



Long-Term Trends in Extreme Rainfall and Impact on Rice Productivity and Vegetation Condition in West Java

Amrya Khaerima^{1, 2}, Rahmat Hidayat^{1*}, Tania June¹, Siswanto²

¹ Department of Geophysics and Meteorology, IPB University, Bogor, Indonesia.

² Indonesian Agency of Meteorology, Climatology, and Geophysics (BMKG)

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Correspondence:

Rahmat Hidayat
Department of Geophysics and
Meteorology, IPB University, Bogor,
Indonesia.

Email: rahmath@apps.ipb.ac.id

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ABSTRACT

Climate change has intensified the frequency and magnitude of extreme rainfall events, posing significant challenges to agricultural productivity in tropical regions such as Indonesia. Understanding the spatial-temporal patterns of extreme indices is crucial for mitigating the risk of crop failure and maintaining regional food security. This study examines the trends and patterns of extreme climate indices and their impact on rice productivity and vegetation conditions in West Java based on spatio-temporal analysis. We utilized several extreme climate indices including RX1day, RX5day, R95p, R99p, CWD, and PRCPTOT for 1991–2023 using daily rainfall data from 242 stations in West Java. We analyzed the relationships between climate variability, annual rice productivity and vegetation density using Normalized Different Vegetation Index (NDVI). Our results reveal increasing trends in the intensity and frequency of RX5day, PRCPTOT, and CWD, particularly in central and northern West Java. But, we found a weak correlation between extreme climate indices and rice productivity, with statistically significant ($p < 0.05$) only in certain areas. The long-term rice productivity showed a decline after 2020, coinciding with the intensification of extreme rainfall. In addition, vegetation density shows significant negative responses to extreme climate indices in several regions. This study provides an integrative framework linking extreme climate indices, agricultural productivity, and vegetation dynamics to support evidence-based climate change adaptation strategies.

KEYWORDS

climate indices, rainfall, rice productivity, spatial analysis, trend

1. INTRODUCTION

Climate change has significantly altered land-cover dynamics and increased the frequency and intensity of extreme climate events in many tropical regions (Sy and Quesada, 2020), including Indonesia. Changes in agricultural land-cover is closely related with vegetation density and crop productivity, causing highly sensitive to climatic variability (Casa et al., 2021; Tenreiro et al., 2021; Bununu et al., 2023). These impacts particularly significant on agriculture sector as it directly affects the growth phase, productivity, and risk of crop failure (Rahman et al., 2017; Sukarta et al., 2018; Amare et al., 2018). In addition, Extreme rainfall variability exacerbates the occurrence of floods and

droughts, which served as main factor reducing food crop productivity in Indonesia (Ruminta et al., 2024). Given that land-cover conditions reflect vegetation responses to environmental stress, monitoring these changes is crucial to understand the responses of agricultural systems to climate extremes.

West Java is one of largest agricultural regions in Indonesia and contributes as major center of national rice production. In 2023, rice production in West Java was 9.10 million tons, contributing more than 15% to Indonesia's total rice production. Its harvested area was 1.58 million hectares, which remains among the largest in the country. However, this high productivity is strongly affected by climate variability and extreme

events, such as heavy rainfall intensity or prolonged wet periods. The West Java Food Crops and Horticulture Protection Agency (BPTPH) reported that during the extreme wet period of 2020–2022, approximately 4,700 hectares of agricultural land experienced crop failure. This highlights the direct impact of extreme climate events, particularly extreme rainfall on agricultural productivity.

Extreme climate events are commonly represented by several indices to capture their duration, intensity, and frequency. The Expert Team on Climate Change Detection and Indices (ETCCDI) has developed several indices, including Rx1day, Rx5day, Consecutive Wet Days (CWD), R95p, R99p, and PRCPTOT to assess rainfall extremes. These indices provide critical information for understanding rainfall anomalies and their implications for climate-related sectors such as agriculture. Excessive rainfall often leads to flooding and waterlogging, which disrupt crop growth cycles, damage root systems, and reduce yield productivity (Manik et al., 2019; Tian et al., 2021). Moreover, prolonged exposure to high wet levels triggers soil degradation and reduce fertility, ultimately diminishing long-term agricultural productivity (Kang et al., 2021). Repeated flooding events may also accelerate land degradation processes (Rupngam and Messiga, 2024), threatening the sustainability of agricultural systems in tropical regions (Sahoo et al., 2026).

To capture the vegetation responses to climate extreme events, remote sensing-based indicators such as the Normalized Difference Vegetation Index (NDVI) has been widely used. NDVI is highly effective to monitor vegetation conditions and detect potential land damage due to environmental stress, including extreme rainfall (Hussain et al., 2023). NDVI fluctuations can reflect changes in greenness level due to unfavorable climatic conditions, such as flooding or lack of light due to thick cloud cover (Gao et al., 2022). The integration of extreme climate data and NDVI has the potential to provide a comprehensive picture of the risk of agricultural land damage in spatial and temporal terms. Previous studies (Hussain et al., 2023; Zhang et al., 2024) have demonstrated significant relationships between extreme rainfall indices and NDVI in tropical and subtropical regions. However, studies that integrate ETCCDI index trend analysis, rice productivity evaluation, and NDVI spatial-temporal analysis simultaneously remain limited, particularly in West Java.

This study aims to (1) identify trends and patterns of extreme rainfall indices in West Java, (2) evaluate the relationship between extreme rainfall indices and rice productivity, and (3) analyze the spatial and temporal relationships between extreme climate indices and NDVI in assessing agricultural land damage.

2. MATERIALS AND METHODS

2.1 Study Area

This study was conducted in the West Java region (Figure 1), which has 18 districts and 9 cities. West Java is located between 106° – 108° E and 6° – 8° S, with 242 of observational rain gauges. This area has diverse topographical conditions, dominated by lowland areas (<500 m) up to 65%, area with elevation 500-1000 m and highland area (>1000 m). The mean annual rainfall was reported about >2000 mm, where the northern and central part has relatively small rainfall compared to the south-west part (Primartono et al., 2025). The topography ranges from low-lying coastal areas in the north to mountains in the central and southern parts, which affect rainfall distribution with other driven factors such as monsoon and convective processes (Rahayu et al., 2023).

2.2 Datasets

The data used in this study are daily rainfall data from 242 observation stations in West Java for 1991–2023. The missing data was filled in using spatial interpolation with the SA-OBS dataset developed by BMKG in collaboration with the Koninkrijk Nederlands Meteorologisch Instituut (KNMI) (Besselaar et al., 2017). Stations were selected based on the criterion of missing data proportion <1% after quality control. MODIS MOD09A1 V6.1 (Surface Reflectance) NDVI data were obtained from NASA LP DAAC at the USGS EROS Center (https://developers.google.com/earth-engine/datasets/catalog/MODIS_061_MOD09A1) by taking the estimated spectral reflectance values of Terra MODIS bands 1 and 2 with a spatial resolution of 500 m, with annual period from 2001 to 2023. Meanwhile, data on rice productivity and the area of crop failure were obtained from the Central Statistics Agency (BPS) and the Ministry of Agriculture (Directorate General of Food Crops). Rice productivity data is annual data at the district/city level in West Java Province. The time range of productivity data varies between districts/cities, depending on the availability of historical data. Each district/

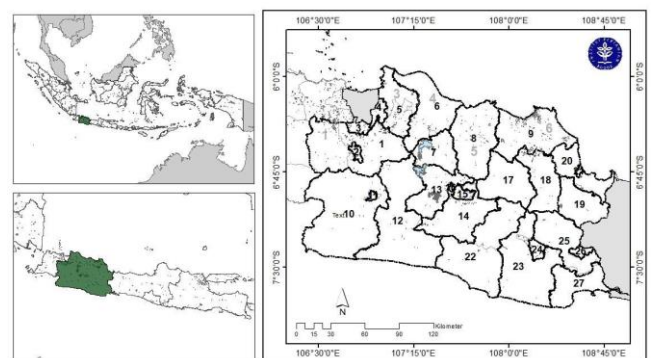


Figure 1 The study area in West Java, Indonesia

city is analyzed based on the length of valid data available without interpolation or data filling. Monthly data on the area of crop failure at the district/city level for the period 2020 to 2023.

2.3 Data Analysis

2.3.1 Calculation of the Extreme Climate Index

The extreme climate index calculation is performed using RClimate software (<https://RClimate-sci.org/>), which is an extension of RClimeDEX by the WMO CCI/WRCP/JCOMM Expert Team on Climate Change Detection and Indices (ETCCDI). This index describes the intensity, duration, and frequency of extreme climate events (Halimatou et al., 2017; Kurniadi et al., 2024). The calculation of indicators using RClimate automatically checks data quality (Table 1). Valid data will be used, while invalid data will be considered missing data and coded as 99.9, with a missing data proportion of less than 1%. After the quality control process is complete, extreme climate indicators can be calculated (Yin et al., 2020), and index trend analysis is performed using linear regression, with a significance test at 95% confidence level ($\alpha = 0.05$).

Table 1 Climate extreme indices

Index	Description	Unit
RX1day	Maximum rainfall in 1 day	mm
RX5day	Maximum rainfall over 5 consecutive days	mm
CWD	Consecutive Wet Days	days
R95p	Annual rainfall amount when RR > 95 th percentile of the data period	mm
R99p	Annual rainfall amount when RR > 99 th percentile of the data period	mm
PRCPTOT	Annual rainfall amount on rainy days	mm

2.3.2 Rice Productivity Analysis

Rice productivity trends in West Java were analyzed using a simple linear regression, and polynomial regression approaches. Linear regression was used to identify the general trend direction in Equation (1).

$$Y = \beta_0 + \beta_1 X + \epsilon \tag{1}$$

Where Y is rice productivity, X is the year, β_0 is the constant, β_1 is the regression coefficient, and ϵ is the error term. This linear model provides general

understanding between precipitation and rice productivity. However, the rice productivity may show non-linear relationship caused by extreme climatic factors (such as excessive rainfall or drought), which cause fluctuating patterns or more complex changes (Ye et al., 2018). Therefore, this study also used a 10th order polynomial regression as in Equation (2).

$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \dots + \beta_{10} X^{10} + \epsilon \tag{2}$$

This approach enabled to capture non-linear patterns that are more consistent with the dynamics of rice productivity, including phases of increase, peak, and decline due to climatic conditions and other environmental factors. Polynomial regression performed reliability in describing long-term variations without assuming a linear relationship (Bruno et al., 2018). The use of these two models is complementary: linear regression provides an overview of general trends, while polynomial regression captures more realistic patterns of productivity fluctuations. Previous analyses have also shown that polynomial regression is often more appropriate than simple linear models for describing the relationship between crop productivity and climate variables (Ray et al., 2015).

2.3.3 Rainfall-Land Cover Analysis

The Normalized Difference Vegetation Index (NDVI) is widely used to monitor the physiological condition of vegetation and identify potential damage to agricultural land due to climate variability. A decrease in the annual NDVI value generally reflects disturbances in plant growth, whether due to drought, flooding, or crop failure (Gao et al., 2022). Spatio-temporal analysis of annual NDVI allows for the interpretation of agricultural land damage dynamics, both seasonally and inter-annually. Areas with consistent downward fluctuations in NDVI periodically can be identified as vulnerable or degraded areas. However, NDVI needs to be combined with climate extreme indices and agricultural productivity to confirm the specific causes of damage, given that low NDVI values potentially caused by other factors such as climate and soil variables (Huang et al., 2021). An analysis of Normalized Difference Vegetation Index (NDVI) trends was conducted to identify changes in annual vegetation conditions in West Java during the period 2001-2023. NDVI trends were calculated using the annual linear regression method on each MODIS MOD09A1 V6.1 data pixel to analyze the relationship between vegetation response to extreme climate conditions, thus conducting a correlation analysis between NDVI and various extreme climate indices that had been calculated. The pearson’s correlation test was

applied to evaluate the strength and direction of the relationship between monthly NDVI values and monthly/annual extreme rainfall indices (such as Rx1day, Rx5day, CWD, R95p, R99p, and PRCPTOT) at each observation location.

The NDVI-based approach is important because this index is sensitive to physiological changes in plants that are influenced by environmental factors. In extreme conditions, such as flooding due to excessive rainfall, NDVI can decline sharply due to decreased photosynthetic activity and canopy structure damage (Chen et al., 2014; Zhao et al., 2024). On the other hand, frequent cloud cover in tropical regions can also affect NDVI variability, requiring long-term analysis to distinguish extreme climate signals from normal seasonal variations (Gao et al., 2022). Therefore, integrating NDVI with extreme climate indices can provide a more comprehensive spatio-temporal picture of vegetation vulnerability to climate anomalies in West Java.

3. RESULTS AND DISCUSSION

3.1 Trends in Extreme Climate Indices

Analysis of extreme rainfall trends showed a predominantly positive trend in almost all extreme climate indices (Table 2). Positive trends in intensity indices (RX1day, RX5day, R95p, R99p), duration (CWD), and frequency (PRCPTOT) indicated an increase in extreme rainfall events in terms of intensity, accumulation, and frequency. These findings showed that climate change modulates rainfall tended to increase in terms of intensity, duration, and frequency (Martel et al., 2021; Posite et al., 2025).

The index with the most positive trend is RX5day (159 posts), which describes the maximum rainfall over five consecutive days. An increase in RX5day indicates that prolonged rainfall is occurring more frequent, thereby increasing the potential risk of flooding and waterlogging in agricultural land. This positive trend was supported by RX1day (137 stations), which represents maximum daily rainfall, so that the combination of RX1day and RX5day indicated that extreme rainfall increases are occurring on both a daily and multi-day scale. In addition, the R95p (132 stations) and R99p (58 stations) indices also show an upward trend, indicating an increase in the occurrence of very wet rainfall (above the 95th percentile) to extremely wet rainfall (above the 99th percentile). Although R99p has fewer positive trends than other indices, the number of stations with "no trend" is relatively high (157 stations), which can be interpreted as meaning that very high category extreme rainfall tends to occur more sporadically. However, when R99p increases along with RX5day

indicates the risk of major flooding becomes more significant.

Table 2 Trends amount in extreme rainfall changes for each index in West Java.

Index	Category	Number of Stations		
		(+)	(-)	No trend
RX1day	Intensity	137	97	8
RX5day	Intensity	159	77	6
R95p	Intensity	132	104	6
R99p	Intensity	58	27	157
CWD	Duration	106	53	83
PRCPTOT	Frequency	147	95	-

Other indices that also show an increase are CWD (number of consecutive rainy days) and PRCPTOT (total annual rainfall). In terms of duration, the CWD index (106 posts) shows a positive trend, indicating an increase in the number of consecutive rainy days in most areas of West Java. This contributes to longer wet periods and can exacerbate the impact of high-intensity rainfall. Furthermore, the PRCPTOT index (147 stations) also shows a positive trend in annual rainfall accumulation. These findings were consistent with increases in the intensity (RX1day, RX5day, R95p, R99p) and duration (CWD) indices, reinforcing that the increase in extreme rainfall has a direct impact on annual accumulation.

In general, the results show that there is an increase in the intensity and accumulation of extreme rainfall in most areas of West Java, which has the potential to increase the risk of hydrometeorological disasters such as flooding that impacts the agricultural sector. Temporal validation was conducted to assess the stability and consistency of the trend direction of extreme climate indices in West Java. The period 1991–2010 was used as the training period and 2011–2023 as the testing period. The validation results show that most extreme indices have consistent trend directions between the two periods, particularly Rx1day, Rx5day, and CWD, which maintain a positive (increasing) trend direction with indications of strengthening in the 2011–2023 period. This indicates a continuing trend of increasing duration and intensity of extreme rainfall in the last decade.

The spatial analysis results show variations in trends between regions (Figure 2), with the trend direction visualization showing the distribution of the Rx1day and Rx5day climate index trends for each rainfall station. An upward-pointing triangle symbol indicates a positive trend (increase in extreme rainfall events), while a downward-pointing triangle indicated a negative trend (decrease in extreme rainfall events)

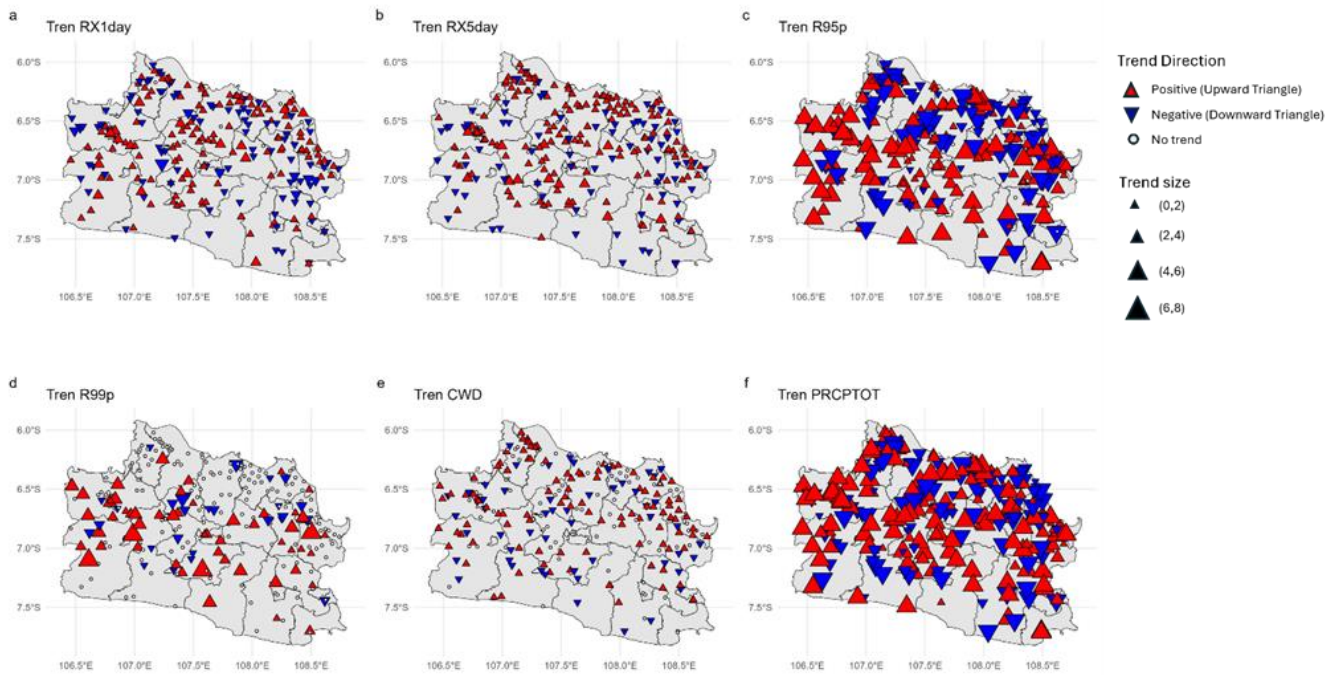


Figure 2 Spatial distribution of annual trends in extreme indices for the period 1991 – 2023. All slope values are calculated from Sen’s estimator, regardless of statistical significance (*p-value*): (a) RX1day; (b) RX5day; (c) CWD; (d) R95p and (e)PRCPTOT

Red is used for positive trends and blue for negative trends. In addition, the size of the triangle represents the magnitude of the trend change, where larger triangles indicate more significant changes than smaller triangles. Rx1day (Figure 2a) and Rx5day (Figure 2b) show positive trends in West Java, especially in central and northern West Java. The Rx5day trend shows a more dominant positive trend than Rx1day, as the regions of Bogor, Sukabumi, Cianjur, Purwakarta, Bandung, Sumedang, Garut, and Ciamis show a consistent increase in five-day rainfall intensity. This condition has the potential to increase the risk of flooding and inundation of agricultural land. These findings are in line with (Kurniadi et al., 2024), which emphasizes the increase in extreme wet events in southern Indonesia and its connection with the increase in agricultural land flooding and vegetative damage to crops (Hussain et al., 2023; Zhang et al., 2024).

The distribution of the CWD climate index trend (Figure 2c) shows an increase in the number of consecutive wet days in most of West Java, although some stations show a negative trend. The R95p climate index (Figure 2d) shows relatively balanced positive and negative trends. Positive trends are more dominant in the central and southern regions, although they are also present in northern West Java, while R99p (Figure 2e) shows an increase in the northern, central, and eastern regions. Meanwhile, PRCPTOT (Figure 2f), which represents the total annual rainfall accumulation on days with rainfall ≥ 1 mm, shows a more varied trend

distribution, with a spatial pattern of positive trends dominating in most areas of West Java, with 147 stations, and negative trends in 95 stations (Table 2). Larger symbol sizes indicate that the change in annual accumulation is quite significant.

In general, these results confirm that increases in intensity (RX1day, RX5day, R95p, R99p), duration (CWD), and frequency (PRCPTOT) collectively increase the risk of hydrometeorological disasters, particularly flooding and agricultural damage in West Java. Future climate projections anticipate similar trends, with increased wet extremes during the rainy season (R95p, RX5day) and an increase in consecutive dry days (CDD) during the dry season. The projections also indicate that extreme values for Rx1d could reach much higher levels compared to historical periods, suggesting that extreme rainfall events will occur more frequent in future.

3.2 Rice Productivity and Crop Failure Threat

Analysis of annual rice productivity trends was conducted based on the availability of historical data, which varied in length between regions, showing varying patterns (Figure 3). In general, long-term (linear) trends show an increase in productivity in areas represented by R^2 , such as Bandung City (0.66), Indramayu (0.56), and Cianjur (0.54), while regions such as Bekasi and Banjar City show a very weak linear relationship ($R^2 < 0.20$), indicating instability or strong

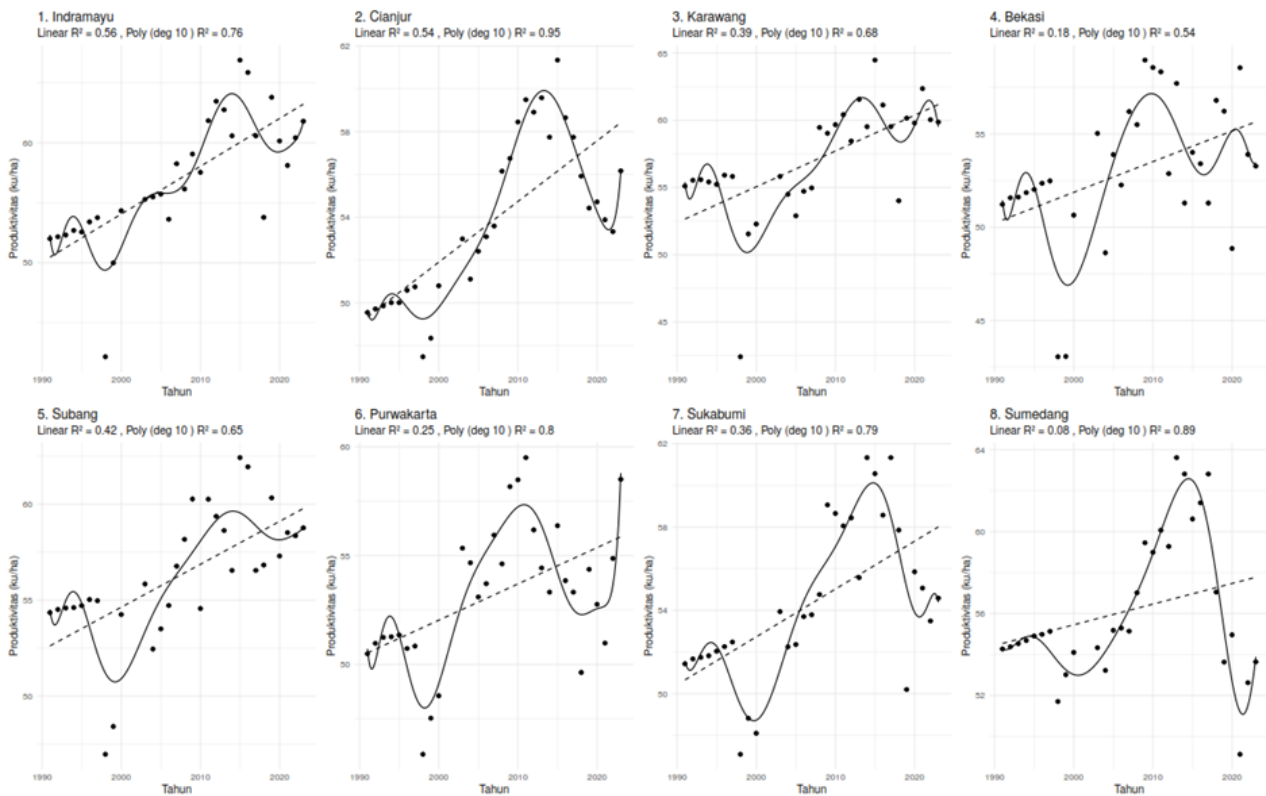


Figure 3 Annual rice productivity trends in eight representative regions of West Java for the period 1991-2023

indicating instability or strong influence from external factors. The linear R^2 value is generally below 0.50. Cities/districts such as Bekasi City, Depok, Cimahi, and Cirebon do not show a consistent pattern of productivity increase, indicating a significant influence of fluctuating climatic and non-climatic factors.

The slope of agricultural productivity during the period 1991–2023 shows an annual increase. In general, productivity increased until it peaked around 2015, then declined after 2020. This decline coincides with a period of increased extreme rainfall events (R99p and RX5day), indicating the influence of extreme climate, although not linear. These findings indicates that extreme rainfall affects food productivity directly resulting high economic costs (Damania et al., 2020), which differed by seasons, periods (Rahman et al., 2017), and local adaptation.

Although the long-term trend in rice productivity shows an increase in some regions (Figure 3), the increasing incidence of extreme rainfall, as indicated by the positive trends in the RX5day and R99p indices (Table 2, Figure 2b, Figure 2e) explain fluctuations and declines in productivity in certain years, as well as an increase in crop failure areas in regions such as Karawang, Subang, and Bekasi in February 2020.

Data on the area of potential crop failure 2020 - 2023 confirms that extreme rainfall events contributed to peak crop failures in certain areas, such as Karawang 4,909 ha, Subang 1,883 ha, and Bekasi 1,519 ha in February 2020; Indramayu 2,304 ha in February 2021;

Sukabumi 4,600 ha and Cianjur 1,310 ha in May 2021; in August 2023 Indramayu had a potential crop failure area of 3,737 ha and 1,172 ha in October 2023; Tasikmalaya in September 2023 covering an area of 1,168 ha; Bekasi in November 2023 covering an area of 1,475 ha.

The results of Pearson's correlation analysis of extreme climate indices and rice productivity in West Java show a significant relationship in several districts/cities with a p -value < 0.05 (Table A2). The contribution of each index differs in each region. Pearson's correlation shows a low R value in most districts/cities. The correlation coefficient (R) values for all indices indicate that there is no strong and direct linear relationship between an increase in extreme events and a decrease in productivity on a regional scale. This is due the non-linear nature of the relationship and the existence of a threshold effect in agricultural systems, which is better explained by polynomial regression. Productivity is influenced by high spatial variability, local adaptation, and non-climatic factors such as pests and agricultural practices, which tend to dominate climate signals on a regional scale (Zhang et al., 2024). Therefore, the relationship between extreme climate and rice productivity requires more in-depth analysis at a more detailed and non-linear scale, both spatially and temporally.

These findings indicate that increased extreme rainfall does not always have a negative impact on rice yields, but the effect is highly dependent on the balan-

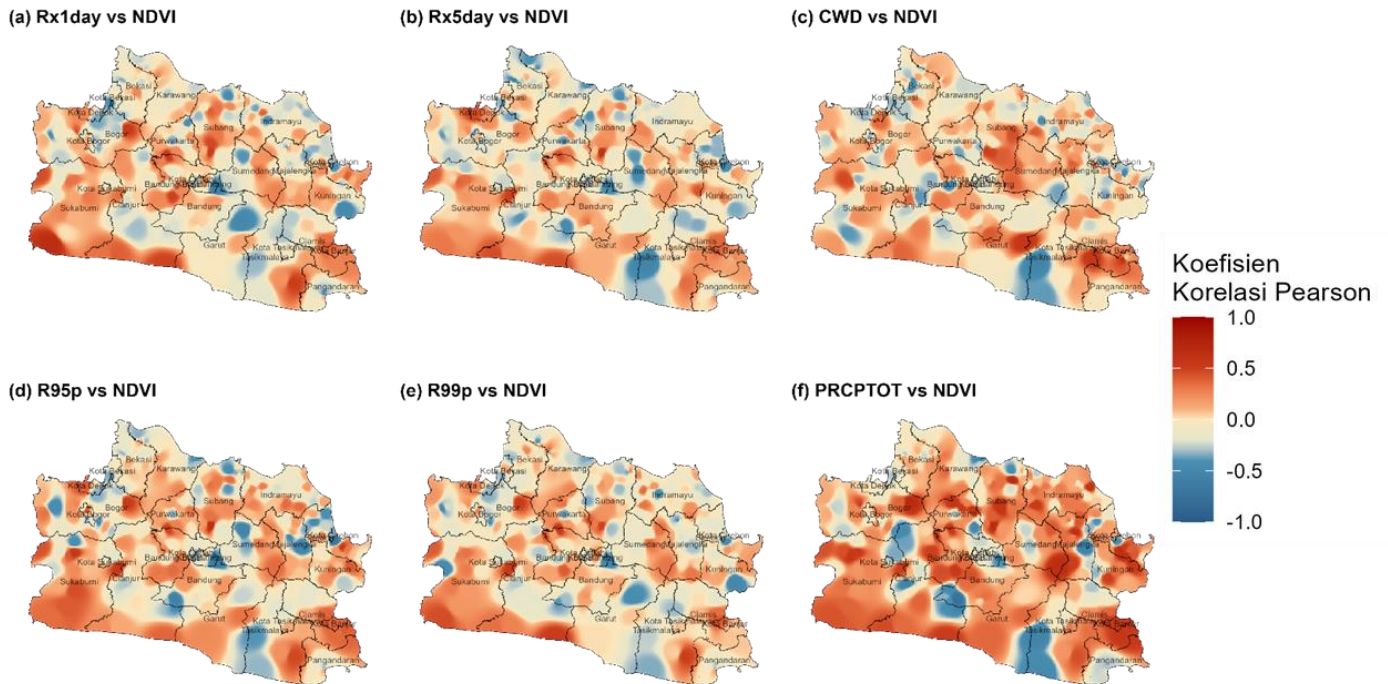


Figure 4 Spatial distribution of the correlation between NDVI and extreme climate index values in the West Java region from 2001 to 2023

ce between water availability and land carrying capacity and agricultural management systems. Increases in the duration and accumulation indices (CWD and PRCPTOT) can support productivity to a certain extent, but when prolonged wet periods are accompanied by successive extreme rainfall events (Rx5day, R99p), productivity tends to decline due to waterlogging and physiological disturbances to plants and crops. Thus, the CWD, Rx5day, and PRCPTOT indices can serve as early warning indicators of rice farming vulnerability to extreme climate risks in West Java.

3.3 Triggering Factors in Study Case 2022

In general, a decrease in NDVI values occurs during periods of extreme rainfall and drought as identified through climate indices, including intensity (RX1day, RX5day, R95p, R99p), duration (CWD), and annual accumulation (PRCPTOT). This showed that NDVI is quite sensitive in capturing the physiological response of plants to abnormal climatic conditions, whether in the form of flooding due to excessive rainfall or drought stress. Analysis of projected rainfall indicated an increasing trend in high-intensity rainfall events which has the potential to affect the dynamics of agricultural land vegetation. Extreme climate indirectly affects the mechanisms of development, growth patterns, and distribution patterns of vegetation in relation to the environment, but the relationship with NDVI varies across different time scales and regions (Yan et al., 2022). Pearson's

correlation analysis between monthly NDVI and extreme climate indices for the period 2001–2023. The results showed of tests indicating variations in the relationship between vegetation conditions and extreme index values (Figure 4).

In Figures 4a and 4b, the correlation between Rx1day and Rx5day with NDVI shows r values ranging from -0.3 to -0.6 in the Bekasi, northern and central Karawang, northern Subang, Indramayu, Purwakarta, northern Sukabumi, northern and central Cianjur, southern Bandung, northern Bogor, western Bogor, western Sumedang, northern Cirebon, southern Kuningan, northern Garut, Tasikmalaya, northern Ciamis, and Pangandaran. This negative correlation indicates that an increase in extreme daily rainfall (Rx1day) and maximum five-day rainfall (Rx5day) is associated with a decline in vegetation health (NDVI). Conversely, a positive correlation may indicate that under certain conditions, extreme rainfall still supports vegetation growth, or the vegetation response indicates that extreme rainfall does not directly cause significant damage. Several studies in Indonesia have also reported an increasing trend in NDVI in many regions over the past decade, but local patterns are influenced by land use, topography, and climate variability, confirming that the identified negative correlation is likely caused by flooding, nutrient loss through leaching, and reduced isolation during periods of extreme rainfall (Furusawa et al., 2023).

Although the Pearson correlation an initial overview of the relationship between NDVI and extreme climate index values, it is important to remember that vegetation responses to extreme events often have a time lag. Further research considering different time lags could provide a better understanding of the impact of extreme rainfall on vegetation health. Regionally and globally, spatio-temporal analysis shows that precipitation extremes can cause lagged and asymmetric responses in NDVI, with dominant negative effects in humid and lowland areas, while in some semi-arid conditions or areas with good drainage infrastructure, extreme precipitation can be beneficial for biomass (Liu et al., 2023; Pei et al., 2021).

4. CONCLUSION

Long-term analysis (1991–2023) in West Java indicates a clear intensification of wet extreme events which confirmed by positive trends in most extreme climate indices. At the regional scale, no strong and direct linear relationship was observed between climate extremes and rice productivity highlighting the complexity of agricultural systems, characterized by non-linear interactions, the dominance of non-climatic factors, and high spatial variability. However, spatial correlation analysis reveals substantial differences in sensitivity of rice productivity across districts/cities. Indices such as R95p and R99p were identified as the key limiting factors in major rice production areas, while the wet duration index (CWD) plays critical role in mountainous areas prone to landslides.

In addition, vegetation responses (NDVI) show negative relationships with extreme rainfall in several areas, indicating the presence of time-lag effects and increased environmental stress on agricultural land. Overall, the increase in the frequency of extreme rainfall contributes to an increased threat of crop failure (puso) in vulnerable areas. This study emphasizes the need for location-specific agricultural adaptation policies to mitigate the increasing climate risks, particularly through the strengthening of drainage systems and water management in low-lying areas that are sensitive to wet extremes.

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ANNEX

Table A1 Temporal Validation of Extreme Climate Index Trends in West Java (Training 1991–2010, Testing 2011–2023).

Indeks	Koefisien Tren (Training)	P-value (Training)	Koefisien Tren (Testing)	P-value (Testing)	Konsistensi Arah	Intensifikasi Tren
RX1day	0.05	0.894	0.44	0.533	Konsisten (+)	Menguat
RX5day	0.32	0.77	0.28	0.84	Konsisten (+)	Menguat
PRCPTOT	-2.08	0.89	13.71	0.712	Tidak konsisten	Menguat
R95p	-1.68	0.612	7.02	0.501	Tidak konsisten	Menguat
R99p	-0.26	0.831	3.32	0.433	Tidak konsisten	Menguat
CWD	0.01	0.954	0.01	0.937	Konsisten (+)	Menguat

Table A2 Pearson correlation between extreme climate indices and rice productivity per district/city. The asterisk (*) indicates the correlation coefficient (R) value that has a statistically significant relationship with rice productivity at a 95% confidence level (p-value<0.05)

No.	District/City	Extreme Index					
		RX1day	RX5day	R95p	R99p	CWD	PRCPTOT
1.	Bogor	0.26	0.31	0.34	0.33	0.43 ^{*)}	0.40
2.	Bogor City	0.32	0.42 ^{*)}	0.37	0.26	0.10	0.23
3.	Depok City	0.17	0.18	0.24	0.31 ^{*)}	-0.17	0.30
4.	Bekasi City	0.36	0.30	0.25	0.34	0.16	0.41 ^{*)}
5.	Bekasi	0.45	0.50	0.59	0.67 ^{*)}	0.29	0.50
6.	Karawang	0.41	0.25	0.48	0.55 ^{*)}	0.02	-0.12
7.	Purwakarta	0.60 ^{*)}	0.28	0.43	0.41	0.34	0.44
8.	Subang	0.38	0.33	0.30	0.35	0.18	0.50 ^{*)}
9.	Indramayu	0.32 ^{*)}	0.11	0.28	0.24	0.27	0.24
10.	Sukabumi	0.59	0.59	0.62 ^{*)}	0.42	0.50	0.58
11.	Sukabumi City	0.22	0.38	0.37	0.29	0.49 ^{*)}	0.48
12.	Cianjur	0.20	0.25	0.14	0.37	0.43 ^{*)}	0.08
13.	Bandung Barat	0.33	0.16	0.40	0.18	0.29	0.46 ^{*)}
14.	Bandung	0.52 ^{*)}	0.46	0.49	0.44	0.43	0.43
15.	Bandung City	-0.02	0.19	0.25	0.03	0.18	0.36 ^{*)}
16.	Cimahi City	-0.02	0.10	0.21	0.03	0.18	0.35 ^{*)}
17.	Sumedang	0.26	0.22	0.21	0.18	0.58 ^{*)}	0.34
18.	Majalengka	0.34	0.32	0.32	0.51 ^{*)}	0.46	0.42
19.	Kuningan	0.42	0.31	0.48 ^{*)}	0.40	0.45	0.30
20.	Cirebon	0.50	0.26	0.59 ^{*)}	0.55	0.46	0.33
21.	Cirebon City	0.09	-0.04	-0.07	-0.07	-0.07	-0.19
22.	Garut	0.27	0.25	0.39 ^{*)}	0.16	-0.02	0.36
23.	Tasikmalaya	0.56	0.48	0.35	0.22	0.39	0.60 ^{*)}
24.	Tasikmalaya City	0.29	0.40 ^{*)}	0.30	0.07	0.32	0.15
25.	Ciamis	0.58 ^{*)}	0.54	0.54	0.39	0.44	0.44
26.	Banjar City	0.56 ^{*)}	0.50	0.51	0.39	0.43	0.43
27.	Pangandaran	0.32	0.30	0.33	0.30	0.43 ^{*)}	0.31

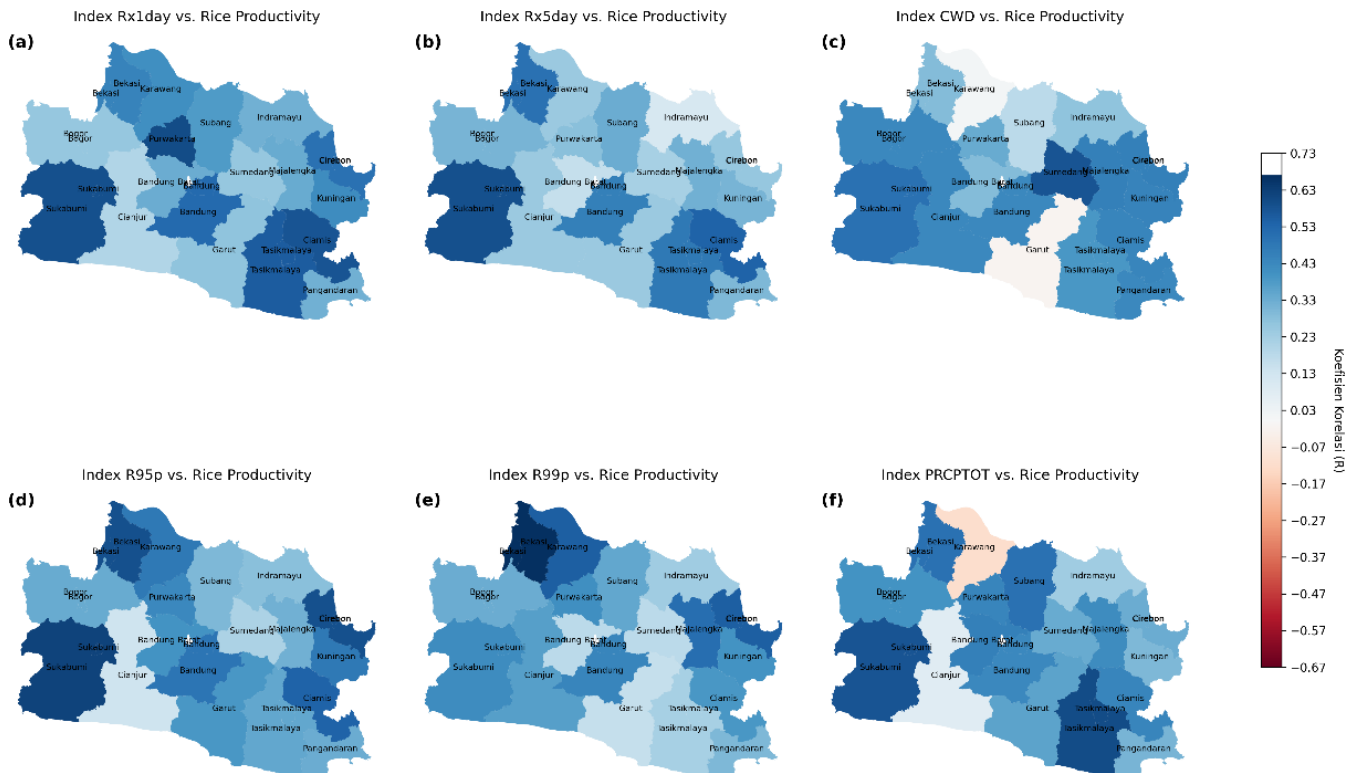


Figure A3 Spatial distribution of Pearson's correlation coefficient (R) between extreme climate indices (a) RX1day; (b) RX5day; (c) CWD; (d) R95p; (e) R99p; and (f) PRCPTOT with annual rice productivity in each district/city in West Java