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Research Article

# Food Crop Productivity and Food Security under Climate Change: A Vulnerability Index Assessment Based on Exposure, Sensitivity, and Adaptive Capacity

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**ABSTRACT**

**Purpose of the study:** This study aims to analyze the impact of climate change on the productivity of major food crops, namely rice, maize, and soybean, and its implications for food security in Banggai Regency, and to identify and map areas vulnerable to climate change based on a regional vulnerability index.

**Methodology:** This mixed-methods study combined qualitative, quantitative, and geospatial analysis. The study examined questionnaires, interviews, BMKG climate records, BPS/Food Crops Agency productivity figures, and BIG geospatial data using regression, correlation, trend, and thematic analysis, alongside a weighted-overlay spatial analysis that produced a composite vulnerability index based on exposure, sensitivity, and adaptive capacity.

**Main Findings:** The results found no statistically significant direct effect of climate change on rice, maize, or soybean productivity between 2014 and 2024. While temperature and rainfall showed a general upward trend, crop productivity moved inconsistently, sometimes in the opposite direction. Interview data corroborated this, suggesting non-climatic factors more strongly influence productivity outcomes. Based on the composite vulnerability index integrating exposure, sensitivity, and adaptive capacity, six sub-districts fell into the moderate vulnerability category, while Balantak alone was classified as having low vulnerability.

**Novelty/Originality of this study:** The novelty of the study lies in integrating climate–productivity time-series analysis, a multidimensional regional vulnerability index, and household food security within a single framework at the same regional level. Consequently, climate adaptation strategies should be tailored to each subdistrict's vulnerability profile rather than applied uniformly, and food security programs should also address non-climatic factors that appear to influence productivity more strongly.

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## 1. INTRODUCTION

Global warming is the rise in the Earth's surface temperature caused by anthropogenic activities, which in turn contributes to broader global climate change [1], [2]. This warming has triggered a range of natural disasters droughts, unstable rainfall, rising temperature and humidity, among other phenomena that have caused damage and failure across various production sectors, agriculture in particular [3]-[5]. Indonesia is one of the countries most vulnerable to climate change [5], [6]. Agriculture plays a vital role in the economy and food security, with staple crops such as rice, maize, and soybean [7] essential to meeting the population's food needs. Yet increasingly unpredictable climate change is already affecting the production patterns of these crops [4], [8].

Research by Hidayatullah & Aulia shows that rising temperatures lead to increased pest and disease outbreaks and a decline in crop quality [9]. Other studies [10], [11] indicate that rising air temperatures due to global warming can affect photosynthesis and respiration in plants. Temperature increases above 30 degrees in rice plants during the flowering period result in a significant decrease in grain yield [10]. The agricultural sector is highly dependent on climatic conditions, so changes in climate characteristics can affect planting times, water availability, plant growth, and agricultural productivity [2], [12]. Rainfall variability, for example, is closely linked to water availability for plants and can have different effects on productivity in different locations [8].

Amid growing climate uncertainty, farmers' capacity to adapt has become central to determining the level of risk their farming systems face [13], whether through adjusted planting schedules, variety selection, water management, crop diversification, or shifts in cultivation practice [14], [15]. Priyanto et al. [16] linked climate adaptation strategies to greater technical efficiency in rice farming in the Special Region of Yogyakarta evidence that climate change's impact on agriculture is shaped not just by the intensity of climatic pressure, but by how well farmers respond to it.

This concept underpins how agricultural vulnerability is measured. Vulnerability is shaped not only by exposure to climate stress, but by a system's sensitivity and the adaptive capacity available to communities. Suciantini et al. show that food-crop farming vulnerability stems from the interplay of climatic factors, land and water resources, and socioeconomic conditions, with the dominant driver varying by region [17]. Estiningtyas et al. [18] further demonstrate that regional-scale vulnerability analysis can integrate exposure, sensitivity, and adaptive capacity indicators to pinpoint areas requiring targeted adaptation strategies. Household food security, meanwhile, is not determined by agricultural productivity alone, though productivity still bears on it. Food security hinges on dietary diversification, production orientation, and alternative income sources. Tacconi et al [19] find that farm diversification strategies and household economic characteristics are linked to dietary diversity among rural households across South and Southeast Asia.

Vulnerability mapping, then, does more than flag which areas are at risk it helps pinpoint what drives that vulnerability, so adaptation strategies can be tailored to context. Yet while the exposure, sensitivity, adaptive capacity approach has informed numerous agricultural vulnerability studies [17], [18], [20], most measure vulnerability in isolation from actual productivity data and household food security within the same region. As a result, the links between climate, food crop productivity, and household food security have rarely been analyzed together within a single integrated framework particularly in eastern Indonesia, where time-series climate and productivity data exist but remain underused. This is the gap this study addresses.

Banggai Regency, located in eastern Indonesia, is no exception to climate change impacts. With agriculture still the backbone of its regional economy [21], the regency faces distinct climate-related challenges: erratic rainfall patterns have driven crop failures [22]-[24], undermining regional food security [25]. Yet no study to date has integrated time-series climate and productivity data with spatial vulnerability mapping across its sub-districts. This gap warrants closer examination, given that both climate change and food security are enshrined in the United Nations' 2015 Sustainable Development Goals (SDGs). This study adopts a mixed-methods approach, combining time-series statistical analysis, household surveys, and geospatial mapping precisely because it can meet these needs simultaneously: measuring climate's effect on productivity while mapping priority intervention areas by vulnerability profile.

Building on this background, the study aims to (a) analyze the effect of climate change on food crop productivity (rice, maize, soybean) and assess food security in Banggai Regency, and (b) map climate-vulnerable zones based on a regional vulnerability index integrating exposure, sensitivity, and adaptive capacity dimensions. The research questions are: (a) to what extent do climate variables annual temperature and rainfall (mm), affect the productivity of paddy rice, maize, and soybean (ton/ha) in Banggai Regency? and (b) how are climate-vulnerable areas mapped based on a regional vulnerability index (exposure, sensitivity, and adaptive capacity) in Banggai Regency?

## 2. RESEARCH METHOD

This study employs a convergent parallel mixed-methods design [26], integrating three components: in-depth interviews with 15 farmers to explore their understanding of and adaptation to climate change; a structured survey of 140 farmers across 7 sub-districts capturing rice, maize, and soybean productivity, analyzed against

2014–2024 BMKG climate data via multiple linear regression; and geospatial mapping through weighted overlay analysis in ArcGIS, combining three parameters (exposure, sensitivity, adaptive capacity) to generate a composite Vulnerability Index [17], [20] identifying climate-vulnerable areas across Banggai Regency.

Sampling was conducted through purposive sampling for both location and informants, based on the subjects' relevance to climate change and food crop issues. Sample locations were determined from BPS data [27] on food crop production centers for 2024, covering seven sub-districts: Batui, Luwuk Utara, Luwuk Timur, Masama, Mantoh, Lamala, and Balantak. Sample size was calculated using the Slovin formula [28] with an 8.3% margin of error, yielding 140 farmer respondents. Samples were allocated proportionally [29] across sub-districts, 20 farmers each, selected via purposive sampling [30] based on the following criteria: (a) actively cultivating food crops (rice, maize, or soybean), (b) at least 5 years of farming experience, (c) minimum landholding of 0.25 hectares, (d) residing in Banggai Regency for at least 3 years, and (e) willingness to participate. Beyond the questionnaire survey, the study also involved 15 key informants, purposively selected, for in-depth interviews.

Three instruments were used in this study. First, a structured questionnaire administered to 140 farmer respondents, covering items on climate change perception (rainfall patterns, temperature), crop failure experience, causes of yield change, adaptation strategies, and information access. These items were developed by adapting the instrument used by Amirat et al. [31], which measured rice farmers' knowledge, perception, and adaptation to climate change in Sulawesi, together with the exposure-sensitivity-adaptive capacity indicator framework from Estiningtyas et al. [18], adjusted to the commodity and field conditions of Banggai Regency. Second, the Household Dietary Diversity Score (HDDS) instrument, adopted directly from Swindale & Bilinsky [32] without modification, comprising 12 food groups consumed by the household in the preceding 24 hours, to measure household food security. The HDDS score (range 0–12) has no universally standardized categorization threshold [32]; for descriptive purposes, the scores were operationally grouped into three categories: low (0–3), moderate (4–5), and high (6–12). These categories were developed solely for descriptive purposes and do not represent standardized HDDS thresholds. Third, a semi-structured interview guide for the 15 key informants, developed based on climate change and adaptation themes identified from the literature review [18].

Data collection procedures were as follows. Primary data were collected through direct questionnaire surveys of 140 farmer respondents across seven sub-districts from June to August 2026, along with in-depth interviews of 15 key informants. Secondary data climate data (BMKG, 2014–2024), food crop productivity data (BPS and the Banggai Regency Food Crops Agency), and geospatial data (BIG) were obtained through official requests or open-access channels from the relevant agencies.

Data analysis employed multiple regression analysis, correlation analysis, trend analysis, thematic analysis, and spatial analysis.

Multiple regression and correlation analyses were conducted to determine whether significant relationships existed between climate variables, particularly temperature and rainfall, and food crop productivity in Banggai Regency. The multiple regression model used in this study is expressed as follows:

$$Y = \alpha + \beta_1 X_1(Temperature) + \beta_2 X_2\ (Rainfall) + \ldots.. + \beta_n X_n \ \ldots (1)$$

Where Y is the dependent variable, represented by food crop production. X represents the independent variables, namely temperature and rainfall. α is the constant, while β represents the regression coefficient.

Correlation analysis was used to measure the strength and direction of the relationship between climate variables, namely temperature and rainfall, and food crop productivity. The correlation analysis equation is presented as follows:

$$r = \frac{n(\sum XY) - (\sum X)(\sum Y)}{\sqrt{\left[n\sum X^2 - (\sum X)^2\right]\left[n\sum Y^2 - (\sum Y)^2\right]}} \ldots (2)$$

Where $r$ is the correlation coefficient, $Y$ is the dependent variable (food crop production), $X$ is the independent variable (climate variable), and $n$ is the number of data pairs. The strength of the correlation was interpreted using Sugiyono's [28] guidelines: 0.00–0.199 (very weak), 0.20–0.399 (weak), 0.40–0.599 (moderate), 0.60–0.799 (strong), and 0.80–1.000 (very strong).

Trend analysis in this study was used to examine patterns of climate change from 2014 to 2024. The equation used for the trend analysis is presented as follows:

$$Y_t = a + b_t \ldots (3)$$

Where $Y_t$ represents the value of the food crop production variable in a given year, a is the constant, and b represents the trend coefficient over a specified period of time.

Thematic analysis was used to examine the results of in-depth interviews with 15 key informants, including farmers and traditional community leaders, who were selected through purposive sampling. Spatial Analysis, Vulnerability mapping was conducted by integrating indicators obtained from the farmer survey, including perceptions of changes in rainfall and temperature patterns, crop failure, production changes, pest and disease disturbances, weather-related changes in planting schedules, adaptation strategies, access to information, and household food security conditions. The indicators were standardized on a 0–1 scale and conceptually grouped into exposure, sensitivity, and adaptive capacity dimensions [17], [20]. A relative vulnerability index was subsequently calculated by aggregating exposure, sensitivity, and the inverse of adaptive capacity using equal weights. The normalization and aggregation procedures followed the composite indicator principles of the OECD/JRC [33], while the vulnerability index approach was adapted from [20].

$$V_i = [E_i + S_i + (1 - AC_i)] / 3 \ldots (4)$$

**Note:** $V_i$ = relative vulnerability score of district $i$; $E_i$ = exposure index; $S_i$ = sensitivity index; and $AC_i$ = adaptive capacity index.

The index values ranged from 0 to 1, with higher values indicating greater relative vulnerability. The index was used to compare the relative vulnerability among the seven sub-districts included in the study and was not intended as an absolute measure of vulnerability across Banggai Regency. For spatial visualization, the index was classified into three equal intervals: low (0.000–0.333), moderate (0.334–0.666), and high (0.667–1.000). This classification was used for visualization purposes, while the main interpretation was based on comparisons of index values across sub-districts.

Table 1. Vulnerability Index

| Index Value | Category |
|---|---|
| 0.000 – 0.333 | Low Vulnerability |
| 0.334 – 0.666 | Moderate Vulnerability |
| 0.667 – 1.000 | High Vulnerability |

## 3. RESULTS AND DISCUSSION

The results of this study include questionnaire data, thematic analysis, trend analysis, correlation and multiple regression analyses, and spatial analysis through vulnerability mapping.

### Questionnaire and Thematic Analysis

The questionnaire involved 140 respondents from seven sub-districts in Banggai Regency. Of the respondents, 99 farmers (70.71%) were male and 41 (29.29%) were female, with most respondents having a senior high school/vocational high school education (37.14%). Overall, the questionnaire results indicate that most respondents had experienced changes in climatic conditions at the farm level. Of the 140 respondents, 126 (90%) reported changes in rainfall patterns, and the same proportion reported changes in temperature. Furthermore, 112 respondents (80%) stated that weather conditions affected planting schedules, while 80 respondents (57.14%) reported having experienced crop failure. The results are presented in the following table 2.

Table 2. Perception Indicators and Crop Failure

| Indicator | Yes | Percentage of Yes Responses | No | Percentage of No Responses | No Response |
|---|---|---|---|---|---|
| Experienced changes in rainfall patterns | 126 | 90.00% | 14 | 10.00% | 0 |
| Experienced changes in temperature | 126 | 90.00% | 14 | 10.00% | 0 |
| Weather conditions affect planting schedules | 112 | 80.00% | 25 | 17.86% | 3 |
| Experienced crop failure | 80 | 57.14% | 60 | 42.86% | 0 |

Then, the questionnaire results regarding changes in farmers' crop yields did not show a consistent trend. The data are presented in Table 3.

Table 3. Changes in Respondents' Crop Yields

| Changes in Crop Yields | Number of Respondents | Percentage |
|---|---|---|
| Increased | 44 | 31.43% |
| Remained unchanged | 55 | 39.29% |
| Decreased | 40 | 28.57% |
| No response | 1 | 0.71% |
| Total | 140 | 100% |

Based on the survey results, changes in crop yields were not solely associated with climate factors. Other factors were also reported, with pest and disease outbreaks identified as the most dominant cause. The data are presented in Table 4.

Table 4. Causes of Changes in Crop Yields

| Cause | Number of Respondents Selecting | Percentage of Respondents |
|---|---|---|
| Pest and disease outbreaks | 84 | 60.00% |
| Changes in rainfall | 79 | 56.43% |
| Changes in temperature/weather conditions | 42 | 30.00% |
| Reduced fertilizer use | 30 | 21.43% |
| Declining soil fertility | 17 | 12.14% |
| Declining seed quality | 10 | 7.14% |
| Others | 3 | 2.14% |

Household food security was analyzed using the Household Dietary Diversity Score (HDDS). Of the 140 respondents, the majority were classified as having a high level of food security. A total of 120 respondents (85.71%) were in the high food security category, while the remaining respondents were classified as having moderate or low food security. The results are presented in Table 5.

Table 5. HDDS Analysis and Household Food Security

| Food Security Category | HDDS Score | Number of Respondents | Percentage |
|---|---|---|---|
| Low | 0–3 | 2 | 1.43% |
| Moderate | 4–5 | 18 | 12.86% |
| High | 6–12 | 120 | 85.71% |
| Total | – | 140 | 100.00% |

Thematic analysis was subsequently conducted based on in-depth interviews with 15 farmers from several research locations in Banggai Regency. The analysis involved identifying statements with similar meanings, assigning initial codes, grouping the codes into subthemes, and developing broader themes to provide a more comprehensive understanding of farmers' experiences.

The findings indicate that farmers' experiences in responding to changing climate conditions were not uniform. Differences in location, cultivated commodities, farming experience, land conditions, access to resources, and adaptation strategies contributed to varying experiences among informants. Nevertheless, several recurring patterns emerged across the interviews. Seven main themes were identified: farmers' perceptions of climate change dynamics, impacts on agricultural production systems, interactions between climatic and non-climatic factors, farmers' adaptation strategies, local knowledge in interpreting seasonal patterns, household capacity and institutional support, and expectations for agricultural sustainability.

**Trend Analysis**

Trend analysis was conducted to examine changes in climate variables, namely temperature and rainfall, as well as the productivity of food crops, including rice, maize, and soybeans, from 2014 to 2024. The results are presented as follows:

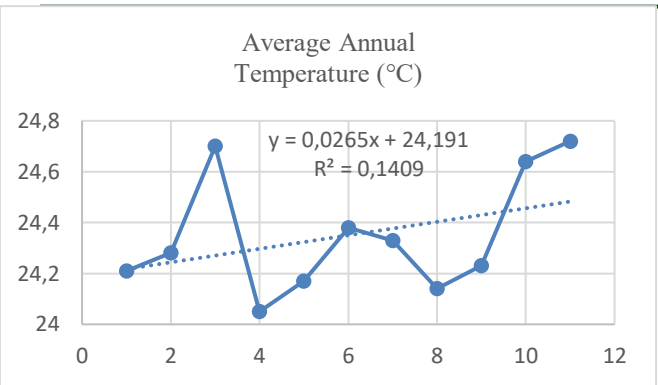



Figure 1. Temperature Trend Analysis

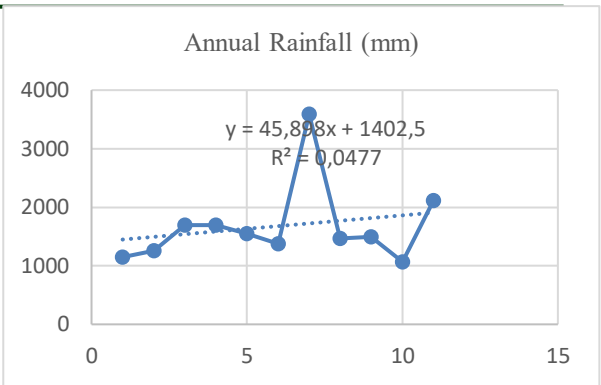



Figure 2. Rainfall Trend Analysis

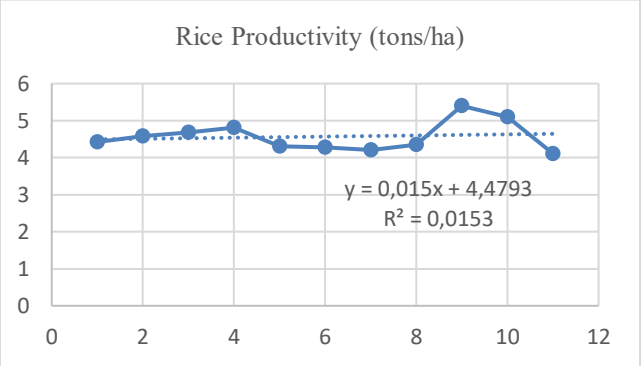



Figure 3. Rice Productivity Trend Analysis

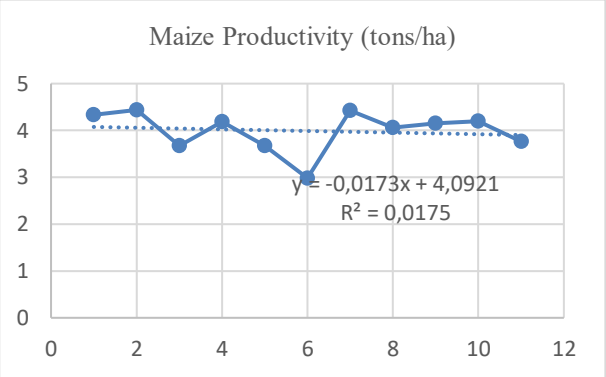



Figure 4. Maize Productivity Trend Analysis

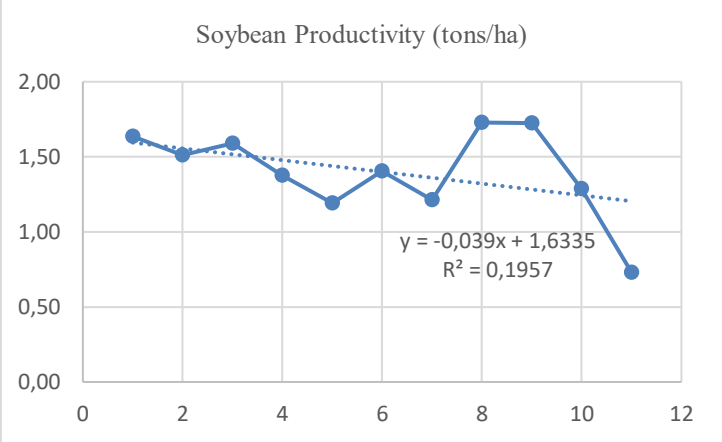



Figure 5. Soybean Productivity Trend Analysis

Overall, the trend analysis indicates that annual average temperature and rainfall tended to increase, while crop productivity showed varying patterns. Rice productivity exhibited a relatively slight increasing trend, whereas maize and soybean productivity showed declining trends. The $R^2$ values for all variables were relatively low, indicating that time was not the sole factor explaining variations in temperature, rainfall, or crop productivity during the observation period. These trend analysis results provide a basis for further examining the relationships between climate variables and crop productivity through correlation and regression analyses.

## Multiple Regression Analysis

Multiple regression analysis was used to examine the partial and simultaneous effects of temperature and rainfall on the productivity of rice, maize, and soybean. Temperature ($X_1$) and annual rainfall ($X_2$) were the independent variables, while crop productivity was the dependent variable (Y). Partial and simultaneous effects were tested using the t-test and F-test, respectively, at a 5% significance level ($\alpha = 0.05$). Before regression analysis, the assumptions were tested using the Shapiro–Wilk test of residual normality for three models: rice, maize, and soybean productivity.

The results showed Shapiro–Wilk significance values of 0.117 for rice, 0.194 for maize, and 0.959 for soybean, all exceeding 0.05. Thus, the residuals of all three models did not show significant deviations from normality. The multiple regression results for rice productivity are presented in Table 6.

Table 6. Multiple Regression Analysis Results for Rice Productivity

| Variable | B Coefficient | Std. Error | Beta | t-value | Sig. | Description |
|---|---|---|---|---|---|---|
| Constant | 5.307 | 13.536 | – | 0.392 | 0.705 | – |
| Temperature ($X_1$) | -0.015 | 0.557 | -0.008 | -0.026 | 0.980 | Not significant |
| Rainfall ($X_2$) | 0.000 | 0.000 | -0.398 | -1.222 | 0.256 | Not significant |

Based on Table 6, the multiple regression equation for rice productivity is: [Y = 5,307 - 0,015X_1 + 0,000X_2]. The constant value of 5.307 represents the predicted rice productivity when the temperature and rainfall variables in the model are zero. The temperature coefficient of −0.015 indicates a negative relationship between temperature and rice productivity. Meanwhile, the rainfall coefficient is shown as 0.000 because its value is very small at the rounding level used in the SPSS output. The t-test results show significance values of 0.980 for temperature and 0.256 for rainfall. Since both values exceed 0.05, neither temperature nor rainfall had a statistically significant partial effect on rice productivity.

Table 7. Model Summary and F-Test of Rice Productivity

| Indicator | Value |
|---|---|
| R | 0.398 |
| R Square | 0.159 |
| Adjusted R Square | -0.052 |
| Std. Error of the Estimate | 0.41165 |
| F-value | 0.755 |
| Sig. F | 0.501 |

The R Square value of 0.159 indicates that temperature and rainfall explained approximately 15.9% of the variation in rice productivity, while the remaining 84.1% was not explained by the model. The F-test significance value of 0.501, which exceeds 0.05, indicates that temperature and rainfall did not have a statistically significant simultaneous effect on rice productivity.

The multiple regression results for maize productivity are presented in Table 8.

Table 8. Multiple Regression Analysis Results for Maize Productivity

| Variable | B Coefficient | Std. Error | Beta | t-value | Sig. | Description |
|---|---|---|---|---|---|---|
| Constant | 17.365 | 14.967 | – | 1.160 | 0.279 | – |
| Temperature ($X_1$) | -0.558 | 0.616 | -0.301 | -0.906 | 0.391 | Not significant |
| Rainfall ($X_2$) | 0.000 | 0.000 | 0.198 | 0.595 | 0.568 | Not significant |

Based on Table 8, the multiple regression equation for maize productivity is: [Y = 17,365 - 0,558X_1 + 0,000X_2]. The temperature coefficient of −0.558 indicates a negative relationship with maize productivity, meaning that higher temperatures tend to reduce productivity when rainfall is held constant. The rainfall coefficient of 0.000 reflects its very small value after rounding. The t-test results show significance values of 0.391 for temperature and 0.568 for rainfall, both exceeding 0.05; therefore, neither variable had a significant partial effect on maize productivity.

Table 9. Model Summary and F-Test of Maize Productivity

| Indicator | Value |
|---|---|
| R | 0.347 |
| R Square | 0.120 |
| Adjusted R Square | -0.099 |
| Std. Error of the Estimate | 0.45517 |
| F-value | 0.548 |
| Sig. F | 0.598 |

The R Square value of 0.120 indicates that temperature and rainfall explained approximately 12.0% of the variation in maize productivity, while the remaining 88.0% was not explained by the model. The F-test significance value of 0.598, which exceeds 0.05, indicates that temperature and rainfall did not have a statistically significant simultaneous effect on maize productivity. The following results present the multiple regression analysis of soybean productivity, as shown in Table 10.

Table 10. Multiple Regression Analysis Results for Soybean Productivity

| Variable | B Coefficient | Std. Error | Beta | t-value | Sig. | Description |
|---|---|---|---|---|---|---|
| Constant | 14.650 | 8.657 | – | 1.692 | 0.129 | – |
| Temperature ($X_1$) | -0.533 | 0.356 | -0.426 | -1.497 | 0.173 | Not significant |
| Rainfall ($X_2$) | Very small* | 0.000 | -0.385 | -1.354 | 0.213 | Not significant |

Based on Table 10, the multiple regression equation for soybean productivity is presented as follows: [Y = 14,650 - 0,533X_1 - 0,0000X_2]. The temperature coefficient of -0.533 indicates a negative relationship between temperature and soybean productivity, while the rainfall coefficient of 0.000 indicates a positive relationship. However, these coefficients cannot be interpreted as statistically significant effects because the t-test results show significance values of 0.173 for temperature and 0.213 for rainfall, both greater than 0.05. Thus, neither temperature nor rainfall had a significant partial effect on soybean productivity.

Table 11. Model Summary and F-Test of Soybean Productivity

| Indicator | Value |
|---|---|
| R | 0.597 |
| R Square | 0.356 |
| Adjusted R Square | 0.195 |
| Std. Error of the Estimate | 0.26327 |
| F-value | 2.214 |
| Sig. F | 0.172 |

The R Square value of 0.356 indicates that temperature and rainfall explained 35.6% of the variation in soybean productivity, while the remaining 64.4% was explained by other factors. However, the F-test ($p = 0.172 > 0.05$) showed no significant simultaneous effect. Overall, temperature and rainfall had no significant partial or simultaneous effects on rice, maize, or soybean productivity. Their explanatory power was highest for soybean (35.6%), followed by rice (15.9%) and maize (12.0%), indicating that most productivity variation was influenced by factors beyond the climate variables included in the model.

**Correlation Analysis**

Correlation analysis was used to measure the strength and direction of the relationships between climate variables (temperature and rainfall) and food crop productivity (rice, maize, and soybean), without implying causality. The results are presented below.

Table 12. Correlation of Temperature and Rainfall with Rice Productivity

| Variable | Pearson's r | Sig. (2-tailed) | Relationship Strength | Direction |
|---|---|---|---|---|
| Temperature – Rice Productivity | -0.040 | 0.906 | Very weak | Negative |
| Rainfall – Rice Productivity | -0.398 | 0.225 | Weak (approaching moderate) | Negative |

The correlation test showed a very weak negative relationship between temperature and rice productivity ($r = -0.040$; $p = 0.906$), indicating that higher temperatures were slightly associated with lower productivity, but the relationship was not statistically significant. Rainfall also showed a weak negative relationship with rice productivity ($r = -0.398$; $p = 0.225$), suggesting a slight tendency for higher rainfall to be associated with lower productivity; however, the relationship was not statistically significant.

These findings are consistent with the regression results, reinforcing that temperature and rainfall were not strongly associated with rice productivity in this study. Correlation of Temperature and Rainfall with Maize Productivity

Table 13. Correlation of Temperature and Rainfall with Maize Productivity

| Variable | Pearson's r | Sig. (2-tailed) | Relationship Strength | Direction |
|---|---|---|---|---|
| Temperature – Maize Productivity | -0.286 | 0.395 | Weak | Negative |
| Rainfall – Maize Productivity | 0.174 | 0.610 | Very weak | Positive |

Temperature showed a weak negative correlation with maize productivity ($r = -0.286$; $p = 0.395$), while rainfall showed a very weak positive correlation ($r = 0.174$; $p = 0.610$). Both p-values exceeded 0.05, indicating no statistically significant relationship between temperature or rainfall and maize productivity. The following presents the correlation results between temperature and rainfall and soybean productivity:

Table 14. Correlation of Temperature and Rainfall with Soybean Productivity

| Variable | Pearson's r | Sig. (2-tailed) | Relationship Strength | Direction |
|---|---|---|---|---|
| Temperature – Soybean Productivity | 0,374 | 0,257 | Weak | Positive |
| Rainfall – Soybean Productivity | -0,328 | 0,325 | Weak | Negative |

Temperature showed a weak positive correlation with soybean productivity (r = 0.374; p = 0.257), consistent with the positive regression coefficient. Rainfall showed a weak negative correlation (r = -0.328; p = 0.325), also consistent with soybean's sensitivity to excess water. However, neither relationship was statistically significant. Overall, all correlation tests across the three crops had p-values > 0.05, indicating no statistically significant relationships between the climate variables and crop productivity. The correlation coefficients ranged from −0.398 to 0.374, indicating very weak to weak associations.

## Spatial Analysis

Spatial vulnerability mapping was conducted by integrating farmer-survey indicators, including perceived changes in rainfall and temperature patterns, crop failure, production changes, pest and disease disturbances, weather effects on planting schedules, adaptation strategies, access to information, and household food security. The indicators were standardized on a 0–1 scale and grouped into exposure, sensitivity, and adaptive capacity dimensions [17], [20]. A relative vulnerability index was then calculated by aggregating exposure, sensitivity, and the inverse of adaptive capacity using equal weights. This approach was adapted from [20], while the normalization and aggregation procedures followed the OECD/JRC principles for composite indicator [33]. The relative vulnerability scores across the study districts are presented in Table 15.

Table 15. Relative Vulnerability Scores by District

| District | Exposure | Sensitivity | Adaptive Capacity | Vulnerability Index | Category |
|---|---|---|---|---|---|
| Balantak | 0.100 | 0.236 | 0.688 | 0.216 | Low |
| Batui Selatan | 0.188 | 0.577 | 0.759 | 0.335 | Moderate |
| Lamala | 0.800 | 0.673 | 0.628 | 0.615 | Moderate |
| Luwuk Timur | 0.875 | 0.610 | 0.676 | 0.603 | Moderate |
| Luwuk Utara | 0.182 | 0.497 | 0.500 | 0.393 | Moderate |
| Mantoh | 1.000 | 0.252 | 0.270 | 0.661 | Moderate |
| Masama | 0.605 | 0.573 | 0.529 | 0.550 | Moderate |

The results show variation in relative vulnerability across the study areas. Mantoh had the highest vulnerability index (0.661), followed by Lamala (0.615), Luwuk Timur (0.603), Masama (0.550), Luwuk Utara (0.393), Batui Selatan (0.335), and Balantak (0.216). Based on the classification, six sub-districts were categorized as moderately vulnerable, while Balantak was classified as having low vulnerability. No district fell into the high-vulnerability category (≥0.667).

The relative vulnerability index was subsequently visualized spatially using QGIS based on the administrative boundaries of the seven study sub-districts. The mapping illustrates the spatial variation in relative vulnerability across the study area.

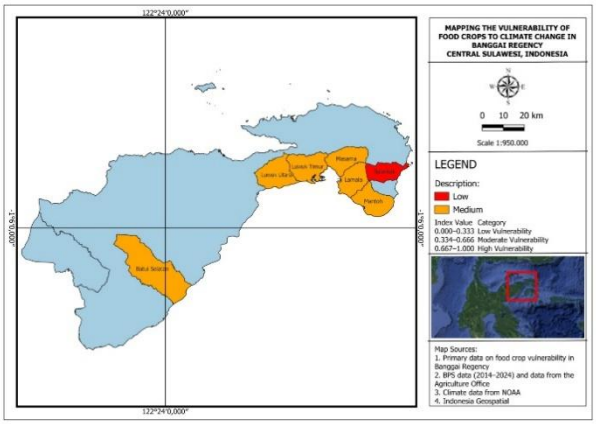



Figure 6. Map of Food Crop Vulnerability to Climate Change in Banggai Regency Using QGIS 3.38

## Farmers' Perceptions of Changing Climate Conditions

The findings indicate that changes in climate conditions in recent years have been widely perceived by farmers in Banggai Regency. Ninety percent of respondents reported changes in rainfall patterns and

temperature, while 80% stated that weather conditions affected planting schedules. In addition, 57.14% had experienced crop failure. These findings suggest that farmers perceive climate change not only as changes in weather conditions but also as a factor influencing farm decision-making, particularly planting schedules and production risk management.

The survey findings were supported by the thematic analysis, in which farmers described changes in seasonal patterns, shifts in the rainy season, changes in rainfall intensity, increasing temperatures, extreme weather events, and growing difficulty in predicting seasonal conditions. These findings demonstrate consistency between the quantitative data and farmers' experiences. Farmers' perceptions were associated not only with changes in average temperature and rainfall but also with shifts in seasonal timing and increasing weather uncertainty, which affected planting schedules.

These findings are also consistent with the 2014-2024 time-series data, which showed an increasing trend in annual average temperature of approximately 0.027°C per year and annual rainfall of approximately 45.90 mm per year, despite substantial year-to-year rainfall variability. This indicates a relationship between farmers' perceptions of changing climate conditions and the observed dynamics of climate data in the study area [34]-[36].

### Climate Dynamics and Food Crop Productivity

Trend analysis revealed an upward tendency in both temperature and rainfall, whereas food-crop productivity exhibited divergent trends. Rice productivity increased by approximately 0.015 tons/ha per year, while maize and soybean productivity declined by approximately 0.017 and 0.039 tons/ha per year, respectively. The coefficients of determination ($R^2$) for these trends were relatively low, indicating that temporal changes accounted for only a limited share of the variation in crop productivity.

This divergence suggests that changes in crop productivity do not necessarily correspond directly to changes in temperature or rainfall. The finding is important because it indicates that the climate-productivity relationship cannot be adequately explained by a simple linear association. Annual rainfall totals may not accurately reflect water availability during critical crop-growth stages, while annual mean temperature may obscure exposure to heat stress during sensitive phases such as flowering and grain filling.

These findings are consistent with Aditya et al. (2021), who found a significant relationship between annual rainfall and rice productivity only in selected study locations in West Kalimantan [8]. This evidence suggests that the rainfall-productivity relationship is context-dependent and influenced by regional characteristics and rainfall distribution. In Sulawesi, Awe et al. (2023) similarly reported that the effects of rainfall and temperature on the production of several horticultural crops in Enrekang Regency were not consistently statistically significant [37]. Pratama and Hukom (2025) [38] likewise found that annual temperature and rainfall had no statistically significant effects on food security, as measured by rice production, in Central Kalimantan, either in the short or long term. Collectively, these findings reinforce the view that climatic variables alone do not fully determine variations in crop production.

### Effects of Temperature and Rainfall on Rice, Maize, and Soybean Productivity

Regression analysis showed that temperature and rainfall did not have a statistically significant joint effect on the productivity of any of the three crops. The F-test yielded p-values of 0.501 for rice, 0.598 for maize, and 0.172 for soybean, all exceeding the 0.05 significance threshold. The individual effects of temperature and rainfall were likewise statistically insignificant. For rice, the p-values were 0.980 for temperature and 0.256 for rainfall. For maize, the corresponding values were 0.391 and 0.568, while for soybean they were 0.173 and 0.213, respectively.

These results do not imply that temperature and rainfall are irrelevant to agricultural systems. Rather, they indicate that annual climate variables alone are insufficient to explain a statistically significant share of the variation in crop productivity. This is reflected in the model's $R^2$ values of 15.9% for rice, approximately 12.0% for maize, and 35.6% for soybean, indicating that a substantial proportion of productivity variation remains unexplained by the two climate variables included in the model.

This finding can be interpreted through the limiting-factor concept, which posits that crop productivity is governed not only by climatic conditions but also by other factors that may constrain plant growth [39]. Crop productivity results from the interaction of multiple growth requirements [40]. When temperature and rainfall remain within the crops' tolerable ranges, other factors including nutrient availability, soil conditions, pests and diseases, seed quality, actual water availability, and cultivation practices may exert greater influence on productivity [39].

The findings are also consistent with Syaranamual and Muyan (2024) [41], who reported that relationships between climatic variables and rice, maize, and soybean yields in Manokwari were not consistently statistically significant. For rice, Aditya et al. (2021) [8] likewise found that annual rainfall was not significantly associated with productivity across most of the locations examined. These findings suggest that climate

productivity relationships are context-specific and shaped by local agroecological conditions [38], farming systems [42], and management practices.

### Integration of Correlation and Regression Results

The correlation analysis revealed a pattern consistent with the regression results. For rice, temperature showed a very weak negative correlation with productivity, while rainfall exhibited a relatively stronger negative association; however, neither relationship was statistically significant. This finding is consistent with previous studies [8], [43] and [41], which reported that rainfall did not have a statistically significant partial effect on rice productivity.

For maize, rainfall showed a very weak positive correlation with productivity ($r = 0.174$), which was not statistically significant ($p = 0.610$), whereas temperature showed a weak negative correlation ($r = -0.286$). Although neither relationship was statistically significant, the direction of these associations remains theoretically relevant. The negative association with temperature is consistent with evidence that high temperatures during flowering and grain filling can impair fertilization and reduce maize yield [44]. Conversely, the positive association with rainfall is consistent with maize's relatively high water requirements, particularly during grain filling, when adequate water availability supports assimilate translocation to the grains [45].

In Malang Regency, rainfall and rainy days were likewise found to have no significant effect on maize productivity, whereas temperature showed a significant effect [1]. Differences in the direction and significance of temperature effects across regions further indicate that climate–maize productivity relationships are context-specific and dependent on local agroclimatic conditions. Ruminta (2024) [34] similarly reported that changes in rainfall without a significant correlation do not necessarily translate directly into changes in maize production or productivity. This may reflect the nonlinear nature of the rainfall–productivity relationship, as both the amount and timing of rainfall determine crop responses.

For soybean, temperature showed a weak positive correlation with productivity ($r = 0.374$; $p = 0.257$), whereas rainfall showed a weak negative correlation ($r = -0.328$; $p = 0.325$). Neither relationship was statistically significant. This finding is consistent with [7], which reported no significant association between extreme weather variables and declining soybean production, attributing much of the decline to agricultural land conversion. BPS data for Banggai Regency also show a reduction in soybean-cultivated area in 2023 and 2024.

The consistent lack of statistical significance across both correlation and regression analyses supports an interpretation grounded in Liebig's Law of the Minimum [46], which posits that crop yield is constrained by the factor most limiting growth [47]. Temperature and rainfall represent only part of this set of factors, alongside nutrient availability, irrigation water, pests and diseases, and cultivation practices [48]. However, the small sample size ($n = 11$) limits the statistical power to detect relatively weak relationships. Therefore, these findings should be interpreted as preliminary evidence rather than definitive evidence of the absence of climate productivity relationships.

The consistency between the correlation and regression results indicates that, over the study period, there was no strong statistical evidence of a direct relationship between annual temperature and rainfall and food-crop productivity. This finding should nevertheless be interpreted cautiously because the analysis covers only 11 annual observations (2014-2024). Moreover, annual aggregation may obscure climate effects occurring at critical crop-growth stages, such as early growth, flowering, and grain filling, where the timing and intensity of rainfall or temperature exposure may have different effects. Thus, the absence of statistical significance should not be interpreted as evidence that no biological relationship exists between climatic conditions and crop productivity.

### Farmers' Adaptation Strategies to Climate Uncertainty

Thematic analysis indicates that farmers are not passive in responding to changing climatic conditions. Their adaptation strategies include adjusting planting schedules, switching crop varieties, diversifying crops, managing water resources, using mulch or raised beds, and engaging in supplementary livelihoods. These findings suggest that the relationship between climate stress and crop productivity is partly shaped by farmers' adaptive capacity. Farmers exposed to similar climatic conditions may achieve different production outcomes depending on their management practices and adaptive capacity [13], [16]. In this study, adaptation was evident in farmers' adjustments to planting schedules based on seasonal conditions, relocation of cultivation sites, fertilizer use, and the utilization of differences in land characteristics [13]. For example, PK, a farmer in Sobol Village, Mantoh District, cultivates maize at two different locations according to seasonal conditions. Maize is planted in the lowland area near the settlement during April–May, whereas planting shifts to a higher-elevation plantation area during October–December, when cooler temperatures provide more favorable conditions for maize growth. Priyanto et al [16] similarly found that improved climate change adaptation strategies may be associated with greater technical efficiency in rice farming. This supports the view that farmers' ability to adapt to changing climatic conditions is important for maintaining agricultural productivity.

### Household Food Security

The HDDS analysis showed that most households had high dietary diversity. Overall, 85.71% of households were classified as having high dietary diversity, 12.86% as moderate, and 1.43% as low. A notable finding is that, among the 40 households reporting declining crop yields, 37 still had high Household Dietary Diversity Scores (HDDS), while only three were classified as moderate. This indicates that declining agricultural production had not directly translated into reduced dietary diversity [49].

Interview findings help explain this pattern. Farmers reported maintaining dietary diversity through crop diversification, supplementary employment, reduced expenditure, and alternative income sources, including casual labor. These strategies function as household-level buffers against production shocks. This finding is consistent with Bai et al. [50], who found that off-farm employment is positively associated with household dietary diversity through higher income and diversified livelihood activities. Nevertheless, high HDDS should be interpreted as evidence of households' capacity to maintain dietary diversity at the time of the study, rather than as evidence that they are fully protected from food-security risks.

### Regional Vulnerability and Differences in Adaptive Capacity

The mapping analysis revealed substantial differences in vulnerability across regions. Mantoh had the highest vulnerability index (0.661), followed by Lamala (0.615), East Luwuk (0.603), Masama (0.550), North Luwuk (0.393), South Batui (0.335), and Balantak (0.216). These differences indicate that vulnerability is not determined solely by exposure to changing climatic conditions. Mantoh experienced high exposure and relatively low adaptive capacity, resulting in higher vulnerability. Lamala was characterized by high exposure and sensitivity, whereas South Batui had relatively strong adaptive capacity, which may have reduced its vulnerability. This pattern is conceptually consistent with Lihawa et al. (2026) [20], who described climate vulnerability as the result of interactions among exposure, sensitivity, and adaptive capacity. Areas with similar levels of exposure may therefore experience different levels of vulnerability because of differences in sensitivity and adaptive capacity. In this study, the thematic findings further support this perspective, as farmers demonstrated varying adaptive capacities through adjustments in planting schedules, crop varieties, crop diversification, water management, and household-level strategies.

The findings suggest that climate adaptation in Banggai Regency should consider the different vulnerability conditions across sub-districts. A uniform adaptation strategy may not address the factors that actually affect farmers in each area. Improving agricultural resilience therefore requires more than providing weather information. Farmers also need better access to water management, quality seeds, fertilizers, pest and disease control, appropriate planting calendars, farm diversification, and stronger economic and institutional support. This is consistent with farmers' responses, which indicate that changes in crop yields were often related to non-climatic factors [51]. This study combines three aspects that are rarely examined together at the same regional scale: climate–productivity trends, regional vulnerability, and household food security measured using HDDS. The combination of time-series data, household surveys, and interviews also provides a basis for comparing quantitative patterns with farmers' experiences. One finding illustrates the importance of this approach: 37 of the 40 households that reported declining crop yields still had high HDDS. Thus, a decline in crop productivity did not necessarily correspond to lower dietary diversity at the household level.

Several limitations should be considered when interpreting these findings. The climate–productivity time-series analysis was based on only 11 annual observations (2014-2024), limiting the statistical power to detect relatively weak relationships. The regression and correlation results should therefore be viewed as preliminary evidence rather than definitive conclusions. The use of annual climate data may also mask variations occurring during critical crop-growth stages. In addition, the analysis covered only seven sub-districts, limiting the extent to which the findings can be generalized to the entire Banggai Regency. The vulnerability index provides a relative comparison among sub-districts rather than an absolute measure of vulnerability, while the 15 in-depth interview participants may not fully represent the range of farmers' adaptation experiences across the study area.

Based on these findings, local adaptation policies should consider the specific vulnerability profiles of each sub-district, particularly in Mantoh, Lamala, and East Luwuk. Such policies should also address non-climatic factors associated with crop productivity, including pest and disease management, access to quality seeds, and improved soil fertility, while strengthening access to climate information and adaptation training in areas with lower adaptive capacity. Future studies should use higher-resolution climate data, particularly monthly or seasonal observations, to better capture climate effects during critical crop-growth stages. Expanding the study area and increasing the number of qualitative informants would also provide a broader basis for interpreting and generalizing the findings.

## 4. CONCLUSION

This

the findings address the main objectives of this study. *First*, multiple regression analysis showed that temperature and rainfall during 2014-2024 had no statistically significant effects on the productivity of rice, maize, or soybean in Banggai Regency, either individually or jointly (all p-values > 0.05). The explanatory power of the models ($R^2$) ranged from 12.0% to 35.6%, depending on the crop. These results are consistent with the correlation analysis, which showed very weak to weak relationships between the climate variables and crop productivity.

*Second*, the regional vulnerability assessment showed that six of the seven study sub-districts (Lamala, East Luwuk, Masama, Mantoh, North Luwuk, and South Batui) were classified as moderately vulnerable, while Balantak was classified as having low vulnerability. None of the assessed sub-districts fell into the high-vulnerability category.

Taken together, these findings suggest that the resilience of the agricultural system to climate change, both in terms of crop productivity and regional vulnerability, cannot be explained by climate exposure alone. Rather, it reflects the interaction of exposure, sensitivity, and local adaptive capacity. Climate vulnerability is therefore multidimensional and context-specific rather than a direct function of the intensity of climate change.

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## AUTHOR CONTRIBUTIONS

Conceptualization, FNL; Methodology, FNL, AS, NL, and WAK; Software, FNL and WAK; Validation, AS and NL; Formal Analysis, FNL, AS, NL, and WAK; Investigation, FNL, SIZ, SM, AS, and NL; Resources, FNL; Data Curation, FNL and WAK; Writing—Original Draft Preparation, FNL; Writing—Review and Editing, FNL; Visualization, FNL; Supervision, AS and NL; Project Administration, FNL, SM, and SIZ; Funding Acquisition, Ministry of Higher Education, Science, and Technology.

## CONFLICTS OF INTEREST

The author(s) declare no conflict of interest.

## INFORMED CONSENT STATEMENT

Before participating in the study, all subjects were provided with detailed information regarding the research objectives, procedures, potential risks, and benefits. All participants voluntarily agreed to participate and provided written informed consent. All images included in this article have been authorized and are the property of the authors.

## USE OF ARTIFICIAL INTELLIGENCE (AI)-ASSISTED TECHNOLOGY

The authors declare that no artificial intelligence (AI) tools were used in the generation, analysis, or writing of this manuscript. All aspects of the research, including data collection, interpretation, and manuscript preparation, were carried out entirely by the authors without the assistance of AI-based technologies.

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