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Assessing The Effects Of Climate Change On Agriculture Productivity Across Rwanda's Provinces And Kigali City

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Abstract. Agriculture is crucial for global food security and economic stability, but it is increasingly threatened by climate change. This study examines the impact of climate change on agricultural productivity in Rwanda's provinces and Kigali city using data from 2003 to 2023. The analysis involved descriptive statistics, trend visualization, and statistical models like the Cobb-Douglas production function and Random Effects model. Findings reveal significant temperature and precipitation variability across regions, with notable warming in certain years and varying trends across provinces. Agricultural productivity was strongly influenced by land use, labor participation, and fertilizer consumption, which explained 87.7% of the variation. The Random Effects model showed that temperature and precipitation also affected productivity, with temperature increases leading to small decreases in crop output. The study highlights the need for adaptive strategies to counter climate impacts, recommending sustainable land management, advanced agricultural training, and climate adaptation measures to ensure food security in Rwanda.

Key words: agriculture productivity and crop; climate change; Cobb Douglas; fertilizer; labor participation and land use.
AMS 2010 Mathematics Subject Classification Objects : 62Pxx; 62-07; 2M15.

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Résumé. (Abstract in French) L'agriculture est cruciale pour la sécurité alimentaire mondiale et la stabilité économique, mais elle est de plus en plus menacée par le changement climatique. Cette étude examine l'impact du changement climatique sur la productivité agricole dans les provinces du Rwanda et dans la ville de Kigali en utilisant des données de 2003 à 2023. L'analyse a fait appel à des statistiques descriptives, à la visualisation des tendances et à des modèles statistiques tels que la fonction de production Cobb-Douglas et le modèle à effets aléatoires. Les résultats révèlent une variabilité importante des températures et des précipitations dans les régions, avec un réchauffement notable certaines années et des tendances variables selon les provinces. La productivité agricole a été fortement influencée par l'utilisation des terres, la participation de la main-d'oeuvre et la consommation d'engrais, qui ont expliqué 87,7% de la variation. Le modèle des effets aléatoires a montré que la température et les précipitations affectaient également la productivité, les augmentations de température entraînant de légères diminutions de la production agricole. L'étude met en évidence la nécessité de stratégies d'adaptation pour contrer les effets du climat, en recommandant une gestion durable des terres, une formation agricole avancée et des mesures d'adaptation au climat pour assurer la sécurité alimentaire au Rwanda.

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1. Introduction

Agriculture is the foundation of global food security and economic well-being. It provides sustenance for billions of people and contributes significantly to national economies Misselhorn et al. (2012). However, climate change poses a growing threat to this vital sector. Rising temperatures, changes in precipitation patterns, and extreme weather events are disrupting Agricultural Productivity systems worldwide. These disruptions can lead to crop yield declines, reduced food security, and economic losses Laborde et al. (2020); Rawat et al. (2024). The combination of climate change and Agricultural Productivity presents a complex challenge. Agriculture itself contributes to greenhouse gas emissions through land-use changes and agricultural practices Calzadilla et al. (2013); Gornall et al. (2010). Therefore, same scenarios were found in distinguish regions around the world.

The African continent is particularly vulnerable to the negative effects of climate change on agriculture. Many African countries are already grappling with arid and semi-arid climates, limited water resources, and poverty Badji et al. (2022). Climate change is expected to exacerbate these existing challenges, leading to increased droughts, floods, and heat stress Müller et al. (2011). Studies in East Africa, have documented the detrimental effects of rising temperatures and erratic Precipitation on staple crops like maize, with significant yield reductions observed by Omoyo et al. (2015). These impacts threaten food security and livelihoods for millions of people who depend on agriculture for their subsistence and income. In African especially East Africa, each country faces unique challenges based on its level of resilience to this concerning situation Change (2016).

In nowadays, Rwanda is facing the challenges like many countries in Africa. Agriculture is a cornerstone of the Rwandan economy, contributed substantially to GDP at 30% value-added share in according to Salim (2024). However, Rwanda's agricultural sector is highly vulnerable to climate change due to its reliance on rain-fed agriculture and hilly topography as presented in Lydie (2022). Past experiences, such as the devastating 2000 drought, have highlighted the detrimental effects of climate extremes on crop yields, particularly maize Byishimo (2017). Research suggests that rising temperatures negatively impact maize productivity in Rwanda, with studies finding a decline in annual yield associated with increases in average temperatures Austin et al. (2020). Anyway, the projections of future climate change scenarios in Rwanda indicate potential increases in temperatures and changes in Precipitation patterns, raising concerns about water availability for agriculture Umutesi (2021).

Climate change poses a significant threat to global food security, impacting Agricultural Productivity worldwide Myers et al. (2017). Developed countries, with their advanced technologies and infrastructure, are better equipped to adapt to changing weather patterns through practices like irrigation and drought-resistant crops Srivastav et al. (2021). However, developing countries often lack the resources and infrastructure to implement such solutions, making them more vulnerable to climate change's effects on agriculture Hatfield et al. (2014). These effects can include erratic precipitation patterns, rising temperatures, and increased frequency of extreme weather events like floods and droughts, all of which disrupt agricultural productivity and threaten food security, particularly for subsistence farmers heavily reliant on rain-fed agriculture Seneviratne et al. (2021).

Agriculture is the backbone of Rwanda's economy, contributing significantly to GDP and employing a large portion of the population of Rwandan at 70% according to Bahati et al. (2022). However, Rwanda's agricultural sector is highly vulnerable to climate change due to its reliance on rain-fed agriculture and limited resources for adaptation. Rwanda experiences erratic precipitation patterns, rising temperatures, and increased frequency of droughts and floods, all of which disrupt Agricultural Productivity and threaten food security Clay and King (2019); Lydie (2022).

Researchers in Rwanda have recently highlighted the impact of climate change on crop yields, particularly its effects on staple foods, wetland maize production, and food insecurity and used a various methods, including literature reviews, field observations, household surveys, a cross-sectional model, and a quasi-experimental design with a control group Austin et al. (2020); Birachi et al. (2020); Rwanyiziri et al. (2019). After reviewing literatures a methodological gap exist, as no study has utilized panel data models to analyze the nuanced effects of climate change on agricultural productivity over time and across Rwanda's regions, which is good to consider individual effects. This research addresses the crucial gap concerning the effects of climate change on agricultural productivity across Rwanda's provinces and Kigali City. By examining that effect, facilitate the development of targeted adaptation strategies and improve agricultural planning in Rwanda's regions.

The contribution of this study is to assess the effects of Climate change on Agricultural Productivity across Rwanda's provinces and Kigali city. Specifically, to identify the trends of climate change in Rwanda's provinces and Kigali city using 2004-2023 datasets, to determine the major factors of Agricultural Productivity in Rwanda, and to examine the effect of climatic change on Agricultural Productivity across Rwanda's provinces and Kigali city.

The paper is organized as follows: The literature review is presented in Section 2. Section 3 is devoted to the materials and method used in this study. The results of our models are described in Section 4. Finally, Section 5 concludes this work with proposed future works.

2. Literature review

Climate change refers to long-term shifts in temperature and typical weather patterns in a place these changes may include variations in precipitation, wind patterns, and extreme weather events. Climate change is primarily driven by human activities that increase heat-trapping greenhouse gases in the atmosphere Jain et al. (2020); Walsh et al. (2020). Climate variables are specific elements of the climate system that influence agricultural productivity Hatfield et al. (2020). Variables like temperature appear oftentimes in this research, temperature refers to the average atmospheric and soil conditions of warmth or coldness measured in degrees Celsius (°C) Rising temperatures can negatively impact agricultural productivity by stressing crops, increasing pest outbreaks, and influencing water availability Lembrechts et al. (2020); Skendžić et al. (2021). And also, precipitation refers to any form of water particles, like rain, snow, sleet, or hail, that fall from the atmosphere and reach the ground Wynne (2008). It plays a crucial role in agriculture, impacting crop growth and overall productivity. However, the relationship between precipitation and agriculture is complex, with both positive and negative consequences, measured in millimeters as suggested in Gornall et al. (2010).

Agricultural Productivity encompasses the activities involved in cultivating crops and raising livestock for food, fiber, and other products this includes practices like planting, irrigation, fertilization, pest control, and harvesting Ortiz-Bobea et al. (2021). Crop productivity refers to the amount of crop yield harvested from a specific area of land over a defined period. It essentially reflects how efficiently crops are grown within a given space. Higher crop productivity translates to greater food production per unit of land, which is crucial for food security, especially with a growing global population Fischer (2015).

Crop productivity index is a standardized measure used to compare crop productivity across different regions, years, or even crop types. It takes into account the total production of a specific crop relative to a baseline value, often the average yield over a historical period Armagan et al. (2010).

Agricultural inputs: are resources used in the production process to cultivate crops and raise livestock. Land Used is one of them, land used refers to the purpose for which land is dedicated, such as cropland, pastureland, or forest. Changes in land use practices can impact agricultural productivity and influence the vulnerability of agricultural systems to climate change Regasa et al. (2021).

Labor used, labor refers to the human workforce employed in agriculture activities, including planting, weeding, harvesting, and livestock care. Labor availability and skills are crucial factors influencing agricultural productivity Iancu et al. (2020). Another remarkable agricultural input is Fertilizer, fertilizer is a substance containing nutrients added to soil to enhance plant growth and crop yield. Fertilizer application can significantly increase agricultural productivity, but its overuse can have environmental consequences Liu et al. (2015).

Population density refers to how many people live in a given area. It's linked to agriculture in a complex way: high density can strain resources and shrink farm sizes, but it can also drive innovation, create better markets for crops, and encourage more intensive farming techniques to produce more food from less land Cumming et al. (2014); Gleave and White (2023). Crucial to define Panel data model and Cobb-Douglas Production Function, The Cobb-Douglas production function is a mathematical model commonly used in economics to estimate the relationship between various agricultural inputs (capital, labor, and technology) and the resulting agricultural output (production) Fertilizer application can significantly increase Agricultural Productivity, but its overuse can have environmental consequences Wang et al. (2021).

Panel data model is the model formulated from panel data analysis and combines observations across time (like annually crop yield) and space (like different regions). This allows researchers to separate the long-term effects of climate change from other factors affecting agriculture, by employing Random or Fixed effects model. Providing a clearer picture of how climate change related to change crop productivity Blanc and Schlenker (2017).

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According to Calzadilla et al. (2013) highlight the global assessment of climate change impacts on agricultural productivity and was aiming to estimate the potential effects of climate change on major cereal crops under various climate scenarios. The problem was climate change which was projected to alter temperature and precipitation patterns globally, potentially disrupting agricultural productivity systems. Crop simulation models were used to assess yield changes under different temperature and precipitation projections.
The study projects significant regional variations in climate change impacts, with some areas experiencing yield reductions and others potential gains. Rising temperatures and changes in precipitation patterns are identified as key threats to global Agricultural Productivity. The study emphasizes the need for adaptation strategies tailored to specific regions and agricultural systems. Review the research conducted by Parry et al. (2004) about the impacts of climate change impacts on food security in developed countries. Was aiming to analyze the potential vulnerabilities and adaptation strategies of developed countries facing climate change. While developed countries may have greater resources for adaptation, climate change can still disrupt Agricultural Productivity and food security.

Literature review and analysis of climate change projections for developed regions. The study suggests that developed countries might face challenges like shifting growing seasons, increased pest outbreaks, and water scarcity due to climate change. However, they may have better adaptation capacity through technological advancements and infrastructure development. The study emphasizes the importance of research and development for climate-resilient crops and improved agricultural practices in developed countries.

Review the related study conducted in Africa like the study of Kurukulasuriya and Mendelsohn (2008) on the analysis of potential adaptation strategies for African agriculture in the face of climate change. Purposed to identify cost-effective adaptation strategies for African farmers to improve agricultural productivity under changing climate conditions. African agriculture is highly vulnerable to climate change due to factors like rain-fed agriculture and limited resources. Economic modeling and analysis of various adaptation options like drought-resistant crops, improved water management, and investments in rural infrastructure. The study suggests that a combination of adaptation strategies, including investments in irrigation, crop diversification, and research on drought-resistant varieties, can offer the most cost-effective approach for African agriculture. The study calls for increased international support and financial resources to assist African countries in implementing effective adaptation strategies.

Review the study conducted by Emediegwu et al. (2022) on the impacts of climate change on agriculture in Eastern Africa. Aimed to synthesize existing research on the challenges and vulnerabilities faced by Eastern African agriculture due to climate change. Eastern Africa is a climate-sensitive region with high dependence on agriculture. Climate change poses a significant threat to food security and livelihoods.
Literature review and analysis of climate projections and agricultural data for Eastern African countries. The study highlights the vulnerability of Eastern African agriculture to rising temperatures, erratic Precipitation patterns, and increased frequency of extreme weather events. These factors can lead to crop yield reductions, water scarcity, and land degradation. The study calls for promoting climate-resilient crops and agricultural practices, improving water management systems, and strengthening regional cooperation for adaptation strategies.

More research were conducted to Rwanda context, according to Mutabazi (2010) perceptions and practices of farmers in Kirehe District, uncovering limited awareness about climate change but noting some adaptation strategies like crop diversification and rainwater harvesting. It called for better communication and extension services to educate farmers and promote effective adaptation strategies. Last but not least Muhire et al. (2015) used crop modeling to estimate potential yield reductions for key crops like maize, beans, and potatoes under various climate change scenarios, identifying rising temperatures and changing precipitation patterns as primary drivers. It recommended developing and promoting climate-resilient crop varieties and improved agricultural practices to mitigate yield losses.

3. Materials and methods

This study adopts a quantitative research design. This approach reliable in the data collection and analysis of numerical data to test hypotheses and establish relationships between variables. Involved collection of quantitative measures to all variables used in the study, to draw statistical conclusions about the research hypothesis. This study used secondary data obtained from reputable Rwandan government agencies. Which was Rwanda Meteorology Agency (Metheo-Rwanda), MINAGRI, National Institute of Statistics Rwanda, and World Bank. The request of data was clearly specifying the desired variables, timeframe (2003-2023), and geographical coverage (each Rwandan province and Kigali city) and timeframe 2004-2023 on Rwanda context.

To identify the trend patterns of climate change in Rwanda's provinces and Kigali City (2004-2023), used data visualization techniques. This approach involved constructing line charts for each variable (annual change in temperature and annual change in precipitation) across all provinces and Kigali City. These line charts shown " picture of the trend" across the entire study period. By identifying the slopes and patterns of these lines, able to discern increases, decreases, or fluctuations in temperature and precipitation across all provinces and Kigali City 2004-2023.

Cobb-Douglas function, before whipping up analytically recipe to understand what drives agricultural productivity in Rwanda (2004-2023), preliminary tests came in, acting as a quality check of data. The first test, stationarity, was checking if variables aren't magically changing fine over time. Needed the data for each variable to be stable and predictable for analysis to be accurate, used ADF test to make a statistical conclusion about the parameter. Multicollinearity test, on the other hand, is like making sure independent variables aren't so similar in prediction of the model. Identified if the factors were analyzing were too intertwined, potentially confusing the model and making the results unreliable. Technique like Variance Inflation Factor (VIF) checking were used when the VIF was less than ten it was suggesting no multicollinearity between variables. Addressing these issues through preliminary tests, set the stage for a robust model. Model built here was Cobb-Douglas production function, Cobb-Douglas production function is a widely used tool for analyzing the relationship between inputs and outputs in various production systems, including agriculture. Developed by Charles Cobb and Paul Douglas (1928), it offers a relatively simple yet effective framework for understanding how changes in agriculture resource allocation influence production levels. Theoretical Underpinnings, the Cobb-Douglas function expresses production (CropPI) as a function of multiple inputs raised to constant elasticities (α):

Model:

$$\begin{aligned} CropPI &= f(LND, LB, FT) \\ \log CropPI &= \alpha_0 + \alpha_1 \log LND + \alpha_2 \log LB + \alpha_3 \log FT \end{aligned}$$

A represents a constant term incorporating factors like technology and efficiency. LND, LB, and FT represent different production inputs (labor, land, fertilizer). α_1 to α_3 represent the output elasticity of each input, indicating the percentage of change in output for a 1% increase in the corresponding input, holding all other inputs constant.
To achieve our second objective of determine the major factors influencing agricultural productivity in Rwanda (2004-2023) – turn to a well-established economic

workhorse, the Cobb-Douglas Production Function.

The Cobb-Douglas function allows to quantify the recipe. It expresses agricultural productivity as a mathematical equation where each ingredient (factor) is raised to a specific power. This power reflects the relative importance of that factors in influencing the final yield. By analyzing this equation and its components, it is simple to determine the major factors that significantly influence agricultural productivity in Rwanda.

Once the model is analyzed, ensure it is reliable. Here, diagnostic tests come into play, acting as a final quality to check. The normality test checks if the errors follow a normal distribution like a well-risen with a symmetrical shape, Shapiro wilk test used to check normality of residuals. Heteroscedasticity, test checks if the errors in the model (the difference between predicted and actual crop productivity) are spread unevenly across the data the Breusch-Pagan / Cook-Weisberg test was used. Finally, autocorrelation used Durbin Watson test to draw conclusion about this check. This ensures the model's assumptions hold true. The results of the statistical tests, including preliminary tests, coefficients, significance levels, and goodness-of-fit measures and diagnostic tests, were presented in tables. The analysis was conducted in STATA version 16. Preliminary tests have been conducted to evaluate the suitability of the time series data for further analysis.

These tests focused on two key assumptions, stationarity and independence of variables. Stationarity ensures that the statistical properties of the data remain constant over time. This is crucial for accurate modeling and forecasting. Independence of variables verifies that the values of the time series at different points are not correlated. This assumption is essential for avoiding bias in the analysis and ensuring reliable results.

A unit root test is used to check if a variable's average (mean) and spread (variance) remain constant over time. This stability is essential for many statistical techniques especially in the analysis of the model with panel data. Tests like the Levin-Lin-Chu (LLC) test helped to identify non-stationary variables (those with trends or changing variance). The null hypothesis of panel units' roots test assumes that variable series are station, since p-value is greater than 0.05 significant level there was not enough evidence to reject null hypothesis and panel data of variable were stationary.

Multicollinearity test was checking if two independent variables being almost identical twins. This redundancy, called multicollinearity, can wreak havoc on model estimates. Techniques like the Variance Inflation Factor (VIF) helped to detect its presence. When $VIF < 5$ was indicating a weak or no multicollinearity issue, VIF between 5 and 10 a moderate level of multicollinearity. $VIF > 10$ Indicated a strong possibility of multicollinearity. Noncollinearity between independent was leading to reliable coefficient estimates.

The Hausman test was last preliminary test and was used to decide whether to use a fixed effects model or a random effects model. The null hypothesis of the Hausman test says that the preferred model is random effects, means that the unique errors are not correlated with the regressors. When a $p < 0.05$, there's not enough evidence to support a null hypothesis suggested a fixed effects model.

Panel data model-Random Effects Model, a common economic model. This model estimates how changes in climatic variables, population density, and agricultural inputs affect agricultural productivity across Rwanda's provinces and Kigali city. The results of the statistical tests, including coefficients, significance levels, and goodness-of-fit measures, interval were presented in tables.

Diagnostic tests were conducted to ensure the model's predictions are unbiased and adhere to the key assumptions. These tests including normality to verify errors term are approximately to zero mean, homoscedasticity test to check equality of variance with error terms, and autocorrelation test to ensure independent among error terms. Normality test, a visual inspection through a histogram was like an x-ray, revealing any asymmetries or unexpected peaks in the residuals. Normality and the histogram resemble a bell curve, can breathe a sigh of relief.

Homoscedasticity Test was ensuring that the variance of residuals is constant across all observations. The Breusch-Pagan test was trusty tool. When the p-value from the Breusch-Pagan test was greater than 0.05 as level of significant was indicating no significant heteroscedasticity, proceed confidently. Autocorrelation test was checking if the error term in one observation is related to the error terms in previous observations.

The Wooldridge test is a statistical method that helps assess the presence of autocorrelation. When the p-value was greater than 0.05 as level of significant, it was indicating no significant autocorrelation. The model constructed here, is panel Model-Random effect model and has two variables dependent variable which is change in annual agricultural productivity and independent variables which are annual change in average temperature, annual change in average precipitation, annual land usage, annual labor participated, annual fertilizer usage, and annual population density.
Model:

$$\begin{aligned} Crop - PI &= f(T, PC, LND, LB, F, PD) \\ Crop - PI_{it} &= \beta_0 + \beta_1 T_{it} + \beta_2 PC_{it} + \beta_3 LND_{it} + \beta_4 LB_{it} + \beta_5 FT_{it} - \beta_6 PD_{it} + \epsilon_{it} \end{aligned}$$

4. Results

This chapter delves into the heart of the research, presenting the findings and their interpretations. Recall that overarching goal was to assess the effects of climate change on agricultural productivity across Rwanda's provinces and Kigali City (2004-2023).

Table 1: Descriptive statistics

Stats	CropPI	T	PC	LND	LB	FT	PD
Mean	2.371	0.003	3.96	317.146	-0.066	0.722	6.286
p50	2.005	0	-10.26	105	0.013	0.260	5.370
Standard Deviation	9.958	0.238	12.702	26.027	0.719	4.427	4.769
Variance	99.177	0.056	161.343	677.452	0.517	19.604	22.746
Range	69.1	1.09	874.29	3670	8.896	29.663	16.567
Min	-33.66	-0.5	-527.87	-560	-4.535	-14.961	0.225
Max	35.44	0.59	346.42	3110	4.361	14.70234	16.7935
Skewness	0.006	-0.01	0.092	0.090	0.041	0.077	-0.0253
Kurtosis	3.076	2.964	3.097	2.943	3.042	3.005	2.999
N	100	100	100	100	100	100	100

The Table (1) shows descriptive statistics highlight paints a fascinating picture of data of annual change of agriculture productivity and factors influencing its productivity 2004-2023. The mean of annual change in crop productivity index is 2.371%, with a standard deviation of 9.958%, suggesting that most annual changes of the observations range from -7.587% to 12.329% at 68% within one standard deviation of the mean. The skewness of 0.006 indicates a nearly symmetric distribution. The kurtosis of 3.076 is close to the normal distribution's kurtosis of 3, indicating a distribution with tails slightly heavier than a normal distribution but not significantly so. The mean annual change in average temperature is $0.003°$C, with a standard deviation of $0.238°$C, indicating most annual changes of the observations lie between $-0.235°$C and $0.241°$C at 68% within one standard deviation of the mean. The skewness of -0.01 suggests a nearly symmetric distribution. The kurtosis of 2.964, slightly less than 3, indicates the distribution is nearly normal with slightly lighter tails.

The mean annual change in land used is $317km^2$, with a standard deviation of $26.027km^2$, indicating most annual changes of the observations range from $290.973km^2$ to $343.027km^2$ at 68% within one standard deviation of the mean. The skewness of 0.09 indicates a slight positive skew, meaning slightly more frequent small increases in land use than decreases. The kurtosis of 2.943 is close to 3, suggesting a distribution close to normal with slightly lighter tails. The mean annual change in labor participation in agriculture is -0.066%, with a standard deviation of 0.719%, indicating most annual changes of the observations range from -0.785% to 0.653% at 68% within one standard deviation of the mean. The skewness of 0.077 indicates a nearly symmetric distribution. The kurtosis of 3.005 is very close to 3, indicating a distribution that is nearly normal. The mean annual change in fertilizer consumption is $0.722kg/ha$, with a standard deviation of $4.427kg/ha$, suggesting most annual changes of the observations range from $-3.705kg/ha$ to $5.149kg/ha$ at 68% within one standard deviation of the mean. The skewness of 0.141 indicates a slight positive skew, meaning slightly more frequent small increases in fertilizer consumption than decreases. The kurtosis of 3.042 is close to 3, indicating a distribution similar to normal.

The mean annual change in population density is 6.286 people/km^2, with a standard deviation of 4.769 people/km^2, indicating the observations range from 1.517 people/km^2 to 11.055 people/km^2 at 68% within one standard deviation of the mean. The skewness of -0.0253 suggests a nearly symmetric distribution. The kurtosis of 2.999 is very close to 3, indicating a nearly normal distribution. Another notable of the descriptive statistics highlight the data assessing major factors of agricultural productivity in Rwanda from 2004-2023 reveals insightful trends. The annual crop productivity index (CropPI), measured in percentage, shows an average slightly above the baseline at 101.632%, with moderate variability (standard deviation of 12.686%) and a nearly symmetric distribution (skewness of 0.0077 and kurtosis of 2.095), indicating stable crop productivity with occasional deviations. The land used (Lnd) in square kilometers averages at 19,364.53 km^2, indicating that land use was fairly consistent over the period.

4.1. Trends of Climate Change Variables

4.1.1. Trend in Annual changes of the average Temperature across Rwanda's Provinces and Kigali City 2004-2023

Figure 1 reveal a general pattern of variability in average annual temperature changes across all regions, with fluctuations of both increases and decreases over the years. This finding aligns highlighted by the study conducted on east Africa, which was indicating rising temperatures but with regional variations Kew et al. (2021). During the period from 2006 to 2009, each region exhibited unique characteristics in temperature variability, experiencing both increases and decreases. Notably, the years 2011, 2015, 2017, and 2021 were marked by significant warming across all regions. The Northern Province displayed the highest variation in temperature changes, indicating greater instability in its climate. In contrast, the Eastern Province showed the lowest variation in temperature changes compared to other regions, suggesting a more stable climate. The Western Province, Kigali City, and Southern Province exhibited moderate variations in temperature changes in most years. In the recent year 2023, Kigali City and the Southern Province ended with an upward trend in annual temperature changes. On the other hand, the Northern, Eastern, and Western Provinces showed a downward trend in temperature changes. This recent divergence highlights the localized nature of climate change impacts across Rwanda.

Fig. 1: Trend in annual change on the average Temperature

4.1.2. Trend in Annual changes of the average Precipitation across Rwanda's Provinces and Kigali City 2004-2023

According to Figure (2), the analysis shows a higher degree of variability in average annual precipitation across all regions, with each region displaying unique characteristics of variation. In most years, there was no consistent pattern of variability across the regions, except in 2007 and 2021 when all regions exhibited similar patterns of increases and decreases in precipitation. Between 2013 and 2016, the Northern Province experienced high variability in precipitation, with significant increases and decreases. In contrast, Kigali City showed opposite trends during this period.

2014-2023, the Northern Province continued to exhibit high variability in precipitation compared to other regions, indicating persistent instability in its rainfall patterns. In the recent year 2023, most regions ended with a downward trend in annual precipitation changes. However, the Northern Province showed an upward trend, highlighting a notable exception to the overall decline. This difference underscores the diverse impacts of climate change on precipitation patterns across Rwanda. Echoing findings from other studies in East Africa that highlight changes in precipitation patterns but with spatial and temporal variations Koutsouris et al. (2016). This variability raises concerns about the unpredictable effects of climate change on precipitation Simelton et al. (2013).

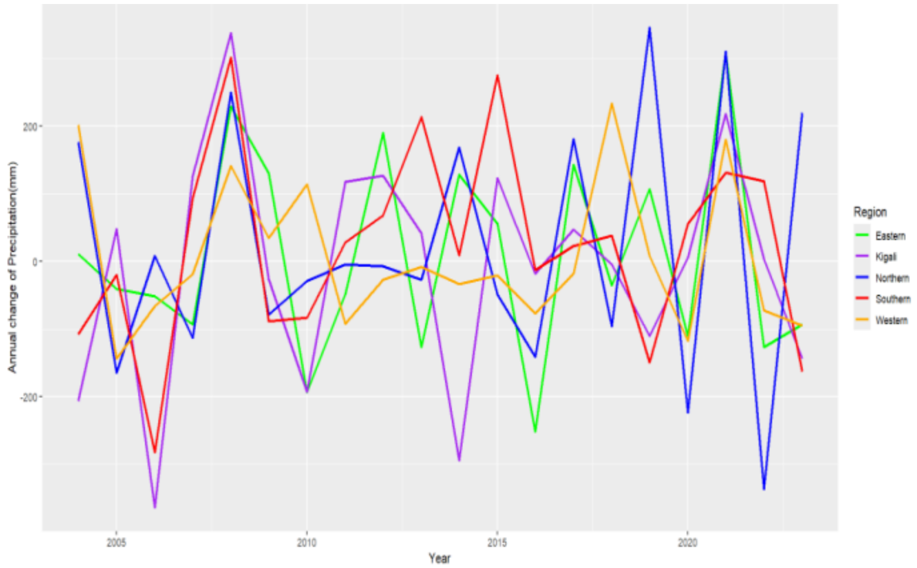

Fig. 2: Trend in annual change of the average Precipitation

While this study provides valuable insights into long-term trends or cycles in climate and agriculture, there are several limitations that should be noted. First, the sample size was limited, which may impact the generalizability of the findings. Second, the study only covered 2003 up to 2023, and future research could benefit from longer time spans. Additionally, the data sources used may have some inconsistencies that could affect the accuracy of the results.

4.2. Major Factors of Agriculture Productivity in Rwanda

To ensure the reliability of the data, a quality must be verified before fitting model. As a result shows, is crucial. The preliminary test of stationarity used the Dickey-Fuller method indicate that most of the variables are stationary, which is essential for reliable time series analysis. Specifically, the test results show that LogLND, LogFT, LogLB, and LogCropPI stationary at 1%, 5%, and 10% significance levels, indicating that these variables do not contain a unit root at level. These findings confirm that the data series do not exhibit persistent trends over time and are suitable for modeling.

The output show the results of the multicollinearity test using Variance Inflation Factor (VIF) for the variables logFT, logLnd, and logLb indicate that multicollinearity is not a concern in this model. The VIF values for logFT, logLnd, and logLb are 1.22, 1.20, and 1.13 respectively, all values are well below the commonly used threshold of 10. The 1/VIF values, which represent the tolerance, are over to 0.1, further confirming the absence of significant multicollinearity. The mean VIF value of 1.18 supports this conclusion, suggesting that the predictor variables in this model do not show problematic levels of collinearity, confirming the stability and reliability of the regression coefficients.

Table 2: Cobb Douglas Function of the Factors of agriculture productivity
C.I.: Confidence Interval

Source	**SS**	**Df**	Number of obs	F(3, 16)		
			20	4.86		
Model	0.142936	3	$Prob > F$	.0136		
Residual	0.156806	16	R-squared	0.8769		
			Adj R-squared	0.8837		
	Coef	**Std. Err**	**t**	**P$>$ |t|**	**[95% C.I.]**	
logLnd	2.719	0.946	2.87	0.010	0.713	4.726
logLb	1.859	1.558	1.19	0.024	-5.164	3.444
logFT	0.004	0.015	0.28	0.040	-0.027	0.036
cons	14.548	12.196	1.19	0.024	8.404	19.306

Table (2) shows the findings on the Cobb-Douglas production function in this analysis sheds light on the key drivers of agricultural productivity (CropPI) across Rwanda's provinces and Kigali city from 2004 to 2023, focusing on land use (LND), labor participation (LB), and fertilizer consumption (FT). The coefficient of determination is statistically significant $p < 0.05$, providing insufficient evidence to support the null hypothesis. The model effectively explains 87.7% of the variation in the crop productivity index due to land, labor, and fertilizer use.

The study was claiming positive effect of the land use on crop productivity index. The finding shows enough evidence to support the claim $(\beta_1 = 2.72, p < 0.05)$. Holding other variables constant, a 1% expansion in agricultural land leads to an estimated 2.72% increase in crop productivity index of Rwanda. This finding aligns with study in other countries, highlighting the importance of cultivated land. Keesstra et al. (2018) observed a 1.02% increase in crop productivity index per increase $1km^2$ of cultivated land.

The study was claiming positive effect of the labor participation on crop productivity index. The finding shows enough evidence to support the claim $(\beta_2 = 1.86, p < 0.05)$. Holding other variables constant, an increase of 1% in agricultural labor translates to an estimated increase of 1.86% in crop productivity index in Rwanda. A study conducted in Kenya observed a positive effect of labor participation on crop productivity according to Qorri et al. (2024).

The study was claiming positive effect of the fertilizer application on crop productivity index. The findings show enough evidence to support the claim $(\beta_3 = 0.004, p < 0.05)$. Holding other variables constant, a 1% increase in fertilizer use translates to an estimated 0.004% increase in crop productivity index of Rwanda. These results align with previous study that has also demonstrated a significant effect, increased fertilizer use and higher crop yields. For instance, a study conducted by Shah and Wu (2019) observed a similar positive effect, where a 1% increase in fertilizer application led to a 0.08% rise on crop yield.

Results in Table (2) show the diagnostic test of the model and reveals several insights. First, The Shapiro-Wilk test for normality of residuals shows a $(p > 0.215)$. This indicates that the null hypothesis, which assumes that the residuals are normally distributed, cannot be rejected at conventional significance levels at 5%. Therefore, the residuals can be considered to follow a normal distribution, suggesting that the model assumptions related to normality are likely satisfied.

The Breusch-Pagan Godfrey test for heteroskedasticity, in this case, p-value of 0.584. Since the p-value is significantly greater than the common significance levels of 5%, fail to reject the null hypothesis of constant variance. This suggests that there is no evidence of heteroskedasticity, indicating that the residuals are homoscedastic. The Durbin-Watson statistic $(DW = 2.0)$ suggests a no autocorrelation in the model's residuals.

4.3. Effects of Climate Change on Agricultural Productivity

4.3.1. Preliminary Test

Levin-Lin-Chu (LLC) unit root tests were performed to assess the stationarity of several variables as preliminary a panel data model, a crucial diagnostic step to ensure the validity of subsequent analyses. The null hypothesis for the LLC test says that the panels contain unit roots, indicating non-stationarity. For the variable annual change on crop productivity index (CropPI) $(p < 0.05)$, enough evidence of to reject the null hypothesis and conclude that CropPI don't contain a unit root at the second difference. Similarly, for annual change in average temperature (T) $(p < 0.05)$ at 5% as significance level indicating strong evidence of don't contain a unit root at the second difference. The variable annual change in average precipitation (PC) $(p < 0.05)$, indicates strong evidence of don't contain an unit root at the second difference.

For annual change on land used (LND) $(p < 0.05)$, suggest strong evidence of don't contain at the 2nd difference. Similarly, the variable annual change in labor participation in agriculture (LB) $(p < 0.05)$, indicating strong evidence of don't contain at the second difference. The annual change in fertilizer application (FT) variable also demonstrates $(p < 0.05)$, indicating strong evidence of don't contain at the 2nd difference. Lastly, for annual change of population density (PD) $(p < 0.05)$, indicating strong evidence of don't contain at the second difference. LLC unit root tests provide strong evidence that all the variables under consideration (CropPI, T, PC, LND, LB, FT, and PD) are stationary, as their $p < 0.05$. This implies that the variables do not contain unit roots.

Multicollinearity test results indicate that VIF values for all the variables are quite low, LND has a VIF of 1.04, LB and T both having a VIF of 1.02, and PC, FT both having a VIF of 1.01 and PD with 10.04. Majority of VIF values are very close to 1 except on population density (PD), suggests that multicollinearity is concern on population density only because its VIF value is greater than 10, others not concern since their VIF values are substantially below the doorstop of 10.

Therefore, to avoid problem may concern to multicollinearity PD don't move to the next step of model fit to make a reliability interpretation of the model coefficients. Hausman results, a null hypothesis of the Hausman test says to adopt random effects. Hausman test revealed that the random effects model is the preferred model $(p > 0.05)$, suggesting that there's no enough evidence to reject null hypothesis. This indicates that the unobserved characteristics of each province and Kigali city (captured by the random effects) are not systematically correlated with the independent variables (temperature, precipitation, land use, labor, fertilizer use, and population density) of the study. Therefore, the random effects model provides unbiased estimates of the relationships between these variables and crop productivity across Rwanda's provinces and Kigali city.

4.4. Panel Data Model- Random Effect Model

The Table (3) offers valuable insights on how climate change, other factors influencing agricultural productivity across Rwanda's provinces and Kigali City from 2004 to 2023. The model is statistically significant, as indicated by an F-statistic $(p < 0.05)$, providing insufficient evidence to support the null hypothesis. The Random-effects GLS regression model demonstrates a good overall fit (R-squared $= 0.72897$) implies variation 72.89% in crop productivity index is explained by annual change in temperature, annual change in precipitation, annual change of land, annual change of labor participation, and annual change of fertilizer consumption.

Table 3: Random-effects GLS regression

CropPI	**Coef.**	**Std. Err.**	**z**	**P$>|z|$**	**[95% Conf. Interval]**	
T	-0.046	4.265	0.1	0.001	-8.314	8.407
PC	-0.00023	0.006	-0.04	0.001	-0.00028	0.012
LND	0.003	0.0015	1.97	0.049	-0.0059	0.025
LB	0.654	1.418	-0.46	0.043	-3.434	2.124
FT	0.112	0.228	0.49	0.002	-0.335	0.56
cons	3.662	1.829	2	0.044	0.076	7.248

Model:

$$CropPI = 3.662–0.04T–0.00023PC + 0.003LND + 0.654LB + 0.112FT$$

The study was claiming negative effect of the temperature on crop productivity index. The finding shows enough evidence to support the claim $(\beta_1 = -0.04, p < 0.05,)$. Holding other factors constant, $1°C$ increase in temperature annually is associated with a 0.04% decrease of agriculture productivity index per annual change. According to Lesk et al. (2016) a decrease of 1.3% in crop productivity index for every 1°C increase in temperature. These findings align with our results, reinforcing the notion that rising temperatures pose a significant threat to agricultural productivity.

The study was claiming positive effect of the precipitation on crop productivity index. The finding shows no enough evidence to support the claim $(\beta_2 = -0.0002, p < 0.05)$. Holding other variables constant, a 1mm increase in precipitation annually is associated with a 0.0002% decrease in CropPI across to Rwandan provinces and Kigali city. This result contradicts studies conducted in regions with more favorable climatic conditions, Almås et al. (2019) observed 1mm increased precipitation observed in 0.12% increases on crop productivity. Factors such as soil type, crop variety, and the specific rainfall patterns may explain these regional differences.

The study was claiming positive effect of the land use on crop productivity index. The finding shows enough evidence to support the claim $(\beta_3 = 0.003, p < 0.05)$. Holding other variables constant, a 1 sq. km increase in arable land annually is associated with a 0.003% increase in Crop productivity index. This highlight factors that can be leveraged to enhance crop productivity. The study was claiming positive effect of the labor participation on crop productivity. The finding shows enough evidence to support the claim $(\beta_4 = 0.654, p < 0.05)$. Holding other variables constant 1% increases in labor participation annually results in a 0.654% increase of crop productivity across Rwanda's provinces and Kigali city.

The study was claiming positive effect of the fertilizer application on crop productivity. The finding shows enough evidence to support the claim $(\beta_5 = 0.112, p < 0.05)$. Holding other variables constant, a 1 kg/ha (one kg/ha) increase in fertilizer usage annually results in a 0.112% increase in crop productivity index across Rwanda's provinces and Kigali. The positive effect of labor participation (LB) emphasizes the importance of agricultural workforce.

4.4.1. Diagnostic Test

Figure (3) shows a histogram of residuals, shown with a superimposed normal distribution curve, indicates that the residuals of the model are approximately normally distributed, centering around the linear prediction value of 0. The bell-shaped curve closely matching the histogram suggests that the residuals do not deviate significantly from a normal distribution, supporting the model's goodness-of-fit. Therefore, the residuals appear to be normally distributed. This supports the result found in Figure (3) hence to satisfy a key assumption of the linear regression model.

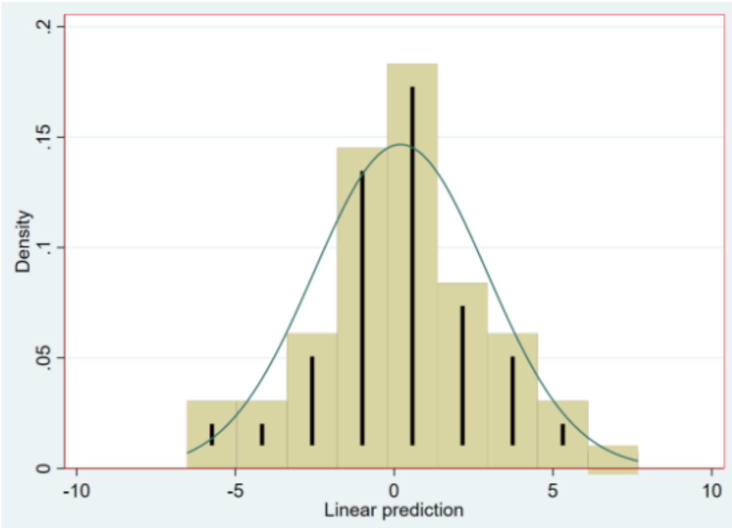

Fig. 3: Trend in annual change on the average Temperature

Results shows $p > 0.05$, indicates no significant evidence of heteroscedasticity in the model's residuals. This implies that the variance of the residuals is constant across observations, satisfying one of the key assumptions of linear regression says to have constant variance within error terms. Consequently, this stability enhances the reliability and efficiency of the model's estimates, ensuring that the standard errors are unbiased, and the inferences drawn from the model are valid. Results, confirms that the test of Wooldridge in the panel indicates $(p < 0.05)$, suggesting no evidence to reject the null hypothesis of no autocorrelation between residuals. This implies a good fit of the model. Autocorrelation test measured the similarity between observations as a function of the time lag between them. Most of the points lie within the confidence interval and show no significant autocorrelation, the residuals are roughly white noise, suggesting that the model is well-fitted.

5. Conclusion and recommendations

5.1. Conclusion

This Research aims to assesses the effect of climate change on agriculture productivity across Rwanda's provinces and Kigali city 2004-2023. Specifically, the study identified trend of climate change indicates, determined factors impacting agricultural productivity, and examined the effects of climate change on Rwanda's agriculture from 2004 to 2023. The study reveals significant variability in both temperature and precipitation patterns across the country's provinces and Kigali City. During the study period, notable warming was observed in 2011, 2015, 2017, and 2021, with the Northern Province displaying the highest variation in temperature changes, while the Eastern Province exhibited the lowest. By 2023, Kigali City and the Southern Province showed an upward trend in annual temperature changes, contrasting with the downward trends observed in the Northern, Eastern, and Western Provinces. Precipitation patterns also varied considerably, with significant increases and decreases recorded in different years. For instance, 2007 and 2021 saw consistent patterns of precipitation variability across all regions, while the Northern Province exhibited the most instability from 2013 to 2023. In 2023, most regions experienced a downward trend in annual precipitation, except for the Northern Province, which showed an upward trend. The study's examination of agricultural productivity through the Cobb-Douglas production function highlights that land use, labor participation, and fertilizer consumption significantly influence crop productivity, explaining 87.7% of its variation. Holding other variables constant, a 1% increase in agricultural land and labor participation is associated with 2.72% and 1.86% increases in crop productivity, respectively. Fertilizer consumption also positively effects productivity, though to a lesser extent and that coefficients are statistically significant at 0.05 significant level. Furthermore, the Random Effects Model indicates that climate change, particularly temperature and precipitation changes, adversely affects agricultural productivity when temperature, precipitation, land, labor, and fertilizer consumption, a crop productivity at 72.89% across Rwanda's provinces and Kigali city. Holding other variables constant, A 1°C increase in temperature and a 1mm increase in precipitation annually lead to 0.04% and 0.0002% decreases in productivity, respectively. Conversely, increasing arable land and labor participation significantly boosts productivity, and that coefficients of all variables are statistically significant at 0.05 significant level. Despite these promising results, the study has some limitations, such as the lack of opinions from local farmers, although this was beyond the scope of our study. These factors should be considered when interpreting the findings and designing future research.

5.2. Recommendations

To effectively address the challenges posed by climate change on Rwandan agriculture, it is essential to have a comprehensive understanding of the specific trends and patterns across the country's provinces and Kigali city between 2004 and 2023. This knowledge serves as a foundation for developing targeted adaptation strategies. Agricultural productivity in Rwanda is influenced by a complex interplay of factors. Sustainable land management practices, such as crop rotation and terracing, are crucial for maintaining soil health and long-term fertility. Additionally, the skills and knowledge of farmers play a pivotal role in optimizing agricultural practices. Furthermore, the judicious use of fertilizers can significantly enhance crop yields while minimizing environmental impacts. Understanding the socioeconomic factors that influence food security, including distribution networks and market access, is equally important for improving agricultural productivity. Climate change is a major threat to agricultural productivity in Rwanda. To mitigate its effects, it is necessary to adopt climate-smart practices like drought-resistant crop varieties and efficient water management techniques. Investing in research and development to create innovative solutions tailored to Rwanda's specific conditions is also crucial. Comprehensive climate change adaptation strategies, including early warning systems and improved infrastructure, should be implemented at both national and regional levels. Exploring alternative farming methods, such as vertical farming, could offer potential solutions for urban areas. By addressing these research questions and implementing the corresponding recommendations, Rwanda can build a more resilient and sustainable agricultural sector capable of withstanding the challenges posed by climate change. Finally, for future work, it is essential to consider non-linear relationships between variables, as this is not always the case in complex agricultural systems.

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