# Spatio-Temporal Modeling of Agricultural Drought in Indramayu Using the NDDI Index (2015-2024)

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**Abstract.** This study examines the spatio-temporal patterns of agricultural drought in Indramayu Regency, Indonesia, using the Normalized Difference Drought Index (NDDI) derived from Landsat imagery between 2015 and 2024. The analysis employed spatial autocorrelation techniques, including Global Moran's I and Local Indicators of Spatial Association (LISA), to identify spatial clustering and persistence of drought conditions. The results show consistent spatial vulnerability, with the southern region forming stable High-High drought clusters across multiple years, while the northern region remains dominated by Low-Low clusters. These findings indicate that drought distribution in Indramayu demonstrates strong spatial persistence and temporal continuity, reflecting long-term environmental and land-use characteristics. A supporting correlation analysis between NDDI and rice productivity ($\rho$ = 0.164; p-value = 0.651) revealed no significant relationship, suggesting that effective irrigation systems have mitigated the impact of meteorological drought on agricultural output. Overall, the study highlights the need for location-specific drought management in spatially vulnerable southern areas to enhance agricultural resilience and regional food security.

**Keyword:** Agricultural Drought, Indramayu, NDDI, Rice Productivity, Spatio-temporal.

## 1. Introduction

Increased frequency, duration, and intensity of drought in various regions have become one of the most significant climate challenges facing the 21st century. According to the World Meteorological Organization (WMO), global warming is currently estimated to be between 1,34 and 1,41 °C compared to the 19th and 20th centuries [1]. Global temperature records were set from 2023 to 2024, mainly due to the continuous increase in greenhouse gas emissions, accompanied by the transition from La Niña to El Niño [2]. Meanwhile, the drought in Indonesia is caused by land use adaptation, suboptimal irrigation systems, and El Niño effects [3]. These then became factors affecting climate dynamics in Indonesia. According to BMKG data 2025, 2023-2024 dry seasons caused by El Niño have resulted in a 50-90% decrease in rainfall in various regions, especially during the 2023 dry season, dry reservoirs and water sources, an increase in hotspots in several regions, and disruption to planting and a decline in food production. In 2025, Indonesia is predicted to experience its peak drought in August [4]. However, the duration of the dry season in 2025 is predicted to be shorter than usual.

This drought phenomenon is linked to climate change [5]. Climate change occurs due to long-term shifts in average weather patterns, caused mainly by human activities. The burning of fossil fuels is the primary source of greenhouse gas (GHG) emissions, such as carbon dioxide ($CO_2$), methane ($CH_4$), and nitrous oxide ($N_2O$). These gases accumulate in the atmosphere and cause the greenhouse effect, which increases the Earth's average temperature. This rise in temperature has resulted in various adverse consequences, including melting ice in the polar regions, rising sea levels, extreme climate patterns, and damaging ecosystems that threaten biodiversity [6].

Advances in remote sensing technology have opened up enormous opportunities for sustainable drought monitoring, especially in the agricultural sector, which is highly vulnerable to climate change. Satellite imagery such as Landsat is instrumental because it provides long-term data with medium spatial resolution that enables comprehensive analysis of changes in vegetation and soil moisture [7]. For example, research in Subang and Karawang shows that the Landsat-based Vegetation Health Index (VHI) can detect significant declines in vegetation health due to drought [8]. This satellite image-based approach allows for large-scale monitoring. It is more efficient than conventional methods such as manual rainfall measurement, field observation, or farmer reports, making it particularly relevant for regions such as the Indramayu Regency, which has complex seasonal patterns and rainfall.

One method that can be used in satellite-based drought monitoring is the Normalized Difference Drought Index (NDDI) [9] [10] [11]. NDDI combines two primary indices, NDVI and NDWI, which reflect vegetation and moisture conditions, making it a more holistic indicator for detecting drought symptoms [12]. NDDI provides more accurate information about drought dynamics because it can simultaneously capture changes in land cover and water availability. Therefore, this approach is important in routine monitoring and spatial-temporal mitigation of drought impacts. A spatial-temporal approach is used to comprehensively understand the relationship between drought variables and environmental factors in space and time to support this analysis. This approach has proven effective in identifying long-term drought patterns and their impact on agricultural yields, as demonstrated by

Rahman et al. [13] analyzed drought impacts in Punjab, Pakistan (2001–2020) using MODIS-derived indices (VCI, TCI, VHI) combined with crop yield residuals, finding severe droughts in 2002 and 2008 that reduced yields by 39% in rice, 34% in sugarcane, and 25% in wheat; regression analysis showed VHI best predicted gram yields ($R^2 = 0.49$), while VCI was strongest for sugarcane ($R^2 = 0.56$) and rice ($R^2 = 0.29$). Their resilience analysis classified gram, sugarcane, and maize as highly non-resilient, wheat and rice as moderately non-resilient, and barley and cotton as more resilient [13]. However, Rahman's study was limited to MODIS coarse-resolution data and retrospective analysis without forward-looking projections. Similarly, Sholihah et al. (2016) assessed agricultural drought in Karawang and Subang using Landsat-based VHI but only for selected years (2000, 2005, 2010, and 2015), providing limited temporal coverage and no predictive insights [14].

To overcome these limitations, this study applies the Landsat-based NDDI approach in Indramayu Regency for 2015–2024 and employs simple linear regression to project drought conditions for 2025 and 2030. This approach is expected to provide a more comprehensive perspective on agricultural drought dynamics and support regional climate adaptation planning in agriculture. This study was conducted to analyze drought in agricultural land in Indramayu Regency from 2015 to 2024 using Landsat data and the NDDI approach [15]. The information generated is expected not only to describe historical conditions but also to be used to support medium-term projections until 2030. This is important for regional policy planning in facing the challenges of climate change while contributing to the achievement of the Sustainable Development Goals (SDGs), particularly in the aspects of food security (SDG 2) and action on climate change (SDG 13) [16]. This study provides a strategic foundation for developing region-based climate adaptation programs and priority sectors.

Previous research on drought analysis in Indonesian agricultural areas using the NDDI approach has been conducted. However, most of it has focused on a limited period and has not included long-term projections. Long-term projections are crucial for anticipating future droughts over multiple years, enabling proactive measures to reduce crop losses and manage water efficiently. Based on these projections, policies can include adjusting planting schedules, promoting drought-resistant crops, improving irrigation and water storage, establishing early warning systems, and supporting long-term climate adaptation programs. This study aims to fill this gap by analyzing the dynamics of agricultural drought in Indramayu Regency from 2015 to 2024 using the NDDI approach and utilizing simple linear regression analysis to forecast drought in 2025. This approach is expected to provide a more comprehensive overview and support more effective climate change adaptation planning at the regional level, while also considering how agricultural drought in one area can be related to surrounding regions; using a spatial model allows the study to capture these inter-regional connections and improve the accuracy of drought monitoring and prediction.

## 2. Research Method

The selection of the study area is a crucial first step, as the physical and socio-economic characteristics of a region strongly influence the dynamics of drought under investigation. Accordingly, this research begins with a detailed description of the study area, followed by a comprehensive explanation of the data sources used, and concludes by outlining the analytical methods applied.

### *2.1. Study area*

This research is located in Indramayu Regency, West Java, which is widely recognized as one of the main rice barns in Indonesia in figure 1. Most of the Indramayu area is agricultural land, primarily technical and non-technical irrigated rice fields, mainly supporting the community's livelihood. The contribution of the agricultural sector, especially rice, makes this area strategic in supporting national food security. With an area dominated by productive rice fields, Indramayu is the center of West Java's rice production [16].

However, Indramayu's agro-climatic conditions are in the coastal area, making it highly vulnerable to seasonal drought. The study shows that drought in this region can occur almost yearly, especially during the long dry period. Severe to extreme drought generally lasts from April to November, with the highest intensity in September, reaching more than 80% of the affected area [17]. The impact of this drought is significant as it directly affects the availability of irrigation water and rice production. With the dominance of the agricultural sector and its vulnerability to drought, Indramayu is a clear example of a productive agricultural region that faces significant challenges in maintaining the food system's sustainability. Therefore, studies on drought in this area are important to support mitigation and adaptation strategies to climate variability.

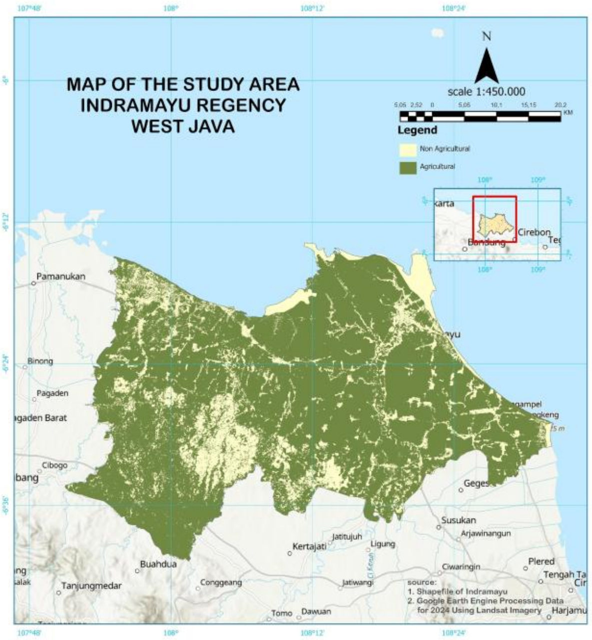


**Figure 1.** Study area.

*2.2. Data*

This study uses three primary data sets to project agricultural drought in Indramayu Regency, they are Landsat 8/9 imagery, administrative data, and agricultural productivity data. The table below explains the three data types and their sources and uses. This combination of remote sensing data and statistical data is used for spatial and temporal analysis of drought conditions in the region.

**Table 1.** Research data.

| Data | Source | Variable Used in Modeling | Data Utilization |
|---|---|---|---|
| Shapefile of Indramayu | Indonesia Geospasial | Administrative Boundary (spatial extent) Subdistrict of Indramayu | Determine administrative boundaries of the study area. |
| Landsat 8/9 Level 2 Imagery | United States Geological Survey (USGS) & Google Earth Engine | NDDI (Normalized Difference Drought Index) | Analyze drought conditions through the NDDI. |
| Average NDDI Data 2015-2024 | Author's processing of Landsat-derived NDDI (2025) | Mean NDDI Value | Used for spatial autocorrelation analysis, including Local Indicators of Spatial |

| | | | |
|---|---|---|---|
| | | | Association (LISA) and Global Moran's I. |
| Rice Productivity Data of Indramayu Regency | Open Data Jabar (2015-2020)<br>Badan Pusat Statistik Jawa Barat (2021-2024) | Rice Productivity (ton/ha) | Analyze the relationship between rice productivity and drought conditions using Spearman's Rank Correlation. |

*2.3. Methods*

This research uses remote sensing data from Landsat 8 and 9 Level 2 satellite imagery from 2015 to 2024. Imagery has been radiometrically corrected and cloud masking has been applied to obtain more representative observations in accordance with real conditions. Subsequently, drought index analysis uses NDDI and simple linear regression statistical models to predict drought in 2025. The flow diagram of this research is shown in figure 2.

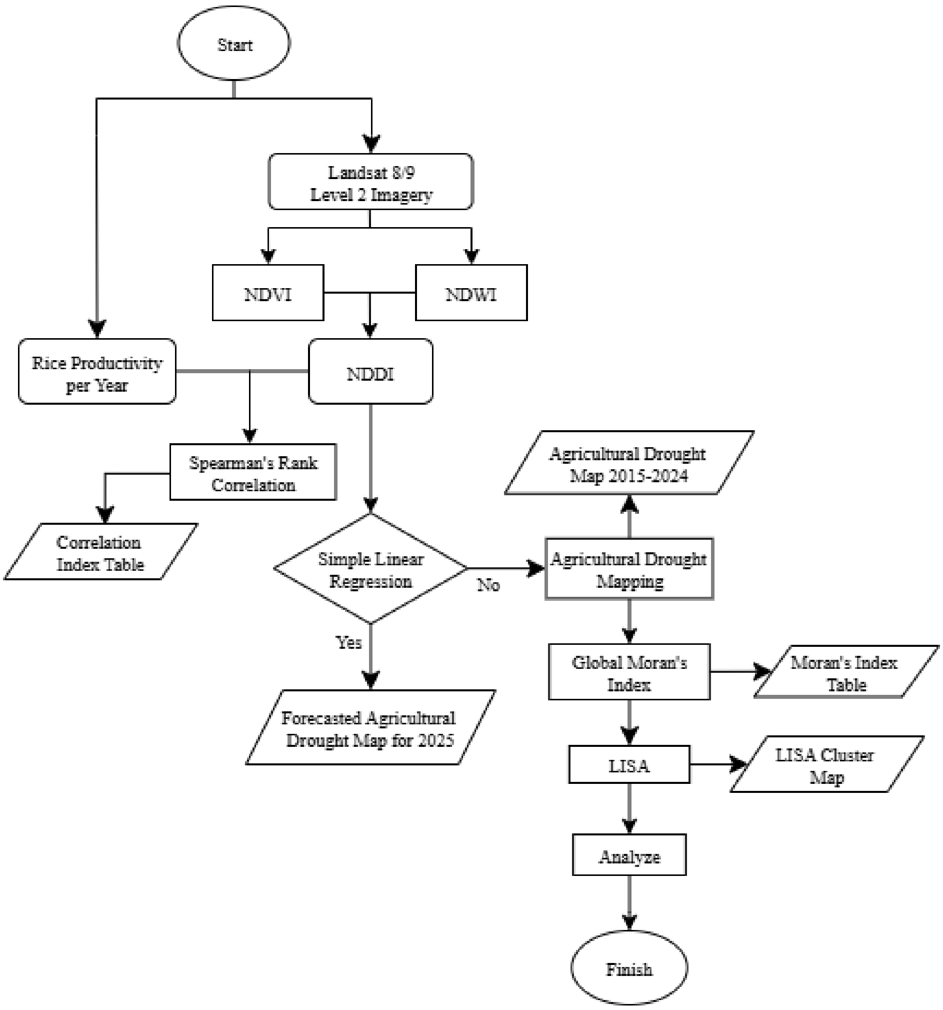


**Figure 2.** Research flowchart

*2.3.1. Spatio-temporal*

Spatio-temporal analysis is an integrative approach that combines two analytical dimensions, namely spatial and temporal. The spatial approach is employed to identify the interrelationships between regions through spatial autocorrelation analysis. Spatial autocorrelation refers to the correlation between the values of a single variable, which indicates the degree of similarity of an object with its neighboring objects in geographic space, thereby explaining the level of homogeneity or heterogeneity among observation locations [18]. The spatial interaction patterns can be examined both globally using the Global Moran's I and locally using the Local Indicators of Spatial Association (LISA) [19]. The spatial relationship among sub-districts was determined using a distance-based spatial weighting matrix (W) to capture proximity effects between locations.

Meanwhile, the temporal analysis utilizes time-series NDDI data at the regency level from 2015 to 2024 to identify drought trends over time. The integration of these two approaches allows for the examination of spatial evolution occurring across temporal dimensions. This enables a deeper understanding of how the spatial patterns of drought have evolved over time.

*2.3.2. NDDI*

NDDI is a drought index derived from calculations of Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) [20]. NDVI is an index for measuring vegetation density and vegetation health obtained from the ratio of the NIR band (band 5) and the RED band (band 4) from Landsat 8 and 9 satellite imagery. This is based on the principle that vegetation health absorbs the RED band and reflects the NIR band [21]. Meanwhile, NDWI is an index used to measure moisture content in vegetation using the SWIR band (band 6) and NIR band (band 5) [22]. The following is the formula used for NDDI:

$$NDDI = \frac{NDVI - NDWI}{NDVI + NDWI} \tag{1}$$

The formulas for obtaining NDVI and NDWI are as follows:

$$NDVI = \frac{Band\ 5 - Band\ 4}{Band\ 5 + Band\ 4} \tag{2}$$

$$NDWI = \frac{Band\ 5 - Band\ 6}{Band\ 5 + Band\ 6} \tag{3}$$

The classification of drought severity based on NDDI values is presented in table 2.

**Table 2.** Drought Categories Based on NDDI Classes

| Classes | NDDI Value |
|---|---|
| No Drought | -1 to +0.2 |
| Mild Drought | 0.2 to 0.3 |
| Moderate Drought | 0.3 to 0.4 |



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| | |
|---|---|
| Severe Drought | 0.4 to 0.5 |
| Extreme Drought | 0.5 to +1 |

*Source: Bhendekar et al. 2025* [23]

*2.3.3. Simple Linear Regression*

Simple linear regression is a statistical method that involves one independent variable and a dependent variable through a straight line equation [24]. The independent variable used is the year from 2015 to 2024 and the dependent variable is the NDDI value per pixel each year, which is then predicted. The formula used is as follows.

$$NDDIpixel = a + b * Years \tag{4}$$

Explanation:

$a$ as the intercept value of NDDI in year-0

$b$ as the upward/downward trend of NDDI in that year

*2.3.4. Spearman's Rank Correlation*

Spearman's rank correlation is used for non-parametric and monotonic measurements, which helps analyze the relationship between two variables [25]. The two variables in this research are the correlation between the average value of NDDI and rice productivity data for each year. The purpose is to determine whether drought severity, as represented by the NDDI index, has a statistically significant association with variations in rice productivity and to provide a complementary perspective to linear correlation analysis, especially when the data may not fully meet the assumptions of normality or linearity.

*2.3.5 Global Moran's I and LISA*

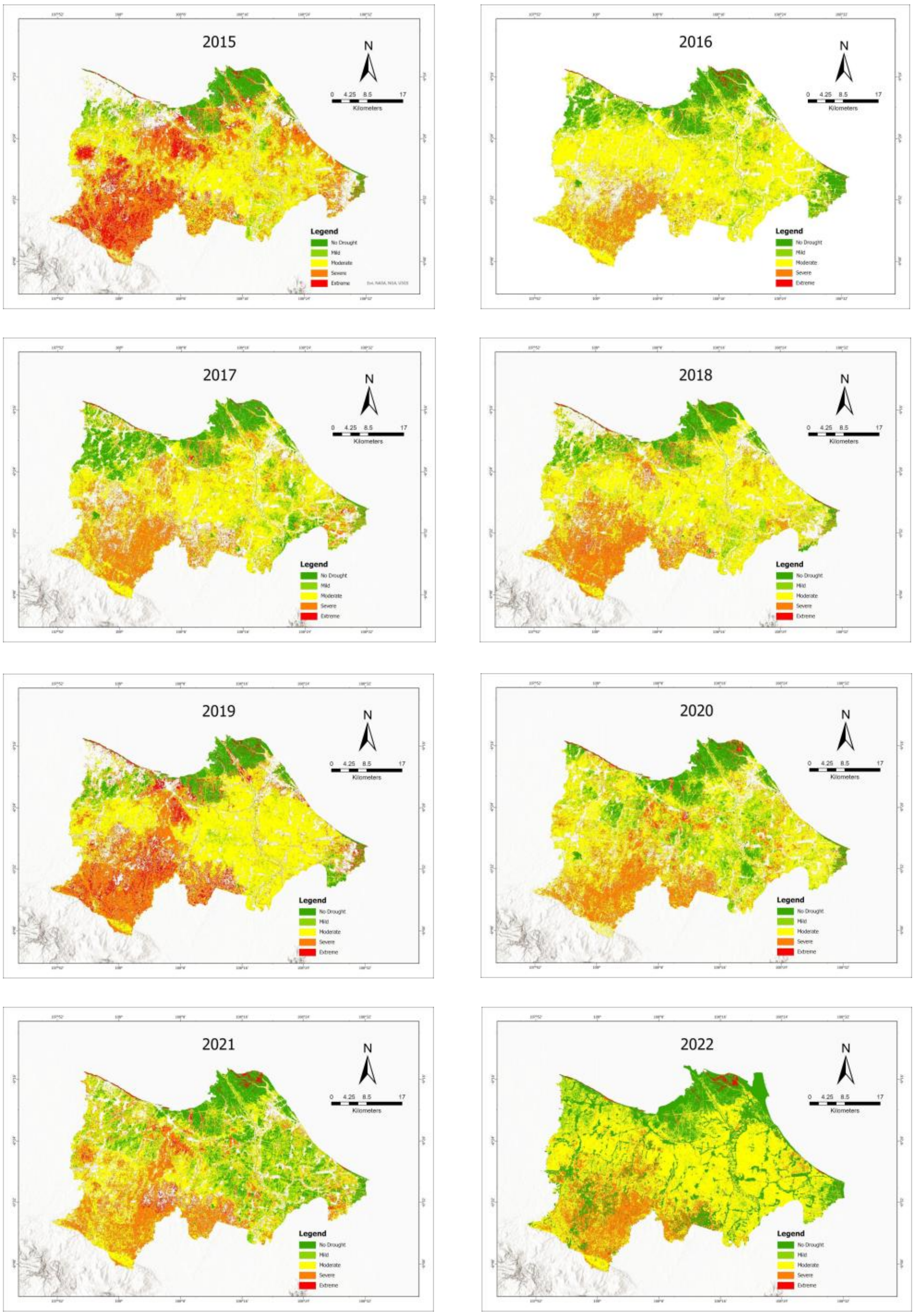
The Moran Index is a statistical test used to examine the presence of spatial autocorrelation [26]. In the drought mapping of Indramayu, Global Moran's I was used to measure the overall spatial patterns of drought in each year. In addition, the Local Indicators of Spatial Association (LISA) identified specific locations of spatial clusters and outliers that share similarities or differences with their surrounding areas [27]. Through the LISA analysis, the mapping results will show clusters with high or low drought levels. By mapping drought conditions from 2015 to 2024, the sub-districts experiencing consistent droughts can be identified.

## 3. Result and Discussion

Following the methodological framework established in the previous section, the analysis was conducted to model and understand drought patterns in Indramayu. The results and their implications are presented and discussed in the following subsections.

*3.1 NDDI 2015-2024 Modeling Results*

The NDDI modeling results for the 2015–2023 period reveal considerable spatial variability in drought intensity across the Indramayu region. Areas represented by red and orange tones correspond to zones experiencing high to moderate levels of drought, whereas yellow and green areas indicate relatively normal to wet conditions. In general, the southern and western parts of Indramayu exhibit a higher frequency and persistence of drought than the northern areas, highlighting a spatial disparity in drought vulnerability within the region.



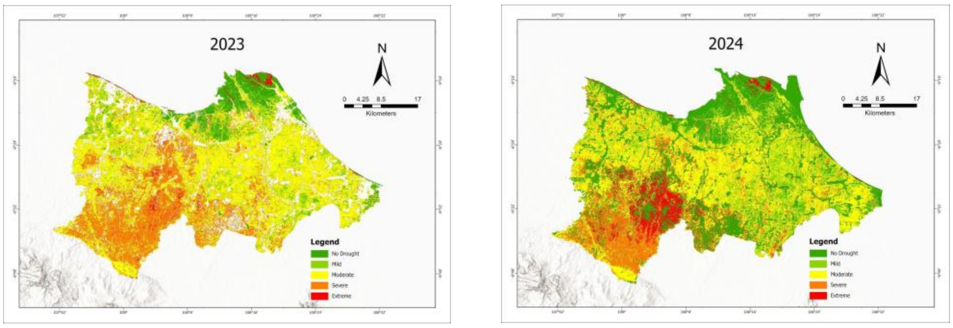



**Figure 3.** Agricultural Drought Maps of Indramayu District for the Period 2015-2024

In 2015, drought conditions peaked, with extensive red and orange zones dominating the entire region, particularly across the southern lowlands. This pattern reflects the influence of a strong El Niño event, which significantly reduced rainfall. By 2016, conditions showed notable improvement, as indicated by the broader distribution of yellow and green areas on the NDDI map, suggesting increased groundwater availability and relatively better moisture conditions. Nevertheless, in 2017, drought conditions re-emerged, particularly in the southern and western parts of the region, although the severity was lower compared to 2015.

The spatial models for the period 2018 to 2020 indicate relatively fluctuating conditions. In 2018, several areas experienced moderate drought, while in 2019, the extent of dry areas increased, especially in the central region. A slight recovery was observed in 2020, with the expansion of yellow and green zones, although several western districts continued to experience moderate drought. These interannual variations suggest the presence of a recurring drought cycle occurring at intervals of approximately two to three years.

Building upon the fluctuating drought patterns observed during 2015-2020, from 2021 to 2023 exhibited less extreme variability. In 2021, orange-colored zones indicating moderate drought remained present in the southern part of the region, although overall conditions were comparatively better than those recorded in 2019. A notable improvement occurred in 2022, when green areas dominated much of the region, reflecting enhanced water availability and a temporary recovery from drought stress.

However, in 2023, moderate drought conditions re-emerged in several western and central districts, demonstrating the persistence of spatially uneven drought risks. The 2024 projection further illustrates a mixed pattern, with predominantly green conditions in the northern areas alongside red-orange zones in the southern region, suggesting the likelihood of localized drought events rather than a widespread phenomenon.

*3.2 Forecasted Agricultural Drought for 2025 Result*

Building upon the historical analysis of drought patterns, a forecast was developed to project potential agricultural drought conditions for the year 2025. The forecast results are visualized in figure 4.

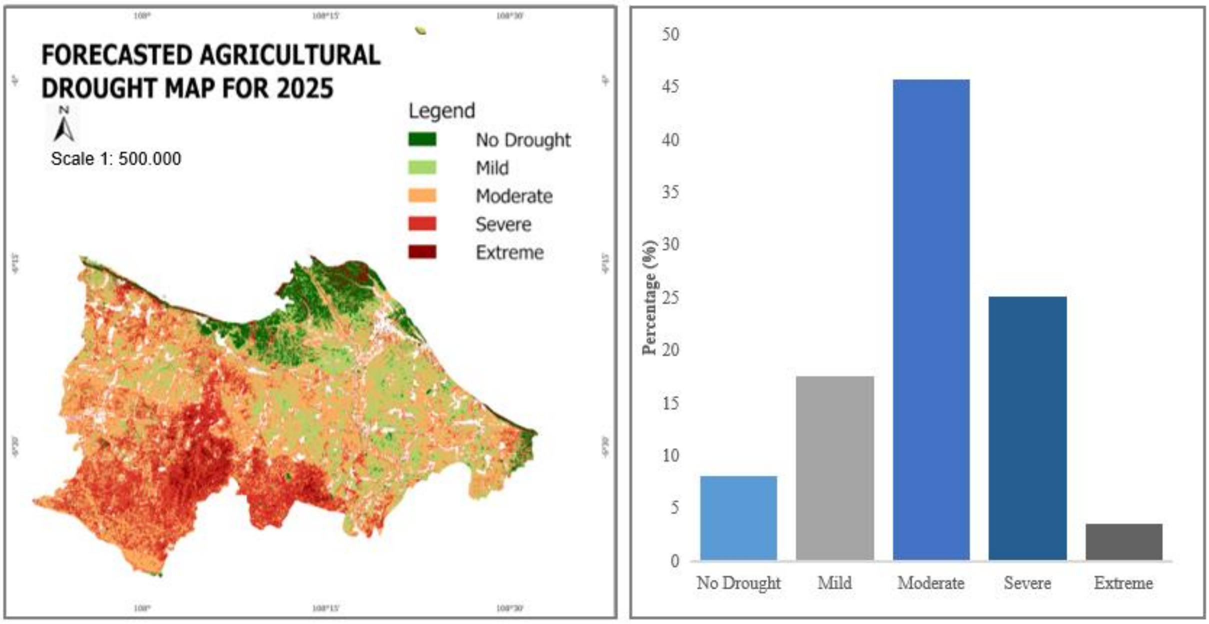



**Figure 4.** Agricultural Drought Forecast Map of Indramayu for 2025

Based on the NDDI model results, the southern region of Indramayu Regency indicates that it will be prone to severe-extreme or moderate to severe drought by 2025. Compared to other regions, there is a risk imbalance between the northern region, which is relatively safe, and the spatial and drought patterns are consistent when viewed from 2015 to 2024. The southern region of Indramayu has the potential to experience a greater reduction in crop yields than the northern region. Therefore, it is emphasized that drought mitigation strategies need to be focused on the southern region of Indramayu. Drought mitigation that farmers can do is to optimally implement risk management, such as pump irrigation from the nearest river or taking groundwater [28].

The estimated drought conditions are relevant as spatial information and as a basis for regional food policy planning decision-making. By combining the spatial information and quantitative analysis produced by the method, mitigation strategies can be directed in a more targeted manner. So, the prediction results show that most of the southern region of Indramayu is expected to fall into the moderate to extreme drought category. In contrast, the northern region is relatively stable, dominating the no drought to mild drought category. This pattern emphasizes the importance of long-term mitigation strategies, such as strengthening irrigation infrastructure and implementing an adaptive planting calendar so that the generative phase of rice does not fall at the peak of the dry season[29].

### *3.3 Analysis Spatial Autocorrelation*

This section focuses on identifying spatial clustering patterns of agricultural drought in Indramayu using Global Moran's Index and LISA (Local Indicators of Spatial Association).

#### *3.3.1 Global Moran's Index Result*

Results of the Global Moran's Index test are presented in table 3.

**Table 3.** Results of Global Moran's Index of Mean NDDI 2015 - 2024

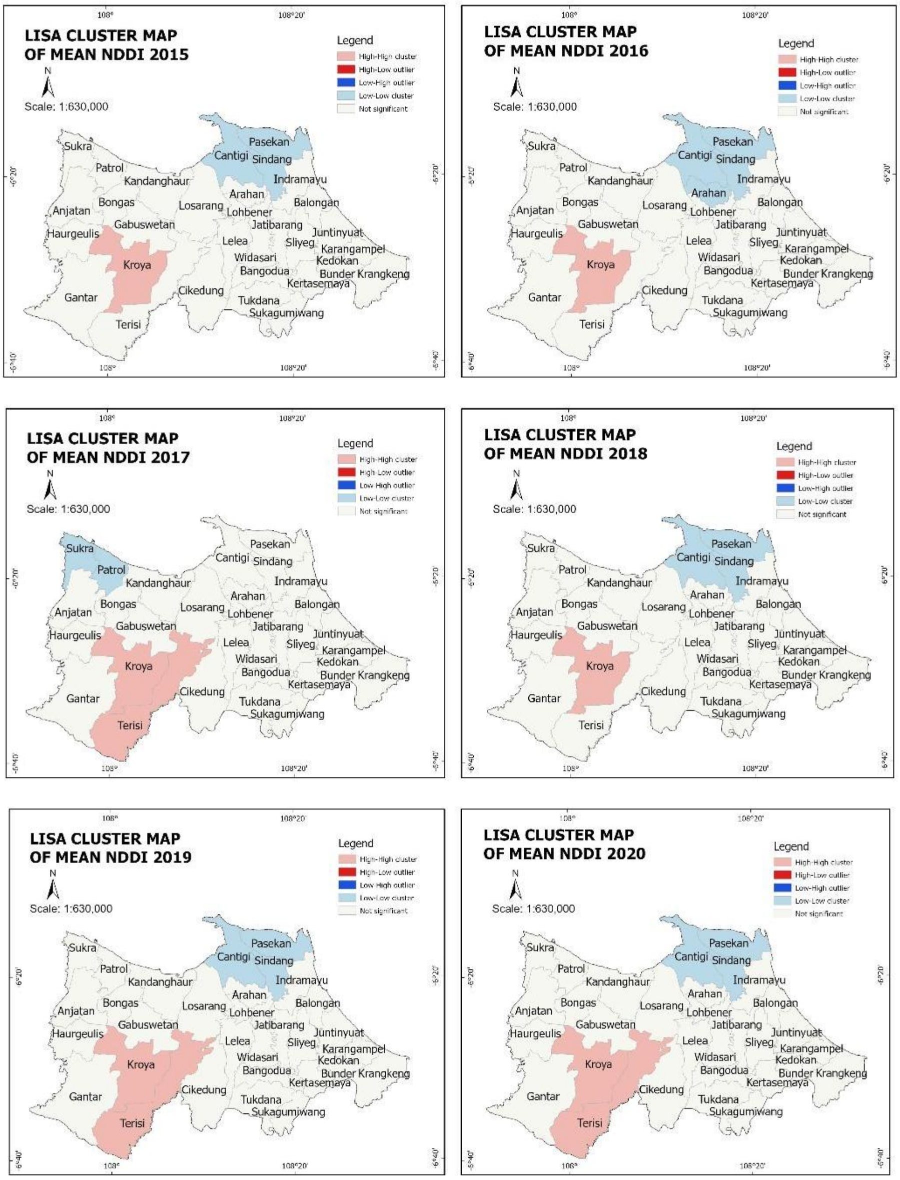
| Year | NDDI's mean | Moran's Index | p-Value |
|---|---|---|---|
| 2015 | 0.391951 | 0.537894 | 0.000007 |
| 2016 | -0.91193 | 0.565508 | 0.000005 |
| 2017 | 0.363515 | 0.522689 | 0.000019 |
| 2018 | 0.346504 | 0.503876 | 0.000017 |
| 2019 | 0.421201 | 0.490253 | 0.000028 |
| 2020 | 0.217825 | 0.471230 | 0.000079 |
| 2021 | 0.180257 | 0.471230 | 0.000079 |
| 2022 | 0.931961 | 0.544270 | 0.000006 |
| 2023 | 0.04985 | 0.628646 | 0.000000 |
| 2024 | 0.239029 | 0.686907 | 0.000000 |

The Global Moran's Index analysis reveals consistently significant spatial clustering of agricultural drought (NDDI) across all years ($p < 0.001$). Positive Moran's I values (0.471-0.687) indicates that areas with similar drought conditions tend to be geographically concentrated. A distinct temporal trend emerges: clustering strength gradually decreased from 2015-2021, reaching its lowest point (I = 0.471), then sharply intensified to peak levels in 2023-2024 (I = 0.687). This reversal suggests increasingly polarized drought vulnerability in recent years.

Notably, drought intensity doesn't directly correlate with clustering strength. Both severe drought years (2016: NDDI = -0.912) and moderate years show strong spatial patterns, indicating that underlying landscape characteristics persistently influence drought distribution regardless of annual varitions. These findings confirm that drought vulnerability in Indramayu maintains strong spatial persistence alongside temporal fluctuations, necessitating location-specific adaptation startegies.

### *3.3.2 LISA Analysis Results*

LISA (Local Indicators of Spatial Association) analysis was conducted to identify local spatial clustering patterns. The results demonstrate consistent drought distribution patterns throughout the research period.



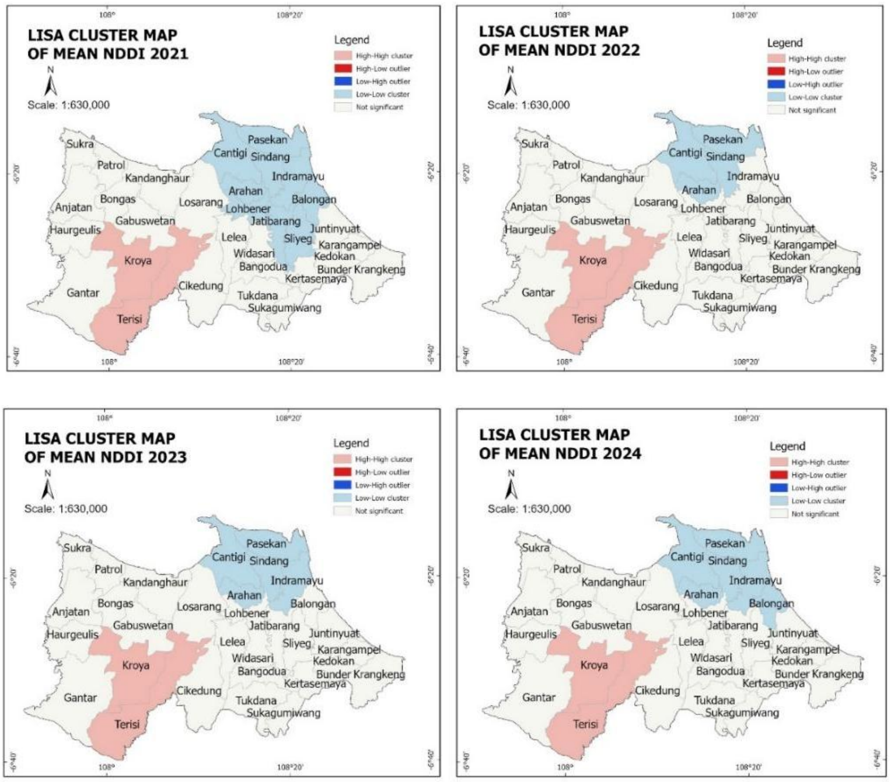



**Figure 5.** LISA Cluster Maps of Mean NDDI 2015 - 2024

The spatial pattern of drought in Indramayu Regency from 2015 to 2024 exhibits a relatively stable dynamic with a spatially persistent characteristic. During the initial period (2015–2016), High–High clusters (areas of high drought intensity) were concentrated in the southern region, particularly in Kroya, while the northern areas such as Pasekan, Cantigi, and Sindang formed Low–Low clusters, indicating zones of higher vegetation moisture. In 2017, a spatial shift occurred as drought expanded toward the central–southern areas (Kroya to Terisi), whereas the northern regions, including Sukra and Patrol, developed new clusters of lower drought intensity. The year 2018 presented a pattern similar to that of 2015, where Kroya and Gantar once again became the core of drought concentration, suggesting a recurring spatial cycle. Between 2019 and 2021, the drought intensified in the south (Kroya and Terisi) while the northern part maintained stable moisture conditions that slightly extended toward central areas such as Arahan, Losarang, Lohbener, and Sliyeg. From 2022 to 2024, the pattern became increasingly consistent, with High–High clusters remaining in the south and Low–Low clusters persisting in the north, covering areas such as Pasekan, Cantigi, Sindang, Indramayu, and Balongan.

Overall, the findings indicate that the contrast between the dry southern region and the moist northern region has become a persistent spatial pattern in Indramayu. Environmental factors such as soil characteristics, water availability, and irrigation systems play a crucial role in maintaining this spatial disparity. Although the spatial structure remains stable, the drought intensity fluctuates from year to year. Therefore, drought mitigation strategies should focus on the more vulnerable southern areas, while the northern region should be preserved through sustainable irrigation management and climate adaptation practices.

*3.4 Relationship between NDDI and Rice Productivity as Supporting Analysis*

In addition to spatial and temporal modeling, a supplementary analysis was conducted to assess the relationship between drought conditions and agricultural productivity. This aims to validate the applicability of the NDDI in representing agricultural drought conditions in Indramayu Regency. The analysis utilized average annual NDDI values and official rice productivity data from 2015 to 2024. The raw data used for the correlation analysis are presented in table 4.

**Table 4.** Relationship between Rice Productivity and the NDDI Index

| Year | NDDI | Rice Produktivity (tons/ha) |
|---|---|---|
| 2015 | 0.391951 | 6.562 |
| 2016 | -0.91193 | 6.531 |
| 2017 | 0.363515 | 5.312 |
| 2018 | 0.346504 | 5.96 |
| 2019 | 0.421201 | 7.701 |
| 2020 | 0.217825 | 5.672 |
| 2021 | 0.180257 | 5.812 |
| 2022 | 0.931961 | 6.042 |
| 2023 | 0.04985 | 6.16 |
| 2024 | 0.239029 | 6.574 |

The complete results of the Spearman's correlation test are presented in table 3.

**Table 5.** Results of Spearman Correlation Test between NDDI and Rice Productivity

| Variable Pair | Correlation Coefficient (ρ) | p-value | Sample Size (n) |
|---|---|---|---|
| Productivity vs. NDDI | 0.164 | 0.651 | 10 |

Table 5 shows a correlation coefficient (ρ) of 0.164, indicating a weak positive relationship between the two variables. However, the significance value (p-value) of 0.651, which far exceeds the standard confidence level of 0.05, indicates that this relationship is statistically insignificant. This means the observed weak relationship is highly likely to have occurred by chance and cannot be generalized. The



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visualization of this relationship is reinforced by the graph in figure 1. The following dual-axis time-series graph illustrates the annual fluctuations of rice productivity and the NDDI values.

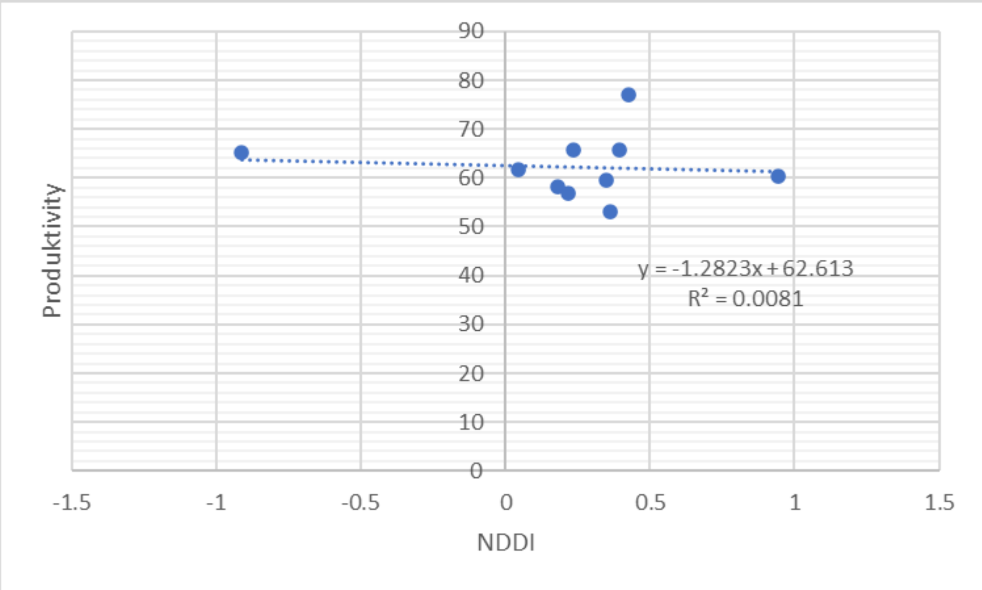


**Figure 6.** Graph of the Relationship between Rice Productivity and the NDDI Index

Figure 6 shows no consistent and clear pattern between the NDDI trend and rice productivity. For instance, in years where the NDDI indicated certain conditions (e.g., negative values suggesting drought), it was not consistently followed by a decrease in productivity. Conversely, productivity showed a relatively stable or fluctuating trend that was presumably more influenced by other factors. This visual result is consistent with and strengthens the finding from the statistical test in table 1, which concluded the absence of a significant relationship.

Thus, based on these three analytical components, the statistical test table, visual graph, and interpretation, it can be concluded that the variation in rice productivity in Indramayu Regency from 2015 to 2024 cannot be adequately explained by the variability of drought conditions represented by the NDDI index at an annual and regency scale. The weak relationship is strongly suspected because the impact of meteorological drought (captured by NDDI) has been successfully mitigated by the effective irrigation systems in this rice-producing region. Furthermore, productivity fluctuations are more likely influenced by other dominant factors such as agricultural policies, the use of inputs (fertilizers and improved seeds), and cultivation techniques applied by farmers.

## 4. Conclusion

This study demonstrates distinct spatio-temporal patterns of agricultural drought in Indramayu Regency, with persistent drought clustering in the southern region across 2015-2024. The spatial-temporal analysis reveals that spatial vulnerability persists regardless of temporal variability, while temporal intensification amplifies existing spatial patterns. Critically, the disconnection between these drought patterns and regency-level productivity underscores irrigation's effectiveness in buffering climate impacts. Although limited by regency-level productivity data that may mask localized impacts, the clear disconnection between spatio-temporal drought patterns and productivity underscores irrigation's effectiveness in mitigating climate risks. Future research should explore district-level relationships, but the present findings already advocate for a dual strategy: spatially-targeted interventions in persistent drought clusters combined with regency-wide optimization of agricultural management practices to ensure long-term food security.

## Acknowledgement

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