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Production impacts of climate change on agricultural livelihoods among smallholder panel households across Ethiopia

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Abstract

This study analyzes the production impacts of climate change on smallholder agricultural households across Ethiopia. Hypothesizing that climate change affects agricultural livelihoods mainly through productive and distributive effects, this article examines an integrated farm [crop, livestock, mixed] production impacts overtime. Methodically, the comprehensive Ethiopian socioeconomic survey (ESS) panel data, and nation-wide observatory 60-years climate data-precipitation and temperature [1960-2019] were merged to form a joint panel database; then analyzed using Ricardian panel model with random effects regression. Objectively, factor productivity, the rate of convergence, the historical, real, and seasonal climate impacts were investigated against net-agricultural return overtime. The applied panel model augments both the temporal, spatial, and individual effects and yields more efficient and consistent estimates than the cross-sectional and time series models. The results revealed that CC poses net-negative, increasing and significant impacts on factor elasticity, percapita farm output, and net-farm revenue [NFR] due to diminishing marginal returns; the progressive temporal impacts; regressive duration impacts; divergence effects on the growth of net-farm return; and mixed regional, farm, and HH impacts. Therefore, introducing institutionalized sustainable livelihoods framework [green institutions, finance, education, training, research, inputs, subsidy, insurance, market] in agricultural production system would enhance sustainable production and improved welfare among smallholder households even under changing climate.

Keywords: Impacts of Climate Change; Agricultural Production; Households; Ricardian Panel Model; Random Effects Regression; Ethiopia

1 Introduction

Climate change [CC] has been impacting agricultural livelihoods through affecting its production, distribution and disposal processes. However, agriculture is the major source of food, income, employment, and growth as nation and individuals [1]. Thus, continuous impact assessment shall provide relevant insights, which thereby shape the behavior of people in reducing production related climatic costs [2]. Because about 99% of climate change is caused by human economic activity and only 1% is attributed to natural process which occurs after many decades [3]. The inherent trade off in agriculture justifies its importance and research priority. The sector has been the major source of GDP [43%] and carbon emission [50%) in Ethiopia. Nationally, the estimated least GDP loss due to CC was 10% per year [4;5]. But nation-wide household level climatic impact study was scant; and even the existing studies were limited in scope or methods.

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The problem statement deals with gap analysis and explains how to fill them via the current study. Gap denotes deviation of expectations from reality. The key research gap and motivation was lack of integrated climate impact studies at household level across Ethiopia. Despite the booming climate research [6; 7; 8;9; 10] impact on agriculture has been inconclusive [11] arguably due to scope and methodological gaps. It involves mixed effects such as benefits and costs, negative and positive, progressive and regressive impacts among mixed groups [12; 13;14]. The impacts remained ambiguous as integrating both human influence, natural process, and time shocks is difficult despite emergence of advanced models. Even with observed climate impacts, the subject is debatable among industrialized and agrarian nations; the poor and the rich; nature and human; growth and environmental quality arguments.

The quest for sustainable agriculture on one hand and vulnerability of agriculture to climate on the other hand, demands an inclusive impact assessment today than ever to facilitate integrated response measures [15; 16;60; 17]. We argue that climate impact studies reveal inconclusive empirical evidences perhaps they hardly combine the scope and methodological differentials [18]. Smallholder agriculture is highly vulnerable to climate. Assessing its effect on production and residual impacts and mapping implications in Ethiopia would be a novel enquiry. Therefore, the key arguments, identified gaps and the way-outs were shown in that order.

We argue that assessing the impacts of climate risk on agricultural livelihoods [19] shall be thematically integrated, temporally dynamic and spatially wider to optimize sustainability. Precisely, four basic research arguments might articulate climatic impacts:

- It involves multiple impacts,
- Temporal impacts,
- Spatial impacts,
- Unit-specific effects.

These operational arguments gain scientific rationality through theoretical and empirical evidences [20; 9; 10;11; 13;14;15]. The inclusion of multiple impact dimensions, different time periods, wider geographical area and unit of analysis may treat biases resulting from omitted variables. What is the major gap w.r.t the above argument?

Most past climate studies conducted in Ethiopia were limited either to narrow geographical scope-district level [21;22; 23;18;19], used time series data [24; 25; 26; 27;28], assumed limited thematic scope (crop, livestock, consumption, adaptation, food security, or poverty); used cross-sectional data with small samples [29; 8;9], used linear methods [30]. Neither too aggregation nor too localization generate robust outputs. Indeed, seizing both the direct, indirect and residual effects that can syndicate both fixed and random effects (30; 23;8; 17) would be difficult. Also, too narrow scope and one-time data can't estimate the dynamic impacts as unit, time and context-related differentials were excluded in such studies. Some scholars [31;32;33] focus on the physical effects rather than socioeconomic impacts. Moreover, the direction and magnitude of the impact remains equivocal (34;30] and so drawing the joint outcome was rare despite the emergence of advanced models. Consequently, this study systematically integrated both the time, farm, and HH-specific disparities and hence generated a combined robust parameter.

The objective of the study was to analyze the production impacts of climate change on smallholder agricultural production among panel households across Ethiopia. Precisely, it;

- Assessed factor elasticity wrt farm production value [crop, Livestock, mixed] given climate change,
- Analyzed the historical impacts of climate change on net-farm revenue [NFR],
- Explained the current impacts of climate change on net-farm revenue [NFR],
- Examined the seasonal impacts of climate change on NFR among HHs.

These objectives are consistent with Ethiopia's CRGE (2011-2030), SDGs (UNDP, 2016), GTP (2010-2015) GTP-II (2016-2020) and Ten years development plan, 2021-2030 [PDC, 2021] both focused on agriculture food security and poverty reduction [35;36;37;].

2 Material and methods

In this section, the methods, data and tools such as SPSS, STATA, GIS, excel were used as climate impact assessment best fits with mixed approach. Mainly, the Ricardian empirical panel model, random effects regression and analyses were made using integrated climate-socioeconomic-agriculture-Household panel data.

Mixed research methods-the descriptive, empirical and panel regressions were used in the study. The empirical methods applied include the production function, Ricardian model (RM), and mixed panel estimation methods. This article is focused on factor productivity and production impacts of climate change. Initially, climate-augmented production function was used to examine factor elasticity of agriculture to the shock, then the Ricardian model measures the impact on farm value, and finally mixed panel regressions were used to estimate the marginal impacts. In short, the factor, output, and induced impact of climate change have been analyzed.

2.1 Theoretical Model

Climate-augmented Production function has been used as the theoretical basis [38; 39;59;40]. Initially, we've adapted simple production function and then included relevant variables including dummies.

Hypothesis: Climate change poses a negative and significant impact on factor productivity on agricultural production among smallholder households' overtime. Before estimating the climatic impacts on farm value, factor sensitivity to classical output shall be assessed. The classical production model assumes two factors [capital and labor] to produce a given output [41]. The technological effect is assumed to be fixed. Thus, the generic static production function is:

$$Q = [A]F[K^{\alpha}L^{1-\alpha}] \dots \dots \dots \dots \dots \dots [1]$$

Where, Q is agricultural output [crop yield, livestock value, mixed value], A is technological constant, F is the technical relationship between inputs & output, K is units of capital (oxen], L is number of labor units, α is elasticity of capital to Q, and $1-\alpha$ is elasticity of labor wrt. Q.

When we augment the temporal factor in to the static production function, the household level panel production function can be given by:

$$Q_{ijt} = [A_{ij}]F_{ijt}\left[K_{ijt}^{\alpha}\, L_{ijt}^{1-\alpha}\right] \dots \dots \dots [2]$$

Where, Q_{ijt} is the output of household [HH] i at farm j in time t; A_{ij} is technical constant of HH i at farm j; F_{ijt}, $K_{ijt,}$& L_{ijt} are respectively the functional relation, units of capital and number of labor for HH i at farm j in time t.

Assuming the theories and empirics on climate economics, we've augmented CC into simple production model to investigate its effect on farm production. Hence, the climate-augmented production function can be presented by:

$$Q_{ijt} = [A_{ij}]F_{ijt}\left[K_{ijt}^{\alpha}\, L_{ijt}^{1-\alpha}G_{ij}^{\sigma}\right] \dots \dots [3]$$

Where, G is the exogenous climate change proxied by the long-run [1960-2019] mean precipitation [PH] and temperature [TH] and their respective means for the first three ESS waves [$\mathrm{PH_1, PH_2, PH_3; TH_1, TH_2, \& \; TH_3}$]. These values were calculated from moving average to control endogeneity and obtain consistent data with the ESS panel. The moving averages for the first [ESS_1], second [ESS_2], & third [ESS_3] waves were computed using 1961-2010, 1962-2012, and 1963-2014 in that order. The statistics were used to proxy the historical & current impact. Besides the long-run impacts, the short-run climate variation[seasonality] affects seasonal production too. Therefore, the seasonal anomalies [S] were included in equation (3) and generates:

$$Q_{ijt} = \left[A_{ij}\right]F_{ijt}\left[K_{ijt}^{\alpha}\, L_{ijt}^{1-\alpha}G_{ij}^{\sigma}\, S_{ij}^{\theta}\right]\dots [4]$$

Where, S is the mean seasonal climate variability; we call it real climate [2011-2016] and is the sum of four seasonal averages of T & P [$\sum_{S=1}^{4}[\theta_S T_{S,i,t} \; and \; \theta_S P_{S,i,t}]$ for the survey period. The four seasons per year are; summer, S_1 [Junuary-Augst], Autumn, S_2 [September -November], winter, S_3 [December-February], and spring, S_4 [March-May] were used for seasonal impacts. This was to isolate seasonal shocks[S] from long-run constants [G] and estimate the seasonal effects. The seasonal means were deducted from their own historical means to create seasonal shocks [deviations]. Finally, the deviations and their squared values were included in our model too.

Moreover, we have augmented the general disturbance term [U] in equation (4), and formed an advanced production function of the form:

$$Q_{ijt} = \left[A_{ij}\right]F_{ijt}\left[K_{ijt}^{\alpha}\, L_{ijt}^{1-\alpha}G_{ij}^{\sigma}\, S_{ij}^{\theta}\, U_{ijt}^{\omega}\right] \dots [5]$$

Where, U is the disturbance term, which capturers the excluded errors in the model; $\omega = 1 - [\alpha - (1-\alpha) - \sigma - \theta]$. Technically, U_{ijt} comprises three errors terms; unit-specific errors, time-specific errors, and random errors. More formally, the general error term is given by:

$$U_{ijt} = \mu_i + \gamma_t + \varepsilon_{it} \dots\dots\dots\dots\dots\dots\dots [6]$$

Where, μ_i is household-specific errors that can control time-invariant changes among HHs; γ_t is time-fixed errors that could control temporary shocks common among HHs, and ε_{it} is the random error independent of regressors, $Z_{i,t}$ and an individual errors, μ_i.

Moreover, symbolizing all endogenous explanatory variables included in equation [5] by Z, a modified production function can be generated as:

$$Q_{ijt} = [A_{ij}]F_{ijt}[G_{ij}^{\sigma}\, S_{ij}^{\theta}\, Z_{ijt}^{\gamma}\, U_{ijt}^{\omega}] \dots\dots [7]$$

Where, Z is vector of time varying factors such as household characteristics including age, sex, education, labor, land, capital, oxen, adaptation, institutions [extension, credit, advise, training], slope, and other dummies variables such as year, farm and region dummies.

Factor productivity to farm yield under climate change can be estimated linearly via transforming the production function [eq. 7] into logarithm. Accounting this argument, the equivalent panel regression equation can be given as:

$$lnQ_{itj} = \alpha + \beta lnQ_{ijt-1} + \theta \grave{S}_{ijt} + \delta G_{ij} + \gamma Z_{ijt} + \omega U_{i,t} \dots (8)$$

Where, $lnQ_{i,t}$ is the natural logarithm of farm output of farming households i, at time t, α is technical constant; β is cofficenct of the first lag output; w hich captures its lagged effect on current production and also it denotes convergence term, t is the 3-ESS waves[ESS_1, ESS_2, & ESS_3].

The sing of beta-coefficient, β denotes the existence of convergence and its value shows the rate of adjustment. While the negative β shows convergence of output to its long-run steady state [i.e. Y/L, y & K/L, k], positive β reveals divergence of growth in the long-run.

Unlike some empirics [42;9;32;33]; we've studied the existence and rate of growth convergence given the typical climate. The convergence effects on steady state values [y, k, c] can be estimated by adopting Solow-Swans convergence hypothesis [40] and empirical evidences [43].

The term $\theta \grave{S}_{j,t}$ is vectors of climate anomalies for farm j at time, t-four seasons, S=1,2,3, & 4. The four-season model provides better out-off sample forecasts than the one season [e.g. annual] model [44]. We included it to analyze short-run and seasonal effects.

2.2 Empirical Model

Climate change would induce net-negative and significant impact on smallholder agriculture [45;38]. To verify this argument, the Ricardian model [RM] was used as a modified empirical model. The model was devised by David Ricardo (1817) to examine the long-run impacts of climate change on agriculture [46;47;39]. Initially, Ricardo assumed that land rent or land value reflects the productivity of agriculture [46]. Later on, the model was relaxed by scholars [42;46; 47] to account environmental changes. The model [i] focuses on farm-level; [ii] assumes constant price; and [iii] augments technological changes [48;8;9;30].

The RM is preferred over general equilibrium models [50] in that it is flexible to augment context-specific factors such as changes in technology, adaption, agronomic practices [49;17] and has widely used in climate impact analysis. Contrarily, the model is criticized for assuming fixed price under changing socioeconomic circumstances [48].

Innovatively, its integrated climate-socioeconomic panel data, comprised crop and livestock production, and captured the individual, spatial and temporal effects in the model. Smallholder farmers are rational and price takers, yet allocate their land to maximize return given climate state. Hence, farmers choose the level of inputs and output that yield maximum return. Given these assumptions, net-farm value (V) from agricultural production under climate change [46] can be estimated by the Ricardian model with an integral:

$$V = \int_{t}^{\infty} [\sum_{i=m}^{n} PQ(X,G,Z) - M'X]\, e^{-\varphi t_{dt}} \ldots \ldots . \ldots \ldots (9)$$

Where, P is vector of exogenous market price per unit of output, Q; X is a vector of purchased inputs except land, M is vector of input prices; t is time; φ is a relevant discount rate (rate of yield growth); i is summation of row vectors, m and column vectors, n.

By replacing terms, Q in equation [8] by V in equation [9] and taking the natural logarithm of V, the linear relationship between farm value and climate change can be created. In our case, land value was proxied by three outcome variables: net crop revenue [NCR], net-livestock revenue [NLSR], & net-agricultural revenue [NFR]. Again, V is computed by deducting mean outcome at BAU from its value at CC [CC_1-CC_0]. The BAU denotes the historical [1960-2019], and current [2011-2016] climate means. While CC_0 shows the mean climate values at BAU, the CC_1 is observations lies ± 1.5 from their means at BAU. However, various transformations such as logarithm were made for statistical conformity.

The utility of farming households given climate change can be estimated through adopting the modified Ricardian panel model with regression equation:

$$\ln V_{itj} = \alpha + \beta lnV_{ijt-1} + \theta \grave{ESS}_{H_{ijt}} + \delta G_{H_{ij}} + \gamma Z_{ijt} + \omega U_{i,t} .. (10)$$

Where, lnV_{it} is natural logarithm of farm value, V_{ijt-1} is the lagged value of the farm, ESS_H is wave-specific historical climate, $G_{H_{ij}}$ is the longtime historical climate means.

The reference period [1960-2019] which represents the business as usual [BAU] scenarios. The mean deviations for historical climate were computed by deducting wave-specific real climate means from the historical means. Equation 10 captures the impact of historical climate and its shocks on farm return. The short-run impacts of climate were measured by deriving ESS wave-specific climate [real climate] means for the historical and real mean values during the survey periods 2011-2016. Thus, *the current impact of climate* was estimated thru running panel regression equation:

$$\ln V_{itj} = \alpha + \beta lnV_{ijt-1} + \theta \grave{S}_{C_{ijt}} + \delta G_{C_{ij}} + \gamma Z_{ijt} + \omega U_{i,t} \ldots (11)$$

Where, S_C *and* G_C respectively indicates the current and historical climate means for the first three ESS waves citrus paribus. Depending on estimation techniques, climate shocks and their squared values were included to estimate the marginal effects. Operationally, climate shocks are mean climate deviations from respective BAU scenario.

Likewise, the *seasonal impacts of climate* were estimated by computing and augmenting seasonal climate means and their deviations from respective references values [see equation 11]. The seasonal climate means and their deviations were calculated by subtracting each of the four historic seasonal climate means from the real climate means [2011-16]. This was made to examine the effect of seasonality on farm utility. Explicitly, the seasonal impacts of climate variability were measured via the modified panel regression equation:

$$\ln V_{itj} = \alpha + \beta lnV_{ijt-1} + \theta \grave{S'}_{s_{ijt}} + \delta G_{s_{ij}} + \gamma Z_{ijt} + \omega U_{i,t} .. (12)$$

Where, S_s &G_s respectively are the seasonal climate shocks for S_1, S_2, S_3, and S_4 ct. paribus. Both seasonal shocks[s] & their squared values [s^2] were used to find the marginal effects.

A series of modeling processes were undertaken [11;12] such as aggregation, disaggregation, linear and non-linear transformation, computing dummies and indices mainly for climate variables and other covariates as innovative and objective transformation process.

2.3 Estimation Methods

Depending on model specifications, panel data can be pooled, fixed, random effects model, and dynamic models [39; 48; 49]. Here, the random effects model was used through OLS and GLS techniques. As merit, panel model integrates both fixed and random effects [42]. Panel models are more efficient and consistent than cross-sectional and time series methods [43]. Satisfying the classical assumptions [endogeneity, heterogeneity, Hausman test] proves statistical proof. The correlation between and within effects of covariates [$X_{i,} Z_i$] and Regressand [y_{it}] with error terms [U_{it}] and lagged regressand [y_{it-1}], shows as which method is best to apply.

Pooled model [PM] simply merges samples together in which individual or time variations [50; 7;11;27] are not allowed; in fixed effects model [FE] the unobservable effects are correlated with observable variables; often endogeneity omit estimates and limit efficiency; so, both PM and FE were not best model in our case [51]. The random effects model [RE] assumes that the between panel differences & within panel errors are caused randomly, and we can estimate coefficients from a distribution with constant parameters. The between transformation-induced RE panel regression equation would be:

$$lny_{it} = \alpha + \beta lny_{it-1} + \theta' X_{it} + \delta G_i + \dot{\delta} G_{di} + \gamma Z_{it} + \dot{\gamma} Z_{di} + \omega U_{it} \text{...} \; [13]$$

In this case, OLS can estimates parameters [$\alpha, \delta, \theta, \beta, \gamma$]consistently, but GLS is more efficient. Mainly the random model assumes absence of correlation within individuals and between panels or errors are caused only randomly. The robust model [RoM] is used when the within panel dependence is assumed [52; 11;17]. Technically robust model is related to random effects model. Hence, equation [14] is our basic panel regression equation. However, relevant statistical tests were made before running the models as explained above.

2.4 The Data

Mainly nation-wide observatory climate data [1960-2019] and the first three waves of the Ethiopian socioeconomic survey-ESS (2011-2016) panel data were used in this study.

The Climate Data: assumed precipitation (millimeter) and temperature (degree Celsius)]. The long-term [60 year] nation-wide station-based monthly precipitation and temperature data [1960-2019] was obtained from national meteorological service agency [53] of Ethiopia; then classified, processed, validated and used for analysis. Temporally, the data was divided into historical (1960-2010), real (2011-2016) and seasonal [quarter-based] climate data. This large data was merged with ESS panel data at woreda, zonal, regional and national levels. The intensive data merging process used geo-referenced coordinates which was included in ESS. Although all level climate values were calculated, for more representativeness woreda-level data was used for analysis. The nearest station data was assumed for each sample HHs. The mean and its deviations were computed for the annual, quarter & monthly figures one-to-one for the historic, current, and seasonal impacts.

The historical climate data took the long-run annual mean precipitation and temperature; the real climate data used three annual means for the same variables which are consistent with the first 3-ESS [2011/12, 2013/14, 2015/16] periods. The mean historical climate [PH, TH], current climate [PC, TC] & seasonal climate [PS, TS] were calculated and included in the model.

Moreover, the current climate means were computed the historical climate [PH1, PH2, PH3 and TH1, TH2, TH3] for BAU, real climate [PC1, PC2, PC3, TC1, TC2, TC3] and seasonal climate [PS1, PS2, PS3, TS1, TS2, TS3] respectively for the first, second & third ESS. Their respective mean climate deviation [PC_PH, TC_TH, Pw1_CP Pw2_CP Pw3_CP Tw1_CT Tw2_CT Tw3_CT]; joint dummies [dPT_HC, dPT_RC] and indices [IPT_HC, IPT_RC] were computed. Hence, the historical, current, seasonal climate and their deviations were used to estimate the past, current, and seasonal impact analysis in that order.

The Socioeconomic Data: The Ethiopian Socioeconomic Survey-ESS (2011-2016) panel data was used as main data. The first three waves [ESS1, ESS2, and ESS3] of ESS were used after a series of data processing. It is a living standards measurement study-integrated surveys on agriculture and was collected through joint project between the World Bank and CSA [54]. ESS is national representative and geo-referenced panel data involving comprehensive socioeconomic, climate and institutional data. The ESS involves three broad datasets-the household data, the agriculture data and community data. Also, institutions, strategies, policies & livelihood patterns were included.

The survey covered nine regional states of Ethiopia, namely Amhara, Oromia, SNNP, Tigray, Afar, Benishangul Gumuz, Gambella, Harari, and Somali region; Addis Ababa, and Dire Dawa. Up to date, it was conducted four times: the ESS_1 in 2011/12, the ESS_2 in 2013/14, the ESS_3 in 2015/16 and the ESS_4 was in 2018/19. But, ESS_4 was not included in the analysis as it was collected after data processing was started on earlier waves.

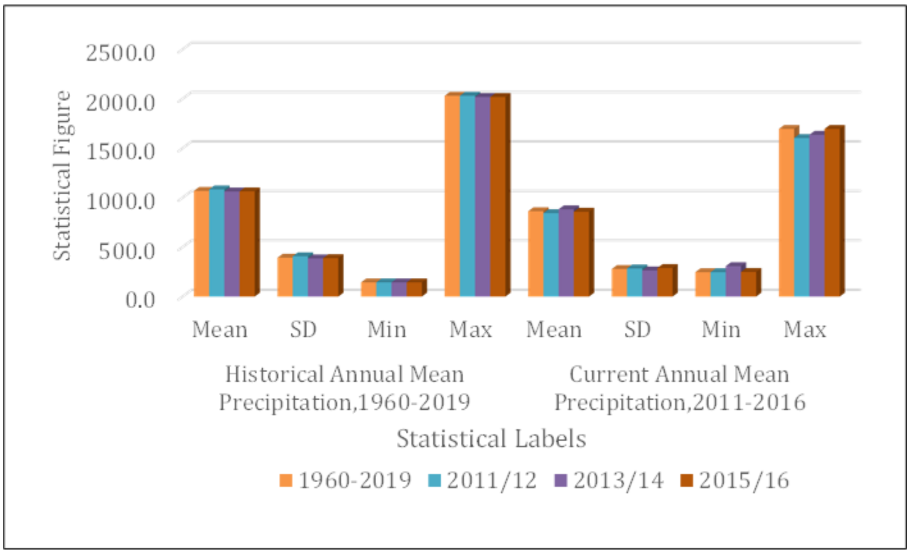
The ESS used multistage stratified sampling based on administrative regions, enumeration areas (EA) and households (HHs). It used regions as strata, selected EAs and HHs in two-stages. The number of EAs rose from 333 (3,969 HHs) in ESS1 to 433 (5,262 HHs) in ESS3. Starting from ESS2, 290, 43, and 100 EAs were included from rural areas, small towns, and urban areas. The total sample HHs included in 3-ESS waves were about 14,333.

2.5 Model Fitness Test

Before running regressions, model adequacy tests such as the Breusch_Pagan test; Hausman test, and multicriticality tests [55; 7; 49] were conducted and verified model fitness for analysis. Then, net-farm revenue [NFR, NCR, and NLSR] was regressed against the exogeneous climate change [variable of interest]; the lagged NFR, endogenous socioeconomic covariates and dummies [control variables] via Ricardian panel model induced Random effects method was used.

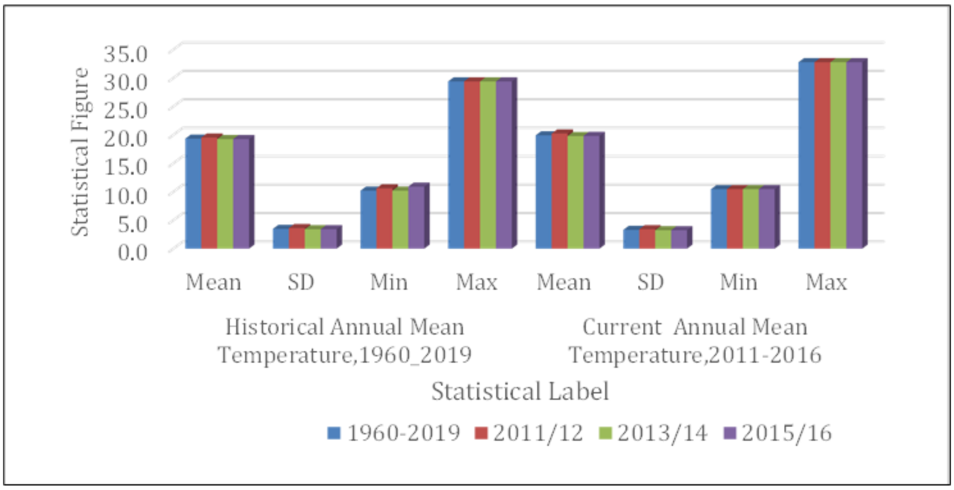
3 Results and discussion

The household-level results were analyzed using the integrated ESS panel data and 60 years station-based national climate data [precipitation and temperature]. Consequently, the results were presented and analyzed starting from descriptive and regression outputs as follows.



Source: Drawn from NMA, 2019[53]

Table 1 Precipitation[mm] Trends in Ethiopia,1960-2019



Source: Drawn from NMA, 2019[53]

Table 2 Temperature [10 °C] Trends in Ethiopia,1960-2019

Precipitation Trends in Ethiopia: figure 1 shows the historical [1960-2019] and the real [2011-2016] annual mean precipitation across Ethiopia. Exactly, the statistic covers representative samples across the nation. The historical, minimum & maximum annual mean precipitation was 1069mm, 144mm and 2031 in that order. The same statistics for real precipitation was 863.5mm, 247mm, and 1696mm. The real rainfall falls below the past mean.

Temperature Trends in Ethiopia: again figur***e*** 2 displays the historical and the real annual mean temperature [℃] across the nation. The statistic shows ESS woredas across Ethiopia. Thus, the historical mean, minimum and maximum annual temperature were 19.3℃, 10.2℃nd 29.4℃ one-to-one. Consistent means for the current temperature were 19.9℃, 10.5℃, 32.8℃ in that order. The real temperature was higher than its historical value; this implies that the current period involved more adverse states than past periods had. Plainly, the current climate exhibited drier rainfall and hotter temperature than its historical cases.

Table 1 Distribution of Precipitation [mm] by Regional States of Ethiopia

Region	Historical Annual Mean Precipitation [1960-2019]				Real Annual Mean Precipitation [2011- 2016]			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Tigray	679.3	104.1	520	958	667.0	230.8	352	1226
Afar	383.0	276.1	144	1061	449.7	142.4	287	678
Amhara	1170.9	275.1	711	1962	829.4	225.3	522	1497
Oromia	1220.5	394.8	552	2031	925.2	282.6	367	1590
Somalie	568.7	139.9	246	774	532.3	160.5	249	795
Ben.Gumuz	1366.5	245.2	1096	1846	1207.4	137.2	921	1465
SNNP	1293.0	314.0	264	2006	1020.3	202.5	247	1696
Gambella	1220.2	228.2	846	1918	1283.2	203.0	801	1565
Harari	720.1	41.4	622	803	757.7	27.1	712	803
Addis Ababa	1116.2	53.6	952	1165	874.0	37.0	766	935
Dire-Dawa	693.3	83.3	550	970	689.1	43.0	615	800
National	*1069.3*	*393.2*	*144.0*	*2031*	*863.5*	*279.3*	*247*	*1696*

Source: Author form NMA, 2019 [53]

Table 2 Distribution of Temperature [0c] by Regional States of Ethiopia

Region	Historical Annual Temperature [1960-2019]				Real Annual Temperature [2011-2016]			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Tigray	20.0	3.6	11.7	28.5	20.1	2.9	14	28.8
Afar	26.9	2.1	20.9	28.9	27.8	2.1	22	30
Amhara	17.9	3.2	10.2	28	18.3	2.0	13	28.3
Oromia	18.0	2.5	11.3	24.5	18.4	2.0	12	22.8
Somalie	22.2	2.8	17.5	29.4	24.2	2.3	20	29.4
Ben.Gumuz	22.3	1.6	18.8	26.2	22.7	1.4	21	26.8
SNNP	18.7	2.3	11.3	28.6	19.8	2.2	10	30.5
Gambella	24.8	3.1	16.9	27.7	26.7	3.6	19	32.8
Harari	19.5	1.6	17.3	22.6	19.3	0.0	19	19.3
Addis Ababa	16.3	1.0	14.5	18.7	15.8	0.6	13	16
Dire Dawa	22.6	2.1	16.4	25.1	22.8	0.0	23	22.8
National	19.3	3.5	10.2	29.4	19.9	3.3	10	32.8

Source: Author form NMA 2019[53]

Distribution of Climate Trends by Regions: the distribution of climate state across regions may involve physical effects on production and related effects. Table 1 shows the distribution of historical and real precipitation [mm] in eleven regional states of Ethiopia.

The mean precipitation decreased from 1069.3 mm in1990-2019 to 863.5mm during the ESS. The minimum rainfall was 144mm [historical] and 279mm [real]. The maximum [max] historical mean precipitation and the real mean precipitation was 2031mm and 1696mm in that order. Table 2 shows the historical [1990-2019] and the actual [2011-2016] temperature trends across Ethiopia. Therefore, the historical and real mean temperature in Ethiopia was 19.3^{0C} and 19.9℃.

The min and max mean for past temp was 10.2℃ and 29.4℃; while the real value for the same variables were 10℃ and 32.8℃ respectively. In sum, the current temperature trends above the historical values across nine regional levels and hence, similar impacts are expected.

3.1 Descriptive Results

Summary of descriptive results on basic variables were shown on table 3 and described. The mean cereal product was about 12.7 quintal per hectare during ESS. Respectively the net-crop and farm revenues were birr 18,712; and birr 22,696. The mean age of HHs heads was 45 years, the mean year of family schooling is 12 years; family size and labor were 5 and 2.5 respectively. The land and oxen were among the main factors of production.

Table 3 Descriptive Statistics of Sample Households [N=14,333] across Ethiopia

Variable	Unit	Mean			
		ESS	**ESS_1**	**ESS_2**	**ESS_3**
Cereal Yield	Quintal/ha	12.7	13.4	12.8	12.4
Cereal Sale	Birr	1,169.5	1,313.7	820.8	1,737.7
Livestock Value	TLU	4.9	5.1	5.0	4.7
Livestock sales	Birr/year	3,405.7	3,493.4	3,556.3	3,209.5
Net-crop Revenue	Birr/year	18,712.1	15,843.9	18,820.5	20,085.1
Net-Farm Revenue	Birr/year	22,695.9	18,510.1	24,015.3	23,385.6
Net-agri. Income	Birr/year	33,434.7	2,3693.0	33,362.2	37,927.6
Age	Year	44.9	44.0	44.2	46.4
Education	Year	12.1	8.6	13.1	13.9
Labour Force	Number	2.5	2.4	2.6	2.6
Family Size	Number	5.2	4.8	5.0	5.6
Land	Hectare	1.0	1.0	1.0	1.1
Oxen	Number	0.8	0.9	0.8	0.8

Source: Estimated by Author, 2022

Factor Elasticity in Agricultural Production given CC*:* factor responses to farm output was observed given the historical climate [BAU] states across Ethiopia. We used it to detect factor contribution. The proxy outcomes were CPV-crop production value [quintal/ha], LSPV-Livestock production value [TLU], and MPV-mixed farm production value [Birr]. For improved precision, the historical climate mean was divided into means of survey waves: ESS, ESS_1, ESS_2, and ESS_3. Among the ESS periods, ESS_3 was the year in which sever CC was occurred and about 14 million people was affected. Factor elasticity was estimated against farm values by allowing farm-driven variation via random effects method. Spatial-heterogeneity & methodical similarity was assumed.

Table 4 summarizes the factor elasticities under typical climate conditions. The classical factors have inverse relation to output given CC. A typical climate has reduced, reversed or delayed factor contribution. Age, education, land, labor, oxen, irrigation, adaptation and slope had affected output. During ESS_3, land, labor, oxen, age and education had negative effect. The institutional factors had mild or negative effects overtime and exclusive effects during extreme periods. During ESS 1% rise in age, education, labor, land, oxen, irrigation, adaptation, slope, & institutions rose MPV at 4%; 11%; 9%;1%; 3.1%;15%;17%; 4.3%; & 2.1%. During ESS3, a 1% change of the variables affected MPV at-3%; -13.4%; -5%; -8%; -5.1%;10.6%; 11.2%; -2.9%; &-2.2%. Unlike others, irrigation [≈11%] & adaptation [11%] had positive effect.

The estimates indicated that factor elasticity kept positive for major covariates during the BAU, but it had negative response on MPV during ESS3. As hypothesized, age and education of HHs [i.e. entrepreneurial skill]; labor; land; oxen [capital] and institutions [rules of the game] revealed negative and significant impact. An increase in age by 1 percent reduces output but by smaller proportion [inelastic to MPV]. A 1% rise in land size diminishes output by nearly equal [8%] but smaller rate under CC. That is the damage caused by CC increases with the size of farm land. Technically, the result signals that CC involves progressive impact wrt. land size. The inverse response institutions may signify use of less suitable or expensive or untimely actions. Therefore, CC imposed a negative effect on MPV relative to regional states, shock periods, and farm types with different levels of significance.

Unlike prior assumption, institutions responded negatively to CC primarily during the ESS3. This result could provide context-specific evidences in that during 2015-16 neither state nor non-state actors nor HHs took pertinent response initiatives. There was little innovative and applied climate smart agricultural schemes, policies, resources, technologies, finance, info, and other special services were given. In simple terms, most of the efforts were traditional which hardly responds to the emerging climatic risks. Besides the orthodox factors, time, region, and farm dummies had negative effects on output. Climatic shocks reduced factor elasticities or increase factor costs, and hence declined output and related benefits. Temporally, the impact of climate was rising overtime with little variation. Shocks poses a negative and significant impact. The results imply that inputs have shown an inverse and large effects on farm values under climate extremes. Climate risk put net-negative effect on factor elasticity [labor, land, capital, experience] and net-farm revenue.

While the long-term climate [BAU] shown mixed impacts in magnitude and direction, the climate shocks mainly involved negative & significant impacts on output. Trends of climate shocks better explains the impact state than the BAU does. Such info provides insight that enable climate response scheme. Generally, climate change affects the supply & productivity of inputs negatively viz. labor, land, capital, and expertise. The above results are consistent with some empirical works [56;6; 23;24;25;27;28; 29; 41]. Therefore, climate change negative impact on factor elasticity which reduces the productive capacity, productivity and return.

Historical Impacts of Climate Change on net-farm revenue [NFR]: examines the long-term impacts of climate on the value of agricultural production. The three farm-specific outcomes were net-crop revenue [NCR], net-livestock revenue [NLSR], and net-farm revenue [NFR] both were in ETB. Having adopted production-induced Ricardian panel model, net impacts of CC on affected HHs was presented in table 5 and analyzed thereafter. Serially, the historical climate & its shocks had a rising impact. The rate of growth of NFR was diverging overtime. This term was proxied by the first lag of outcome variable-L. dv [NCR, NLSR, & NFR].

As indicated in the first row of table 4, the sign of all coefficients was positive, which implies divergence of output growth in the long-run. Unlike normal condition, the rate of growth of agricultural value [NFR] among HHs was declining overtime compared with the steady state level. In our case, the rate of NFR growth was diverging at 2.6%, 3.2%, 2.2% & 4.1% one-to-one during ESS, ESS1, and ESS2 & ESS3. I.e. CC was reducing the amount, utility & productive capacity of farms both further declining both the current & future production and related gains. Such incidences further rise inequality among households & so deteriorate their livelihoods.

In general, the values of BAU, erratic periods, and shocks respectively had a positive, negative, & negative impacts on NFR. The historical-BAU [PH, TH] had positive & significant impact on net return. But the historical climate [PH3 & TH3] during ESS3 & the mean shocks [CP_HP & CT_HT] intricate a negative and significant effect. For example, a 1% rise in BAU rainfall increased NFR at 0.02% ,0.03%, 0.031%; the erratic periods' rainfall affected NFR at 0.55%, 0.5%, 0.6% & 0.8%; & shocks of the same variable reduced NFR at 0.4%, 0.7%, 0.6%, & 0.8% during ESS, ESS1, ESS2 and ESS3. The joint impacts of CC on NFR was estimated at 5%, 4%, 5%, and 6% during the study period.

Similarly, a 1% rise in historical temp [TH], the irregular temp [ESS3]; and its shocks [CT_HT] increased the NFR at 3%, 8.3%, and 0.7 % in that order. A 1 % increase in BAU temp affected the NFR at 2.7 %, 2.8%, 2.9 %, & -3 % during ESS, ESS1, ESS2 & ESS3; but the historical temp shocks declined NFR at 0.5%, 0.6%, 0.6%, and 7% during the same period. Largely, these results indicate that both the historical, irregular periods' and shocks significantly affecting farm return at different directions. While the historical climate had positive impact, all the rest parameters shown negative impacts. These results confirmed the existing empirical evidences [57; 5; 23;26; 45].

Table 4 Factor Elasticity in Smallholder Agricultural Production among HHs Given Climate Change in Ethiopia

Variables	***CPV-Crop Production [Qtl /ha]***				***LSPV-Livestock Production [TLU]***				***MPV-Mixed Production [Birr/HH]***			
	ESS	**ESS_1**	**ESS_2**	**ESS_3**	**ESS**	**ESS_1**	**ESS_2**	**ESS_3**	**ESS**	**ESS_1**	**ESS_2**	**ESS_3**
Sex_hd	0.034***	0.014**	0.034***	0.029***	0.038***	0.0189***	0.031***	0.041***	0.033**	-0.010	-0.09	0.012**
Age_hd	-0.10***	-0.06***	-0.6***	-0.08***	-0.10***	0.02	-0.01	-0.03**	0.04**	0.03*	0.01	-0.03**
Edu_hd	0.034***	0.0164***	0.039***	-0.22**	.0305***	0.057	0.0205***	-0.127**	0.11***	0.106*	0.096**	-0.134***
Labor	0.10**	0.03*	0.01*	-0.12**	0.10***	0.02***	0.03***	-0.03***	0.09***	0.085*	0.8***	-0.05***
Land	0.018**	0.015*	-0.029*	-0.11**	0.001*	0.168***	0.122***	-0.125***	0.10**	0.079*	0.021*	-0.08**
Oxen	.044***	0.03**	0.034***	-0.01***	0.02**	0.04*	0.011*	-0.04**	0.031***	0.038***	0.086***	-0.051***
Irrigation	0.16***	0.14***	0.151***	0.13***	0.14**	0.134**	0.141**	0.140***	0.15***	0.135***	0.15***	0.106***
Adaptation	0.18***	0.12***	0.137***	0.134***	0.162***	0.140***	0.144***	0.138***	0.17***	0.12***	0.14***	0.112***
Slope	0.0210**	0.013**	0.020**	0.028**	-0.020**	-0.008	0-.034**	-0.043**	0.043**	0.032**	0.052**	-0.029**
Institution	0.023**	0.026**	-0.012**	-0.035***	0.020***	0.004**	0.032***	-0.025***	0.021**	0.032**	-0.041**	-0.022***
PH_BAU	0.05**	0.016*	0.025***	-0.255***	0.0152**	0.017	-0.016***	-0.098***	-0.08**	0.019	-0.0285*	-0.083**
TH_BAU	0.002**	-0.001*	-0.005	-0.006***	0.002**	0.006	0.007	-0.008**	-0.006**	-0.004**	-0.004*	0.002*
SP_BAU	-0.062**	0.051*	-0.018**	-0.110**	-0.035**	0.289***	-0.185***	-0.007***	-.234***	-.187**	-0.285***	-0.127***
ST_BAU	-0.003***	0.007*	-0.005*	-0.035**	-0.003***	0.004***	-0.004*	0.002**	.0015***	.002**	-0.0043**	-0.002***
time	-0.025*	0.011	-0.040**	-0.038**	-0.025*	0.010	-0.002*	-0.018**	-.004*	.0015*	0.006*	-0.0059**
farm	-0.021**	0.024**	0.091**	-0.025**	-0.029*	0.056***	0.043***	0.049***	.152***	-.06*	0.129***	0.183***
region	-0.045***	-0.042***	-0.05***	-0.072***	-0.053***	0.028**	0.013	0.021	-.050***	-.026**	-0.035***	-0.051***
_cons	2.585***	3.333***	2.712*	-1.325***	2.60***	-1.448***	-1.25***	-2.66***	6.622***	6.44***	7.016***	-6.65***

*** denotes 1% significance level; ** denotes 5% significance level; and * denotes 10% significance level. Source: Estimated by Author, 2022

Current Impacts of Climate Change on NFR: measures the impact of real CC on net-farm value. The real climate denotes the observed climate state during the ESS. Roughly, both the real BAU, erratic periods', and shocks singly had a positive, negative and negative impacts. Similar to the historical climate, real climate revealed divergence against the 1st lag outcome but has higher levels of significance than the historical case. Both the real precipitation and temperature have largely shown negative impact on net-farm values.

The rate of growth of divergence term at steady state were 2.9%, 2.7%, 2.6%, & 3.1% serially during ESS, ESS1, ESS2 and ESS3. This shows the widening of income inequality among HHs. A 1% increase in real rainfall reduced NFR at 0.5%, 0.4%, 0.5%, and 0.9%%; and that of real temperature reduced NFR at 3.2 %, 3.1%, 3.2 %, & 3.4% during the same period. Relatively the real climate has negative and greater impact than its historical counterpart. The combined impacts of real climate shocks have declined NFR at 8.5%, 7.7%, 8.4%, and 8.9% within the stated periods. Also, the joint index of the historical and real climate [IPT_HC & IPT_RC] climate shocks had shown negative and significant impact but at different rates. The above findings indicated that the historical, irregular periods' and shocks were significantly affecting NFR from different directions. The historical climate had a positive impact, & current extreme & shocks shown negative impacts.

The long-term, short-term and seasonal anomalies show an increasing effect on net-farm return. That is the impact severity declines with time length considered. On average, the shorter the time period, the higher the impact would be and vice versa. In other words, the longer the time length, the smaller the magnitude of climatic impacts and vice versa. Conceptually, the result is consistent with some empirical [58; 7; 23; 48;49; 52; 55] findings. As conclusion, CC poses a regressive duration impact overtime, mixed spatial, farm, and HHs effects against net-farm values.

Seasonal Impacts of Climate Change on NFR: assessed the historical and current seasonal climate variability revealed a negative net-farm return [NCR, NLSR & NFR]. While past BAU estimates had shown mixed impact [positive-normal and negative-shock periods]; the current BAU statistics have a larger negative effect. In table 6, the BAU precipitation and temperature serially had a significant & non-significant response; yet the real precipitation & temperature presumed negative & significant effect. Among four major seasons, the first [summer] & the fourth [spring] seasons had negative effect on net-farm return. While summer season covers months from June to August; spring season contains March to May. Under normal case, summer and autumn seasons are the highest rainy seasons in Ethiopia; but the spring season has occasional showers. Change in climate during these seasons determine crop and livestock production, its return & the farming livelihoods. Since Ethiopia is located in the tropical zone lying between the equator and the tropic of cancer, these [1&4] seasons are vital for farming livelihoods. The result confirms some [58;33;50] evidences.

Table 5 Historical and Current Impacts of Climate Change on Agricultural Production [Net-Farm Revenue] among HHs

Variables	NCR [Net Crop Revenue]				NLSR [Net Livestock Revenue]				NFR [Net-Farm Revenue]			
	ESS	ESS_1	ESS_2	ESS_3	ESS	ESS_1	ESS_2	ESS_3	ESS	ESS_1	ESS_2	ESS_3
The Historical Impacts												
L. dv	0.038***	0.035***	.034***	0.032***	0.046***	0.042***	0.043***	0.035***	0.026***	0.032**	0.022**	0.041**
PH	0.0002**	-0.0002*	0.001**	-0.03**	0.0001***	0.003**	0.002*	-0.0002*	0.002**	0.003***	0.0031***	0.0024***
TH	0.056***	0.055***	0.0148	0.023**	0.017**	0.015	0.055***	0.055***	0.027**	0.028***	0.029***	-0.030***
PH1	0.006***	0.006***	0.006***	0.005	0.005***	0.006***	0.006***	0.006***	0.006	0.001	0.008	0.001
TH1	0.0003	-0.005	0.091***	.025**	.091*	0.091***	-0.005	-0.005	0.021**	0.026	0.026	0.026
PH2	-0.005*	-0.005	-0.015***	-0.05**	-0.014**	-0.015***	-0.005*	-0.005	-0.004	-0.004	-0.004	-0.004
TH2	-0.112	-0.092	-0.198**	-0.166**	-0.243**	-0.198**	-0.092	-0.092	-0.154**	-0.163**	-0.163***	-0.163**
PH3	-0.002**	-0.002**	-0.003**	-0.053**	-0.003***	-0.003**	-0.025**	-0.002**	-0.0055**	-0.005**	-0.006**	-0.008**
TH3	-0.077*	-0.063*	0.113**	-0.091**	0.1612*	-0.113*	-0.063*	-0.063*	-0.080**	-0.075	-0.082**	-0.083
CP_HP	-0.003**	-0.003***	-0.001***	-0.06***	-0.001**	-0.001**	-0.003***	-0.003***	-0.004***	-0.007**	-0.006***	-0.008**
CT_HT	-0.024*	-0.02**	-0.001	-0.004	-0.0027*	-0.00**	-0.021**	-0.02**	-.005**	-0.006**	-0.006**	-0.007**
IPT_HC	-0.05**	-0.03***	-0.04***	-0.07***	-0.045**	-0.02**	-0.03***	-0.05***	-0.05***	-0.04**	-0.05***	-0.06**
The Current Impacts												
L.dv	0.046***	0.038***	0.038***	0.045***	0.059***	0.046***	0.046***	0.038***	0.029***	0.027**	0.026**	0.031**
PC	-0.002***	-0.002***	-0.002***	-0.093**	-0.003***	-0.004***	-0.004***	-0.002***	-0.005**	-0.004**	-0.005**	-0.009**
TC	-0.077**	-0.078***	-0.078***	-0.047***	0.015**	0.0078	-0.008**	-0.078***	-0.032***	-0.031***	-0.032***	-0.034***
Pw1_CP	0.002***	-0.002***	0.002**	-0.003***	-0.002***	0.001	-0.002**	-0.002***	0.001***	-0.001**	-0.001**	-0.001**
Pw2_CP	0.002***	-0.002***	0.002**	0.004***	-0.002***	0.003***	-0.002***	-0.002***	0.003***	0.003***	0.003***	0.003***
Pw3_CP	-0.002***	-0.002***	-0.003***	-0.003***	-0.002***	-0.001***	-0.002***	-0.002***	-0.001***	-0.009***	-0.006***	-0.009***
Tw1_CT	-0.100***	-0.046**	-0.098***	0.001	-0.037***	0.012	-0.046**	-0.046**	0.01	0.012	0.011	0.012
Tw2_CT	-0.078***	-0.024	-0.082***	0.034***	-0.013	0.042***	-0.024	-0.024	0.042***	0.042***	0.042***	0.042***
Tw3_CT	-0.014*	-0.033	-0.018	0-.056***	-0.025***	0.044***	-0.033	-0.033	-0.046***	-0.044***	-0.043***	-0.044***
IPT_RC	-0.085**	-0.066***	-0.084***	-0.098***	0.0835**	0.061	-0.079**	-0.087***	-0.085***	-0.077***	-0.084***	-0.089***

*** denotes 1% significance level; ** denotes 5% significance level; and * denotes 10% significance level. Source: Estimated by Author, 2022

Table 6 Seasonal Impact of Climate Change on Smallholder Agricultural Production [Net-Farm Revenue] among HHs

Variables	ESS			ESS1			ESS2			ESS3		
	NCR	**NLSR**	**NAGR**	**NCR**	**NLSR**	**NAGR**	**NCR**	**NLSR**	**NAGR**	**NCR**	**NLSR**	**NAGR**
The Historical Impact												
L1.	0.032***	0.031***	0.024***	0.032***	0.046***	0.024***	0.031***	0.045***	0.024**	0.032***	0.045***	0.021***
PH_BAU	0.0025**	-0.003***	-0.005***	-0.006***	-0.0003	0.002**	-0.003***	-0.003***	0.003***	-0.006***	-0.002***	-0.006***
TH_BAU	0.047***	0.034***	-0.031**	-0.060**	0.020***	0.024***	0.034***	0.018**	0.025**	-0.060**	-0.014**	-0.004**
PH_ Wi	-0.013**	-0.009***	-0.006***	0.015***	-0.002**	-0.003**	-0.009***	-0.003***	-0.004**	0.015***	-0.001***	-0.006***
PHS1_Wi	-0.007***	-0.002***	-0.0025**	0.011**	-0.0003	0.001**	-0.002***	-0.0008**	-0.001**	0.011**	-0.001**	-0.0035**
PHS2_Wi	-0.003**	0.010***	0.006**	0.004	0.0006	-0.0003	0.010***	0.006	-0.004**	0.004	0.001	0.006**
PHS3_Wi	-0.004***	0.006***	-0.0003	-0.002**	-0.0005	0.001	0.006***	0.0008	0.003***	-0.002**	0.001	-0.0003
PHS4_Wi	-0.008**	0.008***	-0.003**	-0.0014**	-0.002***	-0.001***	0.008***	0.0003	-0.002**	-0.0014**	-0.001**	-0.004**
TH_Wi	0.021**	-0.158***	-0.0048***	-0.024***	-0.049	-0.004**	-0.158***	-0.045**	-0.0025***	-0.024***	-0.051***	-0.0048***
THS1_Wi	0.057	-0.054*	-0.0325**	-0.011**	0.035	-0.021	-0.054*	0.023	0.009	-0.011**	-0.036**	-0.0425**
THS2_Wi	0.129***	0.117***	-0.037	-0.222***	0.01	-0.006	0.117***	0.019	0.01	-0.222***	-0.009	-0.037
THS3_Wi	-0.168***	0.016	-0.066*	-0.031	0.002	-0.002	0.016	-0.009	-0.007	-0.031	-0.047	-0.066*
THS4_Wi	-0.056	0.048*	-0.05**	-0.018**	-0.0002	-0.041**	0.048*	0.008	-0.03	-0.018**	-0.031**	-0.06**
The Current Impact												
L1.	0.033***	0.032***	0.025***	0.034***	0.055***	0.024***	0.032***	0.046***	0.027***	0.034***	0.047***	0.034***
PC_ Wi	-0.005**	-0.008***	-0.055***	-0.005***	-0.003***	-0.026***	-0.008***	-0.001**	-0.032**	-0.005***	-0.004**	-0.06***
PCS1_Wi	-0.006***	-0.002***	-0.06***	-0.0015***	-0.0003**	-0.0005**	-0.002***	-0.0007**	-0.001**	-0.0015***	-0.0025***	-0.06***
PCS2_Wi	-0.006***	0.01	-0.003*	0.007***	-0.003***	0.006***	0.01	0.001	-0.003**	0.007***	0.0005	-0.003*
PCS3_Wi	0.0045***	0.006***	-0.003***	0.002**	-0.0007	0.0025***	0.006***	0.0008*	0.003***	0.002**	-0.0007*	-0.003***
PCS4_Wi	-0.0013**	-0.007***	-0.055***	-0.001***	-0.001***	-0.0007**	-0.007***	-0.0004**	-0.001**	-0.001***	-0.026***	-0.002***
TC_Wi	0.073**	-0.138***	-0.110***	-0.0496**	0.003**	-0.092***	-0.138***	-0.041**	-0.101***	-0.0496**	-0.024**	-0.118***
TCS1_Wi	-0.006**	-0.045*	-0.048***	-0.026***	-0.066***	-0.059***	-0.045*	-0.020*	-0.004**	-0.026***	-0.016***	-0.041***
TCS2_Wi	-0.057*	0.102***	-0.004**	-0.025**	-0.008	-0.078***	0.102***	0.02	0.011	-0.025**	-0.045***	-0.0004**
TCS3_Wi	0.057**	0.01	-0.019	-0.011	-0.057***	0.041***	0.01	-0.008	-0.005	-0.011	-0.005	-0.019
TCS4_Wi	-0.197***	-0.041**	-0.11	-0.052***	-0.015**	-0.111***	-0.041**	-0.09**	-0.003**	-0.052***	-0.008***	-0.050***

*** denotes 1% significance level; ** denotes 5% significance level; and * denotes 10% significance level. Source: Estimated by Author, 2022

In sum, the seasonal variation involves greater impact on farm value than the short-term and the historical climate shocks in that order. Specially, during tESS_3, both the historical and real rainfall and temperature have affected negatively at different levels of significance [5% & 1%].

For specific terms, the positive sign in the first lag of NFR [L1] shows divergence overtime. The growth of lagged outcome was increasing at steady state level, which could widen the inequality among HHs when the cost of climate is increasing overtime. The spillover effects progressively aggravate the initial gap; later on, worsening vulnerability and poverty. Both the historical and real climate shown positive coefficients for all L1; that is even under CC pervious periods' output contributes to the current values and net-returns. Evidently, the BAU climate had affected NFR each 2.4% during the ESS, ESS1 and ESS2; but 2.1% for ESS3.

Mostly seasonal climates negatively affecting NFR mainly during the erratic periods [ESS3]. The historic seasonal precipitation [PHS_BAU] reduced NFR serially at 5% [ESS] & 6% [ESS3], while the historic temperature [THS_BAU] declined NFR at 3.1% [ESS] and 4% [ESS3] serially. The summer historic precipitation affected NFR at -0.25%, 0.1%, -0.1%, and -0.35% in order during ESS & the 3-ESS waves; and the spring historical rainfall declined NFR at 0.3%, 0.1%, 0.2% & 0.4 % during these periods. The corresponding summer temperature had reduced NFR at 3.25%, 2.1%, 0.9% and 4.25%; and that of spring temperature decreased output by 5%, 4.1%, 3%, and 6%. The impact of seasonal climate found to be greater in magnitude than the BAU and real climate risks specially during irregular periods.

Like the historical climate, the real climate has a positive impact on the lagged NFR overtime. The rate of growth of NFR deviation were 2.5%, 2.4%, 2.7%, and 3.4% serially thru ESS, ESS_1, ESS_2 &ESS_3. A 1% change in real climate, mostly involved negative and significant impact on net-farm earrings. The marginal change in real seasonal climate put larger impact on farm-return. The real seasonal precipitation [PCS_W_i] reduced NFR at 5.5%,2.6%,3.2%, and 6%; the real seasonal temperature [TCS_Wi] decreased NFR at 11%,9.2%, 10.1%, and 11.8% during ESS and its waves. The summer and spring climate shocks shown negative effects with variable rate. Summer and spring climate decreased the NFR from 6%-5.5% [perp] and 4.8%-11% [temp] among HHs per year during ESS. Seasonality significantly affects NFR; the summer [S_1] and spring [S_4] seasons involve negative and greater impact than the autumn [S_3] and winter [S_3] seasons do. Increase in rainfall & temperature during dry season's rise NFR the reverse is true for wet seasons (17;19; 30; 44]. In general, CC involves an increasing impacts overtime [future> present> past]; declining effect along time duration [short>medium>long]; fastest, larges, and significant impact during shock periods. These above results are consistent with theoretical and empirical evidences [23;38;39; 44;48;55;56;58;59].

4 Conclusion

Th current study has analyzed the integrated impacts of climate change on agricultural production among smallholder panel HHs across Ethiopia via Ricardian panel model with random effects. As response to the inconclusive empirical evidences, the factor elasticity, the historical, current, and seasonal impacts was analyzed using the representative Ethiopian socioeconomic survey [ESS] panel data; merged with 60 years precipitation & temperature by integrating the temporal, spatial, and unit effects among 14,333 HHs, three-farm types and 11- regional states of Ethiopia.

Climate change impacts agricultural livelihoods thru affecting farm production. It imposes a net-negative, increasing and significant impact on factor elasticity and net-farm revenue impacts; a progressive temporal; regressive duration; mixed regional, farm, HH impacts; and divergence growth effects of net-farm returns. Incessantly, shocks, seasonal, current, and historical climate states put greater impacts on farm values. The joint historical, current and real seasonal climate serially reduces NFR; the summer and spring climate variability reduces NFR. While classical productive factors and institutions show negative sign; adaptation remains positive to farm values. The context-relevant adaptation involves positive impact. The historical, real & seasonal climate induces ever growing impact on factors and farm values.

Therefore, the following recommendations are suggested towards enhancing sustainable agricultural livelihoods:

- Conduct an integrated climate impact assessment which augments both the institutional, socioeconomic, and environmental dimensions grasping the temporal, spatial, and unit-specific factors. Both the historical, current, and seasonal impact inquiries would be an issue of survival yet varied across regions; farms; and households.
- Apply climate smart resource allocation and utilization through joint efforts coordinated among the state and non-state actors to boost productive capacity and maximum gain from farm return.
- Build an integrated agricultural production and development system either to adapt, reduce or reverse the ever-increasing climatic impacts thereby increase production, output and net-revenue.

More generally, the government and people need to institutionalize sustainable livelihoods framework-ISEE through prioritizing the seasonal, current and historical climate shocks in a way that can reduce or reverse the matching risks, maintain production, productivity, and improve welfare overtime even under changing climate system.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors declare that they have no conflicts of interest.

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