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*Research article*

# Spatial Relationships Between Flash Drought and Rice Production in a Tropical River Basin Using Geographically Weighted Regression

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## Abstract

Flash droughts have become a significant hydroclimatic hazard threatening agricultural production amid increasing climate variability. However, studies examining the spatial relationship between flash drought indicators and rice production in the humid tropics are limited. This research aims to assess the impacts of flash droughts on rice production in Bengawan Solo River Basin using a GIS-based geographically weighted regression (GWR) method. Soil moisture (SM), land surface temperature (LST) and rainfall (RF) were employed as independent variables and rice production (RP) as the dependent variable. The results show that flash droughts significantly reduce paddy yield, with all the independent variables having a significant influence ($R^2$ = 71.43%). Residual Moran's I analysis indicated no significant spatial autocorrelation (z-score = -0.5; p-value = 0.6), confirming the robustness of the model. Among the three independent variables, SM and LST were the most statistically significant (probability t value < 0.05). Based on a simulation using the average local GWR coefficient, a 1% decrease in SM combined with a 1% increase in LST potentially reduced rice production by up to 9.62%. These findings demonstrate a strong spatial relationship between flash drought indicators and declining rice production. Consequently, the importance of strengthening mitigation and adaptation strategies to reduce potential future losses in rice production is emphasised.

Keywords: Flash Drought; Rice Production; Geographically Weighted Regression; Tropical River Basin.

## 1. Introduction

Climate change (CC) triggers systemic impacts that affect the balance of natural systems and quality of life (Buchori *et al.,* 2018). Floods and meteorological droughts represent the most pervasive climate change impacts on the world, with Southeast Asia experiencing particularly severe effects, marked by increasing flood frequency (Waiyasusri & Wetchayont, 2025), dry conditions, and prolonged periods of impacts. Drought is a natural event that is becoming increasingly common in various parts of the world (Ault, 2020; Walker & Van Loon, 2023). It is exacerbated by the El Niño phenomenon, which causes longer dry periods and increased drying of the soil (Dutta *et al.,* 2024; Toledo *et al.,* 2024; Zhang *et al.,* 2022). Many countries are experiencing social, economic and environmental impacts due to droughts. Several studies in Africa have examined the social and economic impacts; for example, the research conducted by Mojaki et al. in Lesotho (Mojaki *et al.,* 2024) and by Odongo et al. in Kenya (Odongo *et al.,* 2025). Several European countries, including France, the UK, Ireland, Belgium, Netherlands and Switzerland, have also experienced social and economic impacts from drought (Motta *et al.,* 2025). In addition to economic losses, droughts have an environmental impact, including the disruption of water resources (Sun *et al.,* 2024), resulting in an increase in evapotranspiration (Liu *et al.,* 2025) and increasing soil salinity (Ghasempour et al., 2024), which affects crop health (Duan *et al.,* 2024; Khasanov *et al.,* 2023).

Climate change is causing droughts to become more frequent, and they can occur suddenly, a phenomenon known as flash droughts (Christian *et al.,* 2021; Otkin *et al.,* 2018; Tyagi *et al.,* 2022). These are characterised by increased land surface temperatures; enhanced evaporation; drastic decreases in soil moisture (Ford & Labosier, 2017; Hu et al., 2024) ; warmer and drier air masses (Zeng *et al.,* 2023) ; and stronger winds (Neelam & Hain, 2024). Flash droughts reduce the productive capacity of the soil and pose a threat to food production (Mohammadi & Wang, 2025; Wang *et al.,* 2024). Black predicts that flash droughts will occur more than twice as often in the 21st century (Black, 2024). Research by He et al. and Kimball et al. in North America, utilising satellite data on soil moisture and food production data, reveal that increasing flash drought events had a significant impact on levels of food production (He *et al.,* 2019; Kimball *et al.,* 2019). Furthermore, research in India using data on rainfall, air temperature and soil moisture, as well as on rice and corn production, found that flash droughts reduced production by 10%-15% (Mahto & Mishra, 2020). In line with these studies in North America and India, Hunt et al. found that in Russia flash droughts caused soil moisture levels to decrease, and heatwaves caused wheat production to decline (Hunt *et al.,* 2021). In addition, previous studies conducted by Yao et al. on the Hai River Basin, and Zhao et al. across China, using data on soil moisture, rainfall and air temperature, found that flash droughts negatively impacted crop photosynthesis, resulting in a 40% decrease in gross primary production and reduced food productivity (Yao *et al.,* 2022; Zhao *et al.,* 2024).

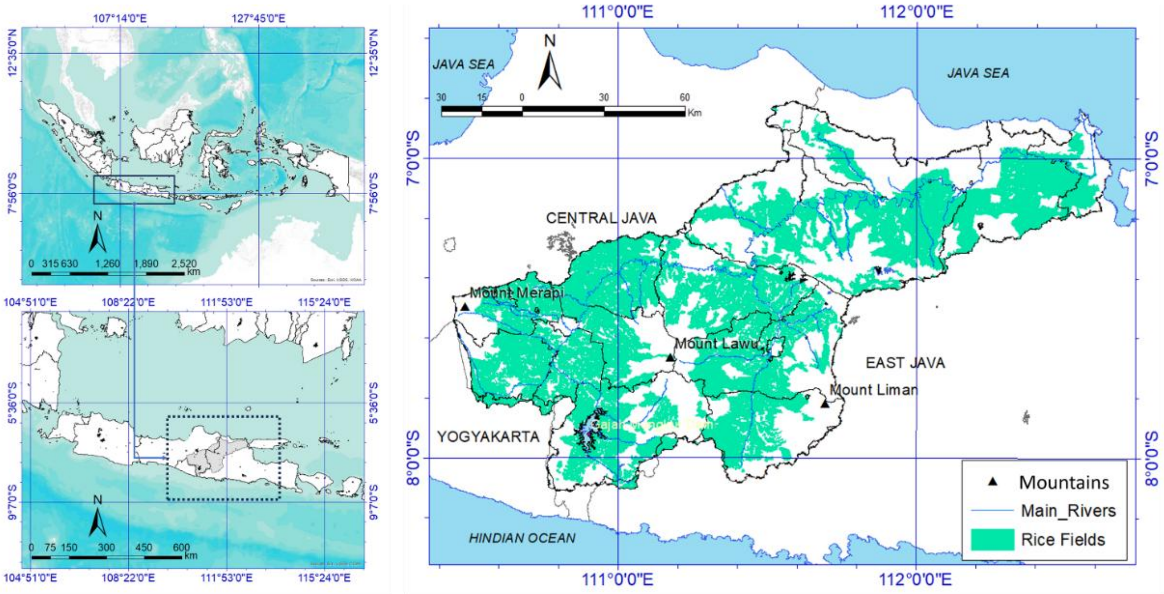
Flash droughts that occur at the beginning of the growing season disrupt plant growth due to water stress resulting from decreased soil moisture (Khasanov *et al.,* 2023; Wang *et al.,* 2025; Xi & Yuan, 2022). Research by Lovino et al. in Latin America, utilising the Soil Water Deficit Index, revealed that flash droughts significantly reduced food crop production, particularly corn and soybeans (Lovino *et al.,* 2025). Previous studies on flash droughts have widely utilised data from satellite imagery and GIS for drought monitoring, spatial mapping and environmental analysis; however, the application of GIS-based spatial statistical analysis to examine the localised impacts of flash droughts on food crop production is relatively limited. Earlier research has predominantly employed descriptive statistics, correlation analysis and ordinary least squares regression analysis to assess the relationships and effects of flash droughts on food crop production. Consequently, the spatial heterogeneity of flash drought impacts across agricultural areas has received less attention. Understanding spatial heterogeneity and its contribution to flash drought impact is a highly relevant topic because each spatial element possesses unique characteristics and may respond differently to changes in rainfall, soil moisture and land surface temperature. In this context, geographically weighted regression (GWR) offers an effective approach to identifying localised spatial relationships and explaining the varying spatial effects of flash droughts on food crop production (Coulibaly *et al.,* 2025; Widjonarko & Maryono, 2021; Yu *et al.,* 2025; Zheng *et al.,* 2024). Research on the impact of flash droughts on food crop production in Asia is limited to South Asia (India) and East Asia (China), with notable exceptions. For instance, research has been conducted in India and China in the continental subtropical region (Mahto & Mishra, 2020; Xi & Yuan, 2022; Zhao *et al.,* 2024). However, research in equatorial areas with tropical rainforest climates, characterised by higher rainfall and longer rainy seasons, is limited. Indonesia is an equatorial country in Asia, characterised by a tropical rainforest climate with high rainfall intensity. It has extensive agricultural land, ranking it among the largest in the world in terms of area. The country faces ordinary droughts and flash drought phenomena. We estimated the flash drought events in Indonesia that occurred over the period 2013-2023, with the most extreme drought conditions reported in 2018 (Hidayah, 2024). However, research on the impact of flash droughts on food crop production is limited. Most studies on flash droughts in the last five years have been conducted in continental areas, employing climate variables and crop production data, and using non-parametric statistics and parametric statistics, such as correlation and regression, to measure the impact of flash droughts (Jin *et al.,* 2019; Liu *et al.,* 2024; Liu *et al.,* 2025; Mahto & Mishra, 2023; Shi *et al.,* 2025; Sun *et al.,* 2024). Most of the research related to Indonesia as a tropical island country has focused on drought monitoring using only satellite imagery data (Avia *et al.,* 2023; Dimyati *et al.,* 2024; Ferijal *et al.,* 2021; Sunusi & Auliana, 2025).

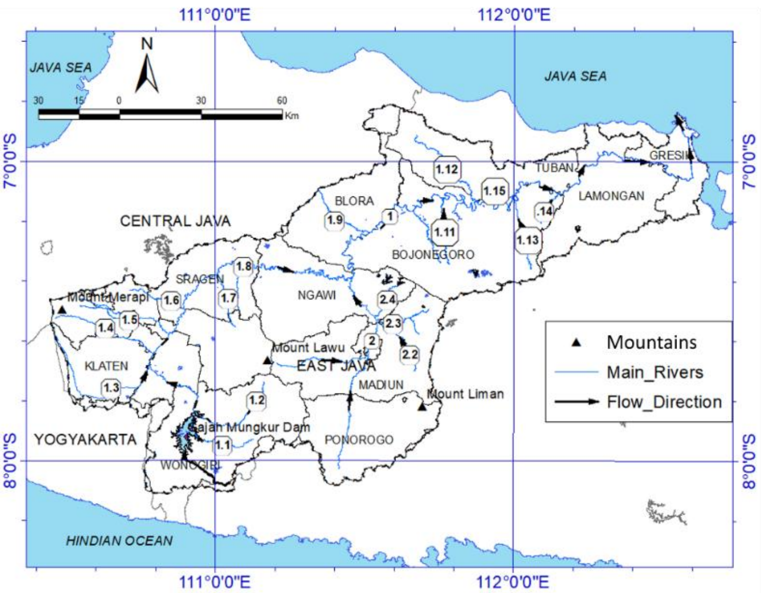
The lack of attention from researchers to flash droughts in the equatorial region makes this phenomenon in Indonesia an area of particular study interest. Our study focuses on Java Island, which is the primary rice production centre in Indonesia, with the Bengawan Solo River Basin (BSRB), the largest watershed on the island of Java, as the research area. It encompasses a diverse ecological landscape, ranging from mountainous regions in the southern part of the basin to lowland regions in the northern part. This study aims to assess the spatial impact of flash droughts on rice production in BSRB, employing GIS-based spatial statistics, in particular GWR (Coulibaly *et al.,* 2025; Widjonarko & Maryono, 2021; Yu *et al.,* 2025; Zheng *et al.,* 2024). It utilised data on rice production, soil moisture, surface temperature, and rainfall. The use of spatial statistics can provide a more comprehensive understanding of the spatial contributions of these three factors to rice production in the BSRB region. The findings offer insights that can help reduce the risks to agricultural sustainability and contribute to achieving the UN Sustainable Development Goals, particularly Goal 2 (Zero Hunger) and Goal 13 (Climate Action), by strengthening food security and mitigating the impacts of climate change (Waiyasusri, *et al.,* 2023). Furthermore, the findings complement the previous research on North America (He *et al.,* 2019; Kimball *et al.,* 2019), India (Mahto & Mishra, 2020), Russia (Hunt *et al.,* 2021), China (Xi & Yuan, 2022; Zhao *et al.,* 2024), and South America (Lovino *et al.,* 2025).

## 2. Research Methods

### 2.1. Study Area

The Bengawan Solo River Basin (BSRB), located on Java Island, Indonesia, is the longest river basin in the country. It traverses the two provinces of Central Java and East Java. The study area is characterised by a humid tropical monsoon climate. It exhibits high spatial variability in annual rainfall, ranging from 1,400 mm to 3,300 mm, with a mean annual temperature of approximately 27 °C and an average monthly evaporation of 3.9 mm. There are two main river systems, the Bengawan Solo and Madiun rivers, both of which are perennial. The hydrological regime is characterised by high peak discharges, with flood flows reaching approximately 1,500 m3 per second in the upstream area and up to 6,000 m3 per second in the downstream area (PUPR, 2015; Sirait *et al.,* 2021) (see Figure 1).




| Code_Number | River Name |
|---|---|
| 1 | Bengawan Solo River |
| 1.1 | Tirtomoyo River |
| 1.2 | Gading River |
| 1.3 | Dengkeng River |
| 1.4 | Gandul River |
| 1.5 | Pepe River |
| 1.6 | Cepu RIver |
| 1.7 | Sragen River |
| 1.8 | Kenatan River |
| 1.9 | Wulu RIver |
| 1.10 | Sumber RIver |
| 1.11 | Ombe RIver |
| 1.12 | Kening River |
| 1.13 | Selokan River |
| 1.14 | Kleco River |
| 1.15 | Rambit River |
| 2 | Madiun River |
| 2.1 | Gandong River |
| 2.2 | Jerowan River |
| 2.3 | Mejayan River |
| 2.4 | Wangon River |

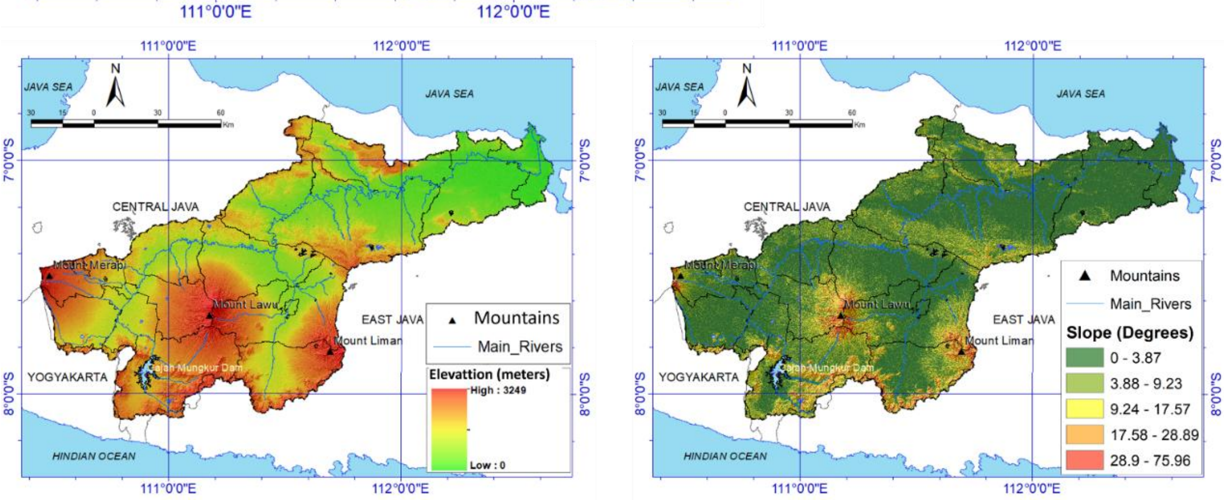



**Figure 1.** Study Area: Bengawan Solo River Basin.

Java Island is the primary food crop production region in Indonesia, contributing around 53% of the national production. On Java Island, BSRB contributes approximately 22% of the total food crop production and covers 18.9% of the island's total agricultural land area. Rice fields in BSRB cover around 45% of the total area, which is supported by 39 dams that play important roles in irrigation, water supply, and flood control.

### 2.2. Data

Landsat 8 satellite imagery was employed to detect flash droughts from 2013 to 2023. The period was selected to capture interannual drought variability during the observed years and to include extreme drought conditions reported in 2018, which was determined by the National Disaster Management Agency (BNPB) as one of the most severe drought years during the study period. Food-related data were obtained from rice production figures published by the Ministry of Agriculture of the Republic of Indonesia, while rainfall data maps were obtained from the Bengawan Solo River Basin Center (BBWS Bengawan Solo). Annual drought data were derived from the Landsat Collection 2 Tier 1 Level 2 Annual NDWI Composite, with monthly data obtained from the 32-Day NDWI Composite, which is accessible via the Google Earth Engine (GEE) platform. Details of the data used in the study are presented in Table 1.

**Table 1.** Research Data.

| Data | Parameter | Period | Sources | Additional Information |
|---|---|---|---|---|
| Paddy Production | Percentage Change in Rice Production | 2013-2023 | Ministry of Agriculture | Dependent Variable |
| Rainfall Intensity | Percentage Change in Rainfall | 2013-2023 | Bengawan Solo River Basin Centre (BBWS Bengawan Solo); Ministry of Public Works | Independent Variable |
| Soil Moisture | Percentage Change in NDWI | 2013-2023 | Landsat 8 processing using GGE | Independent Variable |
| Land Surface Temperature | Percentage Change in Land Surface Temperature | 2013-2023 | Landsat 8 processing using GIS software | Independent Variable |

### 2.3. Methods

#### 2.3.1 Soil Moisture Estimation

Drought identification was conducted using remote sensing methods, including the Normalized Difference Wetness Index (NDWI), to measure soil moisture levels associated with drought. The NDWI calculation employs the green and near-infrared bands and is expressed using the following Equation 1.

$$NDWI = \frac{Green - NIR}{Green + NIR} \tag{1}$$

The NDWI method has proven to be a practical approach for detecting drought patterns in agricultural areas in subtropical regions (Das *et al.,* 2023; Gao, 1996; Gulácsi & Kovács, 2015;. Xu, 2006; Zhang *et al.,* 2022), as well as in tropical countries including Thailand and Indonesia (Amalo *et al.,* 2018; Wijesinghe *et al.,* 2024; Sholihah *et al.,* 2016). NDWI values range from -1 to 1; those approaching negative values indicate dryness, while those approaching +1 indicate soil containing water (Gulácsi & Kovács, 2015; Trinh & Danh, 2019; Valero-Jorge *et al.,* 2022).

Previous studies in Thailand and Indonesia have demonstrated that these thresholds are sufficiently sensitive to identify soil moisture and vegetation stress in tropical agricultural regions. Although NDWI is primarily associated with near-surface wetness rather than root-zone soil moisture, previous studies have shown that it can reflect soil moisture anomalies associated with vegetation stress and agricultural drought conditions. In addition to NDWI, previous agricultural drought studies have utilised other indices, such as the Normalized Difference Drought Index (NDDI) and the Standardized Precipitation Index (SPI), for drought monitoring (Dimyati *et al.,* 2024). These consistently indicate that vegetation water content, soil moisture depletion, and rainfall deficit are important indicators for monitoring droughts in agricultural areas. In this context, NDWI was selected for this study because of its sensitivity to surface moisture conditions and its wide application in remote sensing-based agricultural drought monitoring in both subtropical and tropical regions. The NDWI values are presented in Table 2.

**Table 2.** NDWI Value Classification For Drought Monitoring.

| No | NDWI Value Range | Indication |
|---|---|---|
| 1 | NDWI ≥ 0.7 | Very high moisture content |
| 2 | 0.6 ≤ NDWI < 0.7 | High moisture content |
| 3 | 0.5 ≤ NDWI < 0.6 | Moderate moisture content |
| 4 | 0.4 ≤ NDWI < 0.5 | Low moisture content |
| 5 | 0.3 ≤ NDWI < 0.4 | Weak drought |
| 6 | 0.2 ≤ NDWI < 0.3 | Moderate drought |
| 7 | 0.0 ≤ NDWI < 0.2 | Strong drought |
| 8 | NDWI < 0 | Extreme drought |

Sources: Gulácsi and Kovács (2015), Trinh and Danh (2019), Valero-Jorge *et al.* (2022).

### 2.3.2. Land Surface Temperature Estimation

The process of converting infrared thermal image data (band 10) into land surface temperature data was conducted in four stages (Bobáľová & Opravil, 2025; Jamaludin *et al.,* 2025; Zheng *et al.,* 2024): 1. radiometric correction of Landsat 8 TIRS bands; 2. conversion of the TIRS bands to brightness temperature (BT); 3. calculation of land surface emissivity; and 4. calibration of BT to land surface emissivity for LST. Further details of the LST calculation process are given below.

1. Radiometric correction

Conversion of the digital number of band 10 of Landsat 8 into the top of atmosphere (TOA) spectral radiance using Equation 2.

$$L_\lambda = M_L . Q_{cal} + A_L \tag{2}$$

where $L_\lambda$= TOA spectral radiance ; $M_L$= radiance multiplicative scaling factor ; $Q_{cal}$= pixel DN value ; $A_L$= radiance additive scaling factor

2. Conversion of spectral radiance into brightness temperature (BT) using Equation 3.

$$BT = \frac{K_2}{Ln\left(\frac{K_1}{L_\lambda} + 1\right)} - 273.15 \tag{3}$$

where $BT$= brightness temperature (°C); $K_1$, $K_2$= thermal conversion constants from metadata ; $L_\lambda$= spectral radiance.

3. Calculation of land surface emissivity (LSE)

The LSE calculation began with the estimation of the Normalized Difference Vegetation Index (NDVI), derived from the near-infrared (NIR) and red bands using Equation 4.

$$NDVI = \frac{NIR - Red}{NIR + NIR} \tag{4}$$

NDVI values were then applied to calculate the proportion of vegetation (PV), expressed as Equation 5.

$$PV = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right)^2 \tag{5}$$

Once PV was obtained, LSE was calculated using Equation 6.

$$\varepsilon = 0.004P_v + 0.986 \tag{6}$$

where $\varepsilon$ = emissivity; $P_v$= vegetation proportion

This land surface emissivity formula provides a reliable estimation of surface emissivity for subsequent land surface temperature retrieval.

4. Calculation of LST

LST was determined by adjusting the brightness temperature (BT) from the initial step using land surface emissivity (LSE). This adjustment compensates for the surface's radiative characteristics, resulting in a more precise assessment of true land surface temperature conditions. The formula to calculate the LST is expressed as Equation 7.

$$LST = \left(\frac{BT}{1 + \left(\frac{\lambda BT}{\rho}\right) ln(\varepsilon)}\right) \tag{7}$$

where $LST$= land surface temperature (Celsius), $BT$= brightness temperature ; $\lambda$ = wavelength of emitted radiance - for band 10 Landsat 8 the value is 10.895 µm, equal to 10.895×10−6 m ; $\varepsilon$ = emissivity; $\rho$ =1.438 × 10^-2 m.

### 2.3.3. Modelling of the Spatial Impact of Flash Drought Using Geographically Weighted Regression

Soil moisture, land surface temperature, and rainfall intensity were used as independent variables representing flash droughts, with rice production used as the dependent variable. The geographically weighted regression (GWR) method was employed to assess the spatial impact of flash droughts on food production in BSRB (Coulibaly *et al.*, 2025; Widjonarko *et al.*, 2025; Widjonarko & Maryono, 2021; Zheng *et al.*, 2024). Data on soil moisture growth rates, land surface temperature, rainfall intensity, and food production were employed. The use of growth rates aimed to explain the dynamics of changes in each component of flash drought factors in relation to changes in rice production in BSRB. The process of measuring the impact of flash drought on food crop production in BSRB is shown in Figure 2.

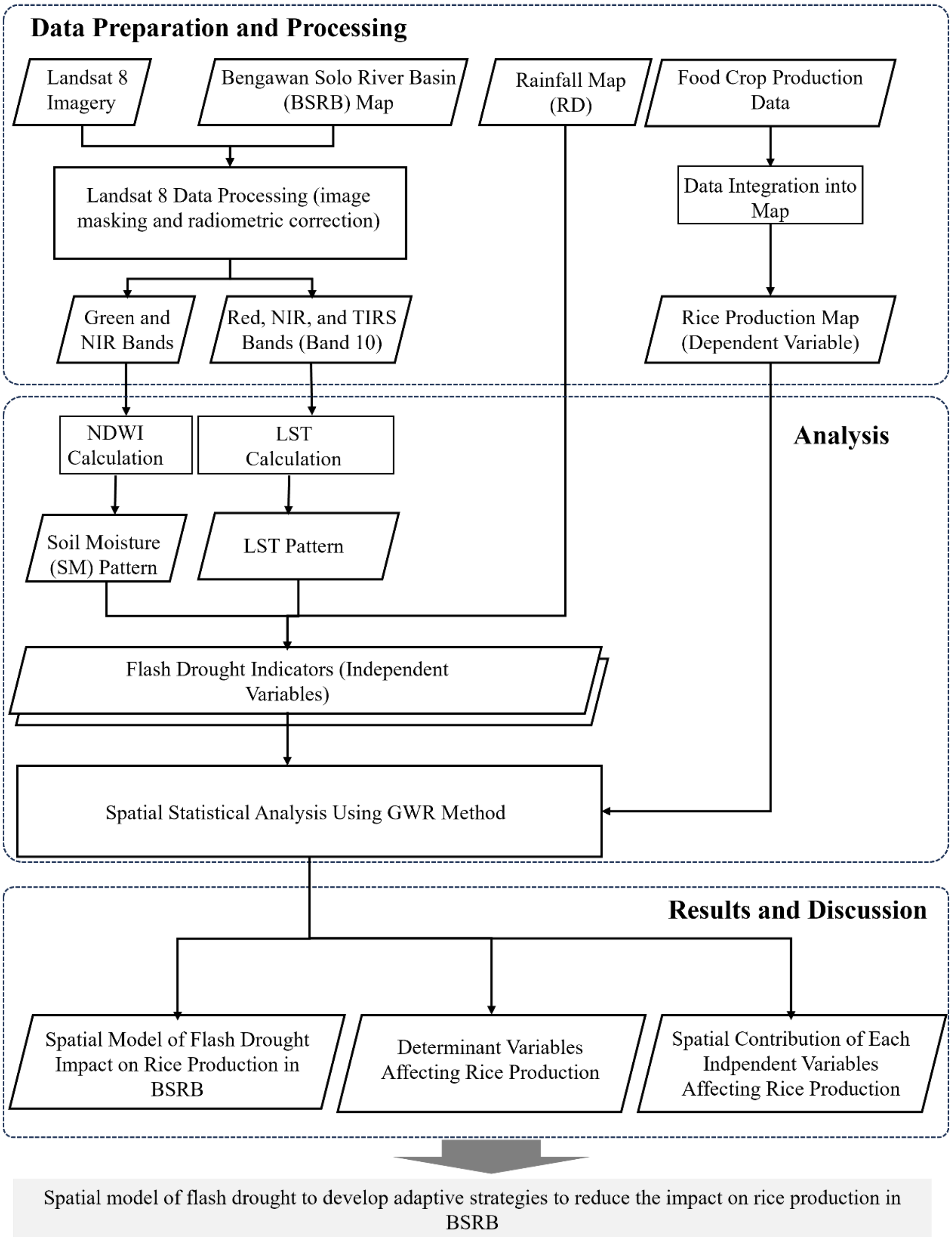



**Figure 2.** Data Processing Flow.

## 3. Results and Discussion

### 3.1. Soil Moisture Pattern in BSRB

Rice field areas in BSRB experienced droughts every year between 2013 to 2023, as indicated by the annual NDWI values, which were generally below zero during the observation period. In our study, lower NDWI values in rice field areas were interpreted as indicating reduced surface moisture conditions associated with drought stress, particularly when accompanied by increased land surface temperature and reduced rainfall. Dry conditions became more pronounced between June and September, when the monthly NDWI values  were lower than the annual ones over the previous 10 years. 2018 marked peak drought severity during the study period. The average annual NDWI value in the rice field area from 2013 to 2023 was -0.39, while during the dry season between June and September this figure dropped to -0.46. These values illustrate the low levels of soil moisture in BSRB, reflecting the conditions of decreased soil moisture that occur throughout the year. Moreover, the potential for flash droughts is heightened during the dry season, with NDWI anomalies reaching as low as -0.61, which is significantly lower than typical drought thresholds. Figure 3 illustrates the drought trends over the period 2013 to 2023 in BSRB.

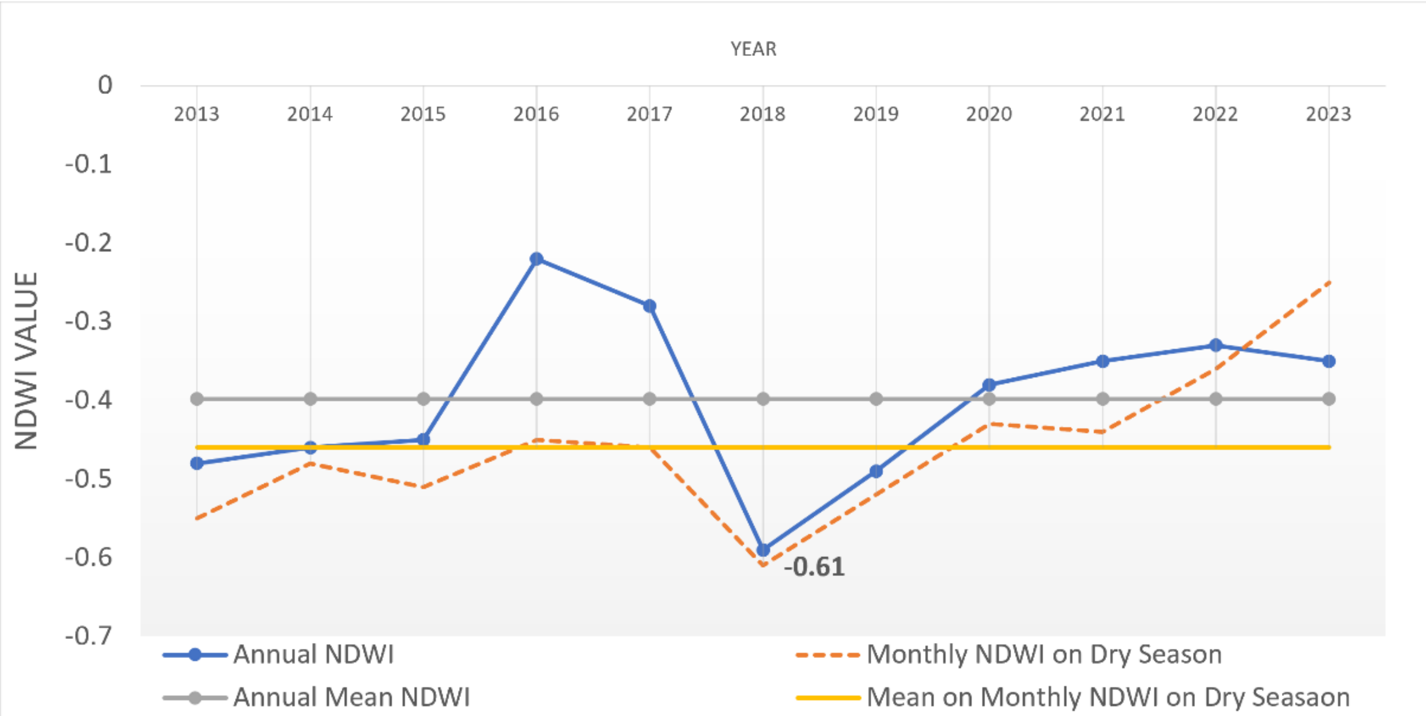



**Figure 3.** Yearly Drought Patterns in Bengawan Solo River Basin based on NDWI, 2013-2023.

Source: Landsat Collection 2 Tier 1 Level 2 Annual NDWI Composite 2013-2023; Landsat Collection 2 Tier 1 Level 2 32-Day NDWI Composite, processed using Google Earth Engine, (2025).

The NDWI classification presented in Table 1 indicates that flash drought identified in BSRB, with extreme drought =occured in 2018. The monthly NDWI values in BSRB indicate the occurrence of droughts during the dry season and are classified as extreme drought conditions (Gulácsi & Kovács, 2015; Patil *et al.,* 2024). The distribution of drought is even from upstream to downstream, although the level of drought is higher in the upstream area than in the downstream region. The lower drought intensity observed in the downstream areas may be related to better water availability and irrigation support. However, these factors were not examined for this study.

The Landsat imagery data from September 2013 to 2023 show a pattern of drought in BSRB, with an average NDWI value in September 2013 of -0.49 (see Figure 4A), falling to -0.61 in September 2018 (see Figure 4B), then increasing to 0.23 in September 2023 (see Figure 4C).  Extreme drought dries the soil, making it difficult for rice roots to absorb essential nutrients, disrupting growth and reducing the ability of the rice to produce grains. The monthly NDWI value in September 2018, which was far from the annual normal average value, indicated a flash drought in the area. On the other hand, the increased NDWI value in 2023 suggests a notable improvement in soil moisture. Higher moisture levels play a crucial role in supporting the growth of rice plants (Deshabandu *et al.,* 2024; Hou *et al.,* 2022; Panda *et al.,* 2021). Figure 4 shows the monthly NDWI spatial pattern in 2013, 2018 and 2023. The NDWI values show that significant flash drought occured between 2013 and 2023, a phenomenon which has important implications for rice production in BSRB. Previous research has focused on the impact of flash drought on plant growth processes and primary production systems, enriched by research results in BSRB, also finding that disruption of the rice plant growth process at the beginning of the dry season correlated with a decrease in paddy rice production in BSRB.

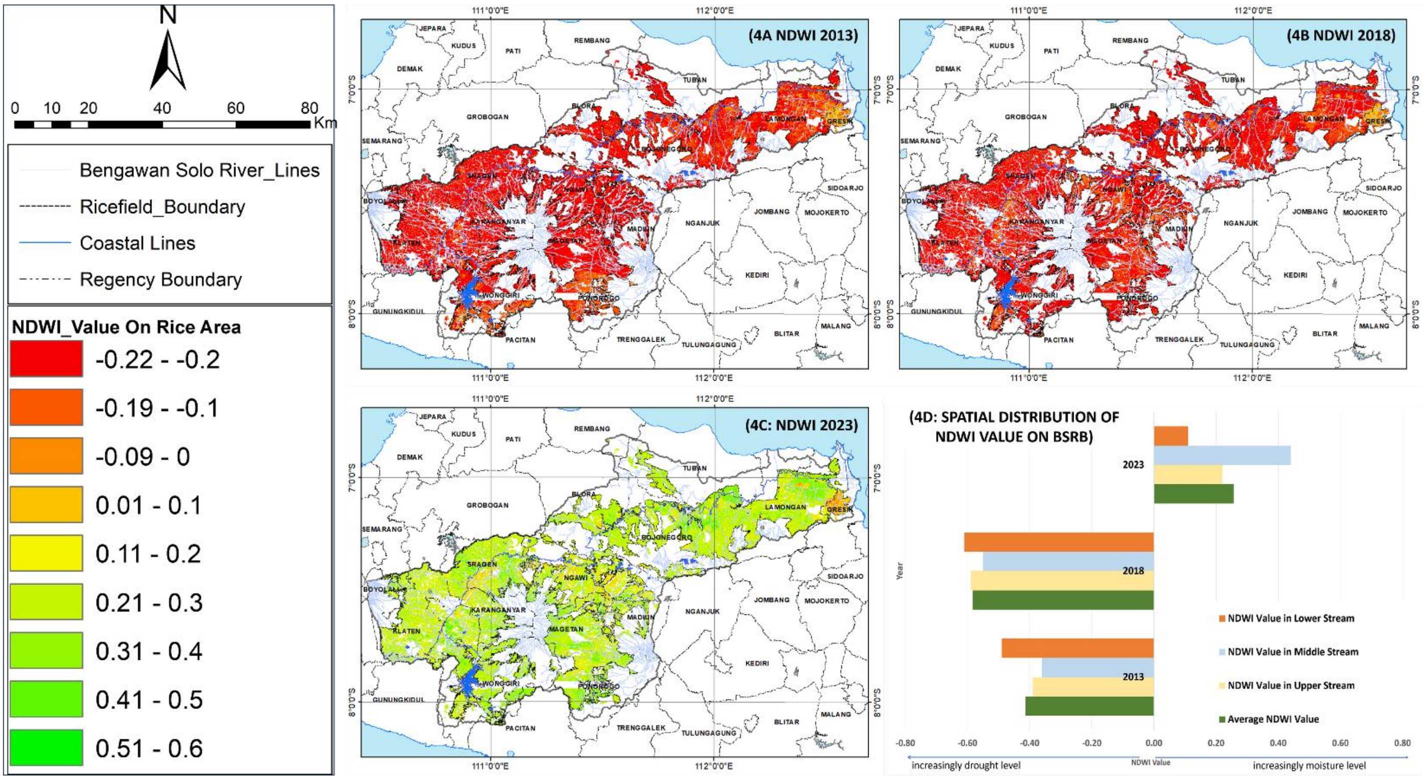



**Figure 4.** Spatial Pattern of Monthly NDWI Values in Rice Field Areas in Bengawan Solo River Basin, 2013 -2023.

## 3.2. Rainfall Pattern

Rainfall intensity in BSRB is generally lower during the dry season (June to September) compared to the annual rainfall pattern, a situation exacerbated by the El Niño phenomenon (Iskandar, Lestrai, & Nur, 2019; Rahma & Ludwig, 2024; Yulihasti, *et al.,* 2009). This low rainfall is associated with the decline in surface soil moisture in most agricultural areas in BSRB. Among the years observed, 2018 recorded the lowest rainfall, which was below the levels of 2013 and 2023. In 2018, the average monthly rainfall was less than 100 mm, combined with a relative rainfall percentage below 85% (BMKG, 2018a), with the Standardized Precipitation Index value ranging between -0.99 and -1.49 (BMKG, 2018b, 2018c), indicating moderate drought conditions (see Figure 5B). Lower rainfall contribute to drier soil and reduced water availability for rice cultivation. Despite the presence of irrigation infrastructure, insufficient rainfall leads to drier conditions in rice fields, inhibiting water uptake by plants and impairing their ability to perform optimal photosynthesis, which ultimately affects plant growth (Chandrasiri *et al.,* 2020; Chen *et al.,* 2024; Wang *et al.,* 2025). Rainfall patterns for the period 2013 to 2023 are presented in Figure 5.

## 3.3. Land Surface Temperature Pattern

Extreme dry season conditions during the observed years have increased LSTs in BSRB. During the dry season of 2013, temperatures ranged from 16°C to 37°C, with an average of 27.72°C (Figure 6A). The average of LST in the rice field area was 27.9°C, slightly higher than the average temperature across BSRB. In 2018, there was a significant increase in land surface temperatures, ranging from 16°C to 43.68°C, with an average of 29.49°C (Figure 6B). Temperatures in the rice field area increased by 5.7% compared to 2013. In 2023, LSTs in BSRB were recorded within the range of 16°C to 41.71°C, with an average of 29.41°C. The average temperature in the rice field area in 2023 was 29.34°C, slightly lower than in 2018 (Figure 6C). Higher than average increases in LST indicate climate variability during the observed years in the study area. A more detailed picture of the pattern of LST changes in BSRB during the period 2013–2023 is presented in Figure 6.

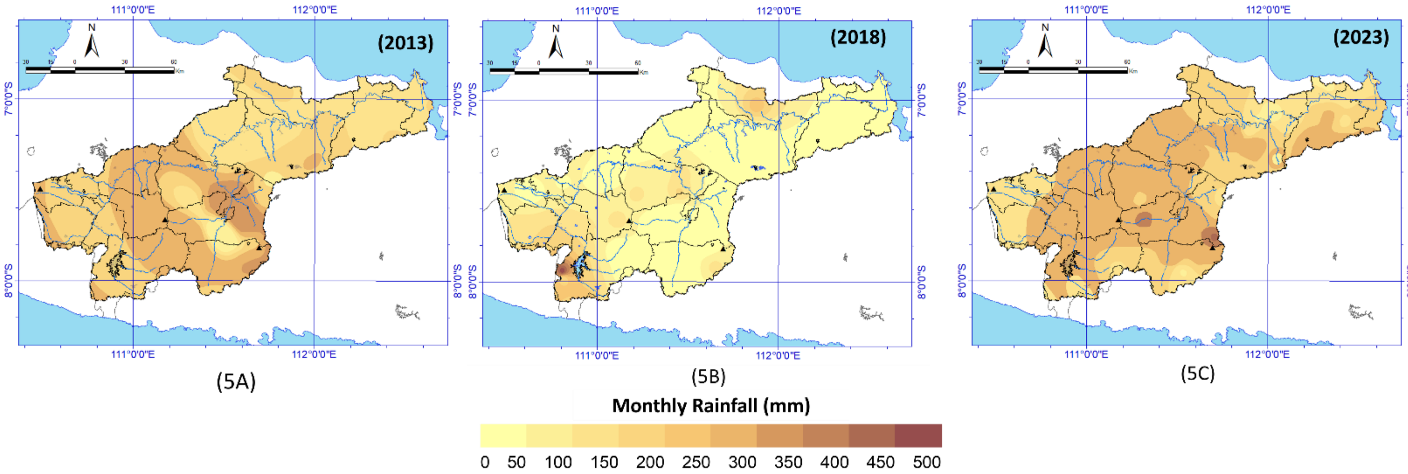



**Figure 5.** Monthly Dry Season Rainfall in the Bengawan Solo River Basin: (5A) 2013 ; (5B) 2018 ; (5C) 2023.

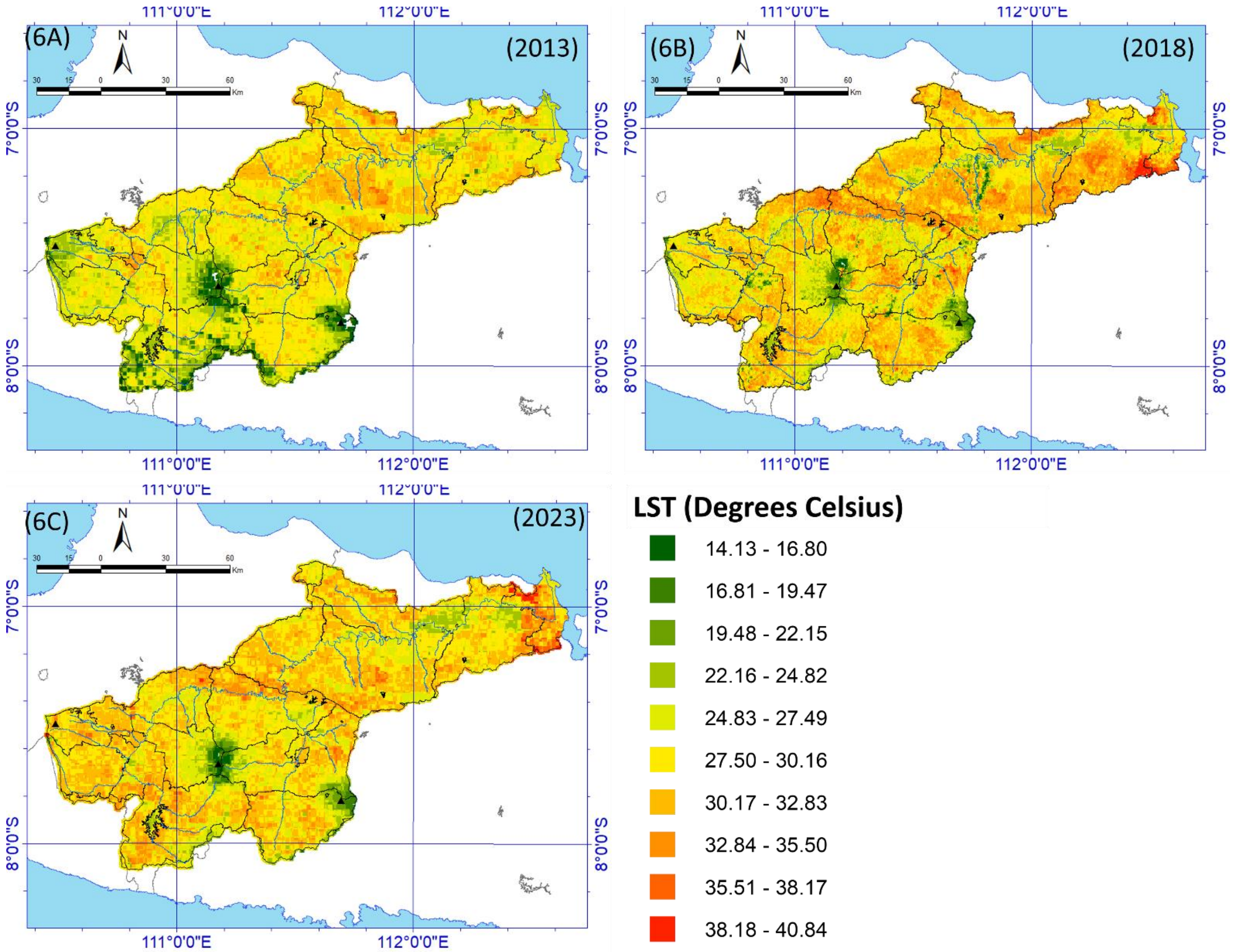



**Figure 6.** Dry Season LSTs in the Bengawan Solo River Basin, 2013-2023.

Previous studies have shown that increasing agricultural land LSTs may increase water stress in rice plants, and potentially reduce productivity in tropical agricultural areas by up to 10% (Lai *et al.*, 2025; Wang *et al.*, 2020). A decline in rice production will occur if the soil surface temperature exceeds the threshold for rice plant growth in tropical areas, which is 25°C-28°C (Shrestha *et al.*, 2022; Xu *et al.*, 2020). The increase in average LST observed in the rice field area of BSRB, reaching 29.4°C in the dry season, may therefore contribute to enviromental stress conditions associated with flash drought events.

## 3.4. Rice Production Trends in BSRB

Rice production in BSRB experienced a significant increase from 2013 to 2016, but continued to decline after 2017. The peak of rice production was in 2016, with a total output of 8.2 million tons, but fell until 2022, reaching approximately 7.1 million tons. However, in 2023 production increased again to 7.2 million tons. The fluctuation is associated with variations in soil moisture, which can influence the growth process of rice plants. However, rice production is also affected by other agriculural factors, such as proximity to water resources, agronomic inputs (seeds, fertilisers) and technological factors, that were not explicitly examined in this study. Complete data on agricultural production in BSRB over the period 2013-2018 are presented in Figure 7.

Rice production, as shown in Figure 7A, shows an increase in the downstream areas of BSRB, which have better irrigation systems. The increase was around 15% in 2016, but slowly decreased up to 2023. Falling rice production coincided with the increase in soil dryness, as indicated by lower NDWI values. The higher rice production, particularly in the middle to downstream areas of BSRB, including Sragen Regency, Ngawi Regency, Bojonegoro Regency, Tuban Regency and Lamongan Regency, is shown in Figures 7B-7E.

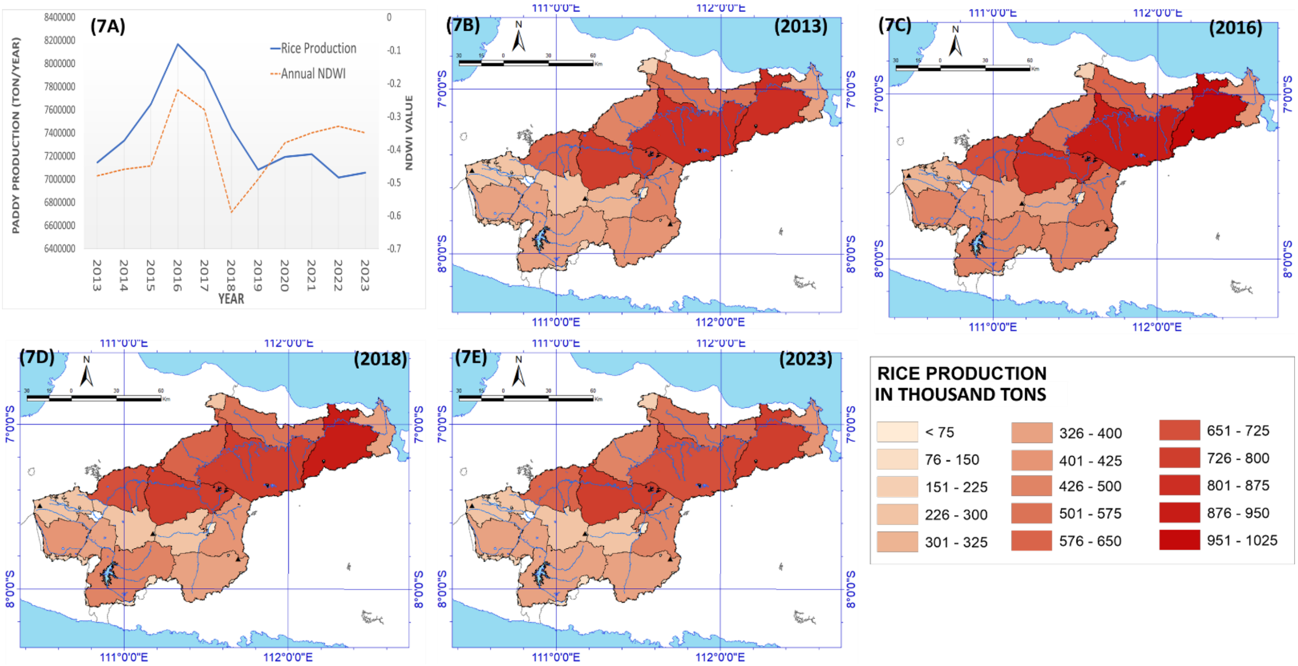



**Figure 7.** Rice Production Trends 2013-2023.

Figures 7B-7E show the spatial distribution of paddy production, with the total downstream being higher than in the upstream area. However, flash drought events, characterised by increased soil dryness and elevated land surface temperature, are associated with reduced rice production in downstream areas, while upstream areas are less affected. The upstream area seems to be more sensivtive to soil dryness compared to the downstream. Rice production in upstream areas fell by up to 12.5% in 2018, coinciding with occurrence of the extreme flash drought conditions; on the other hand, production in the downstream and middle stream areas was not highly impacted, with a fall of 3.7% in 2018 (see figure 7D). This phenomenon continued in 2023, when paddy production in upstream areas fell by 17.3% compared with production in 2016 (see figure 7E).

However, during the 2018-2023 period, the increasing drought intensity also coincided with declining rice production in several downstreams areas of BSRB. This may have also been influenced by irrigation dependency, agricultural practices and local farmer adaptation capacity in lowland rice farming. Irrigated lowland rice farming in Indonesia is very sensitive to drought, as shown in West Nusa Tenggara (Khairulbahri, 2021), East Java (Mulyanti, *et al.,* 2023), Barito Kuala, and in several rice barn provinces in Indonesia (Ansari *et al.,* 2023; Dhamira & Irham, 2020). Therefore, the observed relationship between flash drought indicators and rice production should be interpreted as a spatial association, and not a direct causal relationship.

## 3.5. Impact of the 2018 Flash Drought on Rice Production

The flash drought conditions in BSRB are strongly associated with variations in rice production, particularly during the dry seasons. This situation is inextricably linked to the significant role of the basin in Java's agricultural production. The flash drought that occurred in June–September

2018, intensified by the concurrent El Niño event, had its most severe impacts on water availability, evaporation, and air temperature, thereby increasing stress on plants (Tahasin *et al.,* 2024; Wei *et al.,* 2025).

The results of the T-statistic analysis show that the flash drought pattern indicates strong spatial relationships between flash drought indicators and variability in rice production in agricultural areas in BSRB, where, after the extreme drought of 2018, there was an average decrease in agricultural output of 46,000 tons across BSRB, even though the area of planted land had increased by 10,000 hectares compared to the period before the extreme drought. The area of rice planting in 2013 of 1.2 million hectares increased to 1.21 million hectares in 2018-2023. However, the increase in production area was not directly proportional to the rise in agricultural production. The occurrence of flash droughts may have contributed to the decline in farm output through reduced soil moisture and increased heat stress. The situation in BSRB strengthens previous research in subtropical countries which has shown that the flash drought factor is associated with food production (Hunt *et al.,* 2021; Lovino *et al.,* 2025; Xi & Yuan, 2022; Yao *et al.,* 2022; Zhao *et al.,* 2024). The findings of these studies suggest that flash drought is closely associated with food crop production, not only in subtropical regions, but also in equatorial areas, particularly in BSRB and Indonesia. This situation may be related to their similar climatic characteristics and limitations in water management and irrigation support, which could increase the susceptibility of agricultural systems to drought and flash drought events (Tirtalistyani *et al.,* 2022).

The GWR results indicate spatial relationships between flash drought indicators and rice production variability in BSRB. Soil moisture, rainfall and land surface temperature collectively explained 71.43% of the spatial variation in rice production, as reflected by the coefficient of determination ($R^2 = 0.7143$). Statistically, the magnitude of the determination coefficient in the spatial regression model is very significant; together with the low Akaike Information Criterion Corrected (AICc) value (-718.99), no spatial autocorrelation was found in the residual values, as indicated by the Moran index value of -0.5 and the p value of 0.6. The flash drought parameters that contribute statistically significantly are the soil moisture variable and the soil surface temperature variable, as indicated by the results of the least squares analysis.. The statistical probability values of soil moisture and soil surface temperature are 0.049020 and 0.000971 respectively. Both values are lower than the 0.05 confidence interval used in the spatial regression calculation. The statistical probability value for the rainfall variable is 0.379405 (much higher than the confidence interval used). A summary of the GWR model is presented in Table 3 and Figure 8.

**Table 3.** Summary statistics of the GWR parameters.

| VARNAME | VALUE | Probability (t) |
|---|---|---|
| Neighbors | 31.00 | |
| Residual Squares | 0.96 | |
| Effective Number | 103.39 | |
| Sigma | 0.07 | |
| AICc | -718.99 | |
| R2 | 0.7143 | |
| Intercept | -0.07 | 0.0000000 |
| Soil Moisture Coefficient | 0.006523 | 0.049020 |
| Rainfall Coefficient | 0.007213 | 0.379405 |
| LST Coefficient | -0.090249 | 0.000971 |
| Moran’s Index | | |
| zcore | -0.5 | |
| pvalue | 0.6 | |

Figure 8 shows the intercept values and regression coefficients of the three variables used as indicators of flash drought. Figure 8B shows that the soil moisture coefficient has a positive value across most agricultural areas, indicating a positive spatial association between soil moisture and rice production, which indicates that each increase in soil moisture has the potential to increase rice production. Meanwhile, the negative soil moisture coefficient value exhibits a clustered pattern in lowland agricultural areas. This negative coefficient is located in areas with land surface temperatures exceeding 31°C, and is situated far from the water source network (reservoirs).

Figure 8C illustrates that rainfall coefficient has a positive value across the middle stream areas of BSRB. However, the rainfall variable is not statistically significant in the GWR model ($p = 0.379405$), indicating that its spatial relationship with rice production variability was relatively weak during the study period. In contrast, the land surface temperature variable (Figure 8D) exhibits a predominantly negative coefficient value in almost all agricultural areas, indicating that higher land surface temperatures were associated with lower rice production. The results of the geographical weighted regression are consistent with previous studies, which have highlighted the importance of soil moisture factors in supporting rice plant growth (Deshabandu *et al.,* 2024; Hou *et al.,* 2022; Panda *et al.,* 2021). A decrease in soil moisture levels is commonly associated with increased plant water stress, which may disrupt the growth process and photosynthesis, potentially affecting the growth of rice panicles (Han *et al.,* 2025; Xi & Yuan, 2022).

Furthermore, the negative value of the land surface temperature coefficient suggests that an increase in temperature may reduce the rate of rice production in BSRB. The potential for such a decrease due to increased land surface temperature on agricultural land is due to higher evaporation and lower rainfall. Both factors may contribute to reduced surface soil moisture conditions, which can disrupt the growth process of rice plants. This result aligns with previous studies in the tropical region of South Asia (Lai *et al.,* 2025; Shrestha *et al.,* 2022; Wang *et al.,* 2020; Xu *et al.,* 2020).

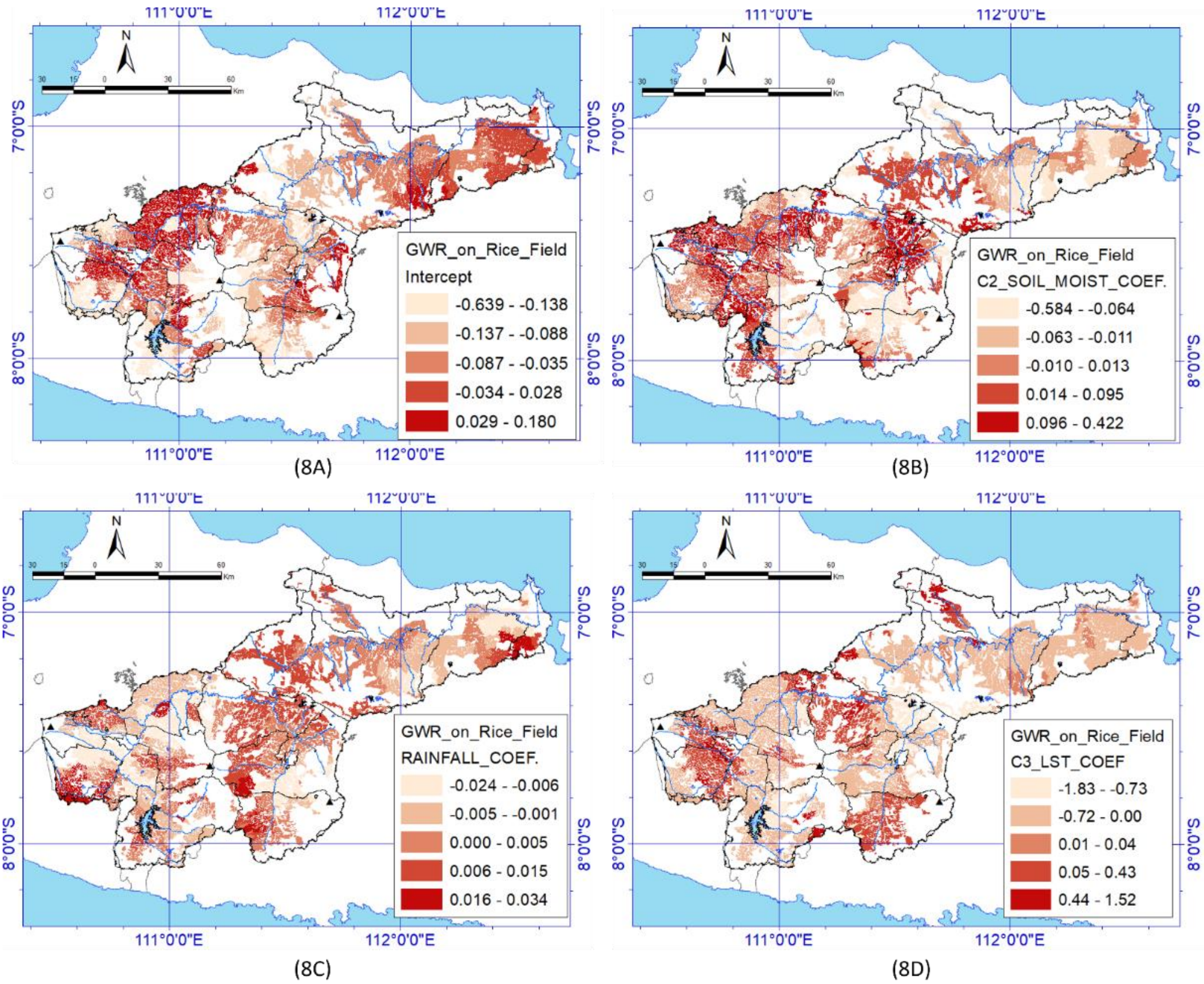



**Figure 8.** Spatial Distribution of the Influence of Flash Drought Factors on Rice Production in BSRB.

The GWR approach indicates significant spatial relationships between flash drought indicators and rice production variability in BSRB. The model explains 71.43% of the spatial variation in production through the combined contribution of soil moisture and land surface temperature. However, these results should be interpreted as spatial associations rather than direct causal effects. The remaining unexplained variation suggests that additional variables may influence rice production in BSRB. These may include the availability of irrigation infrastructure, water management conditions, cropping practices, and farmers' adaptation, which are not explicitly examined in this study. Therefore, future studies should include additional environmental and agricultural variables, longer observation periods, and multiscale spatial data in order to conduct a more comprehensive exploration of the dynamics of flash drought and agricultural crop production in tropical regions.

### 3.6. Discussion

The results indicate that flash drought conditions are spatially associated with variations in food crop production, particularly within BSRB. Such conditions, characterised by a rapid decline in soil moisture, increased land surface temperatures, and lower rainfall, may create environmental conditions that are less favourable for crop growth. The spatial relationship identified in BSRB is consistent with previous studies conducted in subtropical continental agricultural regions, which have reported that flash drought is asscociated with declines in food crop production (Jin *et al.,* 2019; Liu *et al.,* 2025; Mahto & Mishra, 2023; Shi *et al.,* 2025; Sun *et al.,* 2024). GWR analysis successfully identified spatial variability in the relationship between flash drought indicators and rice production across agricultural areas in BSRB. The findings complement and support previous studies that employed parametric statistical approaches (correlation and ordinary least squares regression) to examine the relationship between drought indicators and crop production in mainland China (Liu *et al.,* 2025; Sun *et al.,* 2024), and research in several other food-producing countries in the world such as India and China (Mahto & Mishra, 2023; Shi *et al.,* 2025). Soil moisture and land surface temperature showed stronger spatial associations with rice production variability than rainfall variables in the GWR BSRB model. The results are consistent with previous studies that have identified soil moisture conditions as an important factor associated with food crop productivity (Panda *et al.,* 2021; Stuecker *et al.,* 2018; Yao *et al.,* 2022). Land surface temperature was also spatially associated with soil moisture and crop growth variability. Higher temperatures are generally associated with increased evaporation and reduced surface moisture conditions, particularly during the dry season. These environmental conditions may reduce the suitability of agricultural land for optimal rice growth during the growing season (Lai *et al.,* 2025; Malinová *et al.,* 2026; Tran *et al.,* 2025).

The results of this study suggest that flash drought conditions may contribute to food production variablity in such humid tropical regions. However, our research did not explicitly incorporate several agricultural and environmental variables such as seed qualitiy, fertilisers, soil salinity, humidity and precipitation, which may also influence food crop production variability. The spatial regression results shown in Figure 8A indicate that the relationships between flash drought conditions on rice production varied across rice fields adjacent to surface water sources. Further studies using spatial lag methods or a multiscale spatial approach may help explain the influence of such proximity on rice production variability. Potential explanatory variables may include distance to reservoirs, rivers and irrigation systems. Our in-depth study will serve as a complementary tool for mitigating flash droughts and reducing the vulnerability of food crop production to such conditions, particularly in BSRB and food production centres throughout Indonesia.

The findings regarding the spatial relationships between flash droughts and food crop production in tropical regions, particularly of rice, are also consistent with previous research in subtropical regions, such as those in China (Yao *et al.,* 2022; Zhao *et al.,* 2024); Latin America (Lovino *et al.,* 2025); and Russia (Hunt *et al.,* 2021). However, the tropical characteristics of BSRB, which has higher average temperatures than subtropical regions, may influence the magnitude and spatial variablity of flash drought impacts differently from those observed in subtropical regions. In humid tropical regions such as Indonesia, higher background temperatures in the dry season may increase surface evaporation and reduce surface soil moisture during flash droughts (Ford & Labosier, 2017; Hu *et al.,* 2024), making it difficult for young plant to access the essential nutrients needed during growth, thus disrupting the primary production system during early plant growth. This phenomenon aligns with previous research in China that found disruptions to primary production systems due to flash droughts (Yao *et al.,* 2022; Zhao *et al.,* 2024). The GWR results indicate that the influence of land surface temperature and soil moisture varied spatially accross agricultural areas. Agricultural areas in lowland regions with higher temperatures generally exhibited negative temperature coefficients, suggesting that higher temperature were associated with lower rice production. In contrast, several highland regions in the southern part of BSRB characterised by cooler temperatures of around 19oC-24oC, showed positive temperature coefficients, indicating that moderate increases in temperature may still support rice plant growth because of the relatively cooler temperature conditions. Previous studies have reported that food crops, especially grains, generally grow optimally within a temperature range of around 25oC-28oC (Shrestha *et al.,* 2022; Xu *et al.,* 2020). Such findings suggest that the influence of flash drought on food crop production may vary to according to local environmental characteristics and temperature conditions.

## 4. Conclusion

The results indicate that flash drought in Bengawan Solo River Basin is spatially associated with variations in food crop production, especially that of rice. The GWR analysis indicated soil moisture and land surface temperature as the variables most strongly associated with spatial variability in rice production, while rainfall exhibited a weaker statistical relationship These findings suggest that decreased soil moisture, combined with increased land surface temperatures during the dry season, may reduce the suitability of agricultural land for optimal rice growth in some parts of BSRB. In addition, the study has revealed an interesting fact, that increases in land area for rice production are not always followed by proportional increases in production, indicating that climatic conditions may influence agricultural productivity across the basin.

The findings highlight the importance of spatial drought monitoring for agricultural management in tropical river basins. The spatial variability identified in the study suggests that drought mitigation strategies should consider local environmental conditions, particularly in agricultural areas exposed to higher land surface temperatures and lower surface moisture conditions. Practical adaptation measures could include the strengthening of seasonal drought monitoring systems; improved irrigation water allocation during the dry season; and the development of spatially targeted agricultural management strategies for drought-prone areas. However, the results should be interpreted within the limitations of this study. The GWR approach identified spatial statistical relationships, not direct causal mechanisms, between flash drought indicators and rice production. Furthermore, the study relies primarily on surface indicators obtained from remote sensing, but does not explicitly incorporate other agricultural variables such as irrigation performance, crop management practices, soil characteristics, or farmers' adaptive capacity. Another limitation of the study relates to static data. The spatial regression approach used relies heavily on static spatial data, thus failing to capture the temporal dynamics of flash drought events. These limitations mean that the findings only describe the spatial variation in the impact of flash droughts, poorly reflecting the spatio-temporal dynamics of flash drought events which impact food crop production, particularly that of rice in BSRB.

Future studies should incorporate additional variables and measurement approaches capable of capturing the spatio-temporal dynamics of flash drought and agricultural production. They should also incorporate other factors, as described in the study limitations above. Incorporating such factors that influence agricultural production should provide a more comprehensive explanation of the spatial influence of flash droughts on food crop production. Furthermore, future research is recommended to employ spatial panel regression or a spatial-temporal modeling approach with a timeframe tailored to the planting cycle to better capture the dynamic interactions between flash droughts and changes in rice production. Such an approach would provide stronger support for the development of spatially targeted drought mitigation and food security policies in Indonesia.

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**Author Contributions**

**Conceptualization**: Widjonarko, Hartuti Purnaweni; **methodology**: Widjonarko, Anang Wahyu Sejati; **investigation**: Widjonarko, Maryono; **writing original draft preparation**: Widjonarko, Maryono; **writing review and editing**: Alexander Zipf, Imam Buchori, Anang Wahyu Sejati; **visualization**: Widjonarko. All authors have read and agreed to the published version of the manuscript.

**Conflict of interest**

All authors declare that they have no conflicts of interest.

**Data availability**

Data is available upon request.

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