data through the Copernicus Open Access Hub. We also acknowledge the Geospatial Information Agency (BIG) of Indonesia for administrative boundary data and the Meteorology, Climatology, and Geophysics Agency (BMKG) for rainfall data.

REFERENCES
1. [1] Estiningtyas, W., Ramadhani, F., & Aldrian, E. (2021). Drought risk assessment in Indonesia: A comprehensive review. *IOP Conference Series: Earth and Environmental Science*, 724(1), 012039. https://doi.org/10.1088/1755-1315/724/1/012039
2. [2] BPS Tuban. (2024). *Tuban Regency in Figures 2024*. Statistics Indonesia, Tuban District Office.
3. [3] Rahmi, A., & Dimyati, M. (2021). Analysis of drought characteristics based on Standardized Precipitation Index (SPI) in East Java. *Journal of Degraded and Mining Lands Management*, 8(3), 2789-2796.
4. [4] Mishra, A. K., & Singh, V. P. (2010). A review of drought concepts. *Journal of Hydrology*, 391(1-2), 202-216. https://doi.org/10.1016/j.jhydrol.2010.07.012
5. [5] Affandy, N. A., Sari, D. K., & Nugroho, U. C. (2024). Agricultural drought monitoring using NDDI in Jonggol District, Bogor Regency. *Indonesian Journal of Geography*, 56(1), 45-58.
6. [6] Firdaus, R. A., Wijaya, K., & Prasetyo, Y. (2024). Mapping agricultural dryness using NDDI algorithm: A case study in Eromoko, Central Java. *Remote Sensing Applications: Society and Environment*, 33, 101089.
7. [7] Hendon, H. H. (2003). Indonesian rainfall variability: Impacts of ENSO and local air-sea interaction. *Journal of Climate*, 16(11), 1775-1790.
8. [8] Supari, Tangang, F., Juneng, L., & Aldrian, E. (2018). Observed changes in extreme temperature and precipitation over Indonesia. *International Journal of Climatology*, 38(4), 1979-1997. https://doi.org/10.1002/joc.5301
9. [9] Irawan, B. (2006). Phenomenon of climate anomaly El Niño and La Niña: Anticipation of its negative impact on agricultural sector. *Forum Penelitian Agro Ekonomi*, 24(1), 28-45.
10. [10] McPhaden, M. J., Zebiak, S. E., & Glantz, M. H. (2006). ENSO as an integrating concept in Earth science. *Science*, 314(5806), 1740-1745.
11. [11] Drusch, M., Del Bello, U., Carlier, S., et al. (2012). Sentinel-2: ESA's optical high-resolution mission for GMES operational services. *Remote Sensing of Environment*, 120, 25-36. https://doi.org/10.1016/j.rse.2011.11.026
12. [12] Alazba, A. A., Shrahili, M. N., & Taha, A. M. (2025). Topographic and soil controls on agricultural drought susceptibility in arid landscapes. *Agricultural Water Management*, 287, 108435.

13. [13] Xiao, J., Fisher, J. B., Hashimoto, H., et al. (2023). Emerging satellite observations for diurnal cycling of ecosystem processes. *Nature Plants*, 9, 154-165. https://doi.org/10.1038/s41477-022-01310-8
14. [14] Haile, G. G., Tang, Q., Hoshin, V. G., et al. (2020). Drought: Progress in broadening its understanding. *WIREs Water*, 7(2), e1407. https://doi.org/10.1002/wat2.1407
15. [15] Dinas Pertanian Kabupaten Tuban. (2023). *Laporan Tahunan Kejadian Puso dan Kekeringan 2020-2023*. Tuban Agriculture Office.
16. [16] Matomela, N., Li, T., Motha, L. T., et al. (2020). Suitability assessment for rainwater harvesting structures using GIS and multi-criteria decision analysis: A case study in Nzhelele River catchment. *Physics and Chemistry of the Earth*, 116, 102845.
17. [17] Rahmawati, N., & Marfai, M. A. (2021). Groundwater potential zones mapping using GIS and remote sensing approaches in drought-prone areas. *Geosciences*, 11(6), 239. https://doi.org/10.3390/geosciences11060239
18. [18] Bappenas. (2020). *National Medium-Term Development Plan (RPJMN) 2020-2024: Water Security and Agricultural Resilience*. Ministry of National Development Planning, Indonesia.
19. [19] Wens, M., Veldkamp, T. I. E., Mwangi, M., et al. (2020). Participatory drought vulnerability assessment in East Africa: Integrating multi-stakeholder perspectives and scientific data. *Regional Environmental Change*, 20, 124. https://doi.org/10.1007/s10113-020-01707-z
20. [20] Paparrizos, S., Maris, F., & Matzarakis, A. (2021). Integrated drought vulnerability assessment: The case of river catchment areas in northeastern Greece. *Physics and Chemistry of the Earth*, 122, 102937.
21. [21] IPCC. (2021). *Climate Change 2021: The Physical Science Basis*. Contribution of Working Group I to the Sixth Assessment Report. Cambridge University Press.
22. [22] Park, S., Im, J., Jang, E., & Rhee, J. (2016). Drought assessment and monitoring through blending of multi-sensor indices using machine learning approaches. *Agricultural and Forest Meteorology*, 216, 157-169. https://doi.org/10.1016/j.agrformet.2015.10.011
23. [23] Lobell, D. B., & Field, C. B. (2007). Global scale climate-crop yield relationships and the impacts of recent warming. *Environmental Research Letters*, 2(1), 014002.
24. [24] Simelton, E., Fraser, E. D., Termansen, M., et al. (2009). Typologies of crop-drought vulnerability: An empirical analysis of the socio-economic factors that influence the sensitivity and resilience to drought of three major food crops in China. *Environmental Science & Policy*, 12(4), 438-452.
25. [25] Gorelick, N., Hancher, M., Dixon, M., et al. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 202, 18-27. https://doi.org/10.1016/j.rse.2017.06.031