SPATIO-TEMPORAL MODELING FOR THE ANALYSIS OF HYDROLOGICAL DROUGHT AND ITS IMPACT ON RICE PRODUCTION IN THE UPPER BENGAWAN SOLO BASIN, CENTRAL JAVA, INDONESIA

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ABSTRACT

Hydrological drought is a climate-induced disaster that directly impacts the agricultural sector, particularly rice production. This study aims to model drought in a spatial-temporal context and analyse its impact on rice production in the Upper Bengawan Solo River Basin, Central Java, Indonesia, over the period 2017–2024. The analysis was conducted using Geographic Information Systems (GIS) based on Sentinel-2A satellite imagery, annual rainfall data, and rice production records. Drought severity was quantified using the Normalised Difference Drought Index (NDDI). The results of the drought modelling were validated through correlation and regression analyses with rainfall data and the extent of drought-affected areas. Meanwhile, the impact of drought on rice production was assessed using non-parametric analysis via the LOWESS method. The findings indicate that the spatial-temporal approach is effective in identifying drought distribution and trends. Spatially, severe drought occurred in Wonogiri Regency, covering up to 1,203,014.20 hectares, while temporally, the peak occurred in 2018 with a drought area of 571,438.60 hectares. Validation tests revealed a strong positive correlation between NDDI values and drought extent ($r = 0.84$), and a negative correlation between NDDI and rainfall ($r = -0.74$), indicating that higher NDDI values correspond with wider drought-affected areas and lower rainfall. Linear regression analysis confirmed NDDI as a significant indicator for drought monitoring, with a coefficient of determination $R^2 = 0.706$, suggesting that 70.6% of the variance in drought area can be explained by NDDI, and a statistically significant p-value ($p = 0.009$, $p < 0.05$). Moreover, LOWESS analysis showed a non-linear (U-shaped) relationship between NDDI and rice production, with the highest yields at low NDDI values (2.42–2.44 million tons), declining at medium NDDI levels (~2.20 million tons), and rising again at high NDDI values (2.35 million tons). This pattern suggests that the impact of drought on rice production is not linear and is likely influenced by additional factors such as irrigation infrastructure and crop management practices. Overall, this study affirms that satellite-based spatial-temporal modelling is an effective approach for analysing hydrological drought and understanding its implications for agricultural productivity.

Key-words: *Spatio-temporal modelling; Hydrological drought; Sentinel-2A satellite imagery; Rice production.*

1. INTRODUCTION

Ongoing global climate change is contributing to rising temperatures and increasing instability in atmospheric conditions worldwide, resulting in more frequent extreme weather events (Hadibasyir et al., 2023; Mustikaningrum et al., 2023).

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According to the Meteorology, Climatology, and Geophysics Agency (BMKG), Indonesia is generally experiencing higher-than-average air temperatures. In fact, the average air temperature in September 2024 was the highest ever recorded for that month since 1981 (BMKG, 2025). These climate dynamics are causing fluctuations in regional water availability and have the potential to elevate the risk of drought, ultimately exerting negative impacts on the agricultural sector, particularly rice production (Anna et al., 2024; Arifin et al., 2023; Kumar et al., 2022; Sigit & Anna, 2023).

Drought is a hydrometeorological disaster that frequently affects various regions across Indonesia. Over the five-year period from 2020 to 2024, a total of 1,088 drought-related disasters were recorded, resulting in 23 fatalities, 104 injuries, 6,349,633 people affected, 810 displaced persons, and 11,895 damaged houses. In the Upper Bengawan Solo River Basin, which encompasses the cities and regencies of Surakarta, Boyolali, Klaten, Wonogiri, Sukoharjo, Sragen, and Karanganyar, 36 drought incidents were reported, causing 3 deaths, 4 injuries, 108,742 people affected, 5 displaced persons, and 321 damaged houses (National Disaster Management Agency, 2025).

The severity of the drought's impact has led residents in the study area to become more alert to such disasters, particularly as the region is dominated by food crop agriculture, with approximately 60% of the population engaged in the agricultural sector (Central Java Provincial Statistics Agency, 2024). Prolonged droughts can reduce water availability for irrigation and domestic use (Bibi & Rahman, 2023; Christian et al., 2023; Hussain et al., 2023; Zhang et al., 2023), and diminish rice production, ultimately threatening local food security (Laksono & Nurgiyatna, 2020; Safura & Sekaranom, 2024).

With technological advancements, the detection of hydrological drought can now be conducted rapidly using satellite imagery data through several approaches, including the Normalised Difference Vegetation Index (NDVI), Vegetation Health Index (VHI), Normalised Difference Water Index (NDWI), Land Surface Temperature (LST), and Normalised Difference Drought Index (NDDI). Each approach has its own strengths and limitations. A detailed summary of the advantages and disadvantages of each method is presented in **Table 1**.

Table 1.
Advantages and Limitations of Satellite Image-Based Drought Detection Index Methods.

Method	Drought Detection Process	Advantages	Limitations	Reference
Normalised Difference Vegetation Index NDVI)	Drought detection based on plant greenness	Most widely used for vegetation monitoring	Relies on a single parameter	(Mirzaee & Mirzakhani Nafchi, 2023)
Vegetation Health Index (VHI)	Drought detection based on vegetation health	More accurate than NDVI as it incorporates temperature factors	Requires additional indices	(Zeng et al., 2022)
Normalised Difference Water Index (NDWI)	Drought detection based on moisture and water content	More accurate than NDVI as it incorporates water-related factors	Susceptible to atmospheric interference and open land conditions	(Marfuah & Useng, 2023)
Land Surface Temperature (LST)	Detects drought based on land surface temperature	Capable of detecting drought thermally	Requires calibration due to strong influence of land cover and atmosphere	(Shashikant et al., 2021)
Normalised Difference Drought Index NDDI)	Drought detection combining vegetation, soil moisture, and water	More accurate than other methods as it combines NDVI and NDWI	Requires more complex multispectral data	(Artikanur et al., 2022; Mujiyo et al., 2023)

Meanwhile, drought trends and distribution can be effectively identified through spatio-temporal modelling using Geographic Information Systems (GIS) (Boori et al., 2022; Mohammed et al., 2023). Satellite imagery employed for hydrological drought analysis varies and includes Landsat, MODIS, and SENTINEL. Sentinel-2A satellite imagery is among the most widely used types due to its high spatial resolution and its capability to monitor vegetation and soil moisture regularly (Alonzo et al., 2023; Staszel et al., 2024; Varghese et al., 2021).

Several previous studies have analysed drought using satellite imagery through various vegetation index approaches. Almouctar et al. (2024) analysed drought using the NDVI index and soil surface temperature. Bashit et al. (2022) combined NDVI, NDWI, and LST in their research. Meanwhile, Wolteji et al. (2022) applied a satellite image-based approach incorporating several indices, namely the Normalised Difference Vegetation Index (NDVI), Vegetation Health Index (VHI), Land Surface Temperature (LST), and Normalised Difference Water Index (NDWI).

Regarding the use of spatio-temporal models for drought analysis, Alito and Kerebih (2024) stated that these models play a crucial role in agricultural decision-making, particularly in visualising the distribution and trends of drought within a region. Mirzaee and Mirzakhani Nafchi (2023) also noted that spatio-temporal models are highly effective in identifying variations in vegetation indices across a region and temporal trends. Details regarding the differences between previous research and the current study are presented in **Table 2**. Based on **Table 2**, it is evident that several studies have utilised satellite imagery to analyse drought using various vegetation indices such as NDVI, NDWI, LST, and VHI. Almouctar et al. (2024) and Bashit et al. (2022) combined several indices and validated their results with meteorological data; however, they did not apply spatio-temporal modelling or directly link the results to impacts on agricultural production.

Table 2.

Comparison with Previous Research.

Researcher	Index	Spatio-Temporal Approach	Analysis of Impact on Rice Production	Validation Method	Description
Almouctar et al., (2024)	NDVI and LST	No	No	Correlation validation with weather data & field observations	Focus on detecting vegetative drought and soil temperature
Bashit et al., (2022)	NDVI, NDWI, and LST	No	No	Cross-validation with meteorological data	Focus on vegetation index analysis only
Wolteji et al., (2022)	NDVI, VHI, LST, and NDWI	No	No	Statistical validation against historical data	Utilisation of various types of vegetation indices but no spatio-temporal analysis
Alito & Kerebih, (2024)	NDVI, LST, VCI, TCI	Yes	No	Spatio-temporal model validation with survey data	Emphasises the importance of spatio-temporal analysis in agriculture
Mirzaee & Mirzakhani Nafchi, (2023)	NDVI, NMDI	Yes	No	Temporal trend analysis and statistical validation	Analysing vegetation index trends based on spatio-temporal data
Santhyami, et al., (2024)	Sentinel-2A-based NDDI	Yes (2017–2024)	Yes (Rice production in the Upper Bengawan Solo River Basin)	Validation with statistical tests (correlation, regression, and non-parametric LOWESS analysis)	Combining multispectral imagery, spatio-temporal modelling, and real-world impacts on agricultural production

Wolteji et al. (2022) employed a more comprehensive combination of indices and statistical validation, but the integration of spatio-temporal modelling remained absent. Meanwhile, the studies by Alito and Kerebih (2024), as well as Mirzaee and Mirzakhani Nafchi (2023), are notable for their use of spatio-temporal modelling to observe drought trends and distribution over time, although neither explored the impact of drought on rice production.

In contrast to these previous studies, the present research integrates a multispectral approach using the NDDI with long-term spatio-temporal modelling and directly analyses the impact of drought on rice production. This is accomplished using various validation methods, including correlation analysis, regression analysis, and non-parametric LOWESS analysis. As such, this study offers a novel and comprehensive contribution to the field of drought and food security research. The study presents a robust observation-based drought monitoring model that not only delineates the spatial distribution and temporal dynamics of drought but also provides empirical evidence of the relationship between hydrological drought and declining rice production. The findings of this research can serve as a scientific basis for developing drought mitigation strategies and sustainable agricultural adaptation planning in drought- and flood-prone areas, such as the Upper Bengawan Solo River Basin.

2. STUDY AREA

The study area is the Upper Bengawan Solo Watershed, encompassing seven cities and regencies: Surakarta City, and the regencies of Sukoharjo, Boyolali, Klaten, Wonogiri, Karanganyar, and Sragen. The total area of the watershed spans 3,773.99 km^2. Astronomically, it lies between 110° 13'7.16"E and 110°26'57.10"E longitude, and between 7°26'33.15"S and 8°6'13.81"S latitude. The detailed location and boundaries of the study area are illustrated in **Figure 1**.

According to the Schmidt and Ferguson climate classification, the region falls under the moderate climate category, with an average annual rainfall of 119.45 mm in 2024, an average temperature of 27.4° C, and a mean relative humidity of 76%. The soil types identified in the region include alluvial, andosol, complex soils, grumusol, latosol, lithosol, mediterranean, and regosol. Lithosol is the most dominant soil type, covering 1,465.3 km^2, followed by regosol, which spans 951.3 km^2.

Land use within the watershed is diverse, comprising residential areas, commercial buildings and offices, rice fields, drylands, plantations, vacant land, and water bodies. The topography varies from flat and undulating plains to hilly and volcanic terrain. The majority of the area is relatively flat (with slopes of 0–<5%), covering 2,506.10 km^2.

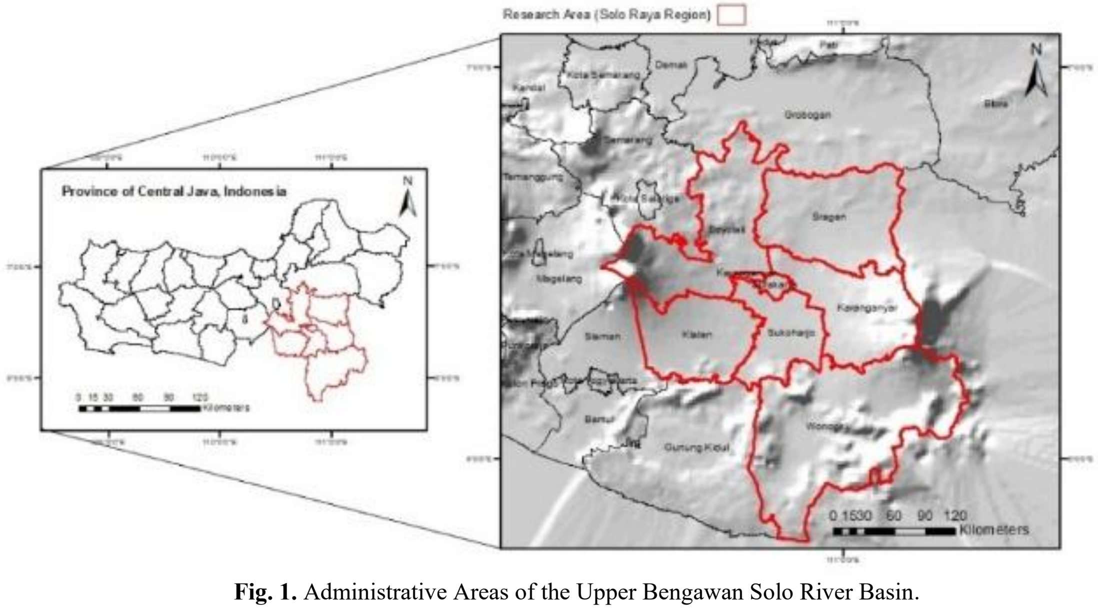

Fig. 1. Administrative Areas of the Upper Bengawan Solo River Basin.

Areas with slopes of 10-<30% account for 931.15 km^2, while the remainder consists of slopes between 5-<10% and above 30%. As of 2024, the population of the Upper Bengawan Solo Watershed reached 6,883,160, with an average population density of 2,689.29 inhabitants per km^2 and an annual population growth rate of 0.68%. The average sex ratio was recorded at 99.34. In the same year, total rice production in the study area amounted to 2,264,832 tonnes.

3. DATA AND METHODS

3.1. Sentinel-2A Satellite Imagery

Sentinel-2A satellite imagery is sourced from the Copernicus Open Access Hub, managed by the European Space Agency (ESA). This imagery is multispectral with high spatial resolution and encompasses 13 spectral bands, including: Band 1 (Coastal Aerosol), Band 2 (Blue), Band 3 (Green), Band 4 (Red), Band 5, 6, and 7 (Vegetation Red Edge), Band 8 (Near Infrared/NIR), Band 8A (Vegetation Red Edge), Band 9 (Water Vapour), Band 10 (Short-Wave Infrared/Cirrus), and Bands 11 and 12 (Short-Wave Infrared/SWIR). The spatial resolution of Sentinel-2A imagery varies by band, with resolutions of 10 m, 20 m, and 60 m (European Space Agency, 2025).

3.2. Image Preprocessing

Sentinel-2A imagery underwent atmospheric correction using the Sen2Cor Level-2A method, followed by geometric correction to align with the local UTM Zone 49S projection system. Annual composites were generated using the median composite approach to minimise the impact of residual cloud cover. Furthermore, spatial resolution enhancement was applied to the 20-metre bands through bilinear interpolation to improve image clarity.

3.3. Image Processing

At this stage, the following activities were carried out: atmospheric correction, geometric correction, image compositing, and image sharpening. Image processing was performed using a Geographic Information System (ArcGIS 10.3). Drought indices including NDVI, NDWI, and NDDI were calculated based on spectral band combinations, serving as indicators of vegetation condition and water availability. NDVI was employed to assess vegetation health, while NDWI was used to detect water content in both soil and vegetation. The NDDI index, combining NDVI and NDWI, served as a more integrated indicator of hydrological drought conditions. The specific formulae used for calculating each index are presented in **Table 3**.

Table 3.

Formulae for Calculating the NDVI, NDWI, and NDDI.

Spectral Vegetation Indices	Formulae	References
Normalised Difference Vegetation Index (NDVI)	$\frac{(\mathrm{NIR} - \mathrm{Red})}{(\mathrm{NIR} + \mathrm{Red})}$	(Ren et al., 2023)
Normalised Difference Water Index (NDWI)	$\frac{(\mathrm{Green} - \mathrm{NIR})}{(\mathrm{Green} + \mathrm{NIR})}$	(Shashikant et al., 2021)
Normalised Difference Drought Index (NDDI)	$\frac{(\mathrm{NDVI} - \mathrm{NDWI})}{(\mathrm{NDVI} + \mathrm{NDWI})}$	(Salas-Martínez et al., 2023)

3.4. NDDI Value Classification

The NDDI drought classification thresholds were adopted from relevant literature (Salas-Martínez et al., 2023) and locally adjusted based on the annual histogram distribution to ensure accurate representation of local conditions. The drought severity classification in the study area is based on NDDI values ranging from -1 to a maximum of 1. In this study, NDDI values are divided into five classes: water body, normal condition, mild, moderate, and severe drought. Further details are presented in **Table 4**.

Table 4.
Drought Severity Classification Based on NDDI Values.

NDDI Value Range	Drought Level
>0.46	Severe
0.4 – 0.6	Moderate
0.2 – 0.4	Mild
0 – 0.2	Normal Condition
≤ 0	Water Body

3.5. Spatio-Temporal Modelling of Hydrological Drought

Spatial modelling was conducted by overlaying annual NDDI maps with administrative boundaries of districts and cities within the Upper Bengawan Solo River Basin, resulting in a drought severity zoning map for each area. Meanwhile, temporal modelling involved analysing annual changes in drought index values over the period 2017–2024. This modelling process utilises Geographic Information System (GIS) technology, which facilitates the simultaneous integration and analysis of spatial and temporal data

3.6. Model Validation

Validation of the spatial-temporal model of hydrological drought in this study was performed using correlation and regression analyses between drought area, NDDI values, and rainfall. Data on drought area and NDDI values were derived from the spatial-temporal modelling results, while rainfall data were obtained from the Central Java Provincial Statistics Agency. Three primary relationships were analysed: (a) the correlation between drought area and NDDI values, (b) the correlation between drought area and rainfall, and (c) the correlation between NDDI values and rainfall. The Pearson correlation formulae applied is as follows:

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \cdot \sum(y_i - \bar{y})^2}} \tag{1}$$

Description:

r: Pearson correlation coefficient (between -1 and 1)
x_i, y_i: Observation values for each variable
$\bar{x}, \bar{y}$: Average value of variables x and y

Interpretation of r values:

$r>0.7$: Indicates a strong relationship
$0.3<r\leq 0.7$: Indicates a moderate relationship
$r\leq 0.3$: Indicates a weak relationship

Significance tests were performed to assess whether the observed relationships were statistically significant at confidence levels of 95% ($p < 0.05$) or 99% ($p < 0.01$). Additionally, simple linear regression was utilised to examine the effect of the independent variable (NDDI) on the dependent variables (rainfall or drought area). The formulae used is as follows:

$$Y = \alpha + bX + \varepsilon \tag{2}$$

Description:

Y: Rainfall (mm/year) and drought area (ha)
X: NDDI index value
α: Intercept (Y value when X= 0)
b: Slope or regression coefficient (average change in Y for every 1 unit increase in X)
ε: Error or residual (difference between observed and predicted values)

3.7. Analysis of Drought Impact on Agricultural Production

This analysis of the impact of drought on agricultural production employs the Locally Weighted Regression (LOWESS) method. The parameters used to assess this impact are NDDI values and rice production data. There are several advantages to using this model, including: (a) the relationship between NDDI values and rice production is non-linear, so a linear regression approach cannot accurately describe the pattern of this relationship; (b) LOWESS is highly flexible because it does not assume a specific functional form such as linear or quadratic, but rather adjusts the curve shape based on local data; and (c) this method is suitable for small datasets. Mathematically, the formulae for this method are as follows:

$$\hat{y}_i = \sum_{j=1}^{n} w_{ij} y_j \tag{3}$$

Description:

$\hat{y}_i$: Estimated value at point xi

w_{ij}: Weight for data point j relative to xi, calculated based on the distance xj to xi,

y_j: Actual value at point j

The weight w_{ij}, is calculated using the tri-cube kernel function:

$$w_{ij} = \left(1 - \left(\frac{|x_j - x_i|}{d_i}\right)^3\right)^3 \quad \text{for } |x_j - x_i| \leq d_i \tag{4}$$

where d_i s the distance to the n-th point from x_i, used as the local neighbourhood range (determined by the parameter frac, which represents the percentage of nearest neighbours).

4. RESULTS

4.1. Spatio-temporal Analysis of Drought within the Study Area

Spatial and temporal approaches are essential for identifying the distribution and trends of drought within the study area. The spatial analysis in this study focuses on classifying drought severity based on its spatial distribution (**Table 5**). Meanwhile, the temporal analysis aims to identify recurring drought trends over multiple years (**Table 6**). This spatial-temporal approach facilitates a more detailed examination of drought dynamics and provides valuable insights into the contributing factors and their impacts on agricultural productivity. Furthermore, the results of the spatial-temporal drought analysis in the Upper Bengawan Solo River Basin are illustrated in **Figure 2**.

Table 5.

Drought Area by Region in the Upper Bengawan Solo River Basin.

No	Region	Area by Drought Category				
		Severe	Moderate	Mild	Normal Condition	Water Body
1	Boyolali	669,649.90	79,661.80	68,319.90	51,063.20	3,998.20
2	Klaten	458,779.50	47,182.50	30,484.20	21,311.50	537
3	Karanganyar	445,737.20	61,256	59,625.20	76,244.80	286.2
4	Sragen	640,449.70	48,066.90	43,640.30	52,473.60	9,659.40
5	Wonogiri	1,203,014.20	127,679.70	94,406.80	89,375.40	16,493.90
6	Sukoharjo	321,648.80	18,956.20	20,489.10	30,918.10	1,005.10
7	Surakarta	4,604.40	33.9	33.7	0	0

Based on **Table 5**, it is evident that Wonogiri Regency experiences the most extensive severe drought, covering an area of 1,203,014.20 hectares, followed by Boyolali, Sragen, Klaten, Karanganyar, Sukoharjo, with Surakarta City having the smallest area of 4,604.40 hectares. Similarly, in the categories of moderate, mild, and non-drought (normal conditions), Wonogiri Regency consistently has the largest area. The distribution of drought severity across the study area corresponds closely to its geographical size.

Table 6.

Drought Area by Years in the Upper Bengawan Solo River Basin.

Year	Area by Drought Category				
	Severe (Ha)	Moderate (Ha)	Mild (Ha)	Normal Condition (Ha)	Water Bodies (Ha)
2017	492,440.60	42,983.50	32,334.20	33,380.90	2,494.60
2018	571,438.60	14,025.50	7,176.80	10,690.60	216.7
2019	184,943.70	1,740.60	267.6	203	15.3
2020	162,143.60	8,718.20	10,720.50	4,358.20	493.5
2021	159,050.10	15,177.90	8,738.00	6,485.40	2,017.20
2022	75,842.50	39,278.30	37,303.50	37,070.50	1,972.50
2023	176,373.50	6,174.80	3,186.10	4,032.80	1,711.50
2024	159,050.10	15,177.90	8,738.00	6,485.40	2,017.20

Based on **Table 6**, the area classified as severely dry fluctuates annually, peaking in 2018 at 571,438.60 ha, before decreasing significantly to 75,842.50 ha in 2022. The area under normal conditions also varies, showing an increase in 2022 (37,070.50 ha) after lower levels in preceding years. Additionally, the extent of water bodies changes each year, reaching its highest in 2017 (2,494.60 ha) and its lowest in 2019 (15.3 ha). A detailed spatial-temporal analysis of hydrological drought in the Upper Bengawan Solo River Basin is illustrated in **Figure 2**. Based on **Figure 2**, the spatial distribution shows that the southeastern part of the watershed, particularly Wonogiri and Sragen, consistently experiences severe drought throughout the year. This pattern is closely related to the hilly topography, which hinders water drainage, and the lower rainfall in these areas compared to the central regions such as Klaten and Sukoharjo.

4.2. Drought Model Validation

The validation of the spatial-temporal modelling results of hydrological drought in this study was conducted using statistical methods, specifically correlation and regression analyses. The variables involved were drought extent, NDDI values, and rainfall (**Table 7**). Data on drought extent and NDDI values were obtained from the spatial-temporal modelling results, while rainfall data were sourced from the Central Java Provincial Statistics Agency. Three primary relationships were examined: (a) the correlation between drought extent and NDDI values, (b) the correlation between drought extent and rainfall, and (c) the correlation between NDDI values and rainfall. The results of the correlation analysis are presented in **Table 8** and **Figure 3**, while the regression results are shown in **Table 9** and **Figure 4**. Based on **Table 7**, it can be observed that this study employs three main variables in the statistical tests (correlation and regression): the area affected by drought (in hectares), the drought index value (NDDI), and the average annual rainfall (mm/year) within the Upper Bengawan Solo River Basin (DAS) for the period 2017‑2024. These three variables exhibit significant fluctuations from year to year. In 2018, the drought-affected area reached its peak, coinciding with a spike in the NDDI value. Conversely, 2022 recorded the highest rainfall and the lowest drought extent. The patterns identified in this dataset provide a critical foundation for statistical testing, both in terms of correlation and regression, to better understand the interrelationship between drought dynamics and the climatic factors that influence them.

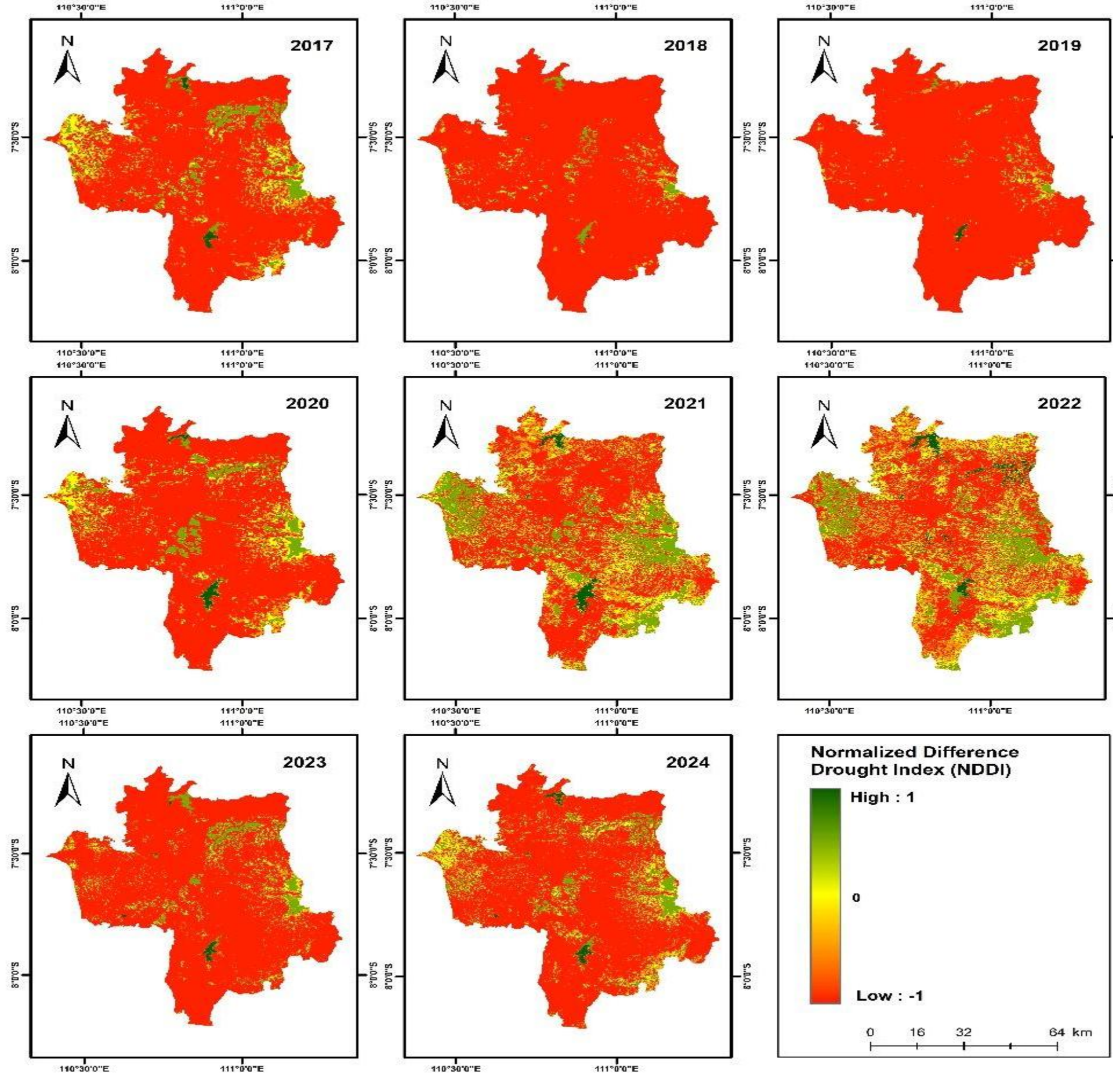

Fig. 2. Spatial-Temporal Map of Drought in the Upper Bengawan Solo River Basin.

Table 7.

Statistical Variables: Drought Area, NDDI Value, and Rainfall (2017–2024).

No	Year	Drought Area (Ha)	NDDI Value	Average Annual Rainfall (mm/year)
1	2017	567,758.30	0.82	65.81
2	2018	592,640.90	0.91	51.52
3	2019	186,951.90	0.76	82.04
4	2020	181,582.30	0.63	71.3
5	2021	182,966.00	0.64	117.13
6	2022	152,424.30	0.52	199.36
7	2023	185,734.40	0.71	165.39
8	2024	182,966.00	0.64	119.45

Table 8.
Pearson Correlation Results Between Research Variables.

Relationship	Correlation Coefficient (r)	p-value	Interpretation
Drought Area vs NDDI Value	0.840	0.009	Strong and statistically significant (positive)
Drought Area vs Rainfall	-0.633	0.092	Moderate and not statistically significant (negative)
NDDI Value vs Rainfall	-0.738	0.037	Strong and statistically significant (negative)

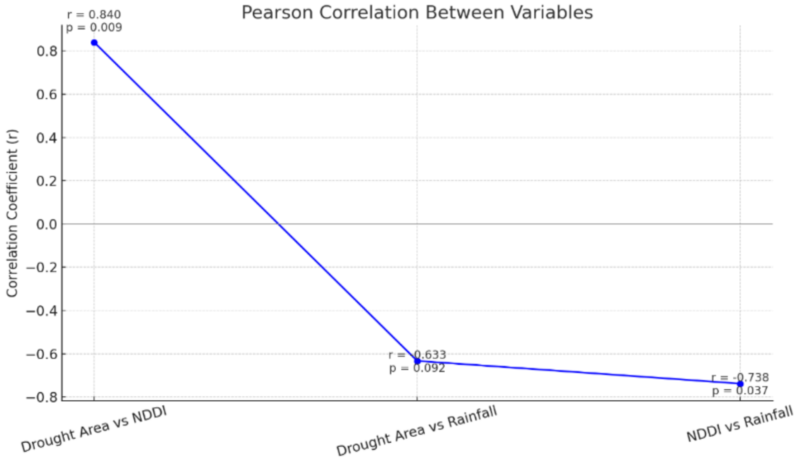

Fig. 3. Graph of Pearson Correlation Test Results between Research Variables.

The results of the Pearson correlation test indicate a strong and statistically significant positive relationship between the drought-affected area and the NDDI value, with a correlation coefficient of 0.840 and a p-value of 0.009. In contrast, the relationship between drought extent and rainfall shows a moderate negative correlation (-0.633), but it is not statistically significant (p-value = 0.092). Meanwhile, the correlation between NDDI and rainfall is strong and negative (-0.738) and statistically significant, with a p-value of 0.037. These findings reinforce that the NDDI is a relatively sensitive indicator in describing drought severity, as it is positively correlated with the expansion of drought-affected areas and negatively correlated with rainfall. On the other hand, the insignificant relationship between rainfall and drought extent suggests that rainfall alone is insufficient to explain the severity of drought impacts. Therefore, the use of composite indices such as the NDDI, which incorporate aspects of vegetation cover and soil moisture is essential for more comprehensive and accurate drought monitoring.

Table 9.
Simple Linear Regression Results Between Research Variables.

Relationship	Regression Equation	R^2	p-value	Interpretation
NDDI Value vs Rainfall	Rainfall = -310.05 × NDDI + 327.20	0.544	0.037	Significant, moderate negative relationship
Drought Area VS NDDI Value	Drought Area = -2,273.45 × Rainfall + 526,934.45	0.401	0.092	Not significant, weak negative relationship
NDDI Value VS Drought Area	Drought Area = 1,268,283.31 × NDDI - 613,426.37	0.706	0.009	Significant, strong positive relationship

Fig. 4. Graph of Regression Test Results Between Research Variables.

Based on **Table 9** and **Figure 4**, the relationship between NDDI and rainfall has an R^2 value of 0.544 and a p-value of 0.037, indicating a moderate negative relationship that is statistically significant. The relationship between rainfall and drought area shows an R^2 of 0.401 and a p-value of 0.092, suggesting a weak negative relationship that is not statistically significant. Meanwhile, the relationship between NDDI and drought area yields an R^2 of 0.706 and a p-value of 0.009, reflecting a strong and statistically significant positive relationship.

These findings indicate that NDDI is a fairly reliable indicator for predicting hydrological drought conditions, given its strong and significant relationship with the extent of drought. In contrast, rainfall does not significantly influence the drought area, which may be due to other factors such as infiltration efficiency, irrigation water use, or soil response time to precipitation. The negative relationship between NDDI and rainfall further confirms that NDDI values tend to increase when rainfall decreases, signaling drought conditions. These results emphasize the importance of using image-based indices such as NDDI for comprehensive spatial and temporal drought monitoring.

4.3. The Impact of Drought on Agricultural Productivity

The analysis of the impact of modelled drought on agricultural production in this study was carried out using the Locally Weighted Regression (LOWESS) method. The parameters used to assess this impact were NDDI values and rice production data (**Table 10**). The complete results of the calculations using this method are presented in **Table 11** and **Figure 5**.

Table 10.

Statistical Variables: Drought Area, and Rice Production (2017–2024).

No	Year	Drought Area (Ha)	Rice Production (Tons)
1	**2017**	567,758.30	2,265,487
2	**2018**	592,640.90	2,353,781
3	**2019**	186,951.90	2,310,156
4	**2020**	181,582.30	2,439,558
5	**2021**	182,966.00	2,196,267
6	**2022**	152,424.30	2,422,889
7	**2023**	185,734.40	2,219,016
8	**2024**	182,966.00	2,264,832

Based on **Table 10**, this study utilises two statistical variables to assess the relationship between drought severity and agricultural productivity: the area affected by drought (in hectares) and annual rice production (in tonnes) within the Upper Bengawan Solo River Basin from 2017 to 2024. Throughout the observation period, both variables exhibit significant year-to-year fluctuations. The most extensive drought area was recorded in 2018, yet rice production remained relatively high. Conversely, the smallest drought-affected area occurred in 2022, which coincided with the peak in rice production. Interestingly, rice yields did not consistently decline during years of more severe drought, indicating that the correlation between these variables is not strictly linear.

Table 11.

Comparison of Actual and Estimated Rice Production Based on LOWESS Against NDDI Values (2017–2024).

No	Year	NDDI Value	Rice Production (Tonnes)	Estimated Production (LOWESS), (Tonnes)
1	**2017**	0.82	2,265,487	2,297,082
2	**2018**	0.91	2,353,781	2,345,025
3	**2019**	0.76	2,310,156	2,265,821
4	**2020**	0.63	2,439,558	2,239,768
5	**2021**	0.64	2,196,267	2,237,174
6	**2022**	0.52	2,422,889	2,422,889
7	**2023**	0.71	2,219,016	2,231,535
8	**2024**	0.64	2,264,832	2,237,174

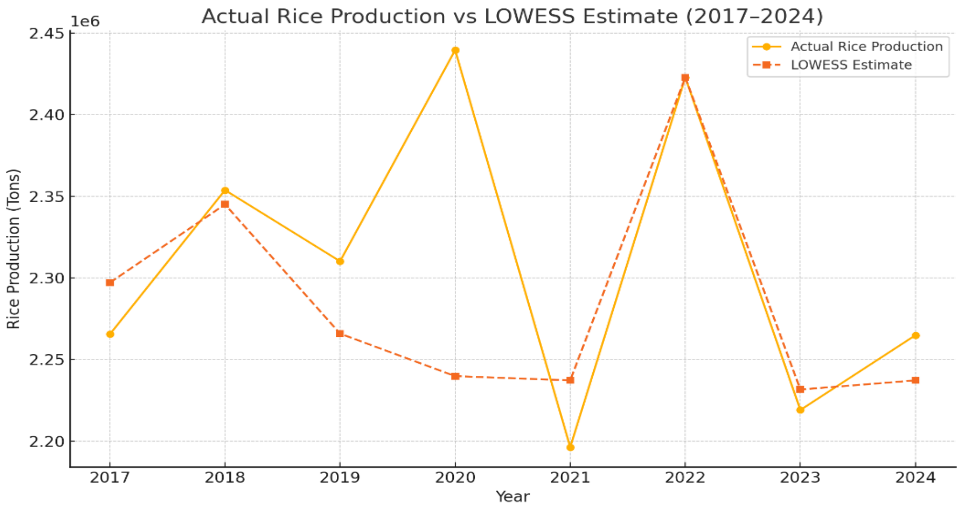

Fig. 5. Comparison Graph of Actual and Estimated Rice Production using the LOWESS Method.

Based on **Table 11** and **Figure 5**, the data points show a non-linear distribution. At lower NDDI values (approximately 0.52–0.63), rice production is relatively high (2.42–2.44 million tonnes). Production then decreases to its lowest point (2.20 million tonnes) at moderate NDDI levels (0.64–0.71), before increasing again at high NDDI values (0.91), with a production of 2.35 million tonnes. The LOWESS curve (red line) follows this pattern: it declines sharply from an NDDI of 0.52 to around 0.70, then rises again towards an NDDI of 0.91. This pattern indicates a non-linear relationship: rice production does not respond monotonically to NDDI values, but instead reaches its lowest point at moderate NDDI levels and is relatively higher at both low and high extremes.

5. DISCUSSION

The spatio-temporal model has proven effective in analysing trends and the distribution of hydrological drought in the Upper Bengawan Solo River Basin. This approach enables the visualisation of drought dynamics both temporally, through annual trend graphs, and spatially, through drought distribution maps across districts and cities. Validation results via statistical tests indicate a very strong positive correlation between drought-affected areas and the drought index (NDDI), with a coefficient ($r = 0.84$; $p < 0.01$), suggesting that increases in NDDI are aligned with the expansion of drought-affected areas. A significant negative correlation was also found between NDDI and annual rainfall ($r = -0.73$; $p < 0.05$), indicating that increased rainfall tends to reduce drought intensity. Meanwhile, a moderate yet statistically insignificant negative correlation was observed between rainfall and drought extent ($r = -0.63$; $p > 0.05$), implying that annual rainfall is not the sole determining factor. These findings are consistent with previous studies (Arias et al., 2024; Bolan et al., 2024; Harini et al., 2022), which have similarly concluded that rainfall is not the primary cause of drought. This supports the application of composite indices such as NDDI in more comprehensively representing drought conditions.

The choice of approach and satellite imagery is critical to determining the accuracy of drought models. This study employed the NDDI method due to its ability to integrate vegetation information (NDVI), soil moisture (NDWI), and water availability, thereby offering more representative drought estimates than conventional methods. These findings align with Salas-Martínez et al. (2023), who affirmed NDDI's effectiveness in identifying hydrological drought. Furthermore, the use of Sentinel-2A imagery supports detailed monitoring of vegetation and soil moisture owing to its high spatial and temporal resolution. This is reinforced by studies by Alonzo et al. (2023) and Staszel et al. (2024), which confirm Sentinel-2A as one of the most suitable multispectral datasets for ecological and agricultural analysis. Nonetheless, satellite imagery interpretation remains constrained by atmospheric disturbances, which may affect data accuracy.

As a vegetation and drought monitoring tool, NDDI offers advantages by integrating various biophysical parameters for rapid and effective identification of hydrological drought. The use of this index enables near real-time field condition estimation and provides reliable information for decision-making. Studies by Del-Toro-Guerrero et al. (2022) and Gelata et al. (2023) also demonstrate that NDDI-based spatio-temporal modelling can accurately assess drought conditions in specific regions. The effectiveness of this method makes it a key component of early warning systems and risk assessments for agriculture and water resources.

The model developed in this study was also applied to analyse the impact of drought on rice production in the study area. The analysis revealed that the relationship between drought extent and rice production is non-linear, necessitating the use of non-linear regression approaches (Cahyono et al., 2023). The LOWESS regression model was adopted to capture this pattern and showed that in several years with severe drought, rice production remained stable or even increased. This suggests the presence of other interventions such as efficient irrigation systems, the adoption of drought-tolerant varieties, and adaptive land management practices. These findings are in line with Del-Toro-Guerrero et al. (2022), who emphasised the critical role of socio-technical factors in maintaining food production resilience under drought stress.

This study provides a significant contribution to the development of remote sensing-based drought monitoring models in Indonesia, particularly for the agricultural sector, which is highly vulnerable to climate change. The integration of spatio-temporal modelling, the selection of appropriate vegetation indices, and rigorous statistical validation result in an analytical framework that is not only accurate but also practical. This model can serve as a foundation for agricultural adaptation planning and drought risk mitigation policy, both at local and national levels.

Future research is recommended to incorporate long-term climatic indices such as the Standardised Precipitation Index (SPI) and the Standardised Precipitation Evapotranspiration Index (SPEI) to enable broader climatological drought analysis. The application of machine learning methods also holds the potential to enhance drought prediction accuracy by integrating multiple data sources. Moreover, integration with field data such as actual harvest yields, irrigation conditions, and local farming practices is crucial to refining the model and producing more precise policy recommendations for addressing climate change challenges in the agricultural sector.

6. CONCLUSIONS

This study successfully mapped the spatial and temporal dynamics of drought in the Upper Bengawan Solo River Basin from 2017 to 2024 using the NDDI index derived from Sentinel-2A imagery. Wonogiri, Boyolali, and Sragen were identified as the most severely affected areas, while urban regions such as Surakarta remained relatively unaffected. This distribution was influenced by topographical conditions, low rainfall levels, and the size of the regions. Temporally, drought exhibited sharp annual fluctuations, peaking in 2018 and decreasing significantly in 2022.

The NDDI index demonstrated a strong correlation with both the extent of drought-affected areas and rainfall, and it proved to be a more reliable predictor than rainfall alone in the linear regression model. This affirms the effectiveness of NDDI as a tool for drought monitoring and early warning systems. Furthermore, the LOWESS model used to estimate rice production based on NDDI values closely approximated actual yields, despite some limitations in years where NDDI values were identical. These findings underscore the potential of remote sensing integration to support food security and sustainable drought management. Future research is recommended to incorporate additional climatic variables and machine learning approaches to improve the accuracy of drought and agricultural yield predictions.

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