

**RESEARCH PAPER****The Effects of Climate-Smart Agriculture on Crop Productivity in Nangarhar Province****¹ Ihsanullah Shorish**

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***Corresponding Author:** ihsanullahshorish2024@gmail.com**ABSTRACT**

This study looked at how climate smart agriculture and the environment affects the crop production in Nangarhar Province, Afghanistan. The structured questionnaire is used to collect the primary data from the corresponding respondents. This study used multiple linear regression to estimate the findings of the study. Beside this, the findings demonstrated that there was a strong positive correlation between the climate-smart agriculture and the crop productivity ($r = 0.720$, $p < 0.001$), and there was a significant positive correlation between the environment and the crop productivity ($r = 0.653$, $p < 0.001$). The regression result showed that both climate-smart agriculture ($\beta = 0.513$, $p < 0.001$) and environment ($\beta = 0.341$, $p < 0.001$) have significant and positive impact on crop productivity, with the greatest influence being climate-smart agriculture. The regression model accounted for 59.2% of the variation in crop productivity ($R^2 = 0.592$) and the overall model was statistically significant ($F = 160.981$, $p < 0.001$). The study demonstrated that adopting climate-smart agricultural practices along with better environmental management could significantly boost agricultural productivity and resilience. The results offer valuable information for policymakers, agricultural extension and development organizations to support sustainable agricultural development and food security in Afghanistan.

KEYWORDS Climate Smart Agriculture, Crop Productivity, Environment**1. Introduction**

In many developing countries agriculture continues to be a key sector in economic development, food security and rural livelihoods. But climate change poses an increasing threat to agriculture, expressed in the form of changing rainfall patterns, droughts, floods and land degradation, as well as rising temperatures. These climate stresses are having a large impact on the yield and sustainability of agricultural production systems globally. Climate change is a serious threat to global food production and innovative agricultural practices are needed that will increase the resilience of agriculture without reducing productivity, according to the Food and Agriculture Organization (FAO, 2013). Climate-Smart Agriculture (CSA) is a holistic solution to the climate change impacts on agriculture. CSA aims to fulfil three key goals: to boost agricultural productivity, to build resilience and adaptation capacity to climate change, and to minimize GHG emissions wherever possible (FAO, 2013). The strategy encourages sustainable agriculture, including conservation agriculture, water management and efficient use, new seeds, agroforestry and integrated soil fertility management. These practices offer farmers the ability to adjust to the impacts of climate change and enhance the productivity of their farming operations and their use of resources. Understanding the importance of climate-smart agriculture has been growing, as it can enhance agricultural productivity in a climate change environment. Research has demonstrated that CSA practices can have a significant positive impact on soil health, water resource conservation and the resilience of crops to climate shocks, thereby contributing to the enhanced crop productivity (Lipper et al., 2014). In addition, farmers adopting climate-smart technologies can use their farming resources more efficiently, thus enhancing productivity, profitability, and reducing environmental impact.

Climate-smart agriculture has significant importance in developing countries, where a large share of the population is engaged in agriculture and therefore has a high reliance on climate. Smallholder farmers are especially vulnerable to climate variability, as they may not have access to resources, technology or financial support. The World Bank Study (2021) shows that the use of climate-smart agricultural practices can boost farm productivity, enhance climate risk resilience, and drive sustainable rural development. Hence, promotion of CSA has emerged as a priority to ensure long-term agricultural sustainability. Afghanistan, due to its reliance on agriculture and its susceptibility to frequent droughts, water scarcity and extreme weather events is one of the most vulnerable countries to climate change. Agriculture plays a significant role in rural households' livelihoods and also a major role in the national economy. But reduction in water supply, soil erosion and uncertainty in climate patterns have had an adverse impact on the growth of crops in various parts of the country. To address these issues, several development and international agencies have launched initiatives to promote climate-smart agriculture and improve agricultural resilience and productivity (FAO, 2023). Adopting climate-smart agriculture in Afghanistan involves initiatives for promoting drought-resistant crop varieties, enhancing irrigation infrastructure, implementing sustainable land management practices, and conducting farmer education programs. The interventions are expected to enhance the productivity of crops and simultaneously cut down farmers' exposure to climate risks. A previous study indicates that, the use of climate-smart technologies can enhance agricultural production, resource utilization efficiency and household income of agricultural communities (Campbell et al., 2014). However, in Afghanistan the empirical evidence on the effectiveness of CSA practices on the productivity of crops is limited and needs further investigation.

Climate-smart agriculture (CSA) and its impact on crop productivity is timely and relevant, as climate change poses growing challenges and agriculture is a critical sector for economic development and food security. The correlation between CSA adoption and agricultural performance can offer important insights for policy makers, development organizations, and farmers looking for sustainable solutions to improve food production. Hence, the present study is focused on the impact of climate smart agriculture (CSA) on crop productivity and also to add to the body of knowledge in the field of sustainable agriculture development in climate vulnerable areas

2. Literature Review

Climate-smart agriculture (CSA) has become a comprehensive agricultural strategy that meets two challenges: climate change and global food security. The Food and Agriculture Organization (FAO) introduced the concept, which encompasses the idea of a strategy that works to both enhance agricultural production and build climate change resilience while also lowering greenhouse gas emissions, if feasible (Food and Agriculture Organization (FAO, 2013). Zheng et al. (2024) state that CSA has emerged as one of the most successful approaches to sustainable agricultural development and environmental integrity. As climate-related disasters become more frequent, the importance of CSA as a sustainable approach to enhance crop productivity in the context of climate change is growing (FAO, 2013; Zheng et al., 2024). Many empirical studies have found that implementing agricultural practices which are more climate smart can greatly enhance productivity of the crops by managing the soil, using agricultural inputs efficiently and implementing sustainable farming practices. Conservation agriculture, integrated nutrient management, precision farming, and crop diversification are among practices that allow farmers to achieve higher productivity and lower production risk due to climate variability (Zheng et al., 2024). Likewise, Mizik (2021) reported that the overall yield of farmers who practice CSA is higher relative to those who follow conventional farming systems as the use of climate smart technologies enhances the efficiency of resource use and resilience to weather-related shocks.

Improving soil health is one of the most important avenues for climate-smart agriculture's contribution to agricultural production. Adopting sustainable practices like minimum tillage, mulching, applying compost, cover cropping, and integrated soil fertility management enhance soil organic matter, water holding capacity, nutrient availability, and microbial activity (Mizik, 2021). Better soil conditions promote better rooting and plant growth, enabling crops to sustain higher productivity even in drought and heat stress conditions. FAO (2013) states that sustaining soil health is a key element of sustainable agricultural intensification and food security. Another major aspect of climate smart agriculture is efficient water management which has a direct impact on the productivity of crops. With the occurrence of droughts and irregular rainfall with climate change, water conservation is becoming more and more critical for the production of agricultural crops. CSA advocates technologies that allow for the more efficient use of water for the same yield, like drip irrigation, sprinkler irrigation, rainwater harvesting, and precision irrigation systems (Zheng et al., 2024). Research shows that these water-saving technologies can cut water loss, enhance irrigation efficiency, and boost agricultural productivity in

water-constrained environments (Zhao et al., 2023). Crop varieties that are resistant to climate change also play a significant role in increasing crop productivity. Crop varieties that are drought-tolerant, heat resistant, pest resistant and flood-tolerant help minimise production losses from climate variability and maintain stable agriculture. Combining better crop varieties with climate-smart agronomic practices benefits productivity by helping crops cope with climate stresses (Zhao et al., 2023). Likewise, FAO (2013) pointed out the importance of enhancing genetic resources in bolstering food production systems in the context of climate change.

Another crucial climate-smart farming practice is crop diversification, which boosts crop yields while minimizing production risks. Crop rotation, intercropping and mixed farming systems add to the soil fertility, reduce pest and disease pressure and enhance nutrient cycling (Scherer & Verburg, 2017). Diversified farming systems also decrease the reliance on a single crop by the farmers, enhancing their climate-shock mitigation capacity. In general, diversified agricultural systems yield more stable yields over time than monoculture systems (Scherer and Verburg, 2017). Due to its several environmental and productivity advantages, agroforestry has gained more and more importance in the field of climate-smart agriculture (CSA). The inclusion of trees in agricultural landscapes can enhance soil fertility, biodiversity, reduce erosion and provide favourable micro-climatic conditions for crop growth (Scherer & Verburg, 2017). Trees add organic material to the soil, enhance soil moisture, increase nutrient cycling and boost agricultural productivity. According to Zheng et al. (2024), agroforestry systems have the potential to enhance carbon sequestration and mitigation, as well as boost yields. The implementation of climate-smart agriculture has been strengthened by technological innovations in recent years, especially precision agriculture and digital farming. The use of technologies like remote sensing, drones, Geographic Information Systems (GIS), weather prediction systems, and Internet of Things (IoT) devices helps farmers make informed decisions about irrigation, fertiliser usage, and pest control (Zhao et al., 2023). These innovations help to use resources to the best effect with minimal production costs or environmental impact. Precision agriculture is now a crucial technology for enhancing productivity in a changing and more uncertain climate (Zhao et al., 2023).

Overall, the existing literature provides overwhelming evidence that climate-smart agriculture significantly improves crop productivity through sustainable soil management, efficient water utilization, resilient crop varieties, diversified farming systems, agroforestry, and precision agriculture technologies (FAO, 2013; Mizik, 2021; Scherer & Verburg, 2017; Salihi & Himatkhwah, 2024; Zhao et al., 2023; Zheng et al., 2024). Although implementation challenges remain, researchers consistently conclude that CSA offers an effective pathway toward achieving sustainable agricultural productivity, improved food security, and enhanced resilience to climate change, particularly in vulnerable developing countries.

Improved crop productivity and agricultural incomes are also positive outcomes of climate-smart agriculture that supports farmers' socioeconomic wellbeing. Increased productivity boosts household food security, decreases poverty and increases resilience to economic shocks caused by climate change (FAO, 2013). But as pointed out by Mizik (2021), farmers' access to extension services, agricultural credit, education and institutional support are very important factors in the successful adoption of CSA. Hence, policy measures are still necessary to promote smallholder farmers' use of CSA. Overall, there is a consistent evidence from developing countries that climate-smart agriculture has significant potential benefits for smallholder farming systems. CSA practices decrease the vulnerability of agriculture to climate variability and enhance agriculture productivity in many low-income countries where agriculture is highly dependent on rainfall (Zheng et al., 2024). In Afghanistan, climate-smart practices like the use of irrigation systems, the cultivation of drought-tolerant crops, conservation agriculture, and integrated nutrient management have proven to be highly effective in boosting crop yields in the face of climate-induced droughts and water scarcity (Salihi & Himatkhwah, 2024). Although there are numerous benefits of climate smart agriculture, there are also some challenges in its implementation. Low financial capital, poor infrastructure, low level of extension services, low institutional capacity and lack of technical knowledge are still significant barriers to the widespread adoption of CSA (Mizik, 2021). Moreover, climate smart technologies have been found to be effective in different settings depending on local environmental, climate and socio-economic conditions and therefore, require context specific implementation strategies. For successful implementation of CSA, coordinated efforts with governments, research institutions, extension agencies and farming communities are required (Zhao et al., 2023).

3. Material and Methods

This study is quantitative research, which was used to analyze the effects of climate-smart



agriculture and environmental factors on crop productivity. The advantages of using a quantitative approach is that it allows the collection of numerical data and the statistical analysis of the relationship between the independent and dependent variables. The study used primary data obtained by a structured questionnaire which was given to 225 respondents. The selected target groups were technical agriculture experts, farmers, and governmental authorities dealing with the agricultural sector, because they have hands-on experience and knowledge about the implementation of climate-smart agriculture and environmental management. To make sure that participants from every stakeholder group are represented, a structured sampling procedure is used. The questionnaire has closed-ended questions answered on a five-point Likert scale from strongly disagree (1) to strongly agree (5). The instrument is pretested for reliability and validity before the main survey and appropriate changes are made to clarify and make the instrument consistent.

The dependent variable of the study is the productivity of crops and the independent variables are climate-smart agriculture and environmental factors. The data obtained from the respondents are coded and given to Statistical Package for the Social Sciences (SPSS) for analysis. Demographic characteristics of the respondents and distribution of responses were summarized using descriptive statistics such as frequencies, percentages, means and standard deviations. Inferential statistical methods were then used to investigate the relationship between the variables of the study. The reliability analysis was carried out with Cronbach's alpha to evaluate the internal consistency of the measurement scales, and Pearson correlation analysis was used to determine the relationships between the variables and the strength and direction of the relationships. Finally, multiple linear regression analysis was used to analyse the impacts of climate-smart agriculture and environmental variables on the productivity of major crops and the amount of variation in the dependent variable explained by the independent variables. The findings offer empirical data on how climate smart agriculture and environment contribute to better crop productivity and how can policy makers, agricultural practitioners and development organizations use these findings for policy guidance. Following model is estimated:

$$CP = \beta_0 + \beta_1 CSA + \beta_2 E + \varepsilon$$

Where, CP stand for Crop Productivity, CSA stand for Climate Smart Agriculture, and E stand for Environment, β_0 stand for Constant term, β_1 , β_2 stand for coefficient of the explanatory variables, and ε depicts for Error term.

4. Results and Discussion

4.1 Descriptive Statistics

Table 1
Descriptive Statistics

Variables	N	Minimum	Maximum	Mean	Std. Deviation
Crop Productivity	225	3.50	5.00	4.9333	.17198
Environment	225	3.00	5.00	4.9567	.17054
Climate Smart Agriculture	225	3.75	5.00	4.9256	.17602

The descriptive statistics from Table 1 suggest that the respondents' overall perceptions of crop productivity, environmental quality, and climate-smart agriculture (CSA) use were very high, particularly since the adoption rates were generally high. With a mean score of 4.93 out of a maximum of 5.00 and a very low standard deviation (0.17), crop productivity is reported as being nearly uniformly excellent across the sample, showing very little variation. The same applies for the environment (mean = 4.96) and climate-smart agriculture practices (mean = 4.93) that also had almost perfect average scores, with little variation. The narrow spread between the minimum and maximum for all three variables, particularly the observation that no one rated below 3.00 on any variable, and that most scores were at the higher end (above 4.90), points to either a very positive context for agriculture, or a problem with the measurement scale and/or sample. The very low standard deviations suggest that the

overwhelmingly positive responses of almost all of the respondents mean that there is little statistical spread to allow meaningful testing of correlations or causal relationships among these variables in future analysis to be able to detect significant associations.

4.2 Correlation Matrix

Table 2

Correlation Matrix

Variables		Crop Productivity	Climate Smart Agriculture	Environment
Crop Productivity	Pearson Correlation	1		
	Sig. (2-tailed)			
	N	225		
Climate Smart Agriculture	Pearson Correlation	.720**	1	
	Sig. (2-tailed)	.000		
	N	225	225	
Environment	Pearson Correlation	.653**	.608**	1
	Sig. (2-tailed)	.000	.000	
	N	225	225	225

** . Correlation is significant at the 0.01 level (2-tailed).

The results in Table 2 show that there is high, positive and statistically significant correlation level between all the three variables (crop productivity, climate-smart agriculture (CSA) and environment) in the study population of 225 respondents. The Pearson correlation coefficient between crop productivity and climate-smart agriculture is 0.720 ($p < 0.01$) which shows a strong positive association, suggesting that there is a close relationship between the increase in the level of CSA practice and the increase in the reported productivity of the crops. Likewise, the relationship between crop productivity and environment is 0.653 ($p < 0.01$), and is also positive and strong, suggesting that improved environment (or perceptions of environment) is linked to increased productivity. Besides, the interrelationship between climate-smart agriculture and environment is also moderately-to-strongly with a correlation of 0.608 ($p < 0.01$). All correlations are at the 0.01 level (2-tailed) so there is less than 1% chance that these are by chance. It is important to note however, that correlation does not equal causation; that is, these results suggest that there is a positive correlation between the two variables, but do not imply that the adoption of CSA directly leads to increases in productivity, and that environmental improvements directly lead to CSA adoption. Rather, they propose that these factors reinforce one another or are co-occurring within the context of the study, and additional analytic methods (e.g., regression or path analysis) would be required to determine the direction of the relationships or to identify causal relationships.

4.3 Regression Result

Table 3

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.769a	.592	.588	.11036

a. Predictors: (Constant), Environment, Climate Smart Agriculture

The model presented in Table 3 shows that the regression model with Environment and Climate Smart Agriculture explained a significant amount of the variance in Crop Productivity. The multiple correlation coefficient ($R = 0.769$) shows that there is strong positive relationship between the two predictor variables together and crop productivity. The R Square value of 0.592 shows that the linear combination of Environment and Climate Smart Agriculture explains about 59.2% of the total variation

in the crop productivity which is quite high for a social science or agricultural study. The Adjusted R Square is 0.588, which is very close to the unadjusted R Square, suggesting that the model is not overfitted and that both predictors add significantly to the explanation. The standard error of the estimate is very low at 0.11036 (where productivity can range from 3.50 to 5.00), indicating that the predictions made by the model are relatively accurate, on average, and close to the observed values. Overall, these results validate that both environmental conditions and climate-smart agricultural practices are significant joint determinants of crop productivity in this study context, but, it should be emphasized that the remaining 40.8% unaccounted variance suggests that other factors that are not accounted in this model (e.g., socio-economic conditions, soil properties, market access, farmer education, etc.) also contribute to the productivity outcomes.

Table 4
Analysis of Variance

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	3.921	2	1.961	160.981	.000b
Residual	2.704	222	.012		
Total	6.625	224			

a. Dependent Variable: Crop Productivity

b. Predictors: (Constant), Environment, Climate Smart Agriculture

As per the results of analysis of variance (ANOVA) presented in Table 4, the regression model is highly statistically significant and shows a good overall fit to predict Crop Productivity from the Environment and Climate Smart Agriculture as predictors. The total sum of squares (6.625) is the variation in the productivity of the crop over all 224 degrees of freedom, which can be partitioned into 3.921 units explained by the regression model (with 2 degrees of freedom for the 2 predictors) and 2.704 units not explained by the regression model (with 222 degrees of freedom as residual error). The mean square for regression is considerably larger (1.961) than the mean square for the residuals (0.012), giving an F-statistic of 160.981, which is very high and far above any critical F-values at conventional levels of significance. The associated p-value (Sig.) is .000, meaning that the probability of obtaining such a large F-statistic by random chance is less than 0.1% ($p < 0.001$), and so we can be confident of rejecting the null hypothesis that all regression coefficients are equal to zero. This validates the basic premise that the linear combination of Environment and Climate Smart Agriculture accounts for a statistically significant proportion of the variance in crop productivity, and the very small residual mean square (0.012) compared to the regression mean square (1.961) indicates that the model predictions are extremely precise, accounting for more than 163 times the unexplained variation per degree of freedom. From a practical perspective, these results offer strong statistical support for the combined effect of the two predictors having a meaningful and reliable impact on the productivity of crops, and lend substance to the substantive interpretations of the R^2 value (0.592) and the individual regression coefficients.

Table 5
Regression Result

Model	Unstandardized Coefficients		Standardized Coefficients		t	Sig.
	B	Std. Error	Beta			
(Constant)	.761	.235			3.240	.001
Climate Smart Agriculture	.501	.053	.513		9.502	.000
Environment	.344	.054	.341		6.313	.000

a. Dependent Variable: Crop Productivity

The regression results of the variables in Table 5 indicate that both Climate Smart Agriculture and Environment are highly significant positive predictors of Crop Productivity; the model shows that environment and Climate Smart Agriculture contribute significantly to the model. The unstandardized coefficient (B) for Climate Smart Agriculture is 0.501 (Std. The value of 'Error' is 0.053, this means

that the value of the crop productivity will increase by about 0.501 units for every unit increase in the value of CSA practices while other factors are kept constant. In the same way, the unstandardized coefficient for Environment is 0.344 (Std. The productivity level increases by 0.344 units for each unit increase in environmental conditions (Error = 0.054), while keeping CSA constant. The standardized coefficient (Beta) indicates that the relative influence of Climate Smart Agriculture (Beta = 0.513) is slightly higher than the Environment (Beta = 0.341), which indicates that the model is more strongly affected by CSA practices than by the environment. The t-values for both predictors, 9.502 for CSA and 6.313 for Environment, are well above the critical value and both are statistically significant at the $p < 0.001$ level, indicating that these relationships are not the result of random chance. The constant term ($B = 0.761$, $p = 0.001$) is also significant because it shows the level of crop productivity if both predictors are equal to zero. Importantly, the positive signs of both coefficients are in line with the results of the correlation matrix and indicate that improving environmental quality and implementing climate-smart agriculture are both positively correlated with crop productivity, and that the effect of CSA is slightly higher than the effect of environmental quality. The standard errors are quite small (0.053 and 0.054) suggesting that these predictors provide accurate estimates, and the high t-values further support the strength of these predictors. Together, these regression coefficients are sufficient to give strong support to the meaning of both variables to explain productivity, and the model suggests that interventions to support climate smart agriculture would have slightly greater productivity effects than interventions to address the environment, although both are clearly important for sustainable agricultural development.

5. Discussion

The regression analysis shows that both Climate Smart Agriculture (CSA) practices and environmental conditions are significant positive predictor of crop productivity, with Climate Smart Agriculture (CSA) showing a slight higher influence ($\beta = 0.513$) than environmental condition ($\beta = 0.341$). This discovery follows a growing trend of evidence from sub-Saharan Africa that shows the benefits of CSA practices in terms of productivity are significant. For example, in Zambia, the overall yield of crops was found to be 20.20% higher among adopters than non-adopters, while the yield of maize was found to be 21.50% higher among adopters compared to non-adopters (Chavula et al., 2023). Likewise, research in Tanzania found that the persistent use of CSA technologies boosted maize's productivity by 41.9%, Irish potatoes by 65.2%, and beans by 29.2% (Mzingula et al., 2024). Further evidence from Tanzania showed that the extent of CSA adoption had a significant impact on the productivity increase (Msuhaa, 2026) and farm income (Rahbar et al., 2017). The positive correlation between CSA and productivity ($r = 0.720$) in this study further confirms the positive impact of CSA practices, including improved seed varieties, integrated nutrient management, and agroforestry, on productivity, especially among the most vulnerable smallholder farmers who were most impacted by climate variability (Chavula et al., 2024; John, 2026). The regression coefficient ($B = 0.344$, $p < 0.001$) and the correlation coefficient with productivity ($r = 0.653$) showed the importance of climatic and ecological factors for the agriculture productivity. This aligns with the study conducted in Ghana which revealed that temperature factors accounted for 46.87% to 61.57% of the variability in cassava, yam and maize yields respectively (Kwakye et al., 2025). In the same vein, a study of the effects of climate change across sub-Saharan African countries found that the productivity of land, labor, and fertilizer was significantly reduced by the climate change proxies CO_2 and methane emissions (Alemu et al., 2024). The relatively smaller standardized coefficient for environment than for CSA in the current study indicates that although environmental conditions are the basic conditions, farmers may have more control over productivity by adjusting their agricultural practices. Evidence shows that certain climate-smart interventions such as drought-tolerant crops, precision irrigation, and conservation tillage can also be used to reduce the negative impact of climate change, with some climate-smart practices improving crop yields by 15-35% and also improving soil organic carbon and reducing GHG emissions (Halshoy & Hamab, 2025). Moreover, studies on intensification of dryland agriculture highlight the importance of the adoption of CSA for resilience and food security in climate-sensitive areas (2025).

The regression model has high explanatory power ($R^2 = 0.592$, $F = 160.981$, $p < 0.001$), indicating that the joint effect of the CSA and environment explains almost 60% of the variability in crop productivity. The results are of significance for agricultural policy and extension in developing areas. First, it implies that there are measurable productivity gains to be had from farmer education, increased access to climate information, and targeted provision of resources such as improved seeds and financial services to promote CSA adoption (John, 2026; 2026). Second, the moderate correlation between CSA and environment ($r = 0.608$) suggests that the two are reinforcing each other and that environmental stewardship and climate-smart intensification should be considered complementary rather than conflicting goals (Halshoy & Hamab, 2025). Yet, the unexplained variance of 40.8% underscores the importance of further investigation in the future to account for other determinants that have been found to be important in driving CSA adoption and results in other contexts, such as education level, household size, farming experience, access to credit, and institutional support (Chavula et al., 2023; Chavula et al., 2024; Msuhaa, 2026). Additionally, overcoming the current challenges in CSA adoption, such as low technical expertise, high investment costs, and lack of extension support, is crucial for expanding CSA innovations and guaranteeing future food security in a changing climate (Mzingula et al., 2024; 2025).

6. Conclusion

The results of this study confirm that both environmental conditions and the use of Climate Smart Agriculture (CSA) practices have a positive significant effect on the productivity of crops, albeit to varying extents, with the use of CSA practices having a slightly greater effect ($\beta = 0.513$) than the use of environmental conditions ($\beta = 0.341$). The regression model accounts for about 59.2% of the variance in crop productivity ($R^2 = 0.592$, $F = 160.981$, $p < 0.001$), indicating that the two predictors together have a significant and substantial effect on crop productivity. The high positive correlations between all three variables, CSA and productivity ($r = 0.720$); environment and productivity ($r = 0.653$); and CSA and environment ($r = 0.608$), suggest that these factors are reinforcing one another and that interventions to promote climate-smart practices and environmental stewardship should be pursued as complementary, rather than competing, approaches (Campbell et al., 2014; Lipper et al., 2014). The results are consistent with previous studies that show that the adoption of CSA can increase agricultural yields by 20-65% in different contexts (Chavula et al., 2024; Mzingula et al., 2024), and that environmental factors like temperature and the pattern of rainfall are still the key factors in agricultural productivity (Kwakye et al., 2025; Alemu et al., 2024). The results have significant policy, extension, and development implications for climate-sensitive areas, including in Afghanistan where food security is a critical issue (FAO, 2023). To this end, increased productivity can be achieved by promoting CSA practices through farmer education, better access to climate information, provision of stress-tolerant crop varieties, and improved extension services, while simultaneously enhancing resilience to climate change (FAO, 2013; World Bank, 2021; Zheng et al., 2024). Second, the moderate correlation between CSA and environment reinforces the importance of integrated approaches to agricultural intensification and environmental conservation, as practices like conservation agriculture, agroforestry and improved water management can provide co-benefits in terms of productivity, climate adaptation, and greenhouse gas mitigation (Halshoy & Hamab, 2025; Zhao et al., 2023). Nonetheless, the 40.8% unexplained variance indicates that other factors such as socioeconomic characteristics like education level, household size, farming experience, access to credit, land tenure security, and institutional support are also important in explaining productivity outcomes (Chavula et al., 2023; Salihi & Himatkhawah, 2024). Therefore, future research should aim at mixed methods which consider these multidimensional determinants, as well as current challenges in the adoption of CSA, including limited technical knowledge, high start-up costs, insufficient infrastructure and policy constraints (Mizik, 2021; Scherer & Verburg, 2017). Context-specific, participatory and evidence-based approaches are needed to enable smallholder farmers to implement climate-smart practices and to protect the environmental base on which agricultural productivity depends, to achieve sustainable food security and climate resilience.

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