Evaluating the impact of climate change on agricultural productivity in Ethiopia

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Abstract

There has been discussion over how various parts of the world's agricultural output may be affected by climate change. The agriculture industry has been adversely impacted on a global scale by recent climate change, resulting in negative effects across all economic sectors. This study aims to assess how Ethiopia's agricultural productivity has been impacted by climate change between 1991 and 2021. By investigating the relationship between agricultural inputs and outputs and concentrating on the effects of climate change on agricultural productivity in Ethiopia's agricultural sector, this study aims to close the gaps above in knowledge. To determine the relationship between the study variables and the data used to analyze how climate change may affect Ethiopia's agricultural productivity, the autoregressive distributed lag (ARDL) approach was used. When everything else is equal, an increase in the coefficient of variation of temperature will, over time, result in a 3.84% increase in the agricultural productivity of land, according to the results of the ARDL technique. Similarly, an increase in the precipitation coefficient as a percentage will result in a 0.48% rise in the land's agricultural productivity. Citrus Paribus, as well as The annual average temperature and precipitation, which are the study's primary variables and are employed as indicators of climate change, have mean values of 23.374 degrees Celsius and 86.938 mm, respectively. Additionally, the lowest recorded temperature during the period of 1991 was 22.92 degrees Celsius, while the highest recorded annual average temperature figure for 2013–2014 was 23.67 degrees Celsius. The findings of the correlation indicate a positive relationship between agricultural output and the following variables: yearly temperature, annual precipitation, fertilizer use, animal stock, and pesticides. The output of agriculture is negatively correlated with other factors, such as labor employment. Ethiopia will encounter difficulties with food security and safety as a result of its growing population. To ensure that there is enough food for the expanding population and to mitigate the negative effects of climate change on agriculture, the Ethiopian government needs to take possible steps. To put it succinctly, the analysis indicates that policy experts and lawmakers should recognize that climate change would alter the total output factors and that, as a result, an adaptation to the total factor of production pattern specific to a county or crop is required.

Keywords: agricultural productivity, climate change, Ethiopia

1. Introduction

Agriculture is considered the most vulnerable to global climate change, the security of food is another issue that needs great concern to all humankind, and the influence of climate change on agriculture has attracted huge attention [1, 2]. Agriculture serves as a primary source of income for many rural communities and bears the brunt of climate change impacts to safeguard the livelihoods of impoverished rural households. Additionally, agriculture plays a crucial role in upholding food security[3, 4]. The agriculture sector's dependence on climate variability is a significant issue for economic progress, given that a large portion of the population resides in rural areas and is involved in both agricultural and non-agricultural pursuits[3, 5]. Farmers continually strive to adjust to fluctuations in weather and climatic conditions. Nevertheless, the broader scope of environmental and global climate changes has heightened the demand for farmers to devise and deploy more extensive resilience strategies [6-8]. One approach to mitigating the risks of climate change and safeguarding livelihoods and local food security is to adjust and adapt within the existing agricultural system. Though the type and scope of adaptation strategies vary from region to region, socio-economic and agro-ecological environments are constantly changing [9-12]. Hence, the production of food is facing disruptions due to shifts in weather patterns and climate change. Investigating the impact of climate change on agricultural productivity in Ethiopia is imperative.

The global population is projected to reach approximately 10 billion, and understanding and addressing these challenges become increasingly crucial[13]. The escalating intensity of extreme weather events and the frequent occurrence of widespread issues significantly impact agriculture. Farmers regularly contend with unpredictable rainfall, pest infestations, and natural disasters. Examples include encountering heavy rains, floods, pests, droughts, and fluctuations in market prices[14-18]. On the other side, in most parts of Ethiopia, climate warming usually shortens the growth cycle of food crops, which leads to demurating the average production [19-23]. Because of the numerous seasonal droughts, there is a spatial and temporal gap between precipitation and irrigation, which ensures adequate challenges in irrigation and water supply [24-26]. In the future, the climate change in Ethiopia may bring more uncertainty in the agricultural productivity. Previously research is conducted in this area for instance, [27-29]. The initial two studies examined how climate change affects agriculture. in this study, authors have investigated the correlation between agricultural productivity with temperature, precipitation, fertilizer, livestock, and pesticides by using an autoregressive distributed lag (ARDL) bounds testing approach to check the association among the study variables. Hence, this research seeks to address the gaps above by examining the interaction between agricultural inputs and outputs, specifically focusing on the impact of climate change on agricultural productivity, a fixed input in the agricultural sector in Ethiopia by using ARDL model time series data that span from 1991-2021.

2. Material and methods

2.1. Data and Data Source

A summary of the secondary sources of data as depicted in Table 1 like agricultural productivity, Agricultural employment sector, fertilizer, Animal stock, and Pesticide were collected from the World Bank Index (WBI). data like annual temperature and annual precipitations can be used in the climate change knowledge portal (CCKP).

Table 1 A summary of the secondary sources of data

Type of variable	Unit of variable	Source
Agricultural productivity	Metric ton	WBI
Agricultural employment sector	Farm labor force	WBI
temperature	Degree Celsius	CCKP
precipitation	mm	CCKP
fertilizer	Metric ton	WBI
Animal stock	Metric ton	WBI
Pesticide used	Metric ton	WBI

Source: WBI= World Bank Index, CCKP= climate change knowledge portal

2.2. Methods

Data was collected through secondary data sources. The results were presented using tables, percentages, graphs, and mean values to give a general picture from which conclusions and recommendations were drawn. Statistical analyses have been carried out to examine the impact of climate change on agricultural productivity in Ethiopia, using the following methods: First, descriptive statistics (i.e., mean and standard deviation) of the variables (both dependent and independent) were calculated over the sample period which states using descriptive statistics methods helps the researcher in picturing the existing situation and allows relevant information. The autoregressive distributed lag (ARDL) approach was applied to assess the association among the study variables with the evidence to evaluate the influence of climate change on Ethiopia's agricultural productivity analysis. Data collected from different sources were analyzed by using the STATA 17 software package (According to Stata Corp (2016), Stata is a comprehensive and integrated statistical software package designed to offer all the necessary tools for data analysis, data management, and graphics. With Stata, you can store and handle both large and small datasets, perform statistical analyses, and generate visually appealing graphs. This software is widely employed by health researchers, especially those dealing with extensive datasets, given its robust capabilities that enable versatile data manipulation. It's crucial to emphasize that while Stata is a powerful statistical tool, it's not the sole option available. There are numerous other statistical software programs that you may encounter in my professional journey involving data analysis. Based on the literature the net agricultural output adjusted for input costs, is hypothesized to be influenced by various factors for each time, denoted as t. These factors include the area of land available (At), the area of annual precipitation (Pr), the level of labor employed in the agriculture sector (Lt), the temperature (Tt), the quantity of animal stock (St), the amount of fertilizer used (Ft), and the volume of pesticides used (Pt). This relationship can be represented in the equation 1 as follows:

$$Yt = f(Lt, Tt, Pr, At, Ft, St, Pt) \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (1)$$

Where:

Lt Represents the amount of labor engaged in the agriculture sector during the period t.

At denotes the total area of cultivated land per period t.

Ft denotes the quantity of fertilizer applied during period t.

St represents the number of livestock units available during period t.

Pt represents the volume of pesticides used during period t.

Tt represents the annual temperature recorded during period t.

Pr signifies the annual precipitation observed during period t.

Agricultural productivity can be evaluated through either single-input factor productivity or total factor productivity. In this study, a single-input productivity measure has been utilized due to data availability constraints. This choice is primarily influenced by the critical importance of land productivity in Ethiopia, where there is a fixed amount of arable land, varying adaptability to technology, and a steadily growing population over time.

Consequently, Equation (2) will be divided by the area of land dedicated to agriculture (At).

$$\frac{Yt}{At} = f\left(\frac{Lt}{At}, \frac{Tt}{At}, \frac{Pr}{At}, \frac{Ft}{At}, \frac{St}{At}, \frac{Pt}{At}\right) \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (2)$$

Now, by introducing climate change indicator variables, specifically the coefficient of variation in average temperature and the coefficient of variation in average precipitation, we can account for the impact of climate on agricultural productivity. It's important to note that these variables are beyond the control of the farmer and were previously omitted.

Consequently,

$$y = f(l, f, s, p, temp, perc)$$

Where:

- perc- represents the coefficient of variation in precipitation.
- temp- represents the coefficient of temperature variation.

The generalized ARDL model can be defined as follows:

$$Y_{t=}\alpha_0 + \sum_{i=1}^{p} \alpha_0 \Delta Y_{t-i} + \sum_{i=0}^{q} \delta_i \Delta X_{t-i} + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \mathcal{E}_t$$

Based on the equation presented above, the model utilized in this study can be expressed as follows:

$$AP_t = \beta_1 L_t + \beta_2 A_t + \beta_3 F_t + \beta_4 S_t + \beta_5 P_t + \beta_6 T_t + \beta_7 Pr_t$$

Where:

- $APt\ is\ denotes\ agricultural\ productivity\ of\ land\ t.$
- $Lt\ is\ represents\ the\ amount\ of\ labor\ engaged\ in\ the\ agriculture\ sector\ during\ time\ period\ t.$
- $Ft\ is\ denotes\ the\ quantity\ of\ fertilizer\ applied\ during\ time\ period\ t.$

- *St is represents the number of livestock units available during time period t.*
- *Pt is represents the volume of pesticides used during time period t.*
- *Tt is represents the annual temperature recorded during time period t.*
- *Pr is signifies the annual precipitation observed during time period*
- β1 to β7 are s of associated independent variables.

2.2.1. Unit root test

A unit root test is a fundamental tool for detecting non-stationarity in time series data. Non-stationary processes can arise in two main forms: trend stationary, where the trend can be predicted from past observations, and difference stationary, where the process is not predictable from past data points. As a result, many time series variables exhibit stationarity only after differencing. However, differencing can lead to a loss of long-term properties or information regarding the equilibrium relationships between the variables being studied. Various tests are available to assess the presence of unit roots, including the Durbin-Watson (DW) test, the Dickey-Fuller (DF) test (1979), the Augmented Dickey-Fuller (ADF) test (1981), and the Phillips-Perron (PP) test (1988). It's worth noting that these tests represent only a selection of the available methods for conducting unit root tests.

Dicky-Fuller (DF) test: As per the specification outlined by Dickey and Fuller in their article titled "Distribution of the Estimators for Autoregressive Time Series with a Unit Root," they have provided a method for testing the presence of a unit root in an autoregressive model.

Augmented Dicky Fuller (ADF) test: The distinction between the DF and ADF tests for stationarity is related to the characteristics of the error term. When the error term is uncorrelated, the Dickey-Fuller (DF) test can be applied. However, if the error term exhibits correlation, then the Augmented Dickey-Fuller (ADF) test becomes necessary. In the ADF test, lagged values of the dependent variable are incorporated as well.

Phillips Perron (PP) test: Nonparametric statistical techniques are employed to tackle the issue of serial correlation in the error terms by introducing lagged difference terms. This approach is taken because the asymptotic distribution of the Philip-Perron (PP) test aligns with that of the Augmented Dickey-Fuller (ADF) test statistic.

2.2.2. Lag Length Selection Criterion

The ARDL method involves estimating a total of (p + 1) k regressions to determine the most suitable lag length for each variable, where p represents the maximum number of lags and k is another parameter. The choice of the model can be made using model selection criteria such as Schwartz-Bayesian Criteria (SBC) and Akaike's Information Criteria (AIC). SBC is recognized for favoring a more parsimonious model by selecting the smallest possible lag length, while AIC tends to favor a model with the maximum relevant lag length. To apply these criteria, calculate the following statistics for the system at each lag length and choose the model with the lowest AIC or SBC value.

3. Result and Discussion

3.1. Summary of Descriptive Statistics of the Variables

Table 2 shows that in the data that runs from 1991 to 2021 for descriptive Statistics of analysis, the Variable's average level of gross agricultural output per input land is found to be $44.67 while its standard deviation, minimum, and maximum values exhibited $22.435, $8.974, and $78.645 per kilometer square, respectively. These values reveal that there is a huge variation over time for agricultural output per land since the value of standard deviation is less than its mean. The study's main variables which are used as indicators of climate change, annual average temperature, and precipitation, have shown a mean value of 23.374 degrees Celsius and 86.938 mm, respectively. Further, the maximum annual average temperature value was registered in 2013- 2014 to be 23.67 degrees Celsius while the minimum value during the period 1991 was 22.92 degrees Celsius which were registered. The mean amount of fertilizer used per area of land was found to be 20.156 kg per square kilometer which also exhibited a slightly lower level of the standard deviation of 10.594 kg per square kilometer. During the study period, the minimum and maximum values are 5.702 kg and 44.26 kg per square kilometer, respectively. One of the main inputs for our agricultural production in Ethiopia, animal stock, has registered a mean value of 80.365 livestock units per square kilometer. the other main input for the agricultural sector in Ethiopia, agricultural labor, has been found to employ 73.232 employees per square kilometer. Further, the minimum and the maximum values are 42 and 126.9 number of employees per square kilometer, respectively.

Table 2 Summary of Descriptive Statistics of the Variables

variable	Mean	Std. Dev	Min	Max
Agriculture gross ou~t	44.67	22.435	8.974	78.645
Temperature	23.374	.245	22.92	23.67
Precipitation	86.938	6.581	74.4	101.4
Fertilizer	20.156	10.594	5.702	44.26
Pesticide	2292.292	1728.248	235	4128.1
Labor	73.232	5.228	63.234	78.33
Livestock	80.365	27.107	42	126.9

3.2. Trends of variables

The growth in agricultural productivity, as depicted in Figure (a), can be attributed to a series of strategic initiatives implemented by the Ethiopian government, particularly since around 2003. These initiatives encompass multifaceted support systems aimed at enhancing the agricultural sector. Investments in infrastructure, such as roads and irrigation systems, have facilitated better access to markets and improved transportation of agricultural goods. Additionally, the government has prioritized research and development, leading to the introduction of advanced farming techniques, high-yield crop varieties, and more efficient agricultural practices. Extension services play a crucial role in disseminating knowledge and providing technical assistance to farmers, enabling them to adopt modern technologies and best practices. Furthermore, subsidies for inputs like seeds and fertilizers have made essential resources more accessible to smallholder farmers, empowering them to increase their productivity and yields. This comprehensive approach to agricultural development has not only boosted productivity but has also contributed to food security, poverty reduction, and overall economic growth in Ethiopia. As a result, the agricultural sector has become a cornerstone of the country's economy, driving progress and prosperity for rural communities and the nation as a whole.

The trend depicted in Figure (b) highlights the relationship between fertilizer usage and agricultural productivity in Ethiopia. The observed constancy in fertilizer use up to 2002 suggests a relatively stable agricultural landscape during that period. However, as the curve becomes progressively steeper in the years following 2002, it indicates a significant increase in fertilizer application.

Several factors contribute to this trend, including population growth and the consequent rise in demand for food production. With a growing population, there is heightened pressure on farmers to increase their yields to meet the increasing food requirements of the nation. In response, farmers intensify their agricultural practices, relying more heavily on inputs such as fertilizers to enhance soil fertility and crop productivity. Moreover, as agricultural productivity becomes increasingly crucial for food security and economic development, farmers are incentivized to adopt modern farming techniques that often require greater fertilizer application. This intensification of agricultural practices is reflected in the sharper upward trend in fertilizer usage over time. Overall, the correlation between fertilizer use and agricultural productivity underscores the pivotal role of fertilizers in sustaining and enhancing crop yields in Ethiopia. However, it's essential to ensure sustainable fertilizer management practices to mitigate environmental risks and promote long-term agricultural resilience.

The trend illustrated in Figure (c) highlights the growth trajectory of animal stock in Ethiopia, indicating a steady increase over time with a sharper upward curve post-2002. This upward trend mirrors the expansion in agricultural productivity, suggesting a correlation between livestock rearing and overall agricultural output. Several factors contribute to this trend. Firstly, as mentioned, the rising Ethiopian population has led to increased demand for meat, dairy, and other livestock products. This demographic pressure necessitates an expansion of livestock production to meet the growing dietary needs of the populace. Additionally, urbanization plays a significant role in shaping dietary preferences and driving the demand for animal products. As more people migrate to urban areas, there is a shift towards diets that include a higher proportion of animal-based foods. This shift is driven by factors such as increased disposable income, exposure to urban lifestyles, and cultural influences, all of which contribute to a greater demand for livestock products. Moreover, advancements in agricultural practices, including improved animal husbandry techniques, veterinary services, and access to better-quality feed, have contributed to the growth of the livestock sector. These advancements have enabled farmers to raise healthier and more productive animals, thereby increasing overall agricultural productivity. The correlation between animal stock growth and agricultural productivity underscores the interconnectedness of livestock rearing and crop production within the broader agricultural system. A holistic approach to agricultural development that integrates both crop and livestock sectors is essential for ensuring food security, poverty alleviation, and sustainable rural livelihoods in Ethiopia. Additionally, it's crucial to address challenges such as disease management, land degradation, and resource constraints to ensure the long-term viability and resilience of the livestock sector.

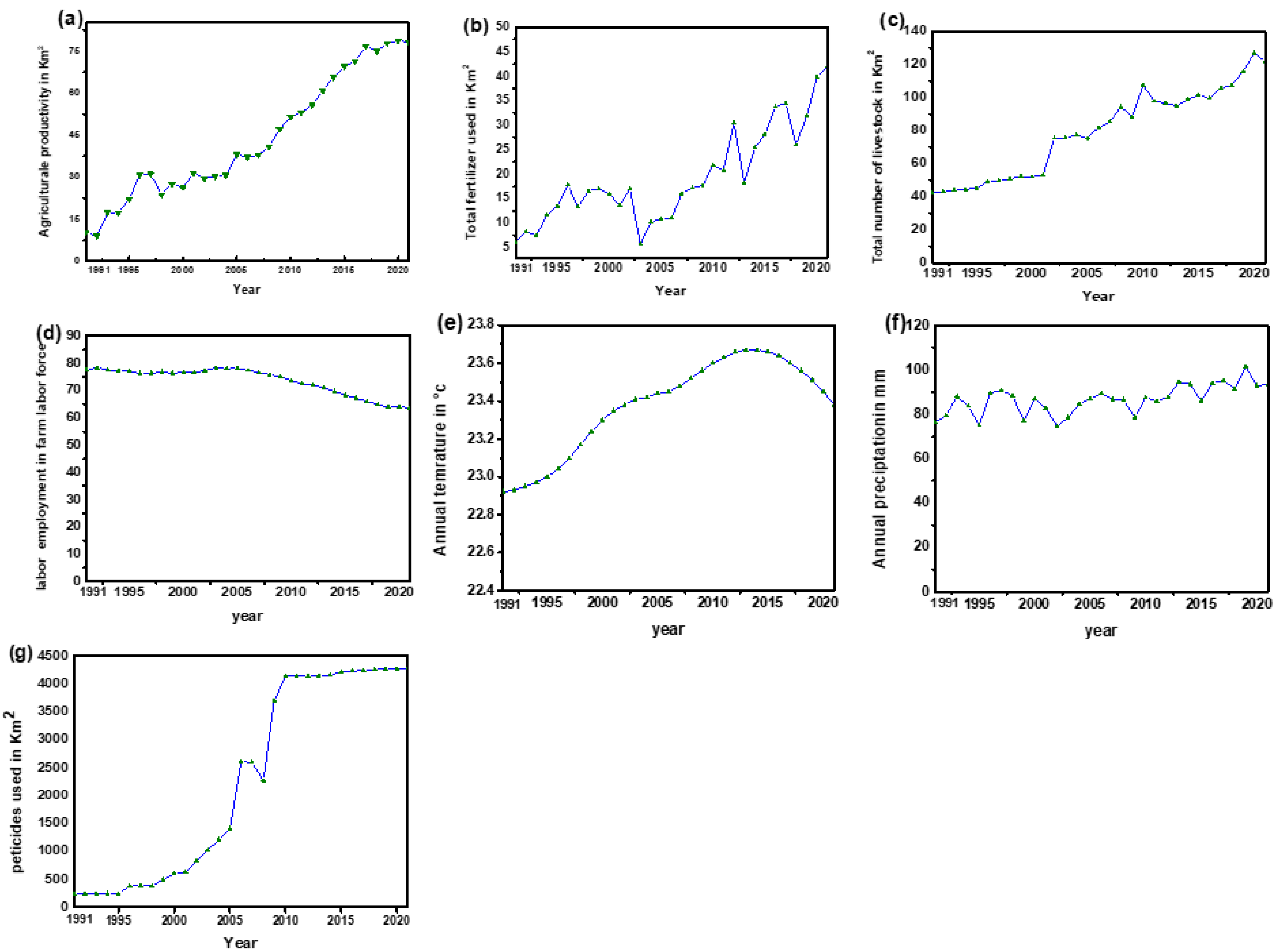

Figure 1 (a) Agricultural productivity per year, (b) Fertilizer used per year, (C) Animal stock per year, (d) Labor employment per year, (e) annual temperature per year. (f) annual precipitation per year and (g) Pesticides used per year.

The trend depicted in Figure (d) regarding labor employment in agriculture reveals a notable shift in dynamics, particularly after 2005. While there is consistency in the trend before 2005, with a change observed thereafter, the growth becomes flatter, suggesting a decrease in labor employment alongside agricultural productivity gains. This inverse relationship indicates a negative correlation between labor employment and agricultural productivity during this period. Several factors contribute to this phenomenon. One significant factor is the increasing adoption of automation and technological advancements across various industries, including agriculture. As farmers embrace mechanization, precision farming techniques, and advanced machinery, the demand for manual labor in agriculture diminishes. Jobs that are routine and repetitive, such as planting, harvesting, and field maintenance, are increasingly being replaced by automated systems and machinery, leading to a reduction in labor employment. Furthermore, the shift away from labor-intensive agricultural practices towards mechanized farming not only increases efficiency and productivity but also reduces the overall labor requirements in the agricultural sector. This trend is further exacerbated by factors such as rural-to-urban migration, as young people seek employment opportunities in non-agricultural sectors and demographic changes that affect the composition of the rural workforce. While the decline in labor employment may initially seem concerning from a socio-economic perspective, it is important to recognize that increased productivity resulting from technological advancements can lead to overall economic growth and improved living standards. However, policymakers must address the potential challenges associated with job displacement and ensure the availability of alternative employment opportunities, as well as invest in education and training programs to equip the workforce with the skills needed for emerging industries. Additionally, measures to mitigate the impact on marginalized communities and promote inclusive growth should be prioritized to ensure a more equitable transition to a technologically advanced agricultural sector.

The trend depicted in Figure (e) regarding annual temperature fluctuations suggests variability within a relatively narrow range, typically between approximately 22.9 and 23.66 degrees Celsius. This range indicates a consistent pattern of temperature variation over time, with fluctuations occurring around a central value. However, without a clear upward or downward trend, it's difficult to ascertain any trend-dependent movement solely based on the provided information. Annual temperature fluctuations within this range can be influenced by various factors, including seasonal variations, weather patterns, and natural climatic cycles. Additionally, localized factors such as altitude, proximity to water bodies, and land use patterns can also contribute to temperature variability in specific regions. It's essential to consider longer-term data and conduct a more comprehensive analysis to determine if there are any discernible trends or patterns in temperature variation over time. The trend-dependent movement would require consistent directional changes in temperature over an extended period, which may indicate underlying climatic shifts or trends, such as global warming or regional climate change. To gain a deeper understanding of temperature dynamics and their implications, further analysis incorporating historical data, climate models, and regional climatic trends would be necessary. This holistic approach can provide valuable insights into the drivers of temperature variability and inform decision-making processes related to climate adaptation and mitigation strategies.

The trend depicted in Figure (f) regarding inter-seasonal rainfall from 1991 to 2021 reveals a fluctuating pattern with variations swinging between approximately 60.9 and 100 mm of rainfall. This variability in rainfall can significantly impact agricultural productivity, as it directly influences soil moisture levels, crop growth, and overall agricultural output. The correlation between rainfall patterns and periods of famine in Ethiopia is well-documented. When annual precipitation falls below average, it can severely limit agricultural production, leading to food shortages and famine. The two major periods highlighted in the graph, 1995 and 2002, where Ethiopia experienced low average annual precipitation of 75mm and 74mm respectively, coincide with significant challenges in food security and famine conditions. Fluctuations in rainfall and temperature conditions can have far-reaching consequences beyond agricultural productivity. Insufficient rainfall can lead to shortages of potable water, exacerbating water scarcity and sanitation challenges. Loss of soil fertility due to inadequate moisture and prolonged drought conditions can further reduce agricultural yields and threaten food security. Moreover, soil erosion and land degradation are exacerbated during periods of erratic rainfall, as extreme weather events such as heavy rainfall followed by drought can accelerate soil erosion processes. This degradation of natural resources undermines the resilience of rural communities and exacerbates vulnerability to climate-related shocks. Addressing the challenges posed by fluctuating rainfall patterns requires a multifaceted approach that includes investments in water resource management, climate-resilient agricultural practices, and disaster preparedness measures. Building infrastructure for water storage and irrigation can help mitigate the impacts of drought while promoting sustainable land management practices that can enhance soil health and resilience. Additionally, early warning systems and social safety nets are essential for providing timely assistance to vulnerable populations during periods of food insecurity and famine. By addressing both the immediate impacts and underlying drivers of vulnerability, Ethiopia can build resilience to climate change and promote sustainable development.

The trend illustrated in Figure (g) regarding the use of pesticides shows fluctuations during the first decade of the study, followed by a consistent upward trend in the two consecutive decades after 2003. This increasing trend in pesticide usage reflects various dynamics within the agricultural sector, including changes in cropping patterns and pest management practices. One factor contributing to the observed trend is the evolving landscape of crop cultivation. Changes in the types of crops grown, driven by market demand, agronomic factors, and climatic conditions, can influence the prevalence and types of pests encountered by farmers. If there is a shift towards crops that are more susceptible to pests or diseases, farmers may respond by increasing their use of pesticides as a means of pest control and crop protection. Additionally, as agricultural productivity becomes increasingly important for meeting food security and economic development goals, farmers may intensify their pest management efforts to safeguard their yields. This intensification can involve the use of chemical pesticides to combat pests and reduce crop losses, particularly in regions where alternative pest management strategies may be limited or less effective. However, while pesticides can effectively control pests in the short term, their indiscriminate use can have adverse environmental and human health impacts. Pesticide runoff can contaminate water sources, harm non-target organisms, and contribute to the development of pesticide resistance in pest populations. Furthermore, exposure to pesticides poses risks to farmworkers, consumers, and ecosystems. To address these challenges, it is essential to promote integrated pest management (IPM) approaches that combine various pest control methods, such as biological control, crop rotation, and the use of resistant crop varieties, with judicious pesticide use. By adopting IPM strategies, farmers can minimize reliance on chemical pesticides while effectively managing pest populations and preserving ecosystem health. Additionally, regulatory frameworks and extension services play a crucial role in promoting safe and sustainable pesticide use practices, ensuring that farmers have access to information, training, and resources to make informed decisions about pest management. By promoting responsible pesticide use and supporting integrated pest management approaches, policymakers can help mitigate the environmental and health risks associated with pesticide use while ensuring the long-term sustainability of agricultural production.

3.3. Unit root test

Table 3 reveals that all lag selection information criteria have shown similar optimal lag lengths except for all variables at the same time. Using this result further the variables have been diagnosed for the presence of unit root test based on the Augmented Dickey-Fuller and Phillips-Perron testes. Both methods try to asses if the variables and their lagged values have a serial correlation. In this test, our objective is to reject our null hypothesis that states there is a unit root test which implies that the variable is not stationary. If the variable has been found nonstationary (i.e. if we fail to reject our null hypothesis) at level, then their first difference is checked using the same procedure.

Results from Table to of the ADF unit root test imply that two of the variables the researcher considering are stationary at level. The variables are climate indicators coefficient of variation of temperature and precipitation. The calculated t-value -6.32226 and 6.43163] or CV of temperature and precipitation respectively is less than the 1% critical value. Hence, we have sufficient evidence to reject our null hypothesis stating there is a unit root. The same result has been exhibited by the intercept and trend model. Then, for those variables, a unit root is observed an ADF has been run on their first difference both using the intercept term only and intercept & trend term models. Before regression of the model is executed both dependent and independent variables have been checked for the presence of unit root. The stationary test is performed using augmented Dickey fuller and Phillips-Perron testes. One of the requirements of these tests is to find the optimal length of the lagged variables. Hence, here the optimal lag length is shown according to the information criteria of AIC, the HQIC, and SBIC.

Table 3 Optimal lag level selection

Variable	Optimum Lag
Agriculture gross output per km2 of land in metric tone	5.37439 [1]
Annual average temperature	-6.32226 [4]
Annual average precipitation	6.43163 [1]
Fertilizer used per km2 of land	6.14355 [2]
Pesticides used per km2 of land	14.5929 [4]
Labor employment per km2 land	1.80075 [4]
Animal Stock per km2 of land	6.73839 [1]

As shown in Table 4 the results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron unit root tests have provided valuable insights into the stationarity properties of the variables considered in the study. The confirmation that all variables are stationary after a first difference is crucial for conducting a time-series analysis, particularly in the context of estimating an Autoregressive Distributed Lag (ARDL) model. Here are some key points to further discuss the implications of the stationarity results and the suitability of using an ARDL model: - The stationarity of a time series is essential for ensuring the reliability and validity of statistical analyses, such as regression models. A stationary time series has a constant mean and variance over time, making it easier to model and interpret the relationships between variables accurately. In this case, the ADF and Phillips-Perron tests have indicated that the variables in consideration exhibit stationarity properties either at the level or after a first difference. The concept of order of integration (I) refers to the number of differencing operations required to make a non-stationary time series stationary. A series with an order of zero (I(0)) is considered stationary at the level, while a series with an order of one (I(1)) requires one difference to achieve stationarity. In this study, the log of coefficient of temperature and precipitation variables are found to be I(0), indicating they are stationary at the level, while the other variables are I(1), requiring one difference for stationarity. The ARDL model is a popular econometric technique used to analyze relationships between variables in a time series framework. It is particularly well-suited for situations where both the dependent and independent variables are integrated in different orders (i.e., a mix of I(0) and I(1) variables). Given that the variables in your study exhibit either I(0) or I(1) properties, the ARDL model is an appropriate choice for estimating the relationships between agricultural productivity and its determinants. One of the key advantages of the ARDL model is its flexibility in accommodating mixed orders of integration among variables. By allowing for cointegration and error correction mechanisms, the ARDL model can capture both short-term dynamics and long-term relationships between variables. This makes it a valuable tool for analyzing complex relationships in economic and social research, such as the impact of climate variability on agricultural productivity in Ethiopia. The stationarity results and the choice of the ARDL model have important implications for policy formulation and decision-making in the context of agricultural development. By using a robust econometric approach like ARDL, policymakers can better understand the causal relationships between climate variables, agricultural inputs, and productivity outcomes. This knowledge can inform targeted interventions, resource allocation, and adaptation strategies to enhance agricultural resilience and sustainability in the face of climate change. In conclusion, the stationarity results obtained from the ADF and Phillips-Perron tests confirm the suitability of employing an ARDL model to analyze the relationships between climate variables, agricultural inputs, and productivity in Ethiopia. By leveraging the strengths of the ARDL framework, researchers can gain valuable insights into the dynamics of agricultural systems and inform evidence-based policy decisions to promote food security, environmental sustainability, and economic development in the agricultural sector.

Table 4 Augmented Dickey-Fuller unit root test

	Level				First Difference				
	Intercept		Intercept &trend		Intercept		Intercept &trend		I(d)
Variable	t-value	p-value	t-value	p-value	t-value	p-value	t-value	p-value	
Agriculture gross output per km2 of land in metric tone	2.777	1.950	-2.016	-3.576	-4.471***	-1.950	-6.268***	-3.580	I(1)
Annual average temperature	1.806	-1.95	4.593	-3.576	-0.116	-1.95	-2.05	-3.58	I(1)
Annual average precipitation	0.266	-1.95	-4.67	-3.576	-7.621***	-1.95	-7.421***	-3.58	I(1)
Fertilizer used per km2 of land	0.903	-1.95	-2.476	-3.576	-7.708***	-1.95	-8.371***	-3.58	I(1)
Pesticides used per km2 of land	1.172	-1.95	-1.433	-3.576	-4.737***	-1.95	-5.207***	-3.58	I(1)
Labor employment per km2 land	-3.651	-1.95	-1.076	-3.576	-2.394***	-1.95	-3.566***	-3.52	I(1)
Animal Stock per km2 of land	1.69	-1.95	-3.244	-3.576	-6.093***	-1.95	-7.018***	-3.58	I(1)

The correlation Table 5 Provides valuable insights into the relationship between agricultural productivity and various factors. The positive correlation between agricultural productivity and annual temperature, annual precipitation, total fertilizer used, pesticide used, and total number of livestock suggests that an increase in these factors leads to an increase in agricultural productivity. This makes intuitive sense as favorable weather conditions, adequate use of inputs like fertilizer and pesticides, and a higher number of livestock can all contribute to higher agricultural output. On the other hand, the negative correlation between agricultural productivity and the amount of labor engaged in agriculture is an interesting finding. This suggests that as the amount of labor increases, agricultural productivity decreases. This could be due to various factors such as inefficiencies in labor utilization, lack of mechanization, or even diminishing returns to labor in certain agricultural activities. The significance level indicated by the asterisk (*) is important as it shows that the relationships observed in the correlation table are statistically significant at a 95% confidence level. This means that there is a high probability that the observed correlations are not due to random chance. Overall, the correlation table provides valuable information for policymakers, researchers, and practitioners in the agriculture sector. It highlights the importance of factors like climate conditions, input usage, livestock management, and labor efficiency in influencing agricultural productivity. Further analysis and research can help in understanding these relationships better and formulating strategies to enhance agricultural productivity sustainably.

Table 5 Correlation coefficient

variables		Agricultural productivity	annual temperature	annual precipitation	total fertilizer used	pesticides	Agricultural employment	total no. of livestock
Agricultural productivity	Pearson Corr.	1	0.78393*	0.71505*	0.89618*	0.92388*	-0.93833*	0.92852*
Agriculture productivity	Sig.	--	1.82E-07	6.18E-06	9.47E-12	1.26E-13	6.66E-15	5.22E-14
annual temperature	Pearson Corr.	0.78393*	1	0.44508*	0.56776*	0.86232*	-0.55545*	0.84214*
annual temperature	Sig.	1.82E-07	--	0.01211	8.64E-04	4.53E-10	0.00118	2.87E-09
Annual precipitation	Pearson Corr.	0.71505*	0.44508*	1	0.63102*	0.60742*	-0.70359*	0.59114*
annual precipitation	Sig.	6.18E-06	0.01211	--	1.41E-04	2.90E-04	1.01E-05	4.62E-04
total fertilizer used	Pearson Corr.	0.89618*	0.56776*	0.63102*	1	0.77963*	-0.92475*	0.80029*
total fertilizer used	Sig.	9.47E-12	8.64E-04	1.41E-04	--	2.35E-07	1.07E-13	6.52E-08
pesticides	Pearson Corr.	0.92388*	0.86232*	0.60742*	0.77963*	1	-0.81323*	0.93968*
pesticides	Sig.	1.26E-13	4.53E-10	2.90E-04	2.35E-07	--	2.70E-08	4.88E-15
Agricultural employment	Pearson Corr.	-0.93833*	-0.55545*	-0.70359*	-0.92475*	-0.81323*	1	-0.81765*
Agricultural employment	Sig.	6.66E-15	0.00118	1.01E-05	1.07E-13	2.70E-08	--	1.97E-08
total no. of livestock	Pearson Corr.	0.92852*	0.84214*	0.59114*	0.80029*	0.93968*	-0.81765*	1
total no. of livestock	Sig.	5.22E-14	2.87E-09	4.62E-04	6.52E-08	4.88E-15	1.97E-08	--

3.4. Long-run estimation result of the ARDL models

The findings from Table 6 highlight the significant impact of climate variability on agricultural productivity in the long run. Specifically, the positive effects of the log of coefficient of variation of temperature (LN_CVT) and the log of coefficient of variation of precipitation (LN_CVP) on agricultural productivity indicate that a more dynamic and variable climate can benefit agricultural output. Let's delve deeper into the implications of these results: The positive impact of temperature and precipitation variability on agricultural productivity suggests that a certain level of variability in these climatic factors can stimulate crop growth and enhance overall productivity. Fluctuations in temperature and precipitation can provide the necessary conditions for optimal plant growth and development, leading to higher yields.

Agricultural systems that are resilient to climate variability, as indicated by the positive coefficients of LN_CVT and LN_CVP, are better equipped to adapt to changing environmental conditions. This resilience allows farmers to capitalize on favorable weather patterns and mitigate the negative impacts of extreme weather events, ultimately improving agricultural productivity over the long term. The estimated percentage increase in agricultural productivity associated with a one-percentage-point increase in the coefficient of variation of temperature (3.84%) and precipitation (0.48%) underscores the significant influence of climate variability on land productivity. These results suggest that embracing and managing climate variability can lead to tangible improvements in agricultural output. Farmers and policymakers can leverage these findings to implement sustainable agricultural practices that enhance resilience to climate variability. Strategies such as crop diversification, water management, and soil conservation can help mitigate the risks associated with variable climate conditions and optimize agricultural productivity in the long run. In conclusion, the positive impact of temperature and precipitation variability on agricultural productivity underscores the importance of adaptive strategies in agriculture. By embracing and managing climate variability, stakeholders can harness the benefits of a dynamic climate system to improve land productivity sustainably. Implementing resilient agricultural practices that consider climate variability can contribute to long-term agricultural productivity gains and ensure food security in the face of changing environmental conditions.

Table 6. Long-run representation results of the ARDL model

Agricultural output perkm2	Coefficient	Std. err.	t	P>t	[95% conf. interval]	
ADJ						
Agricultural output perkm2	-1.612	0.203	-7.950	0.004	-2.257	-0.967
Annual average temperature	3.838	4.103	0.940	0.419	-9.218	16.894
Annual average precipitation	0.480	0.059	8.200	0.004	0.294	0.667
Fertilizer used per km2 of land	0.240	0.117	2.040	0.134	-0.134	0.613
Pesticides used per land	-0.004	0.001	-3.140	0.052	-0.008	0.000
Labor employment per km2 land	-1.110	0.319	-3.480	0.040	-2.126	-0.094
Animal Stock per km2 of land	0.534	0.096	5.550	0.012	0.228	0.841

4. Conclusion and recommendations

The agricultural output and rural incomes of an economy are expected to be adversely affected by climate change. To reduce the possible losses in agricultural productivity, rational adaptation is therefore pursued. This study's primary goal was to evaluate how Ethiopia's agricultural output was affected by climate change between 1991 and 2021. According to the findings of the ARDL approach, there is a long-term correlation between agricultural production and the coefficient of variation of temperature. Specifically, an increase of 3.84% in the coefficient of variation of temperature over time will increase the agricultural productivity of land. Similarly, a 0.48% increase in the coefficient of variation of precipitation will raise the agricultural production of the area whereas the other things are constant. The annual average temperature and precipitation, which are the study's primary variables and are employed as indicators of climate change, have mean values of 23.374 °C and 86.938 mm, respectively. Furthermore, the lowest recorded temperature during the period of 1991 was 22.92°C, while the highest recorded annual average temperature value during the 2013–2014 period was 23.67°C. The variables' analysis results include temperature, precipitation, animal population, pesticides, and fertilizer have a positive correlation with agricultural output. Conversely, there is a negative correlation between agricultural productivity and employment in the agricultural sector. Based on the findings of the current study, it is recommended that possible steps should be taken by the Government of Ethiopia to adopt new policies and modern technology regarding accurate weather forecasting, and preventive and direct actions are also needed to develop and underpin an improved irrigation system. Enhancements in farmland infrastructure are necessary to effectively tackle the challenges posed by future climate change. In conclusion, the study highlights the need for immediate action to address the adverse effects of climate change on agricultural productivity in Ethiopia. By implementing targeted policies, investing in modern technologies, and enhancing human capital development, stakeholders can build resilience in the agricultural sector and ensure sustainable food production amidst changing environmental conditions. Recognizing the complex interplay between climate change, agriculture, and rural livelihoods is essential for designing effective adaptation strategies that protect farming communities and promote long-term agricultural sustainability.

Declaration

Author contributions A.M.; conceptualized the project; curated the data; M.M, conducted the formula analysis; A.M.; A.D., and M.M.; developed the methodology, and while A.M wrote the original draft all authors participated in the subsequence review and editing process.

Finding: Not applicable

I confirm that the data included here is accurate and comprehensive. I hereby certify that this work has not been previously published and has not been submitted for publication to any journal.

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