

NUMERICAL SIMULATION OF THE EFFECT OF RAINFALL ON INCREASING CORN YIELDS TO SUPPORT FOOD SECURITY

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Received: 03/09/2026 | Revised: 11/09/2026 | Accepted: 05/10/2026 | Published: 14/10/2026

Abstract

Rainfall variability and climate change can increase uncertainty in corn productivity, particularly in rain-fed farming systems. This study aims to analyze the relationship between rainfall and corn productivity, develop a numerical simulation model, evaluate productivity responses to changes in rainfall, and examine how these findings can be used to support local food security. The study employed a quantitative approach based on rainfall data, corn productivity, and agronomic parameters across 10 harvest seasons at the Buah Page Dua Farmers' Group in Rumah Sumbul Village. Rainfall data from the 90 days prior to harvest was used as the input variable, while corn productivity served as the output variable. The analysis was conducted using correlation, quadratic function modeling, calibration, Leave-One-Out Cross-Validation (LOOCV), and scenario simulations of rainfall changes ranging from -30% to +30%. The results show a relatively weak linear relationship between rainfall and productivity, with a Pearson correlation coefficient of 0.0696. The simulation model produced the equation $Y(R) = 7.547011 - 0.0116913R + 0.0000199827R^2$, with an MAE of 0.0950 metric tons/ha, an RMSE of 0.1108 metric tons/ha, and a MAPE of 1.60% during the calibration phase. LOOCV validation yielded an MAE of 0.1438 metric tons/ha, an RMSE of 0.1717 metric tons/ha, a MAPE of 2.43%, and an R^2 of -0.9743. The simulation showed a nonlinear response of productivity to changes in rainfall. The model can be used as a scenario simulation tool to support adaptation analysis and corn production planning based on local conditions, but it cannot yet be used as a universal prediction model. Future research needs to integrate more comprehensive agronomic and water balance parameters to improve the model's ability to represent field conditions.

Keywords: food security; numerical simulation; rainfall; corn productivity; mathematical modeling.

INTRODUCTION

Food security is one of the global challenges that is becoming increasingly complex as climate variability and environmental changes affecting agricultural production systems intensify. Corn (*Zea mays* L.) is a strategic commodity that serves as a source of food, animal feed, and industrial raw materials; therefore, the sustainability of its productivity makes a significant contribution to both national and global food security. Various studies have shown that corn productivity is strongly influenced by climatic factors, particularly rainfall, air temperature, soil moisture, and water availability during the plant's growth phases (Maitah et al., 2021; Ocwa et al., 2023; Rezaei et al., 2023). Climate change—characterized by rising global temperatures, shifts in precipitation patterns, and an increase in the frequency of extreme weather events—has the potential to reduce crop yield stability and increase uncertainty in agricultural production. (Rezaei et al., 2023) reports that climate change has had a significant impact on the productivity of various food crops worldwide, whereas (Ocwa et al., 2023) shows that climate change and fertilization practices are the dominant factors affecting corn productivity and global food security. Rainfall is one of the most critical environmental factors determining the success of corn cultivation because it is directly related to the availability of water that plants can utilize. Corn plants have different water requirements at each growth stage, so a mismatch between rainfall amounts and water requirements can lead to a decline in productivity (Sura et al.,

2024). Research (Maitah *et al.*, 2021) shows that rainfall, temperature, and water deficit have a significant relationship with corn production. In addition, (Xiang *et al.*, 2024) This indicates that changes in rainfall distribution due to climate change affect the balance between crop water requirements and natural water availability. Insufficient rainfall can cause drought stress, while excessive rainfall can increase the risk of waterlogging, erosion, nutrient leaching, and physiological disorders in plants, ultimately leading to reduced crop yields (Ma *et al.*, 2024). Thus, the relationship between rainfall and corn productivity is determined not only by the amount of rainfall, but also by the temporal distribution of rainfall, soil conditions, and the characteristics of the local agroecosystem.

Various studies have been conducted to analyze the effects of rainfall and climatic factors on crop productivity using statistical methods, remote sensing, and mathematical modeling. (Qudriyah *et al.*, 2022) analyzing the effect of rainfall on crop productivity estimates using Sentinel-2A data, whereas (Roem *et al.*, 2024) indicates a relationship between changes in rainfall and temperature and corn production in Karawang Regency. On a global scale, (Zhao *et al.*, 2025) found that approximately 46% of the variation in corn productivity can be explained by the variability of key climatic factors. (White *et al.*, 2025) also show that rainfall during critical growth stages and heat stress account for most of the variation in annual crop yields. These results indicate that climatic factors play an important role in corn productivity, but their effects often vary by region and are influenced by local conditions.

Other studies show that the relationship between rainfall and crop productivity is not always linear. (Wang *et al.*, 2022) found that nonlinear regression models were better able to explain variations in corn productivity than linear models across various corn-producing regions in China. (Fu *et al.*, 2025) This indicates that the response of corn productivity to rainfall varies by region and is influenced by initial soil moisture, soil erosion, and a reduction in sunlight duration due to rainfall. These findings suggest that changes in rainfall do not always result in proportional changes in productivity; therefore, a mathematical approach capable of representing the nonlinear relationships among variables is needed.

Advances in computing technology have spurred the use of simulation models to analyze complex agricultural systems. Simulation models make it possible to evaluate various climate change scenarios without having to wait for those changes to actually occur in the field. (Haris Bahrin & Saputra Ishak, 2023) using DSSAT to validate and analyze corn production under specific cropping systems, whereas (Ferdiansyah, 2020) to develop a maize growth simulation model to describe the plants' response to variations in planting distance. (Disasa *et al.*, 2025) shows that the simulation model is capable of evaluating the sensitivity of corn yields to changes in temperature and precipitation under various future climate scenarios. The study (Irmak *et al.*, 2022) It also shows that changes in rainfall can account for nearly half of the variation in corn yields in rain-fed farming systems. These findings demonstrate that numerical simulations can serve as an effective analytical tool for understanding the impact of climate change on crop productivity.

From the perspective of applied mathematics, numerical simulation provides a framework that allows relationships between variables to be represented as mathematical functions so that they can be analyzed quantitatively. Mathematical models are not only used to describe actual conditions, but also enable the exploration of various hypothetical scenarios to support decision-making. (Chidzalo *et al.*, 2022) to develop a multivariate stochastic model that integrates rainfall, temperature, and evapotranspiration to predict corn yields under changing climate conditions. Research (Taremwa *et al.*, 2026) shows that rainfall, soil moisture, solar radiation, and growing season duration are the dominant factors in a climate-data-based model for predicting corn productivity. On the other hand, the interpretive model developed by (Zhang *et al.*, 2026) shows that the interaction between climatic factors and crop management factors has a significant effect on the predicted corn yield.

In addition, various studies on numerical modeling and data analysis have shown that complex relationships between variables can be better represented through mathematical approaches that account for interactions and the nonlinear characteristics of the data. These approaches have been used in various fields to support data-driven decision-making and the analysis of complex systems (Sinaga *et al.*, 2026). Therefore, the development of a numerical simulation model based on local data is relevant for examining the relationship between rainfall and corn productivity under specific agroecosystem conditions.

Although various studies have developed climate-based corn productivity models, most of these studies have been conducted at the regional or national level and therefore do not fully represent the local characteristics of a given area. In fact, productivity responses to changes in rainfall can vary due to differences in soil conditions, cultivation systems, crop varieties, and other environmental factors. Furthermore, research specifically aimed at developing numerical simulation models based on local data to describe the nonlinear relationship between rainfall and corn productivity remains relatively limited. This research gap highlights the need to develop mathematical models that are more context-specific and aligned with the characteristics of local data.

Based on these issues, this study aims to develop a numeric simulation model based on local data to analyze the relationship between rainfall and corn productivity in Rumah Sumbul Village. The model was constructed using historical rainfall data, corn productivity data, and supporting agronomic parameters, and was then used to evaluate productivity responses to various rainfall change scenarios. The research results are expected to contribute to the development of applied mathematical modeling in agriculture and provide a quantitative basis to support agricultural adaptation strategies and food security planning based on local conditions.

LITERATURE REVIEW

Corn productivity results from the interaction between climatic conditions, water availability, soil characteristics, and cultivation practices. Among these climatic factors, rainfall is one of the most important variables because it is directly related to water availability during plant growth. (Maitah et al., 2021) shows that variations in precipitation and temperature are associated with changes in corn production, whereas (Rezaei et al., 2023) emphasizes that changes in rainfall patterns and rising temperatures due to climate change can affect crop yield stability. From a food security perspective, (Ocwa et al., 2023) It also shows that climate change, along with fertilization practices, is an important factor affecting corn productivity. However, the impact of rainfall cannot be understood solely by looking at the total amount, because corn's water requirements vary at each stage of growth. (Xiang et al., 2024) demonstrates the importance of the balance between precipitation and plant water requirements, whereas (Ma et al., 2024) shows that excessive rainfall can also reduce yields by disrupting growing conditions and reducing nitrogen use efficiency.

The relationship between rainfall and corn productivity is also not always linear. (Wang et al., 2022) found that the response of corn yields to climate variability exhibits complex characteristics, such that a nonlinear approach can provide a better representation than a simple linear relationship. These findings are supported by (Fu et al., 2025), who showed that the response of corn yields to rainfall events varies across regions and is also influenced by initial soil moisture, erosion, and changes in sunshine duration. Meanwhile, (Zhao et al., 2025) demonstrated that key climate variables can explain part of the variation in corn productivity on a large scale. These differing findings indicate that the magnitude of rainfall's influence depends heavily on the scale of analysis, agroecosystem characteristics, rainfall distribution, and the environmental variables included in the model. Thus, relying solely on linear correlations risks oversimplifying relationships that are, in reality, nonlinear and context-dependent.

Modeling and simulation approaches have been widely used to represent these complex relationships. Chidzalo et al. (2022), for example, developed a multivariate stochastic weather model that integrates rainfall, temperature, and evapotranspiration into maize yield predictions. (Irmak et al., 2022) used modeling to evaluate changes in rain-fed and irrigated corn yields under various climate change scenarios, while (Disasa et al., 2025) utilized simulation to analyze the sensitivity of corn production to changes in temperature and precipitation. In the Indonesian context, (Bahrin et al., 2023) used DSSAT for the validation and analysis of corn production, while (Ferdiansyah, 2020) developed a corn growth simulation based on variations in planting spacing. The strength of this approach lies in its ability to conduct scenario experiments without having to wait for changes in field conditions to occur. However, models involving many parameters generally require more comprehensive agronomic and climatological data, making their application in locations with limited data availability more difficult.

Recent literature also shows a trend toward multivariate and data-driven models. (Taremwa et al., 2026) identified rainfall, soil moisture, solar radiation, and growing season length as key factors in predicting corn productivity, while (Zhang et al., 2026) demonstrated that the sensitivity of corn yields to climatic conditions is also influenced by cultivar characteristics and management factors. These findings highlight the differences between simple models that emphasize a single climate variable and complex models that incorporate various agronomic factors. Complex models have the potential to provide a more realistic representation of the system, but simple models still hold analytical value when the research objective is to isolate the response patterns of a single variable and conduct scenario exploration using local data.

Based on this study, there is a research gap in the development of a simple, locally data-driven numerical simulation model that specifically evaluates the nonlinear relationship between rainfall and corn productivity at the farmer group level. Some previous studies have focused on regional or national scales, used complex crop models, or integrated multiple variables simultaneously. These conditions do not fully capture the productivity response in local agroecosystems with specific cultivation characteristics. Therefore, this study develops mathematical functions based on local rainfall and productivity data to simulate changes in rainfall. This approach is not intended as a universal predictive model, but rather as a numerical experimental tool to understand the direction and magnitude of productivity responses to changes in rainfall, while also serving as a foundation for the development of models that

can subsequently integrate temperature, evapotranspiration, soil moisture, crop water requirements, and other agronomic factors.

METHOD

This study employs a quantitative approach using mathematical modeling and numerical simulation to analyze the effect of rainfall on corn productivity. This approach was chosen to generate measurable quantitative relationships and predictions based on local data that can support technical decision-making and food security policies.

This study involves the Buah Page Dua Farmers' Group in Rumah Sumbul Village as a research partner that plays a role in:

- Provision of corn productivity data
- Validation of simulation model results
- Direct implementation of research findings

The involvement of partners is expected to enhance the relevance and usefulness of the research findings in addressing real-world needs in the field.

A research flowchart was developed to illustrate the stages of activities that have been carried out and those that will be undertaken during the research period.

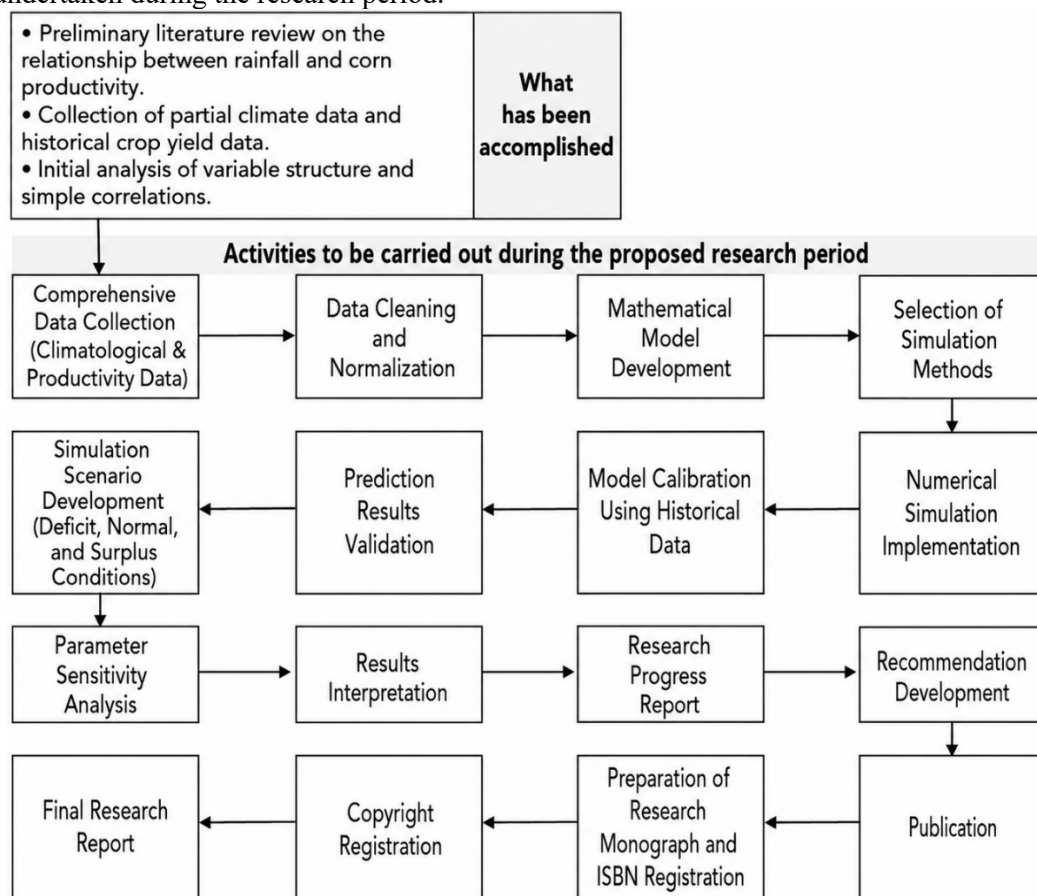


Figure 1. Stages of the Research Methodology

The research method used in this study consisted of several sequential stages, beginning with activities conducted prior to the study and continuing through the stages carried out during the research period. In the initial stage, the researcher conducted a literature review on the relationship between rainfall and corn productivity, collected some climate data and historical crop yield data, and performed a preliminary analysis of variable structure and simple correlations. This stage aimed to gain an initial understanding of the data characteristics and the relationships among the variables to be used in the simulation.

Subsequently, the study continued with the collection of comprehensive data, including climatological data, corn productivity data, and supporting agronomic parameters. The data obtained were then cleaned and normalized to remove inconsistent data, handle missing values, and standardize the data format so that it was ready for use in

the analysis phase. Afterward, a mathematical model was developed to describe the relationship between rainfall and corn productivity based on the available historical data.

The next step is to select a simulation method that aligns with the data characteristics and research objectives. The selected method is then implemented as a numerical simulation to evaluate how corn productivity responds to changes in rainfall. To ensure the simulation results are reliable, calibration is performed using historical data, followed by validation of the simulation results by comparing the simulated values with actual data.

Based on the validated model, several simulation scenarios were developed, consisting of rainfall deficit, reference (normal), and surplus conditions. The results of each scenario were then analyzed using sensitivity analysis to determine the extent of changes in productivity resulting from changes in rainfall parameters. Next, the simulation results were interpreted to gain a more comprehensive understanding of the impact of rainfall variations on corn productivity.

The final stage of the research includes preparing a research progress report, formulating recommendations based on simulation results, publishing scientific papers, compiling a book of research findings along with ISBN registration, registering the book's intellectual property rights (IPR), and preparing the final research report. All of these stages are designed to produce research outputs that not only contribute to science but can also be used as a basis for decision-making in corn cultivation management and climate-data-driven food security planning.

RESULTS AND DISCUSSION

1. Characteristics of the Research Data

The research data consists of daily rainfall data for the period January 1, 2023–June 30, 2026, productivity data based on harvest seasons, and agronomic parameters. The rainfall data consists of 1,277 daily observations with values ranging from 0 to 49.90 mm/day and an average of 3.21 mm/day. The high variability in rainfall is evident from the standard deviation of 4.93 mm/day, which is greater than the mean value. On an annual basis, the highest rainfall occurred in 2025 at 1,254.82 mm, while the 2026 data only covers January–June and therefore cannot be directly compared to a full year.

The productivity data consists of 10 harvest seasons: three in 2023, three in 2024, three in 2025, and one in 2026. The rainfall used as the main variable is the accumulation over the 90 days prior to harvest. This period was chosen because the crop's growth period ranges from 95 to 98 days, thus representing the majority of the crop's growth period.

Table 1. Descriptive statistics for the research variables

Variable	N	Minimum	Maksimum	Mean	Standard Deviation
Harvested area (ha)	10	51	56	53,5	1,58
Rainfall over 90 days (mm)	10	198,73	382,94	283,21	79,73
Average rainfall (mm/day)	10	2,21	4,25	3,15	0,88
Yield (metric tons)	10	290,7	339,92	318,59	14,35
Productivity (metric tons/hectare)	10	5,7	6,12	5,95	0,13
Crop age (days)	10	95	98	96,2	1,32
Water requirement (mm/season)	10	451,5	466,5	456,75	6,82
Average temperature (°C)	10	26,8	27,6	27,17	0,25
Humidity (%)	10	76	82	79,1	1,85
Evapotranspiration (mm/day)	10	4	4,5	4,21	0,17

Yields showed relatively less variation than rainfall. The minimum yield was 5.70 metric tons/ha and the maximum was 6.12 metric tons/ha, whereas the 90-day rainfall had a much wider range, namely 198.73–382.94 mm. These conditions suggest that changes in yield cannot be explained solely by cumulative rainfall.

Agronomic parameters also indicate relatively consistent cultivation conditions. All observations were conducted on Latosol soil using a non-irrigated system, with 15-15-15 NPK fertilizer and urea. The varieties used were BISI-18 in seven growing seasons and Pioneer 32 in three growing seasons.



Figure 2. Rainfall over 90 days and corn yield per harvest season

Figure 2 shows that significant changes in rainfall are not always followed by corresponding changes in productivity. This observation serves as the basis for further analysis of the relationship through correlation and nonlinear modeling.

2. The Relationship Between Rainfall and Corn Productivity

Observations over 10 harvest seasons showed that rainfall 90 days before harvest ranged from 198.73 to 382.94 mm, while productivity ranged from 5.70 to 6.12 metric tons per hectare. In the first season of 2025, rainfall reached a high of 382.94 mm with a yield of 6.04 metric tons per hectare. In contrast, in the second season of 2025, rainfall was only 201.80 mm, but the yield reached 6.12 metric tons per hectare.

Table 2. Rainfall over 90 days and productivity per harvest season

Year	Season	90-Day Rainfall (mm)	Yield (metric tons/hectare)
2023	1	262,87	5,7
2023	2	227,18	5,86
2023	3	381,59	5,85
2024	1	228,51	5,93
2024	2	221,47	6,06
2024	3	380,25	6
2025	1	382,94	6,04
2025	2	201,8	6,12
2025	3	346,81	6,07
2026	1	198,73	5,9

Pearson's correlation was used to test for a linear relationship. The coefficient obtained was $r = 0.0696$, while Spearman's correlation yielded $\rho = -0.1515$. Both values indicate that the linear relationship and monotonic trend between 90-day cumulative rainfall and productivity across 10 harvest seasons are relatively very weak.

These results do not imply that rainfall is unimportant for crops. Rather, they indicate that cumulative rainfall alone is insufficient to explain productivity. Rainfall distribution, water requirements, evapotranspiration, temperature, humidity, growth stages, and soil conditions must be taken into account in the interpretation of these results.

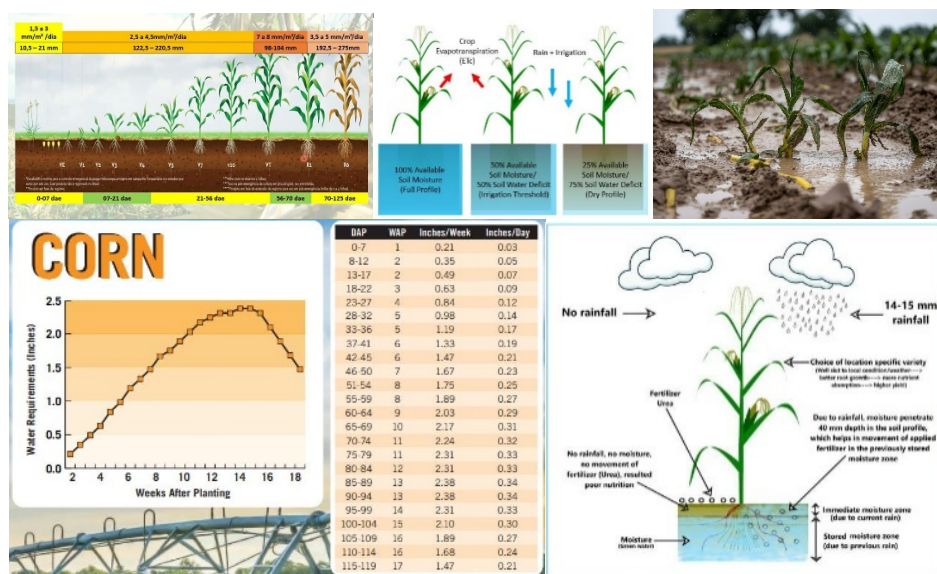


Figure 3. The Relationship Between 90-Day Rainfall and Productivity and the Quadratic Response Function

3. The Role of Agronomic Parameters

An analysis of agronomic parameters shows that variables other than rainfall have different relationships with productivity. Temperature exhibits the highest correlation coefficient, while humidity has a negative relationship. Evapotranspiration also shows a relatively strong positive relationship.

Table 3. The Relationship Between Agronomic Parameters and Productivity

Parameter	Pearson Correlation	Interpretation
90-day rainfall	0,0696	Very weak
Plant age	0,396	Moderately positive
Water requirements	0,363	Moderately positive
Average temperature	0,877	Very strong positive
Humidity	−0,518	Moderately negative
Evapotranspiration	0,636	Strong positive

Temperature showed a positive correlation of 0.877, while evapotranspiration showed a correlation of 0.636. However, these correlation values cannot be directly interpreted as a cause-and-effect relationship because there were only 10 observations and some parameters exhibited relatively little variation. Agronomic parameters are more appropriately used as a context for interpreting the model's response.

The difference between water requirements and rainfall also indicates that rainfall cannot be directly equated with crop water availability. The average water requirement reached 456.75 mm/season, while the average rainfall over 90 days was 283.21 mm. The difference between the two was 173.54 mm; however, this difference cannot yet be termed an actual water deficit because it does not account for effective rainfall, infiltration, runoff, soil storage capacity, and soil moisture.

4. Development and Calibration of Numerical Simulation Models

Because the linear relationship between rainfall and productivity is very weak, the analysis was continued using a quadratic response function. The general form of the model used is:

$$Y(R)=a+bR+cR^2$$

where Y(R) is the simulated corn productivity and R is the rainfall 90 days before harvest.

Calibration using 10 observations yielded the following equation:

$$Y(R)=7,547011-0,0116913R+0,0000199827R^2$$

The coefficient of determination for the model is $R^2 = 0.1786$, or 17.86%.

Table 4. Calibration Results for Actual and Simulated Productivity

Year	Season	Actual (metric tons/hectare)	Simulation (metric tons/hectare)	Error (metric tons/hectare)
2023	1	5,7	5,855	−0,155
2023	2	5,86	5,922	−0,062
2023	3	5,85	5,995	−0,145
2024	1	5,93	5,919	0,011
2024	2	6,06	5,938	0,122
2024	3	6	5,991	0,009
2025	1	6,04	6	0,04
2025	2	6,12	6,001	0,119
2025	3	6,07	5,896	0,174
2026	1	5,9	6,013	−0,113

The calibration evaluation yielded an MAE of 0.0950 metric tons/ha, an RMSE of 0.1108 metric tons/ha, and a MAPE of 1.60%. The actual–simulated error values ranged from −0.174 to 0.174 metric tons/ha.

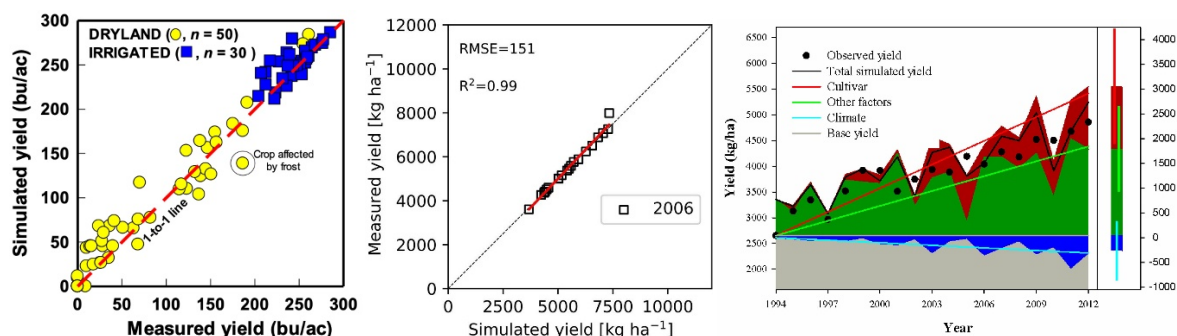


Figure 4. Comparison of Actual Productivity and Calibration Results

Although the MAE, RMSE, and MAPE values are relatively small, the R^2 value of 17.86% indicates that a model using only rainfall as an input is not yet capable of explaining most of the variation in productivity. Thus, the closeness of the simulated values to the actual values should not be interpreted to mean that rainfall is the sole determinant of productivity. This finding actually reinforces the importance of agronomic parameters in model interpretation.

5. Model Validation Using Leave-One-Out Cross-Validation

Since there were only 10 harvest seasons in the dataset, validation was performed using Leave-One-Out Cross-Validation (LOOCV). In each iteration, one observation was used as validation data, while the other nine observations were used to calibrate the function. This process was repeated until every observation had been used as validation data.

Table 5. LOOCV Validation Results

Year	Season	Actual (metric tons/hectare)	Validated Yield (metric tons/hectare)	Error
2023	1	5,7	5,988	-0,288
2023	2	5,86	5,936	-0,076
2023	3	5,85	6,06	-0,210
2024	1	5,93	5,916	0,014
2024	2	6,06	5,913	0,147
2024	3	6	5,987	0,013
2025	1	6,04	5,981	0,059
2025	2	6,12	5,939	0,181
2025	3	6,07	5,81	0,26
2026	1	5,9	6,091	-0,191

The validation results yielded an MAE of 0.1438 metric tons/hectare, an RMSE of 0.1717 metric tons/hectare, a MAPE of 2.43%, and an R^2 of -0.9743. The increase in MAE and RMSE compared to the calibration stage indicates that the model's performance declines when applied to observations not used in the function-fitting process.

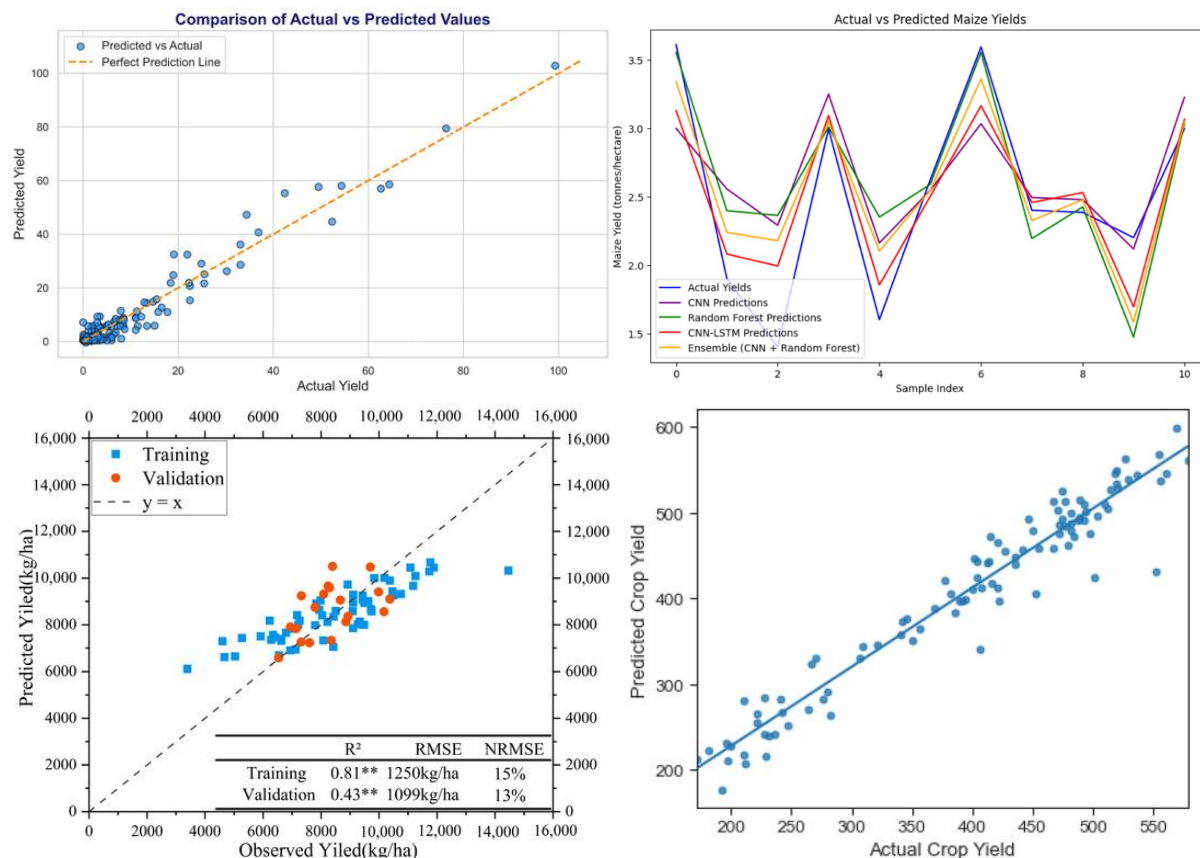


Figure 5. Comparison of Actual Productivity and LOOCV Validation Results

These results indicate that the model is not yet suitable for use as a universal predictor of corn productivity. The model is better suited as a numerical experimental tool for evaluating productivity responses to changes in rainfall within the limits of the study data.

6. Simulation of Rainfall Change Scenarios

The average 90-day rainfall value of 283.21 mm was used as the reference condition. This value was established as a reference because the study has not yet identified a physiological threshold that can be used to experimentally determine the optimal rainfall. Therefore, the term “reference” should be understood as a numerical baseline rather than a biological optimum.

The scenarios were conducted by varying rainfall by -30%, -20%, -10%, 0%, +10%, +20%, and +30% relative to the reference value.

Table 6. Results of the rainfall change simulation

Condition	Change	Rainfall (mm/90 days)	Simulated Productivity (metric tons/hectare)	Change from Reference
Defisit berat	-30%	198,25	6,01	2,91%
Defisit	-20%	226,57	5,92	1,37%
Defisit ringan	-10%	254,89	5,87	0,51%
Referensi	0%	283,21	5,84	0,00%
Surplus ringan	10%	311,53	5,84	≈0,00%
Surplus	20%	339,85	5,88	0,68%
Surplus tinggi	30%	368,17	5,95	1,88%

The simulation results show a nonlinear and non-monotonic pattern. Simulated productivity decreases from low rainfall conditions toward the reference value, then increases again as rainfall increases. Under the reference condition of 283.21 mm, simulated productivity is 5.84 metric tons/ha. The -30% scenario yielded 6.01 metric tons/ha, while the +30% scenario yielded 5.95 metric tons/ha.

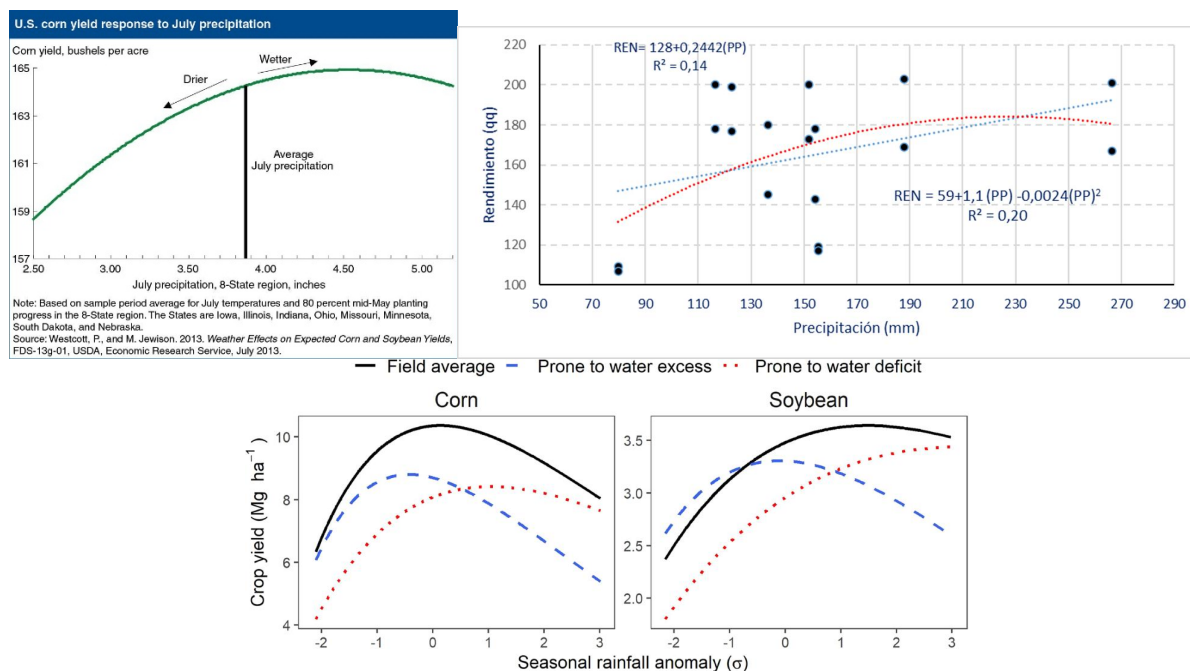


Figure 5. Productivity responses to scenarios of changes in rainfall

This pattern is a mathematical consequence of the quadratic function derived from the dataset. Therefore, the finding of a -30% deficit resulting in higher simulated productivity should not be interpreted to mean that water deficiency biologically increases corn productivity. A biological interpretation requires more comprehensive data on the water balance and the physiological conditions of the plants.

7. Sensitivity Analysis

The sensitivity analysis shows that changes in rainfall within a range of $\pm 30\%$ result in relatively small changes in productivity. The largest change occurred in the -30% scenario, amounting to 0.17 metric tons/hectare, or 2.91%, compared to the reference scenario. In the $+30\%$ scenario, the change in productivity was 0.11 metric tons/hectare, or 1.88%.

Table 6. Sensitivity of productivity to changes in rainfall

Changes in Rainfall	Rainfall (mm)	Yield (metric tons/hectare)	Δ Yield (metric tons/hectare)	Δ Yield (%)
-30%	198,25	6,01	0,17	2,91
-20%	226,57	5,92	0,08	1,37
-10%	254,89	5,87	0,03	0,51
0%	283,21	5,84	0	0
10%	311,53	5,84	0	$\approx 0,00$
20%	339,85	5,88	0,04	0,68
30%	368,17	5,95	0,11	1,88

The elasticity of productivity with respect to rainfall is also relatively low. For the -30% scenario, the elasticity is approximately -0.097 , while for the $+30\%$ scenario, it is approximately 0.063 . An absolute elasticity value less than one indicates that, in the simulation function, productivity is relatively inelastic with respect to changes in rainfall within the range of scenarios used.

8. Discussion

The results of the study indicate that the relationship between rainfall and corn productivity in the dataset cannot be adequately explained by a linear relationship. A Pearson correlation coefficient of 0.0696 indicates a very weak linear relationship, while the quadratic model yields a non-monotonic response pattern. These findings suggest that rainfall is one environmental factor, but not the sole determinant of corn productivity.

The role of agronomic parameters reinforces this interpretation. Temperature has the strongest correlation with productivity in the dataset, at 0.877, followed by evapotranspiration at 0.636. In contrast, humidity shows a negative

correlation of -0.518 . However, since there are only 10 seasons of observations, this relationship cannot be used as evidence of causality. Agronomic parameters are better suited to explain why yield responses do not always directly follow changes in rainfall.

Another important finding is the difference between rainfall and crop water requirements. The average water requirement of 456.75 mm/season is higher than the average rainfall of 283.21 mm/90 days. However, this difference cannot yet be considered an actual water deficit because it does not account for effective rainfall, infiltration, runoff, soil storage capacity, and soil moisture. Thus, this study shows that cumulative rainfall cannot be used as the sole indicator of crop water status.

From a modeling perspective, the quadratic function produced relatively small absolute errors during the calibration stage, with an MAE of 0.0950 metric tons/ha and a MAPE of 1.60% . However, an R^2 value of 0.1786 indicates that the model explains only 17.86% of the variation in productivity. The lower performance in the LOOCV, as indicated by an MAE of 0.1438 metric tons/ha, an RMSE of 0.1717 metric tons/ha, a MAPE of 2.43% , and an R^2 of -0.9743 , highlights the model's limited generalizability.

Therefore, the model's primary contribution in this study is more appropriately characterized as a numerical simulation model for scenario experiments, rather than as a universal predictive model. This approach allows researchers to evaluate the direction and magnitude of changes in the mathematical response when rainfall is increased or decreased. Consequently, the model can serve as a foundation for developing more complex models by incorporating temperature, evapotranspiration, water requirements, soil moisture, soil characteristics, crop varieties, and other agronomic factors.

In the context of local food security, information regarding productivity responses to changes in rainfall can be used as one of the considerations in production planning. Actual productivity in the dataset ranges from 5.70 to 6.12 metric tons per hectare, with an average of 5.95 metric tons per hectare, while simulated productivity ranges from 5.84 to 6.01 metric tons per hectare. This discrepancy indicates that factors other than rainfall play a role in determining productivity.

Thus, the research findings have two implications. First, mathematically, the response of productivity to rainfall in the dataset is nonlinear, so a simulation approach is more informative than simply using linear correlation. Second, agronomically, the simulation patterns should not be directly interpreted as the biological response of plants because the model uses only rainfall as its primary input. Future developments need to incorporate water balance components and agronomic parameters more comprehensively so that the model can represent plant growth mechanisms more realistically.

CONCLUSION

This study successfully developed a numerical simulation model to analyze the relationship between rainfall and corn productivity based on local data from the Buah Page Dua Farmers' Group in Rumah Sumbul Village. The results show that the linear relationship between cumulative rainfall 90 days before harvest and corn productivity is relatively weak; therefore, the productivity response is more accurately represented using a simulation model in the form of a quadratic function. The resulting model can be used to evaluate various scenarios of rainfall changes and demonstrates that the productivity response is nonlinear under both rainfall deficit and surplus conditions. Furthermore, the simulation results provide a quantitative overview that can serve as a tool for agricultural adaptation analysis and corn production planning at the local level. However, since the model still uses rainfall as the primary variable, future research is recommended to integrate other agronomic parameters—such as temperature, evapotranspiration, soil moisture, crop water requirements, and soil characteristics—into the model to improve its representational capacity and the validity of the simulations under field conditions.

ACKNOWLEDGMENT

The author would like to express gratitude to the “Direktorat Jenderal Riset dan Pengembangan, Kementerian Pendidikan Tinggi, Sains, dan Teknologi” for the support and funding provided, which enabled this research to be successfully carried out. Appreciation is also extended to all parties who provided support in conducting the research and supplying the data used in this study.

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