Discover Sustainability

Research

The impacts of climate change on peasant's crop production in major crop producing zones in Ethiopia

Abrha Megos Meressa[1,2] · **Lewoye Bantie**[3]

Received: 30 May 2024 / Accepted: 4 November 2024
Published online: 27 November 2024

Abstract
This study aims to investigate the repercussions of climate change on crop production, focusing on cereals, pulses, oilseeds, and vegetables, and explore factors that influence crop productions in major agricultural producing zones in Ethiopia. Employing the One-step system GMM and Two-step system GMM methodologies, the study analyzes production dynamics from 2003/04 to 2021/22 within 21 selected zones spanning the Amhara, Oromia, Benishangul Gumuz, SNNP, and Sidama regions. Key factors influencing cereal production, including lagged production, the number of private peasant holders, land area, fertilizer application, precipitation, maximum average temperature, relative humidity, and regional factors are identified. Notably, precipitation emerges as a critical determinant affecting cereals, pulses, and oilseeds negatively. The study underscores the imperative for diversifying crops and reducing dependence on rain-fed agriculture. It proposes leveraging erratic rainfall patterns by constructing small-sized irrigation dams to capitalize on excess water during heavy rainfall seasons. Moreover, the adoption of temperature-resistant crop varieties and collaborative efforts with local administrations at various administrative levels are recommended to expand irrigated land, thereby bolstering resilience against climate variability and safeguarding rain-fed agriculture.

Keywords Agriculture · Geography · One-step GMM · Two-step GMM · Peasants · Ethiopia

1 Introduction

Agricultural production in developing countries has grown increasingly vulnerable to the impacts of climate change, which poses significant challenge to both farm productivity and livelihoods [1, 2]. Limited resources and adaptive capacities makes it difficult for these nations to combat the adverse effects of climate variability [3, 4]. As climate and environment are inextricably related to agricultural productivity [5], the challenge posed by climate change surpass all other global obstacles to food production and the expansion of agro-based businesses [6]. Despite the sector's vulnerability, many rural inhabitants in developing nations still rely primarily on rainfed agriculture for their livelihood. Food security in these regions depends on consistent rainy seasons with sufficient rainfall and favorable temperatures [7]. However, the increasingly unpredictable nature of the rainy season and subsequent rainfall shortages diminish crop yield, potentially leading to food insecurity.

✉ Abrha Megos Meressa, abrha.megos.meressa@nmbu.no; abrhamgs3@gmail.com; Lewoye Bantie, lewoyebantie@gmail.com | [1]Department of Economics, College of Business and Economics, Mekelle University, Mekelle, Ethiopia. [2] Faculty of Environmental Science and Natural Resource Management, Norwegian University of Life Sciences (NMBU), Ås, Norway. [3]Faculty of Business and Economics, Department of Economics, Addis Ababa University, Addis Ababa, Ethiopia.

Climate change is gradually emerging as one of the most important local and international policy problems because of its significant potential influence on economic results and global character [8, 9]. climate change impacts on water availability for irrigation and crop yield [10]. In order to create successful national adaptation programs and international climate-policy agreements, it is crucial to understand the economic effects of climate change on a particular country. The structure of developing nations' economies which frequently makes them more vulnerable to climate-related shocks and the need to ensure the genuine participation of developing nations in climate change agreements, make it particularly important to quantify the impact of climate change on the overall economy [11].

The agricultural sector in Ethiopia which continues to dominate and make a significant contribution to the economy also remains vulnerable to extreme climate change impacts [12, 13]. The sector accounts for roughly 65 percent of employment, 38 percent of GDP, and 72 percent of exports in the country in 2020 [14]. The study by Zerssa, Feyssa [14] further added that about 81 percent of the 118 million population in the country relied on agriculture for their livelihoods. However, this sector has been less productive for a long period, and the country has not yet maintained food security. This problem is particularly severe in rural areas of the country where peasants are in desperate need of agricultural land.

Climate change impacts have direct impacts on spatial and temporal changes in precipitation and temperature [10] consequently, contributed to decreased water availability for irrigation [15]. The climate of Ethiopia is noted for its history of extremes such as drought, flooding, and shifting trends in temperature and precipitation patterns [16]. A multitude of factors including poor and traditional agricultural farming technology, fragmented, ineffective and inefficient agricultural policy, unimproved market structure and linkage, poor institutions, and loss of soil fertility and degradation especially in high crop producing regions contribute to the low productivity of agriculture in the country [14, 17]. The recent civil war that broke in northern Ethiopia, Tigray, and its neighboring areas of Amhara and Afar, in November 2020 is expected to precipitate the adverse impacts of the climate on agricultural production and livelihoods in the region [18]. However, drought has the most devastating effect on crop production and made Ethiopia dependent on food aid for decades [19]. Therefore, this study investigates the impact of climate change on agricultural crop production focusing on cereals, pulses, oil seeds, and vegetable production in Ethiopia.

Most studies in developing countries use the production function as a deterministic function related to the output level. Other studies have investigated the impacts of climate change on crop production using different models. For instance, Adamu and Negeso [20] used real agricultural growth domestic product as the dependent variable and labor force, mean annual temperature, rainfall, and agricultural land as the independent variables; Zaied, Cheikh [21] studied agricultural crop production and climate variables for 1979–2011 using a time series approach; Attiaoui and Boufateh [22] used panel regional data from 1975 to 2014 and found that climate change negatively affects cereal output in Tunisia; Guntukula and Goyari [23] used a panel data approach from 19,956-2015 and they found that the average minimum temperature has a significant unfavorable effect on maize yield in the country.

Most studies in Ethiopia also have been conducted based on a data in single specific geographic regions and apply computable general equilibrium analysis (CGE). For instance, Kindu, Mohammed [24] in Jama Werda; Belay and Mengistu [25] in Muga watershed in the upper Blue Nile basin; Hawaria, Demissew [26] in Arjo Dedessa; Sertse, Khan [27] in Raya Azebo; Warsame, Sheik-Ali [28] in Somalia region etc. These studies only considered specific types of agricultural commodities: Bedeke, Vanhove [29] assessed the impact of climate change on maize producers and smallholder farmers; Chemura, Mudereri [30] on coffee; Lemessa, Watebaji [31] on Potatoes; Emeru [32] on Teff; and Zewdu, Hadgu [33] on Sorgum; Aleminew and Abera [34] on wheat. Previous studies for example, Solomon, Simane [35], Gebreegziabher, Stage [36], Ferede, Ayenew [37] and Robinson, van Meijl [38] employed country SAM, whereas Borgomeo, Vadheim [39], Holden, Lofgren [40], Tekle and Simane [41], and Berhanu [42] used village SAM to assess the effect of climate change on agricultural productivity. The selection of crop type and crop production largely depend upon the local socio-economic conditions [43]. In addition, CGE analysis works under some key assumptions on the values of the parameters and functional forms. Furthermore, these studies did not differentiate the effects of climate change on different agricultural crops. Most of the previous studies see [41, 44] did not consider the temporal aspects of climate change impacts on agriculture. Therefore, it is fruitful and practical to fill this gap by examining the consequences of climate change on the major crop producing zones in Ethiopia.

This study links climate change to total crop production to close the knowledge gap, add to the body of knowledge, and inform national policy by using dynamic panel data models to examine the impact of climate change on crop production in major crop production zones in Ethiopia. Therefore, the objectives of the study are evaluating the historical and projected impacts of climate change on cereal, pulse, oilseed, and vegetable production in major agricultural zones across Ethiopia; analyzing the factors influencing crop production dynamics, including lagged production, land area, fertilizer application, precipitation, maximum average temperature, relative humidity, and regional factors, and apply

One-step system GMM and Two-step system GMM methodologies to model production dynamics from 2003/04 to 2021/22, examining the relationship between climate variables and crop yields.

1.1 Conceptual framework

Various methods including the integrated assessment model (IAM) approach (sometimes called the 'production function' approach); the hedonic (or Ricardian) approach, and panel data models proposed by Deschenes and Greenstone [45], etc. were used to estimate the consequences of global climate change for the agricultural sector. The panel data models significantly differ from other alternative models such as the Ricardian (hedonic) method [45, 46]. The estimated parameters are first cleared of the impact of any unobserved time-invariant elements under an additive separability condition. Second, once the regional fixed effects are accounted for in the model, using land values as the dependent variable is no longer practical. This is because land values represent long-term weather averages rather than yearly variations from these averages, and such factors do not vary over time [47]. This method may be used to assess the impact of climate change on agricultural land values, even if the land values are not the dependent variable. In this study, we specify stochastic production function to calculate the impact of temperature and precipitation increases on agricultural earnings.

The stochastic production function of crop production for the zone (i) in the year (t), Y_{it}, is represented as follows:

$$Y_{it} = f\left(X_{it};\beta\right) + \varepsilon_{it} \tag{1.1}$$

where ε is the stochastic term with mean $E\left(\varepsilon_{it}\right) = 0$ and variance $V=\sigma^2$, and β is the production term variable to be estimated. The estimation of the equation $f\left(X_{it};\beta\right)$ provides the effects of the independent variables on mean crop production, $E\left(Y_{it}\right)$. The explanatory variable X_{it} will be used in the model to include a constant, rainfall (precipitation), relative humidity, number of holders, area covered in a hectare, fertilizer used in quintals, annual maximum mean temperature, and annual minimum temperature.

A one-step system GMM and a two-step system GMM can be employed to conduct the dynamic panel data model estimation with predetermined variables and fitted these models with robust standard errors to facilitate comparison. Dynamic panel data models offer advantages in controlling for measurement errors, unobserved panel heterogeneity, omitted variable bias, and endogeneity of the lagged dependent variable [48, 49]. The system GMM approach has the advantage of smaller bias and greater efficiency compared to other estimators [48–53] is opted its suitability to make a comprehensive comparison of the data.

2 Method and materials

2.1 Data

This study used secondary data to examine how climate change has affected the production of Ethiopian private peasant holders in major crop-producer zones. The Ethiopian National Metrology Agency (NMA) and Central Statistical Agency (CSA) of Ethiopia provided the datasets. The sources mentioned above were used to compile an annual panel series of data on net crop production, land input available for each crop production, weight of fertilizer used, annual minimum average temperature, annual maximum average temperature, relative humidity, and annual average precipitation for each zone. The study's timeframe measured in terms of the Gregorian calendar ranges from 2003/04 to 2021/22. The information was gathered based on the dataset's accessibility and applicability of the variables to the investigation. The researcher was limited to 2003/04–2021/22 because of the availability of data on crop production before 2003/04.

Annual Crop Production $\left(lnY_{ijt}\right)$: This is the total amount of crop production (cereals, pulses, oilseeds, and vegetables) in zones during the yearly period in quintals.

Mean Annual Rainfall (ln $\left(\text{precipitation}_{ijt}\right)$: Mean rainfall (mm) is the arithmetically averaged total amount of precipitation recorded over a year for each selected zone.

Number of Holders $\left(ln(HH_{ijt}\right)$: total number of agricultural households that produced a certain type of crop in zone j at time t.

Area Covered in Hectare $\left(\text{lnACH}_{ijt}\right)$: This is the total land arable area covered by a certain crop at zone j in time t.

Fertilizer $\left(lnFrt_{ijt}\right)$: it is the total amount of fertilizer in quintals used by a crop per year.

Mean Annual Maximum Temperature $\left(lnAMaxT_{ijt}\right)$: The mean maximum annual temperature refers to the average of the maximum temperatures of a year, taking the mean average of the hottest month of the year in zone j for a certain year.

Mean Annual Minimum Temperature $\left(lnAMinT_{ijt}\right)$: The mean annual temperature refers to the minimum temperature of a year, taking the mean average of the coldest month in Zone j in a certain year.

Relative Humidity $\left(lnRH_{ijt}\right)$: The quantity of water vapor in an air–water combination relative to the maximum amount is known as the relative humidity (RH). RH is a comparison between the saturation humidity ratio at a specific temperature (dry-bulb) in zone j in a given year and the humidity ratio of a specific water–air combination.

2.1.1 Crop production data

This study used yield data for four major crops in the country's agricultural production, which accounts for more than 90 percent of crop production in the country, namely cereals, pulses, oilseeds, and vegetables. The crop production data were obtained from agricultural sample surveys conducted by the Central Statistical Agency (CSA) of Ethiopia starting from 2003/04. To maintain the zonal-level reporting units for the years from 2003/04, the total production for each zonal classification was based on the 1995 EPRDF zonal classifications from each region.

Thus, this study covered 21 zones located in five administrative regions, according to the current administrative classification of the country. Specifically, the study focused on seven zones from the Amhara region: East Gojjam, West Gojjam, North Gondar, South Gondar, North Wollo, South Wollo, and North Shewa; five regions from the Oromia regional state, namely West Wollega, East Wollega, Jimma, West Shewa, Arsi, West Arsi, and South West Shewa; five zones from SNNP, namely Gurage, Woilata, Keffa, Gammogofa, and Silitie; one from the Simada region Sidama zone in the previous administration; and lastly, one zone Metekel from Binishangul Gumuz.

The above-mentioned zones were selected for their high production. During the 2021/22 period, in the Amhara region, the total crop production was 112,528,693.08 quintals, from which the crop production in the above seven zones was 101,350,573, which was 90.07 percent of the total crop production in the region. From the Oromia region, 175,542,709.96 quintals were produced, and from these 131,875,519 quintals, which was 75.12 percent of the total production in the region. From the Benishangul Gumuz region during 2021/22, 7,097,770.88 quintal was produced and out of this, 4,220,555.17 quintal was produced in the Metekel region which accounts for 59.46 percent of the total production in the region. From the SNNP region, 26,529,237.41 quintals were produced, and from this, the above five selected zones produced 19,973,330 quintals, which accounted for 75 percent of the total production. Finally, the Sidama region which produced 2,643,012.56 quintals was included in this study. During the 2021/22 period in the country, 327,903,521.41 quintal crop yields were produced. Of these, the selected zone 260,062,989.73 quintal crop was produced, accounting for 79.31%.

In this study, the Tigray region was not included because data were not available during 2021/22, and the war in the northern part of the war affected crop production in the region. As a result, the researchers did not include it in the study. Other regions and zones were not included in the study because they were not major crop production areas.

2.1.2 Rainfall data and climate change data

A panel data series of rainfall data for 21 stations across five regions of Ethiopia, namely Amhara, Oromia, SNNPR, Benishangul Gumuz, and Sidama was used to collect data on the mean minimum temperature, mean maximum temperature, mean annual precipitation, and relative humidity. Missing values for the climate change-related variables at the station level were interpolated using a moving average method, as the moving average approximated the series better than regressing the rainfall climate change series variables (mean minimum temperature, mean maximum temperature, mean annual precipitation, and relative humidity) of the nearby station on the stations for which missing data were reported.

2.2 Data analysis and empirical model

We employed both a one-step system GMM and a two-step system GMM to conduct the dynamic panel data model estimation with predetermined variables and fitted these models with robust standard errors to facilitate comparison. The system GMM approach was opted after a comprehensive comparison of the data. This choice was motivated by the fact that in addition to the difference in GMM, the model for its smaller bias and greater efficiency compared to other estimators [48–53].

Panel data has the advantage of enabling one to better understand the dynamics of adjustment since most connections are dynamic [see 54, 55]. According to Baltagi and Baltagi [56], Sul [57]), Tsionas [58] and Parker [59], dynamic relationships are characterized by the inclusion of a lagged dependent variable among the regressors [54]. The overall structure of an autoregressive model of order p with extra regressor Xit can be defined as follows for a dynamic panel data approach [56].

$$Y_{it} = \theta_1 Y_{it-1} + \dots + \theta_p Y_{it-p} + X'_{it}\beta + \alpha_i + \varepsilon_{it}; t = 1, \dots, T, i = 1, \dots, N \tag{2.1}$$

The basic formulation of Eq. (2.1) simplifies into a first-order model in our situation, where i is a time-invariant individual effect whose treatment may be constant or random and ijt is a disturbance term considered to be uncorrelated with Xit. In a dynamic model, the reverse is true because it will rely on i regardless of how we treat the latter opposing to a static panel data model, where choosing between fixed or random effects yields a consistent and efficient estimate [60]. Applying a within-subject estimator to a first-order autoregressive model yields consistent estimates only when the number of periods *T* is very large [61]. Likewise, Arellano and Bond [62] introduced a two-step procedure, that is a consistent and efficient estimator, based on differencing and instrumenting, where the first step consists of differencing the dynamic equation to remove individual effects (***α***$\boldsymbol{\alpha_i}$) [54, 63]. Described the first step of the procedure as follows:

$$\Delta Y_{it} = \theta_1 \Delta Y_{it-1} + \dots + \theta_p \Delta Y_{it-p} + \Delta X'_{it}\beta + \Delta\varepsilon_{it} \tag{2.2}$$

Δ is the first-order differential equation expressing the change in the dependent variable due to the effect of its lagged value and exogenous regressors. Assuming that $\boldsymbol{\varepsilon_{it}}$ is serially uncorrelated in this aspect; otherwise, estimators are inconsistent. The second step is instrumental variable (IV) estimation of the first-differenced (FD) model using acceptable lags of the dependent variable as instruments. These steps, according to Drukker [64]), result in consistent estimates while the fixed- or random-effects panel data estimators are not appropriate for the FD equation. Ordinary least squares on the FD data produce inconsistent estimates, in contrast to a static model, because the regressor $\boldsymbol{\Delta Y_{it-1}}$ correlates with the error $\boldsymbol{\Delta\varepsilon_{it}}$, even if $\boldsymbol{\varepsilon_{it}}$ is serially uncorrelated. For serially uncorrelated $\boldsymbol{\varepsilon_{it}}$, the FD model error term $\boldsymbol{\Delta\varepsilon_{it} = \varepsilon_{it} - \varepsilon_{it-1}}$ and $\boldsymbol{\Delta Y_{it-1} = Y_{it-1} - Y_{it-2}}$ are correlated since $\boldsymbol{Y_{it-1}}$ depends on $\boldsymbol{\varepsilon_{it-1}}$. However, $\boldsymbol{\Delta\varepsilon_{it}}$ and $\boldsymbol{\Delta Y_{it-k}}$ are uncorrelated for $\boldsymbol{k \geq 2}$, opening the possibility of IV estimation using lagged variables as instruments [63].

Depending on the previous justifications, the estimated equations are specified in the levels and first-differenced forms as follows:

$$\begin{aligned} lnY_{ijt} = &\beta_0 + \beta_1 \ln\left(Perci_{ijt}\right) + \beta_2 \ln\left(HH_{ijt}\right) + \beta_3 ln\left(\mathrm{ACH}_{ijt}\right) + \beta_4 ln\left(Frt_{ijt}\right) \\ &+ \beta_5 ln\left(MinimumAMT_{ijt}\right) + \beta_6 ln\left(RH_{ijt}\right) + \beta_7 ln\left(MaximumAMT_{ijt}\right) \\ &+ Dummy(region) + \alpha_i + u_i \end{aligned} \tag{2.3}$$

$$\begin{aligned} \Delta lnY_{ijt} = &\beta_{1\Delta} lnY_{ijt-1} + \beta_2 \Delta \ln\left(Perci_{ijt}\right) + \beta_{3\Delta} \ln\left(HH_{ijt}\right) + \beta_{4\Delta} ln\left(\mathrm{ACH}_{ijt}\right) + \beta_{5\Delta} ln\left(Frt_{ijt}\right) \\ &+ \beta_6 \Delta ln\left(MinimumAMT_{ijt}\right) + \beta_7 \Delta ln\left(RH_{ijt_{ijt}}\right) + \beta_8 \Delta\left(MaximumAMT_{ijt}\right) + \Delta u_i \end{aligned} \tag{2.4}$$

All variables are in the natural logarithmic form. Where, lnY_{ijt} the natural logarithm of annual crop production for zone j; $lnPerci_{ijt}$ is the natural logarithm of the mean annual precipitation for zone j; HH is the total number of holders of the crop in zone j and time t; ACH is the total area covered in a hectare in zone j at time t; Frt is the total amount of fertilizer in quintal used in zone j at time t; minimum AMT is the mean minimum annual temperature in zone j at time t; maximum AMT is the mean maximum annual temperature in zone j at time RH is the relative humidity in zone j at time t; dummy (region) is the zone in which regions are located,α_i is the crop production item-specific fixed effect; $U_{it} \sim N(0, \sigma^2)$ is the random term; α_i and u_{it} are independently and identically distributed.

Equation (2.3) is first estimated to determine the determinants of crop production using the most recent version of the Arellano/Bond GMM estimation to investigate the determinants of crop production. The Arellano-Bond method results in several instruments (for large T), leading to a potentially poor performance of asymptotic results (when the number of groups is small), thus we employed the least possible number of instruments [55]. The Stata/SE 15.1 computer software was used for the estimation.

3 Results

3.1 Panel unit root and diagnostics tests

Before starting the analysis, we attempted to investigate the nature of the production trends for the crops over the study period. Figure 1 presents the trends of production and land productivity (production per hectare) for the four crop types. The results show that the production of cereals has the highest share in the study regions followed by pulses while the oilseed takes the lowest share. In terms of productivity, on the other hand, vegetables and cereal crops is higher compared to the pulse and oilseeds.

Then, we check the stationarity of the data. Although the unit root test is commonly thought of as a time series phenomenon, checking stationarity for panel datasets offers more power and advantages than the time series stationary test. In empirical analysis, nonstationary data are frequently viewed as a challenge. Working with nonstationary variables might lead to erroneous regression findings that are useless for further inferences. Since Hadri [65] and Im, Pesaran [66] unit root tests are valid when the number of periods (years in this study) is small and the number of persons (zones in this study) is large, those two tests were utilized in this study. The Hadri LM test allows for non-normality and is based on a within-estimate. The Im-Pesaran-Shin (IPS) test is more general than LM, and it is based on the combination of independent Dickey-Fuller tests in addition to IPS, allowing heteroskedasticity, serial correlation, and non-normality.

Table 1 reports the results of panel unit roots. According to the results in Table 1, we reject the null hypothesis that the variables are non-stationary and conclude that all variables are stationary.

Based on the results presented in Table 2 on cereal production, the Hansen J test indicates no issues with over-identifying restrictions, as the value falls within the range of 0.05–0.9 [67]. This finding suggests that the AR (1) term is statistically significant, with *p*-values of 0.010 for the one-step system GMM and 0.013 for the two-step system GMM. However, the AR (2) term is found to be insignificant, with *p*-values of 0.61 for the one-step system GMM and 0.328 for the two-step system GMM. This indicates the presence of negative first-order autocorrelation, although it does not suggest inconsistencies in the results. From the diagnostic result, failure to reject the null hypothesis of no second-order serial correlation implies that the original error term is not serially correlated and that the moment conditions are correctly specified (i.e., the p values of AR (2) are greater than 0.05).

Similarly, the Hansen J test results on the pulse production presented in Table 1 show a value greater than 0.05 indicating that there is no over-identification issue in this context. The AR (1) term is found to be significant, with a *p*-value of 0.004 for the one-step system GMM and 0.033 for the two-step system. The AR (2) term is found to be insignificant,

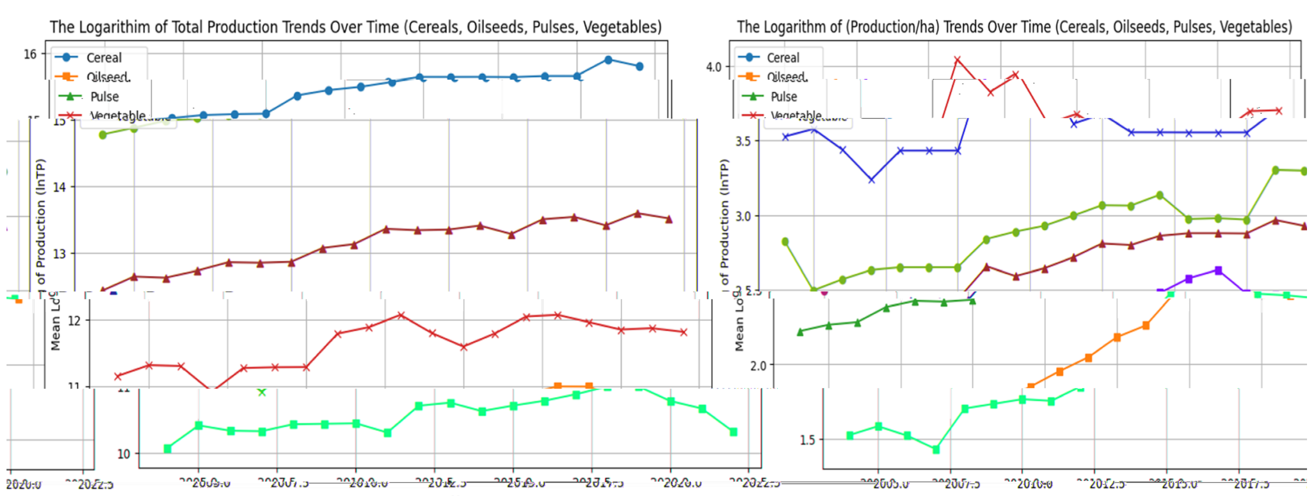

Fig. 1 Trends of production (left) and production per hectare (right) of the four crop types over 2003/04 to 2021/22. Source: Authors' computation using Stata 15.1 from CSA (2023), NMA (2023)

Table 1 Panel unit root test

Variables	Harris-Tzavalis unit-root		Levin-Lin-Chu unit-root	
	t-statistics	P	*t*-statistics	P
Ln_TP_quintal_cereals	0.095	0.000	−6.106	0.000
Ln_TP_quintal_pulse	0.009	0.000	−10.023	0.000
Ln_TP_quintal_oilseed	0.031	0.000	−4.855	0.000
Ln_TP_quintal_vegetable	0.345	0.000	−3.215	0.000
Ln_NH$_{jt_}$cereals	−0.099	0.000	−10.965	0.000
Ln_NH$_{jt_}$pulse	−0.032	0.000	−11.621	0.000
Ln_NH$_{jt_}$oilseed	−0.045	0.000	−10.206	0.000
Ln_NH$_{jt_}$vegetable	−0.567	0.000	−8.453	0.000
Ln_AH$_{tj_}$cereals	0.002	0.000	−8.217	0.000
Ln_AH$_{tj_}$pulse	−0.032	0.000	−10.793	0.000
Ln_AH$_{tj_}$oilseed	0.007	0.000	−7.734	0.000
Ln_AH$_{tj_}$vegetable	0.008	0.000	−12.128	0.000
Ln_Fertlizer$_{tj}$ cereals	0.2116	0.000	−7.457	0.000
Ln_Fertlizer$_{tj}$ pulse	0.1155	0.000	−5.784	0.000
Ln_Fertlizer$_{tj}$ oilseed	0.2605	0.000	−8.054	0.000
Ln_Fertlizer$_{tj}$ vegetable	0.123	0.000	−4.456	0.000
Ln_percpitation$_{tj}$	−0.0368	0.030	−12.428	0.000
Ln_TMPmin$_{tj}$	−0.0627	0.115	−6.968	0.000
Ln_TMPmax$_{tj}$	−0.0927	0.141	−4.751	0.000
Ln_RELHUM	−0.1733	0.053	−8.380	0.000

Source: Authors' computation using Stata 15.1 from CSA (2023), NMA (2023)

with a *p*-value of 0.647 for the one-step. In the validity analysis of the entire model for oil seed production in Table 1, the model is suggested as valid as the *p*-value for the specified model was greater than 0.05. The autoregressive AR (1) term was found to be statistically significant, with a *p*-value of 0.002 for the one-step system GMM model and 0.001 for the two-step system model. However, the AR (2) term was deemed insignificant, with respective *p*-values of 0.32 for the one-step system GMM and 0.378 for the two-step system GMM. This suggests the presence of a negative first-order autocorrelation, although it does not indicate inconsistencies in the results. From the result in Table 1, the Hansen J test shows a case of no over-identifying restrictions and indicates the validity of the entire model in this context. The AR (1) term is found to be significant with a *p*-value of 0.001 for the one-step system GMM and 0.002 for the two-step system GMM. The AR (2) term is found to be insignificant, with a *p*-value of 216 for the one-step system GMM and 0.840 for the model two-step system. This implies the presence of a negative first-order autocorrelation even though it does not imply inconsistencies in the results.

3.2 Estimation result for agricultural production

Table 2 shows that the coefficient of lagged cereals production is positive and statistically significant at a 1 percent level, indicating an autoregressive level of cereals production. Since the lagged value has a considerable significant effect, we understand that the dynamic specification of the model outperforms the static panel data. Based on the two-step results, for instance, a one percent increase in cereal production of the previous year increases current production by about 0.07 percent, ceteris paribus. This could be because farmers could respond to previous year's higher production and productivity of cereals by growing more cereals vice versa. From this, reduced production in the previous years would discourage them to grow cereals in the next year. As a result, lagged cereal production is positively associated with the current year's cereal production.

Likewise, the number of peasant holders has a positive and significant effect on cereal production. The concept behind this demonstrated a higher number of private peasants. According to the FAO [68] report, smallholder farmer produces 80 percent of the world's food, and increasing the level of private smallholder farmers will result in increasing the production level of cereals in each zone. In absolute terms, when the number of private peasant holders increases by one percent, other things remain unchanged; the total production of cereals of zones grows by some 0.14 percent. The other

Table 2 Regression result of the cereal, oilseeds, pulses, and vegetable production equation

Dependent variable	Log (total cereal production in quintal)		Log (total pulse production in quintal)		Log (total oilseed production in quintal)		Log (total vegetable production in quintal)	
Variables	One-step GMM	Two-step GMM	One-step GMM	Two-step GMM	One-step GMM	Two-step GMM	One-step GMM	Two-step GMM
Ln_l.TP_quintal	0.07***	0.07***	−0.01	−0.03	0.00	0.00	0.01	0.07***
Ln_NHjt	0.19***	0.14**	−0.04**	−0.07**	0.55***	0.47***	0.59***	0.64**
Ln_AHtj	0.34**	0.43***	1.12***	1.09***	0.63***	0.57***	0.56***	0.55***
Ln_Fertlizertj	0.22***	0.20***	0.91***	0.80***	0.06	0.07	0.12***	0.11**
Ln_percpitationtj	−0.06**	−0.06***	−0.05**	−0.04**	−0.47***	−0.44***	0.08**	0.05**
Ln_TMPmintj	−0.01	−0.04	0.27**	0.31***	−0.00	−0.32*	−0.52	−0.28
Ln_TMPmaxtj	−0.54***	−0.53**	−0.54***	−0.51***	−0.97***	−0.88***	−0.73***	−0.59***
Ln_RELHUM	0.14***	0.10*	0.14***	0.13***	0.60***	0.59***	−0.52***	−0.47***
Dummy = Amhara	0.71***	0.57***	0.66***	0.67***	0.45***	0.42***	−0.72***	−0.65***
Dummy = Oromia	0.74***	0.61***	0.51***	0.52***	0.45**	0.42**	−0.47***	−0.41***
Dummy = Benishangul Gumuz	0.82***	0.77***	0.38**	0.50**	1.57***	1.21***	−0.57**	−0.57**
Dummy = SNNP	0.50***	0.44***	0.38***	0.48***	−1.38***	−1.21***	−0.06	0.19
Constant	4.12**	3.90***	2.63***	3.54***	−7.37***	−4.26***	2.25	0.95

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively

Source: Authors' computation using Stata 15.1, CSA (2023), NMA (2023) control variable that determines the total production of cereals is the Area covered by cereals in hectares. Treated as a proxy for total production of cereals, the area in hectares has a positive and significant effect on the total production of cereals. For every one percent increase in the Area covered by cereals in a hectare, production of cereals tends to boost by 0.43 percent, ceteris paribus. The fertilizer variable has also positive and significant determinants of cereals production. Other things remain constant; increasing the level of fertilizer used by 1 percent resulted in increasing the level of cereals production by 0.20 percent.

The precipitation variable has a negative sign with a statistically significant effect on total cereals production. For every one percent increase in the precipitation, production of cereals tends to decline by 0.06 percent, ceteris paribus. Intuitively it would mean that high rainfall could reduce production through for instance damage from oxygen deficit as a consequence of soil waterlogging after heavy rain; bending of the stem; loss of soil nutrients; and plant anchorage failure since the topography of the major producer of cereals is found in highland topography of Ethiopia which are adversely affected by heavy erosion and heavy summer rainfall. For instance, Beillouin, Schauberger [69] demonstrated that excessive rainfall can adversely affect maize yields in the USA in proportions similar to extreme drought. These impacts may become more frequent in the future given the expected increase in the frequency of extreme precipitation events.

Regarding the temperature variable, the minimum average temperature has a negative and insignificant effect on cereals production. The maximum average temperature has a negative and significant effect on cereals production. For every one percent increase in the maximum temperature, production of cereals tends to decline by 0.53 percent, ceteris paribus. Variations in climate models can partly explain the co-occurrence of climate variables unfavorable to the production of cereals. For instance, comparing recent major droughts in Ethiopia, similar preceding high air temperature and soil water anomalies were observed preceding 2006, 2010, and 2021 droughts in Ethiopia. Yet, the area under droughts and factors aggravating the effect of the drought are distinct: severe soil drying caused by preceding rainfall deficits and high evaporative demand before summer in 2022, and high evapotranspiration linked to extremely warm and sunny conditions in spring in 2020 reduced the level of the growth rate of cereals production in the major producer zones in the country.

Relative Humidity has a positive and significant effect on crop production in a one-step system GMM result. This is because relative humidity (RH) directly influences the water relations of plants and indirectly affects leaf growth, photosynthesis, pollination, the occurrence of diseases, and finally economic yield. Relative humidity has an indirect effect on photosynthesis. When relative humidity is low, transpiration occurs and the plant experiences water deficiencies. Water deficits cause partial or full closure of stomata and increase mesophyll resistance blocking the entry of carbon dioxide. Even if relative humidity has a positive relationship with crop production very high relative humidity and very low relative humidity (extreme) hurt cereals production. On plant leaves, high RH encourages the rapid germination of fungus spores. Crops produced using irrigation produce less than those planted with the same quantity of water from rainfall when exposed to the same amount of solar radiation. This is because irrigation has minimal effect on the dry environment, which independently inhibits crop development. Regional dummy variables, Sidama (0), Amhara (1), Oromia (2), Benishangul Gumuz (3) and SNNP (4) regional administrations. Sidama regional adminstration is a base category since it produces the least cereal production throughout the study. Based on the findings presented in Table 2, it can be inferred that a significant crop production gap exists between regions. Zones located in Benishangul Gumuz exhibit the highest potential for cereal production, followed by those in the Oromia and Amhara regions.

The results in Table 2 show that areas covered by pulse, fertilizer application, precipitation, minimum average temperature, maximum average temperature, relative humidity, and regional dummy variables were identified as significant factors influencing pulse production in selected major pulse producer zones. However, the lag in pulse production was deemed insignificant among the remaining variables. The number of private peasant holders of the pulse has a significant and negative effect on pulse production. For every one percent increase in the private peasant holders, production of pulse tends to decline by 0.07 percent, ceteris paribus. It would mean that increasing the smallholders has a higher tendency to reduce the annual pulse production. Increasing the level of smallholders causes the shortage of land per capita and this in return reduces the mass production of the pulse. If a household has two-hectare arable land of pulse and in the coming year he gives half one-hectare arable land to his incoming son with the new family, it automatically reduces pulse production through the substitution effect of pulse arable land by other crops. In addition, increasing number of holders automatically exacerbates soil erosion; and severe degradation and this in turn decreases the level of pulse production in Ethiopia. The findings by Hordofa, Menkir [70], Amenu and Mamo [71], Neelakantam and Naidu [72] are among those studies that reveal consistent results to ours.

The variable ln_AHtj, log of area in hectare, has a positive and statistically significant coefficient on the regression for pulse production. For every one percent increase in the arable land for the pulse in a hectare, production of pulse tends to increase by 1.09 percent, ceteris paribus. Previous studies by Merga and Haji [73], Naik and Nethrayini [74] and Siddiq, Uebersax [75] also displayed findings in line with this study. Similarly, fertilizer variable is also found to have positive and significant effect on pulse production. Other things remain constant; increasing the level of fertilizer used by 1 percent resulted in increasing the level of pulse production by 0.801 percent. The studies by Galpottage Dona, Schoenau [76], Yadav, Benbi [77], and Kenngott, Riess [78] also reported that increasing the level of fertilizer improved pulse production.

Regarding the climate change variables, precipitation has a significant and negative effect on pulse production. Based on the two-step system GMM result, a one percent increase in precipitation decreases pulse production by about 0.04 percent ceteris paribus. This is because erratic and unpredictable rainfall during the sowing stage, early vegetative growth stage, and the flowering stage of pulses resulted in damage to pulse production. The other supporting reason is erratic rainfall resulted in flooding and soil erosion which in turn reduce the fertility of the soil. Our findings related to precipitation variables are also in line with previous empirical studies such as Potts, Huxman [79], Robertson, Bell [80], Thomey, Collins [81], and Mar, Nomura [82].

Mean minimum Temperature has a significant and positive effect on pulse production. Based on the two-step system GMM result, a one percent increase in mean minimum temperature resulted in increasing pulse production by about 0.31 percent ceteris paribus. Increasing the moderate temperature can increase the rate of reproductive development, which shortens the time for photosynthesis to contribute to fruit or seed production. The other determining variable that affects pulse production is maximum temperature, other things remain constant, a one percent increase in the level of maximum temperature resulted in decreasing the level of pulse production by 0.51 percent. This is because the maximum and elevated temperature on pulse production is determined to have a highly significant effect due to the global warming pressure. Due to high temperatures at every stage of pulse producer zones, pulse production is increasing at a decreasing rate even if the number of holders is increasing from time to time. High temperature considerably influences the oilseed by affecting several physiological injuries like leaf abscission, leaf scorching, senescence, and root and shoot growth limitation that subsequently leads to a reduction in yield. Moreover, high temperature affects photosynthetic membranes followed by ion leakage, enlargement of grana stacks, and aberrant stacking, alters the activities of carbon metabolic enzymes, starch accumulation, and sucrose production.

Relative humidity has a significant and positive effect on pulse production. Other things remain constant; increasing the level of relative humidity by 1 percent resulted in 0.14 percent, ceteris paribus. This is because a relative humidity of 40–60% is suitable for most of the crop plants. Very few crops like pulse can perform well when relative humidity is 80% and above. As a result, increasing the level of relative humidity automatically improved the total production of pulse in the country.

Based on the findings presented in Table 2, it is evident that there exists also a substantial disparity in crop production across regions. Zones within the Amhara region exhibited the highest potential for pulse production, followed by those in the Oromia and Benishangul Gumuz regions. In the results from Table 2, it is observed that several variables, including the number of private peasant holders, area in hectares, precipitation, average annual maximum temperature, relative humidity, and regional dummy variables, are significant determinants of oilseed production. Conversely, variables such as lag of oilseed production, fertilizer usage, and average minimum temperature were found to be insignificant. The number of holders has a significant and positive effect on oilseed production. For every one percent increase in the number of holders of oilseed, production of oilseed tends to increase by 0.55 percent, ceteris paribus. This is because to get more income, private peasant tends to shift from consumption-based crops to commercial-based crops which in turn increases the production of oilseed. Our findings related to the number of holders variables are also in line with previous empirical studies including Ukolova and Dashieva [83], Bastron, Mesheryakov [84], and Piras, Botnarenco [85]. Area in hectare has a positive and significant effect on oilseed production. For every one percent increase in the arable land for oilseed in a hectare, production of oilseed tends to increase by 0.57 percent, ceteris paribus. The studies by Lundin [86], Némethová and Vilinová [87], and [88] also reported similar findings. In this case, fertilizer is found to have no significant effect on oilseed production despite its positive coefficient.

Regarding the climate change variables, precipitation has a negative and significant effect on oilseed production. For every one percent increase in precipitation, production of oilseed tends to decrease by 0.44 percent from the two-step system GMM as described in the table below, ceteris paribus. At a certain level, the amount of precipitation during the rainy season might yield a negative impact on oilseed development. This is due to heavy erratic and variable rainfall in Kiremit and Meher season rainfall led to crop damage in certain zones in Ethiopia.

The other determining variable that affects oilseed production is maximum temperature, other things remain constant, a one percent increase in the level of maximum temperature resulted in 57 decreasing the level of oilseed production by 0.88 percent. This is because the maximum and elevated temperature on oilseed production is determined to have a highly significant effect due to the global warming pressure. Due to high temperatures at every stage of oilseed producer zones, oilseed production is increasing at a decreasing rate even if the number of holders is increasing from time to time. High temperatures have a significant impact on crops by causing physiological damage such as leaf abscission, leaf burning, senescence, and restricted root and shoot development, which ultimately reduces output. High temperatures also influence photosynthetic membranes, grana stack growth, ion leakage, and aberrant stacking. High temperatures change the activities of carbon metabolic enzymes, starch accumulation, and sucrose synthesis by down-regulating certain genes involved in carbohydrate metabolism.

Relative humidity has a significant and positive effect on oilseed production. Other things remain constant, for every one percent increase in the level of relative humidity, it boosts the level of oilseed production by 0.6 percent. This is because when abundant humidity is available and other factors of the environment are favorable there will be rapid cell division and enlargement and it favors the vegetative phase of growth of oilseed. According to the findings presented in Table 2, it is evident that there exists a substantial disparity in crop production across regions. The zones situated in the Benishangul Gumuz region exhibit the highest potential for oilseed production, followed by those in the Amhara and Oromia regions.

The results in Table 2 also demonstrate that the number of holders, area in hectares, fertilizer in quintals, precipitation, maximum temperature, relative humidity, and regional dummy variables, except the SNNP region, were significant variables that affected the production of vegetables. The coefficient on the lagged vegetable production is not statistically significant under one-step GMM. Regarding the non-climate variables that affect the production of vegetables, the number of private peasant holders of vegetables has a positive and significant effect on vegetable production. Other things remain constant, every one percent increase in the number of private peasant holders of vegetables will boost the total vegetable production in the zones. The area in hectare covered by vegetables also has a positive and significant effect on vegetable production. Increasing the level of arable land for vegetable production by one percent will boost the total vegetable production by 0.55 percent, ceteris paribus. Fertilizer also has a positive and significant effect on vegetable production. For every one percent increase in the level of fertilizer, vegetable production will be increased by 0.11 percent, given other things remain constant.

Regarding climate change variables, precipitation has a positive and significant effect on vegetable production. Rainfall is important for the growth and development of vegetables as it provides the necessary water for plant growth and reproduction through their production stage. Increasing the level of precipitation will increase the growth of vegetables and reproduce them 61 within a short period. Maximum temperature is found to have a negative and significant effect on vegetable production. Other things remain constant, for every one percent increase in the level of average maximum temperature, it decreases the level of vegetable production by 0.59 percent. This is because high temperatures can accelerate chlorophyll breakdown, resulting in early yellowing, and hasten the softness, wilting, and dehydration of vegetables [89, 90]. The remaining variables, such as lag in vegetable production, average minimum temperature, and relative humidity, have insignificant effects on the production of vegetables.

4 Discussion

The findings of this study contribute significantly to understanding the key factors influencing the production of cereals, pulses, oilseeds, and vegetables in Ethiopia, especially under varying climate and agricultural conditions. In line with the introduction, where the relevance of climate change and agricultural inputs was highlighted, this discussion will elaborate on the implications of the results for Ethiopian agriculture and broader food security concerns.

Cereal Production: The significant and positive influence of the lagged cereal production variable on current production emphasizes the autoregressive nature of cereal farming, confirming that prior yields affect future cultivation decisions. This dynamic model, in contrast to a static one, highlights how farmers adapt to past performance by adjusting their production levels in subsequent years. This finding aligns with studies by Arellano and Bond [62] that emphasize the importance of accounting for dynamic relationships in agricultural production. When farmers experience higher production in one season, they are likely to replicate those practices, such as planting more cereal crops, as suggested by this study's results.

The positive and significant effect of the number of peasant holders on cereal production also aligns with global reports that smallholders contribute substantially to food production [68]. Ethiopia's reliance on small-scale farmers supports this notion, as increasing the number of peasant farmers proportionally increases cereal output. However, challenges such as land degradation and inefficient farming techniques still need to be addressed to optimize productivity. This affirms the need for targeted policies that support smallholder farmers, particularly in accessing modern inputs and technologies, to maintain and improve productivity.

Pulse Production: In the case of pulse production, the findings reveal a more complex relationship. While the area cultivated has a positive and significant effect on pulse production, the number of smallholders surprisingly has a negative effect. This could be attributed to land fragmentation, where the subdivision of land reduces the efficiency and scalability of production, as noted in Hordofa, Menkir [70] and Amenu and Mamo [71]. Fragmented land use could hinder the ability to practice high-yield pulse farming, as smaller plots may not be well-suited to large-scale agricultural practices. Furthermore, soil degradation due to overuse by smallholders may explain the decline in production, a concern that has been previously highlighted in studies on Ethiopian agriculture [72].

The significant negative impact of precipitation on pulse production indicates that excessive rainfall can damage crops, likely through flooding and soil erosion, as observed in the Ethiopian highlands. This finding aligns with Potts, Huxman [79], Thomey, Collins [81], and Mar, Nomura [82], who noted that excessive rainfall during critical growth stages can negatively affect yields. Given the irregular rainfall patterns in Ethiopia, as described by CSA (2023), addressing water management practices, such as efficient irrigation and flood control measures, becomes crucial.

Oilseed Production: The study results indicate that oilseed production is significantly influenced by the number of holders and the area cultivated, but fertilizer usage was found to be insignificant. This contradicts the assumption that increased fertilizer usage directly correlates with higher yields, as suggested by Galpottage Dona, Schoenau [76], Yadav, Benbi [77], and Kenngott, Riess [78]. This insignificance might reflect inefficiencies in fertilizer application methods or the need for better training in fertilizer use among farmers. The negative impact of precipitation and maximum temperature on oilseed production underscores the vulnerability of this crop to climate variability. High temperatures and excessive rainfall could reduce oilseed yields by causing physiological stress on plants, an similar findings are also reported by Ukolova and Dashieva [83], Bastron, Mesheryakov [84], and Piras, Botnarenco [85].

Vegetable Production: For vegetable production, the significant effect of climate variables, particularly precipitation and maximum temperature, indicates that these crops are highly sensitive to environmental conditions. The positive effect of rainfall on vegetable production aligns with findings from Verón, Blanco [91], Kyei-Mensah, Kyerematen [92], and Wang, Li [93], suggesting that consistent water availability is essential for vegetable growth. However, high temperatures negatively affect vegetable yields, possibly due to accelerated chlorophyll breakdown and reduced water retention, as noted by [89, 90]. This suggests that while rain-fed agriculture remains vital, temperature control measures, such as shading and irrigation, are necessary to mitigate the adverse effects of rising temperatures.

The significant role of relative humidity in improving both oilseed and vegetable production highlights the importance of atmospheric moisture in sustaining plant growth. Relative humidity affects several physiological processes, including water absorption and photosynthesis, and optimal humidity levels are critical for maximizing yields, as documented by Peyrous [94], Boudhan, Joubert [95], and Vatansever, Tulbek [96].

Climate Change and Agricultural Resilience: The negative effects of increased precipitation and rising temperatures on most crops reaffirm the vulnerability of Ethiopian agriculture to climate change. As anticipated in the introduction, where the study addressed the mounting challenges posed by erratic weather patterns, these findings underscore the urgent need for adaptive strategies. Ethiopian agriculture, which is predominantly rain-fed, requires robust climate-resilient practices, such as improved irrigation systems, drought-resistant crop varieties, and agroecological zoning to mitigate these impacts.

Regional Disparities: The regional dummy variables in this study show significant disparities in crop production across Ethiopia, with regions such as Benishangul Gumuz, Amhara, and Oromia outperforming Sidama and SNNP. This suggests that geographic and climatic differences play a crucial role in agricultural productivity. Regions with better infrastructure, access to markets, and favorable environmental conditions, like Benishangul Gumuz, are better positioned to maximize production. These results echo the observations of Lundin [86], Némethová and Vilinová [87], and [88], who noted that regions with more developed agricultural systems and resources tend to exhibit higher productivity levels.

5 Conclusion and policy implications

This study provides critical insights into the multifaceted impacts of climate change on Ethiopian agriculture, focusing on key crops—cereals, pulses, oilseeds, and vegetables across important production zones. Using one-step and two-step GMM methods with panel data from 2003/04 to 2021/22, the analysis reveals both the socio-economic factors and climatic risks that shape agricultural productivity. For cereals, lagged production, the number of peasant holders, land area, and fertilizer usage positively influence yields, reinforcing the importance of improving agricultural inputs and the role of smallholder farmers. However, the significant risks posed by precipitation variability and temperature extremes highlight the increasing vulnerability of this staple crop to climate change. This underscores the need for targeted climate adaptation strategies to safeguard food security.

In pulse production, the significance of land area and fertilizer use in boosting yields contrasts with the detrimental effects of erratic precipitation and temperature fluctuations. Pulses, which are key to nutritional security, are particularly vulnerable to climate-induced shocks. Similarly, oilseed production benefits from land area and peasant participation, yet temperature, precipitation, and relative humidity variations significantly impact yields. Vegetable production, too, is shown to rely on adequate land and fertilizer use, but it remains vulnerable to extreme temperatures and precipitation patterns. These findings underscore the complex interaction between socio-economic factors, agricultural practices, and climate conditions. To ensure sustainable agricultural productivity and food security in Ethiopia, comprehensive adaptation strategies that integrate technological innovations and policy interventions are crucial.

5.1 Policy implications

The study's findings carry important policy implications. First, promoting land consolidation among smallholders could enhance agricultural efficiency, particularly for crops like pulses where land fragmentation is a critical issue. Second, targeted interventions aimed at improving climate resilience, such as training on climate-smart agricultural practices, are essential for mitigating the adverse effects of temperature and rainfall variability. Finally, region-specific agricultural policies that consider the unique climatic and geographical factors influencing each area would help optimize production across Ethiopia's diverse agro-ecological zones.

Future research should focus on identifying tailored adaptation measures for different crop types, allowing for more effective responses to climate variability. This would enhance crop-specific resilience and productivity across the diverse agricultural landscape of Ethiopia.

Author contributions Abrha Megos Meressa: Conceptualization, Writing– review and editing, Supervision. Lewoye Bantie: Conceptualization, Methodology, Validation, Formal analysis, Writing—original draft, Review.

Funding This study did not receive any external funding.

Data availability The data can be provided upon reasonable request to the corresponding author.

Declarations

Competing interests The authors declare no conflict of interest regarding the publication of this paper.

References

1. Chevuru S, et al. Copernicus global crop productivity indicators: an evaluation based on regionally reported yields. Climate Serv. 2023;30:100374.
2. Ahmad MI, et al. Climate change variability adaptation and farmers decisions of farm exit and survival in Pakistan. Climate Serv. 2024;33:100437.
3. Ahmad MI, et al. Does rural livelihood change? Household capital, climate shocks and farm entry-exit decisions in rural Pakistan. Front Environ Sci. 2023;10:857082.

4. Zubair A. et al. Impacts of climate change on rural livelihoods of Muzaffargarh farming community, Punjab, Pakistan. 2022.
5. Arora NK. Impact of climate change on agriculture production and its sustainable solutions. Environ Sustainab. 2019;2(2):95–6.
6. Kountios G. The role of agricultural consultants and precision agriculture in the adoption of good agricultural practices and sustainable water management. Int J Sustainable Agricult Manag Inf. 2022;8(2):144–55.
7. Lansbury Hall N, Crosby L. Climate change impacts on health in remote indigenous communities in Australia. Int J Environ Health Res 2022;32(3):487–502.
8. Aryal JP, et al. Climate change and agriculture in South Asia: adaptation options in smallholder production systems. Environ Dev Sustain. 2020;22(6):5045–75.
9. Sultan B, Defrance D, Iizumi T. Evidence of crop production losses in West Africa due to historical global warming in two crop models. Sci Rep. 2019;9(1):12834.
10. Kaini S, et al. Representative general circulation models selection and downscaling of climate data for the transboundary Koshi river basin in China and Nepal. Int J Climatol. 2020;40(9):4131–49.
11. Chandio AA, et al. Sustainable maize production and climatic change in Nepal: Robust role of climatic and non-climatic factors in the long-run and short-run. Environ Dev Sustain. 2023;25(2):1614–44.
12. Conway D, Schipper ELF. Adaptation to climate change in Africa: challenges and opportunities identified from Ethiopia. Glob Environ Chang. 2011;21(1):227–37.
13. Yalew AW, et al. Climate change, agriculture, and economic development in Ethiopia. Sustainability. 2018;10(10):3464.
14. Zerssa G, et al. Challenges of smallholder farming in Ethiopia and opportunities by adopting climate-smart agriculture. Agriculture. 2021;11(3):192.
15. Kaini S, et al. Impacts of climate change on the flow of the transboundary Koshi River, with implications for local irrigation. Int J Water Resour Dev. 2021;37(6):929–54.
16. Malede DA, et al. Recent approaches to climate change impacts on hydrological extremes in the Upper Blue Nile Basin. Ethiopia Earth Syst Environ. 2022;6(3):669–79.
17. Kifle T, Ayal DY, Mulugeta M. Factors influencing farmers adoption of climate smart agriculture to respond climate variability in Siyadebrina Wayu District, Central Highland of Ethiopia. Climate Serv. 2022;26:100290.
18. Ghebreyohannes T, et al. Challenges and resilience of an indigenous farming system during wartime (Tigray, North Ethiopia). Agron Sustain Dev. 2022;42(6):116.
19. Marie M, et al. Farmers' choices and factors affecting adoption of climate change adaptation strategies: evidence from northwestern Ethiopia. Heliyon. 2020;6(4):1.
20. Adamu MK, Negeso KD. Effect of climate change on agricultural output in Ethiopia. J Econ Devel Environ People. 2020;9(3):6.
21. Zaied YB, Cheikh NB, Rahmoun M. On the effects of climate variability on agricultural crops: evidence from an in-transition economy. Environ Econ Policy Stud. 2023;25(2):143–59.
22. Attiaoui I, Boufateh T. Impacts of climate change on cereal farming in Tunisia: a panel ARDL–PMG approach. Environ Sci Pollut Res. 2019;26:13334–45.
23. Guntukula R, Goyari P. The impact of climate change on maize yields and its variability in Telangana, India: a panel approach study. J Public Aff. 2020;20(3):e2088.
24. Kindu G, et al. Assessment of Projected Climate Change Impact on Wheat (*Triticum aestivum* L.) Production with Coping Strategies at Jamma Wereda, Ethiopia. Earth Syst Environ. 2023;7(1):267–81.
25. Belay T, Mengistu DA. Impacts of land use/land cover and climate changes on soil erosion in Muga watershed, Upper Blue Nile basin (Abay). Ethiopia Ecol Proc. 2021;10(1):1–23.
26. Hawaria D, et al. Effects of environmental modification on the diversity and positivity of anopheline mosquito aquatic habitats at Arjo-Dedessa irrigation development site. Southwest Ethiopia Infec Dis Poverty. 2020;9(1):1–11.
27. Sertse SF, et al. Farm households' perceptions and adaptation strategies to climate change risks and their determinants: evidence from Raya Azebo district, Ethiopia. Int J Dis Risk Reduct. 2021;60:102255.
28. Warsame AA, et al. Climate change and crop production nexus in Somalia: an empirical evidence from ARDL technique. Environ Sci Pollut Res. 2021;28(16):19838–50.
29. Bedeke S, et al. Adoption of climate change adaptation strategies by maize-dependent smallholders in Ethiopia. NJAS-Wageningen J Life Sci. 2019;88:96–104.
30. Chemura A, et al. Climate change and specialty coffee potential in Ethiopia. Sci Rep. 2021;11(1):8097.
31. Lemessa SD, Watebaji MD, Yismaw MA. Climate change adaptation strategies in response to food insecurity: the paradox of improved potato varieties adoption in eastern Ethiopia. Cogent Food Agricult. 2019;5(1):1640835.
32. Emeru GM. The perception and determinants of agricultural technology adaptation of teff producers to climate change in North Shewa zone, Amhara Regional State, Ethiopia. Cogent Econ Financ. 2022;10(1):2095766.
33. Zewdu E, Hadgu G, Nigatu L. Impacts of climate change on sorghum production in North Eastern Ethiopia. Afr J Environ Sci Technol. 2020;14(2):49–63.
34. Aleminew A, Abera M. Effect of climate change on the production and productivity of wheat crop in the highlands of Ethiopia: a review. Agric Rev. 2020;41(1):34–42.
35. Solomon R, Simane B, Zaitchik BF. The impact of climate change on agriculture production in Ethiopia: application of a dynamic computable general equilibrium model. Am J Clim Chang. 2021;10(1):32–50.
36. Gebreegziabher Z, et al. Climate change and the Ethiopian economy: a CGE analysis. Environ Dev Econ. 2016;21(2):205–25.
37. Ferede T, et al. Agroecology matters: Impacts of climate change on agriculture and its implications for food security in Ethiopia. Global food security: Emerging issues and economic implications, 2013: p. 71–112.
38. Robinson S, et al. Comparing supply-side specifications in models of global agriculture and the food system. Agric Econ. 2014;45(1):21–35.
39. Borgomeo E, et al. The distributional and multi-sectoral impacts of rainfall shocks: evidence from computable general equilibrium modelling for the Awash Basin. Ethiopia Ecol Econ. 2018;146:621–32.

40. Holden S, Lofgren H, Shiferaw B. Economic reforms and soil degradation in the Ethiopian highlands: a micro CGE model with transaction costs. in International Conference on Policy Modeling (EcoMod2005) June. 2005.
41. Tekle Z, Simane B. Impact of climate change on household poverty in Ethiopia: application of a dynamic micro-simulation approach. Ethiopian J Devel Res 2014;36(2): 19_46–46.
42. Berhanu W. Informal crossborder livestock trade restrictions in eastern Africa: Is there a case for free flows in Ethiopia-Kenyan borderlands? Ethiopian J Econ. 2016;25(1):95–119.
43. Kaini S, Gardner T, Sharma AK. Assessment of socio-economic factors impacting on the cropping intensity of an irrigation scheme in developing countries. Irrig Drain. 2020;69(3):363–75.
44. Belay A, et al. Knowledge of climate change and adaptation by smallholder farmers: evidence from southern Ethiopia. Heliyon. 2022;8(12):1.
45. Deschenes O, Greenstone M. Using panel data models to estimate the economic impacts of climate change on agriculture. Handbook Climate Change Agricult. 2011;2011:112–40.
46. Fezzi C, Bateman I. The impact of climate change on agriculture: nonlinear effects and aggregation bias in Ricardian models of farmland values. J Assoc Environ Resour Econ. 2015;2(1):57–92.
47. Guntukula R. Assessing the impact of climate change on Indian agriculture: evidence from major crop yields. J Public Aff. 2020;20(1):e2040.
48. Biresselioglu ME, et al. Estimating the political, economic and environmental factors' impact on the installed wind capacity development: a system GMM approach. Renewable Energy. 2016;96:636–44.
49. Gulcemal T. Financial globalization, institutions and economic growth impact on financial sector development in fragile countries using GMM estimator. J Bus Econ Finance. 2021;10(1):36–46.
50. Soto M. System GMM estimation with a small number of individuals. Barcelona: Institute for Economic Analysis; 2007.
51. Jung H, Kwon HU. An alternative system GMM estimation in dynamic panel models. 2007: Institute of Economic Research, Hitotsubashi University.
52. Bun MJ, Windmeijer F. The weak instrument problem of the system GMM estimator in dynamic panel data models. Economet J. 2010;13(1):95–126.
53. Jung H, Kwon HU, Jeon G. An alternative system GMM estimation in dynamic panel models. J Econ Theory Econometr. 2015;26(2):57–78.
54. Bayiley YT. Macroeconomic and firm-specific determinants of bank performance: a one-step system GMM dynamic panel model. Innovations. 2021;87:275–87.
55. Mohammed N. Analysis of the Ethiopian agricultural export performance: a dynamic panel data analysis. 2022, st. Mary's university.
56. Baltagi BH, Baltagi BH. Econometric analysis of panel data. Vol. 4. 2008: Springer.
57. Sul D. Panel data econometrics: common factor analysis for empirical researchers. 2019: Routledge.
58. Tsionas M Panel data econometrics: empirical applications. 2019: Academic Press.
59. Parker S. Panel Data Econometrics: Common Factor Analysis for Empirical Researchers. 2020.
60. Verbeek M. A guide to modern econometrics. Wiley. 2008.
61. Greene WH. Econometric analysis. Pearson Education India. 2003.
62. Arellano M, Bond S. Some tests of specification for panel data: monte Carlo evidence and an application to employment equations. Rev Econ Stud. 1991;58(2):277–97.
63. Cameron AC, Trivedi PK. Microeconometrics: methods and applications. Cambridge: Cambridge University Press; 2005.
64. Drukker DM. Econometric analysis of dynamic panel-data models using Stata. In: Summer North American Stata Users Group meeting. 2008.
65. Hadri K. Testing for stationarity in heterogeneous panel data. Economet J. 2000;3(2):148–61.
66. Im KS, Pesaran MH, Shin Y. Testing for unit roots in heterogeneous panels. J Econometr. 2003;115(1):53–74.
67. Roodman D. A short note on the theme of too many instruments. Center for Global Development Working Paper. 2007;125(10.2139).
68. FAO, Food and Agricultural Organization of the United Nations Statistics Annual Population. Rome. 2021.
69. Beillouin D, et al. Impact of extreme weather conditions on European crop production in 2018. Philos Trans R Soc B. 1810;2020(375):20190510.
70. Hordofa T. et al. Irrigation and rain-fed crop production system in Ethiopia. Impact Irrigat Poverty Environ Ethiopia. 2008: p. 27–36.
71. Amenu BT, Mamo GS. Impacts of population pressure on agricultural production and farming practices of households: the case of Essera Woreda in Dawro Zone, SNNPR. Ethiopia Earth Sci. 2021;10(6):298–314.
72. Neelakantam T, Naidu PD. Agricultural contribution in development of Ethiopia issues and challenges. ITIHAS J Indian Manag. 2016;6(1):38–54.
73. Merga B, Haji J. Economic importance of chickpea: production, value, and world trade. Cogent Food Agricult. 2019;5(1):1615718.
74. Naik V, Nethrayini K. Impact assessment of National Food Security Mission (NFSM) on pulses production in Karnataka, India-An economic analysis. Asian J Agricult Ext Econ Sociol. 2019;33(1):1–12.
75. Siddiq M, Uebersax MA, Siddiq F. Global production, trade, processing and nutritional profile of dry beans and other pulses. Dry beans and pulses: Production, processing, and nutrition, 2022: p. 1–28.
76. Galpottage Dona WH, Schoenau JJ, King T. Effect of starter fertilizer in seed-row on emergence, biomass and nutrient uptake by six pulse crops grown under controlled environment conditions. J Plant Nutrition, 2020;43(6): 879–95.
77. Yadav SK, Benbi DK, Toor AS. Effect of long-term application of rice straw, farmyard manure and inorganic fertilizer on potassium dynamics in soil. Arch Agron Soil Sci. 2019;65(3):374–84.
78. Kenngott KG, et al. Flood pulse irrigation of meadows shapes soil chemical and microbial parameters more than mineral fertilization. Soil Syst. 2021;5(2):24.
79. Potts DL, et al. Resilience and resistance of ecosystem functional response to a precipitation pulse in a semi-arid grassland. J Ecol. 2006: p. 23–30.
80. Robertson TR, et al. Precipitation timing and magnitude differentially affect aboveground annual net primary productivity in three perennial species in a Chihuahuan Desert grassland. New Phytol. 2009;181(1):230–42.

81. Thomey ML, et al. Effect of precipitation variability on net primary production and soil respiration in a Chihuahuan Desert grassland. Glob Change Biol. 2011;17(4):1505–15.
82. Mar S, et al. Impact of erratic rainfall from climate change on pulse production efficiency in lower Myanmar. Sustainability. 2018;10(2):402.
83. Ukolova AV, Dashieva BS. Study of the Labor Resources of Peasant (Farm) Households by Production Type. In: Sustainable Agriculture: Circular to Reconstructive, vol. 1. Springer; 2022. p. 229–41.
84. Bastron A. et al. Prospects for the use of microwave technologies in the production of oilseeds and their processing. In: IOP Conference Series: Earth and Environmental Science. 2021. IOP Publishing.
85. Piras S, et al. Post-Soviet smallholders between entrepreneurial farming and diversification. Livelihood pathways in rural Moldova. J Rural Stud. 2021;82:315–27.
86. Lundin O. Consequences of the neonicotinoid seed treatment ban on oilseed rape production–what can be learnt from the Swedish experience? Pest Manag Sci. 2021;77(9):3815–9.
87. Némethová J, Vilinová K. Changes in the Structure of Crop Production in Slovakia after 2004 Using an Example of Selected Crops. Land. 2022;11(2):249.
88. Yilmaz H, Avkiran B. Analysis of canola (rapeseed) production cost and income in context of oilseeds production support policies: a case study from Trakya region of Turkey. Економика пољопривреде. 2020;67(2):483–93.
89. Liu X, et al. Heavy metals in soil-vegetable system around E-waste site and the health risk assessment. Sci Total Environ. 2021;779:146438.
90. Yu L, et al. Distribution characteristics of microplastics in agricultural soils from the largest vegetable production base in China. Sci Total Environ. 2021;756:143860.
91. Verón SR, et al. Desertification and ecosystem services supply: the case of the Arid Chaco of South America. J Arid Environ. 2018;159:66–74.
92. Kyei-Mensah C, Kyerematen R, Adu-Acheampong S. Impact of rainfall variability on crop production within the Worobong Ecological Area of Fanteakwa District. Ghana Adv Agricult. 2019;2019:1–7.
93. Wang X, et al. Vegetable oil-based nanofluid minimum quantity lubrication turning: Academic review and perspectives. J Manuf Process. 2020;59:76–97.
94. Peyrous R. The effect of relative humidity on ozone production by corona discharge in oxygen or air–a numerical simulation–part ii: air. 1990.
95. Boudhan R, et al. Influence of air humidity on particle filtration performance of a pulse-jet bag filter. J Aerosol Sci. 2019;130:1–9.
96. Vatansever S, Tulbek MC, Riaz MN. Low-and high-moisture extrusion of pulse proteins as plant-based meat ingredients: a review. Cereal Foods World. 2020;65(4):12–4.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.