E-ISSN: 2962-6110
P-ISSN: 2964-7843
JSRET
jsret.knpub.com
Journal of Scientific Research, Education, and Technology

Climate Change and Disaster Impacts on Rose Production: The Moderating Role of Farmer Institutions and Socioeconomic Characteristics

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ABSTRACT

This study aims to analyze the factors affecting rose production, including climate and disaster impacts, farmer group membership, partnership, gender, age, and education. The research uses a quantitative approach with secondary data obtained from the Horticulture Household Survey (STH) conducted by the Central Java Bureau of Statistics, involving 107 farmers. Data were analyzed using multiple linear regression with the Ordinary Least Squares (OLS) method. The results show that, simultaneously, all independent variables significantly influence rose production, as indicated by the Prob(F-statistic) value of 0.0251 (< 0.05). However, partially, only age and education have a positive and significant effect on production, while climate and disaster impacts, farmer group membership, partnership, and gender do not show significant effects. These findings suggest that farmers' human capital plays a more important role than environmental and institutional factors in determining production outcomes. The study implies that improving farmers' education and experience is crucial to increasing productivity. Strengthening extension services and training programs is recommended to enhance farmers' adaptive capacity and technical skills. Future research should include additional variables such as land size, input use, and technology adoption to provide a more comprehensive analysis.

Keywords: *Climate Change, Farmer Characteristics, Partnership, Regression Analysis, Rose Production*

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INTRODUCTION

Climate change is a global challenge that is increasingly impacting the agricultural sector, particularly in terms of productivity and yield stability. Climate variability, such as shifts in rainfall patterns, rising temperatures, and the increased frequency of extreme events and natural disasters, directly impact agricultural production systems. Horticultural commodities, including roses, are highly sensitive to agroclimatic changes because they require relatively stable environmental conditions to produce optimal quality and quantity. Various studies have shown that climate change has caused declines in crop yields in various regions of the world, posing a serious threat to food security and the sustainability of agribusiness (IPCC, 2021; Ray et al., 2019; Lobell et al., 2011).

The impact of climate change on the agricultural sector is not only direct through changes in environmental conditions, but also indirect through increased disaster risks such as floods and droughts. A study by Wheeler and von Braun (2013) confirmed that climate change increases agricultural production and increases farmers' vulnerability to risk. Furthermore, Lesk et al. (2016) found that extreme weather events significantly reduce global food crop production. In horticultural crops, temperature and rainfall can trigger plant stress, increase pest and disease attacks, and reduce yield quality (Ahmed et al., 2018; Challinor et al., 2014). This indicates that the impact of climate change on agricultural production is a complex phenomenon influenced by various factors.

In facing these challenges, farmer institutions such as farmer groups and agribusiness partnerships are crucial in increasing adaptive capacity. Membership in farmer groups allows farmers to gain access to information, technology, and social networks that support agricultural risk management. Meinzen-Dick et al. (2014) stated that local institutions play a crucial role in increasing farmer resilience by strengthening social and collective capital. Furthermore, agribusiness partnerships can increase farmer access to markets, capital, and technology, thereby contributing to increased production efficiency and stability (Barrett et al., 2012; Bellemare, 2012). Therefore, institutions can function as an adaptation mechanism to the impacts of climate change.

In addition to institutional factors, farmer characteristics also influence their ability to adapt to climate change. Research by Deressa et al. (2009) showed that farmers' education level, age, and experience significantly influence their choice of adaptation strategies. Farmers with higher levels of education tend to be quicker to adopt technological innovations and adaptive agricultural practices. Meanwhile, Bryan et al. (2009) found that socioeconomic factors play a significant role in determining farmers' responses to climate change. Therefore, analysis of agricultural production needs to consider individual factors in addition to environmental and institutional factors.

Although various studies have addressed the impacts of climate change, institutional factors, and farmer characteristics separately, there is still a gap in research in integrating these three aspects into a single analytical framework, particularly for horticultural commodities such as roses. Most studies focus on staple food crops and have not explored high-value commodities that are highly sensitive to climate change. Therefore, this study aims to analyze the effects of climate change and natural disasters on rose production, as well as examine the role of farmer groups, partnerships, and farmer characteristics in influencing production. Furthermore, this study aims to determine whether farmer institutions are capable of mitigating the negative impacts of climate change on production.

This research is expected to make an important contribution to the development of sustainable agricultural science and practices. Theoretically, this study integrates environmental, institutional, and individual characteristics into a comprehensive analytical model. Practically, the results can inform policy development to strengthen farmer institutions and increase adaptive capacity to climate change. Thus, this research not only provides academic contributions but also has real potential to support the resilience of the agricultural sector amidst global climate change (Challinor et al., 2014; Wheeler & von Braun, 2013).

METHOD

This study employed a quantitative approach with an explanatory survey design. The aim was to analyze the relationship between independent and dependent variables and to examine the influence of environmental factors, institutional factors, and farmer characteristics on rose production. The quantitative approach was chosen because this study focuses on hypothesis testing and statistical analysis of relationships between variables.

The subjects in this study were horticultural farmer households cultivating roses. The study population refers to horticultural farmer data recorded in the Horticultural Household Survey (STH). The sample size for this study was 107 respondents, selected based on the availability of data relevant to the research variables. Therefore, the unit of analysis in this study was farmer households involved in rose production.

The data used in this study were secondary data obtained from the Horticultural Household Survey (STH) conducted by the Central Java Provincial Statistics Agency. This data includes information related to horticultural production, farmer characteristics, farmer group membership, partnerships, and perceived impacts of climate change and natural disasters. The data collection procedure was carried out through documentation and processing of available secondary data. Next, the data was selected and adjusted to meet the research variable requirements before further analysis.

Data analysis in this study was conducted using multiple linear regression analysis to examine the influence of independent variables on rose production, which served as the dependent variable. The analytical model used included variables such as the impact of climate change and natural disasters, farmer group membership, partnerships, and farmer characteristics such as gender, age, and education. Prior to the regression analysis, classical assumption tests were conducted, including normality, multicollinearity, and heteroscedasticity tests, to ensure model feasibility. Data processing was performed using Eviews12, and the analysis results were interpreted based on regression coefficient values, partial significance tests (t-tests), and simultaneous analysis (F-tests).

$$Y = \alpha+\beta_1X_1+\beta_2X_2+\beta_3X_3+\beta_4X_4+\beta_5X_5+\beta_6X_6+\varepsilon$$

Description:

Y = Rose production

X_1 = Climate & disaster impact

X_2 = Farmer group membership

X_3 = Partnership

X_4 = Gender

X_5 = Age

X_6 = Education

α = Constant
β = Regression coefficient
ε = Error

Table 1. Hypothesis Testing

No	Hypothesis Statement	Test Method	Test Criteria
1	The impact of climate change and natural disasters has a negative impact on rose production.	Partial t-test	H_0 is rejected if Sig < 0.05 and the coefficient β_1 is negative
2	Membership of farmer groups has a positive effect on rose production.	Partial t-test	H_0 is rejected if Sig < 0.05 and the coefficient β_2 is positive
3	Partnership has a positive impact on rose production	Partial t-test	H_0 is rejected if Sig < 0.05 and the coefficient β_3 is positive
4	Gender influences rose production	Partial t-test	H_0 is rejected if Sig < 0.05
5	Age affects rose production	Partial t-test	H0 is rejected if Sig < 0.05
6	Education has a positive effect on rose production	Partial t-test	H_0 is rejected if Sig < 0.05 and the coefficient β_6 is positive
7	The impact of climate, farmer group membership, partnerships, gender, age, and education simultaneously influence rose production.	F test	H_0 is rejected if Sig < 0.05

FINDING AND DISCUSSION

RESEARCH RESULT

Statistic Description

The characteristics of rose farmers in Central Java indicate that this sector is still dominated by relatively older male farmers with low levels of education. This condition has important implications for the productivity and sustainability of rose farming. The dominance of older farmers can hinder farmer regeneration, while low levels of education have the potential to limit the ability to adapt to environmental and technological changes, as seen in Table 2.

Table 2. Characteristics of Rose Farmers in Central Java

Characteristic	Farmer Quanntity	Presentase (%)
Gender:		
Male	91	85,05
Female	16	14,95

Total	107	100
Age (Year):		
25-40	9	8,41
41-55	25	23,36
56-70	58	54,21
>70	15	14,02
Average	77	100
Education:		
Not finished elementary school	47	43,93
finished elementary school	32	29,91
Junior High School	20	18,69
Senior High School	8	7,48
Collage	0	0

Source: Primary data processed, 2026

Based on the research results, the majority of rose farmers are male, representing 91 people (85.05%), while female farmers make up only 16 (14.95%). This indicates that rose farming activities in Central Java are still dominated by male labor. This is generally because work in the agricultural sector, particularly horticulture, requires relatively greater physical effort. Furthermore, men tend to play a primary role in farm decision-making.

The age distribution shows that the majority of farmers are between the ages of 56 and 70, representing 58 people (54.21%). This indicates that most rose farmers are in the elderly category. Meanwhile, young, productive-age farmers (25–40) comprise only 9 people (8.41%). This indicates the phenomenon of aging farmers, where the younger generation tends to be less interested in participating in the agricultural sector. Older farmers generally have more experience, but on the other hand, they tend to be slower to adopt innovations and new technologies (Vasco et al., 2024).

The education level of rose farmers is predominantly low. Forty-seven (43.93%) did not complete elementary school, and 32 (29.91%) only completed elementary school. Meanwhile, 20 (18.69%) farmers had a junior high school education and only eight (7.48%) had a high school education. None of the respondents had a college education.

Classical Assumption Test

Before interpreting the estimation results, the regression model must first undergo classical assumption tests to ensure that the estimators fulfill the properties of the Best Linear Unbiased Estimator (BLUE) as stated in the Gauss–Markov theorem (Gujarati & Porter, 2009). The classical assumption tests employed in this study include normality, multicollinearity, heteroskedasticity, and autocorrelation.

Normality Test

Normality was tested using the Jarque-Bera test. Based on the results obtained with EViews, the Jarque-Bera test probability value is 0.145, which is greater than the 5% significance level ($\alpha = 0.05$). Therefore, it can be concluded that the residuals are normally distributed. Overall, the classical assumption test conducted indicates that the estimated model meets the OLS assumptions, so the model estimation can be continued.

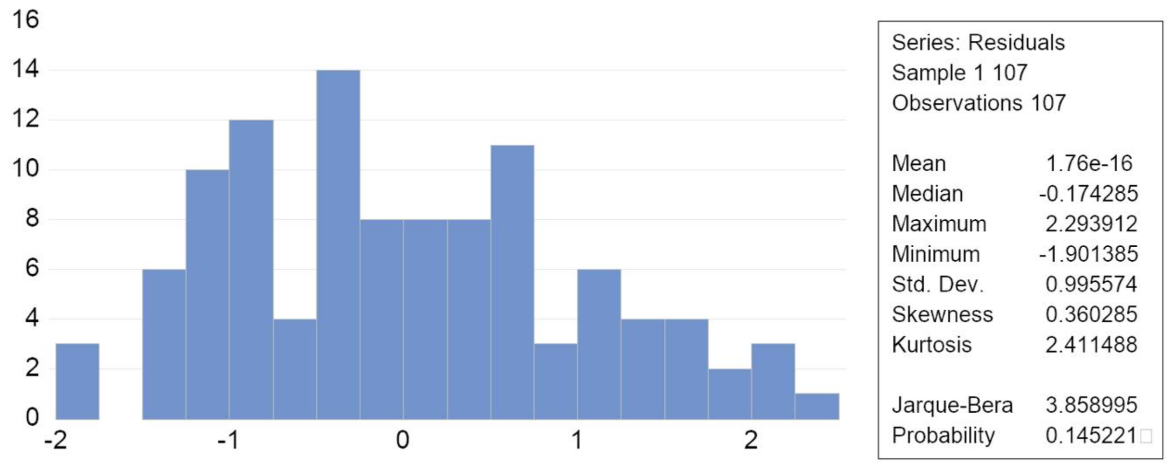

Figure 1. Jarque Bera Test Ouput - Normality Test

Multicollinearity Test

Table 3. Multicollinearity Test Output

Variable	Coefficient Variance	Uncentered Vif	Centered Vif
X_1	0.067350	25.83217	1.044390
X_2	0.103750	41.50368	1.204063
X_3	0.935620	408.2129	1.017962
X_4	0.075689	12.31100	1.117972
X_5	0.024796	22.18238	1.723358
X_6	0.015642	7.632523	1.556760
C	4.473278	491.6124	NA

Source: Author’s calculation using Eviews

The classical assumption test requires that the OLS regression be free from multicollinearity. Multicollinearity can be detected using the Variance Inflation Factor (VIF). If the VIF value is less than or equal to 10, it can be concluded that the model is free from multicollinearity. However, if the VIF value exceeds 10, then multicollinearity exists among the independent variables. Based on Table 2, it can be observed that each independent variable has a VIF value less than 10; therefore, it can be concluded that the model is free from multicollinearity.

Autocorrelation Test

The autocorrelation test is conducted to determine whether there is a correlation among the error terms in the regression model. One of the methods to test the presence of autocorrelation is the Durbin Watson (DW) test. The DW statistic ranges between 0 and 4, with the hypotheses as follows:

Autocorrelation exists if DW < dL or DW > (4 – dL).
No autocorrelation exists if dU < DW < (4 – dU).
Inconclusive if dL < DW < dU or (4 – dU) < DW < (4 – dL).

Based on the EViews calculation, the Durbin–Watson (DW) value is 1.89. Referring to the Durbin Watson table for 107 observations (n = 107) and six independent variables (k = 6), the critical values at the 95% confidence level are dL = 1.56 and dU = 1.8. Accordingly, since the DW value satisfies the second hypothesis (1.8 < 1.89 < 2.2), it can be concluded that the production function model does not exhibit autocorrelation.

Heteroscedasticity Test

In this study, heteroscedasticity was examined using the Harvey test. The decision criterion is based on the probability value of the F-statistic: if the Prob. F-statistic exceeds the chosen significance level (α), the model is considered free from heteroscedasticity. The EViews results show a Prob. F-statistic of 0.94, which is higher than 0.05 (α = 5%). Therefore, it can be concluded that the model does not exhibit heteroscedasticity.

Model Fit Test

Table 4. Results of Rose Production Estimation Using the OLS Estimation Method

Variable	Coefficient	Std. Error	t-Statistik	Prob
C	0.414573	2.266371	0.182924	0.8562
X_1	0.048118	0.264831	0.181693	0.8562
X_2	-0.671654	0.340722	-1.971269	0.0515*
X_3	0.450037	1.038559	0.433328	0.6657
X_4	-0.275752	0.292226	-0.943623	0.3476
X_5	0.451348	0.161116	2.801392	0.0061**
X_6	0.304170	0.129356	2.351413	0.0207**
R Suqare	0.132039			
Prob(F-statistic):	0.025100**			
Durbin-Watson stat:	1.892330			

5% and 10% significance levels are denoted by ** and * respectively.
Source: Author's calculation using Eviews

Based on the regression results, the Prob(F-statistic) value was obtained at 0.0251, which is smaller than the 5% significance level (0.05). This indicates that simultaneously all independent variables (Climate & disaster impact, Farmer group membership, Partnership, Gender, Age, and Education) have a significant effect on the dependent variable (Rose Production). Thus, the regression model used in this study is suitable for use in the analysis.

Based on the results of the partial test (t-test), the Climate & disaster impact variable has a probability value of 0.8562 (> 0.05) so it does not have a significant effect on Rose production. The Farmer group membership variable shows a probability value of 0.0515, which is slightly above the 5% significance level, so it is not significant but close to significant (borderline), with a negative coefficient indicating that increasing Farmer group membership tends to decrease SER01. Furthermore, the Partnership and Gender variables each have probability values of 0.6657 and 0.3476 (> 0.05), so both do not have a significant effect on Rose production. Meanwhile, the Age variable has a probability value of 0.0061 (< 0.05), which means it has a positive and significant effect on Rose production, so that an increase in Age will increase Rose production. Similarly, the Education variable with a probability value of 0.0207 (< 0.05) also has a positive and significant effect on Rose production.

DISCUSSION

The results of this study indicate that, simultaneously, all independent variables significantly influence rose production, as indicated by the Prob(F-statistic) value of 0.0251 (<0.05). However, partially, only age and education had a positive and significant effect on rose production, while climate and disaster impacts, farmer group membership, partnerships, and gender did not show a significant effect. This finding suggests that individual farmer characteristics, particularly age and education, play a more dominant role in determining production outcomes compared to institutional and environmental factors. The positive effect of age may reflect accumulated farming experience, which improves decision-making and farm management efficiency. Similarly, higher levels of education likely increase farmers' ability to adopt innovations and implement better cultivation techniques, leading to increased productivity.

These findings are consistent with previous research highlighting the importance of human capital in agricultural productivity. For example, Deressa et al. (2009) found that education significantly influences farmers' adaptive capacity and decision-making in responding to environmental changes. Similarly, research by Bryan et al. (2009) and Abdulai and Huffman (2014) showed that education and experience are key determinants of technology adoption and agricultural performance. However, the insignificant effects of climate and disasters in this study contrast with the findings of Lobell et al. (2011) and Lesk et al. (2016), which showed that climate variability and extreme weather events significantly reduced agricultural productivity. This discrepancy may be due to differences in scale, data type (micro vs. macro), or farmers' adaptation strategies that mitigate climate impacts at the local level (Amasthi et al, 2024).

Furthermore, the insignificant effects of farmer group membership and partnerships contrast with studies emphasizing the role of institutions in improving agricultural yields. Meinzen-Dick et al. (2014) argue that farmer organizations improve access to information, resources, and collective action, while Barrett et al. (2012) suggest that partnerships can improve market access and efficiency. The lack of significance in this study may indicate that these institutions are not functioning optimally or that their benefits are not distributed evenly among farmers.

Despite these insights, this study has several limitations. First, the relatively low R-squared value (13.2%) indicates that most of the variation in rose production is explained by factors outside the model, such as farm size, input use, technology adoption, and market conditions. Second, the use of secondary data limits the ability to capture more detailed behavioral and environmental variables. Third, the cross-sectoral nature of the data limits the analysis's ability to capture dynamic changes over time, particularly those related to climate variability.

The findings of this study have important implications for policy and future research. From a practical perspective, efforts to increase rose production should focus on enhancing farmers' human capital through education, training, and extension services. Furthermore, strengthening farmer institutions such as groups and partnerships is necessary to ensure they function effectively in supporting farmers. For future research, it is recommended to include additional variables such as farm size, input use, and technology adoption, as well as apply panel data or a longitudinal approach to better capture the impact of climate variability over time. By addressing these aspects, future studies can provide a more comprehensive understanding of the determinants of agricultural production.

CONCLUSION

This study concluded that, simultaneously, climate and disaster impacts, farmer group membership, partnerships, gender, age, and education significantly influence rose production. However, partially, only age and education showed a positive and statistically significant effect on production, indicating that farmers' human capital plays a more decisive role in determining production outcomes. Meanwhile, climate and disaster impacts, farmer group membership, partnerships, and gender did not have a significant effect, suggesting that these factors may not optimally influence production or that their effects are mediated by other variables not included in the model.

These findings highlight that improving farmers' knowledge, skills, and experience is crucial for increasing rose production. Therefore, policies and programs should prioritize education, training, and extension services to strengthen farmer capacity. Furthermore, the relatively low explanatory power of the model suggests that other important factors, such as land area, input use, and technology adoption, should be considered in future research to gain a more comprehensive understanding of the determinants of agricultural production.

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