



## Article

# The Long-Run Impacts of Temperature and Rainfall on Agricultural Growth in Sub-Saharan Africa

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**Abstract:** Agricultural sector is significant for Sub-Saharan African countries and is highly exposed and sensitive to climate change. This study aims to investigate the overall long-run impacts of temperature and precipitation on agricultural growth in 32 Sub-Saharan African countries. As proposed by Chudik and Pesaran, our estimations are based on augmented autoregressive distributed lag (ARDL) modelling and panel estimators with multifactor error structures. We estimate the “dynamic common correlated long-run effects (DCCE)” through the cross-sectionally augmented distributed lag (CS-DL) approach as well as through the cross-sectionally augmented autoregressive distributed lag (CS-ARDL). For robustness check, we also consider the cross-sectionally augmented error correction method (CS-ECM) and the common dynamic process augmented mean group (AMG). The study suggests that rising temperatures have significantly developed a negative long-term relationship with the agricultural growth in Sub-Saharan Africa. At the same time, the long-run effect of precipitation is less important and not statistically significant in most estimations. According to the CS-DL approach, the negative impact of a 1°C rise in temperature could be as high as a 4.2 to 4.7 percentage point decrease in the agricultural growth rate. The results indicate that the warming climate has considerably damaged the agrarian activities in Sub-Saharan Africa, necessitating adaptive climate measures to avoid any food scarcity or economic stagnation in agricultural driven African countries.

**Keywords:** climate change; agricultural growth; Sub-Saharan Africa; multifactor error structures; cross-section dependence; long-run effects



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## 1. Background

With the rising concerns of global warming, agricultural activities are highly exposed and sensitive to climate change around the world [1,2]. As agricultural activities are vulnerable to variability in temperature, precipitation, and extreme weathers such as droughts and floods, the risk is undertaken by the agricultural sector is significant [3–8]. For developing countries and regions that rely primarily on agricultural production, the risk induced by climate change could be devastating. Being able to quantify the impact of climate change, especially the long-run impact on the agricultural sector, is crucial for taking effective adaption measures for climate change.

For Africa, 95% of the continental land area is in the tropical and subtropical zone, with warm weather and low precipitation. Many of the African countries are least developed

countries relying primarily on agricultural productions, except a few countries such as South Africa and Libya. Agricultural production accounts for 20 to 30% of the gross domestic product and 55% of the export in Africa, and there are more than 21 countries with agricultural production accounting for more than 30% of their gross domestic product (GDP) (World Bank 2007). Therefore, a potential loss in agricultural output may impose progressive burdens on such economies in Africa.

In recent decades, a vast literature provides evidence of climate affecting the economic growth of African countries [1,9–13]. There are relatively few studies on the impacts of changes in temperature and precipitation on agricultural growth in Africa, with existing studies mainly falling into the following two streams. The first branch focuses on the impacts of temperature and precipitation on yields of several selected crops in a few representative African countries [14,15]. In the second stream, the interest is on the effects of temperature and precipitation on the net revenue of a specific country or region [16,17].

However, there are two apparent drawbacks in previous studies. Firstly, the measurement of climate change used is not representative of the place where major agricultural activities take place. In most of the earlier studies, the weather datasets considered are from the intergovernmental panel on climate change (IPCC) [18]. Such datasets provide the overall climate of the whole country considering non-productive zones (semi-arid, steppe, and desert climates) and may bring biases in results specifically when the sectoral (agricultural, industrial, and service) outputs are of concern.

Instead, Dell, Jones, and Olken [11] have provided population-weighted datasets relying on Terrestrial Air Temperature and Precipitation: Gridded Monthly Time Series, Version 1.01 [19]. Using geospatial software, the climate data are aggregated by Dell, Jones, and Olken [11] to achieve the country-year-level data weighted by population distribution. The population-weighted climate data better captures the climate effects on economic activities. Since a large proportion of economic activity leads the population growth in its surroundings, it deserves more attention in consideration of climate change. Consequently, we use this dataset to analyze the aggregate effects of temperature and precipitation on agricultural growth in Africa.

Secondly, the econometric methodologies considered in most previous studies ignore parameter heterogeneity and cross-section dependence in the model residuals. It is rational to assume that different economies may have quite different responses to global climate changes. In terms of agricultural activities, the impact of changing precipitation in developed countries with advanced irrigation systems should be less significant than in less developed countries relying primarily on natural rainfall for irrigation. In most previous studies, ordinary or generalized least square estimations of the mean regressions are considered, which, except for country-specific intercepts, impose parameter homogeneity. In consideration of different climatic and geographical characteristics, the effects of climatic shocks are likely to be heterogeneous across different African countries. In such a case, least square models imposing parameter homogeneity are fundamentally misspecified and may produce biased estimations.

Moreover, in the case of panel analysis of the impacts of climate change across geographic areas, most of the panel estimations have neglected to control the cross-sectional dependence in the model residuals. Under the possibilities that unobservable common factors, such as common price shocks and global financial risks, caused by trade and interactions across countries, affect most of the African countries, neglecting the unobservable cross-sectional dependence may lead to biased estimates and incorrect inferences [20,21].

Recently, certain studies have provided the solution of cross-sectional dependence. Pesaran [20] proposes the “common correlated effects” (CCE) estimation, using cross-sectional averages of the regressors and the dependent variables to proxy for the unobserved common factors. Based on the approach of Pesaran [20], Chudik and Pesaran [22] propose the “dynamic common correlated effects” (DCCE) by adding a sufficient number of lags of cross-sectional averages for the heterogeneous panel data models with lagged dependent variables or weakly exogenous variables.

When the interest is majorly on the long-run effects based on a more general autoregressive distributed lag (ARDL) specification, [23] call the estimation augmented by cross-sectional averages to filter out the effects of unobserved common factors as a cross-sectionally augmented ARDL (CS-ARDL) approach. More importantly, Chudik, Mohaddes, Pesaran, and Raissi [23] propose a cross-sectionally augmented distributed lag (CS-DL) approach to estimate the long-run effects directly. The CS-DL approach is based on a distributed lag representation that does not feature lags of the dependent variable, while allowing for residual factor error structure and weak cross-sectional dependence of the idiosyncratic errors. As mentioned in Chudik, Mohaddes, Pesaran, and Raissi [23], the main drawback of computing the long-run effects from the CS-ARDL approach is due to the inclusion of the lagged dependent variable. When the sum of the AR coefficients in the ARDL specification is close to 1, the long-run estimates are susceptible to outlier estimates. In this paper, we consider both CS-ARDL and CS-DL approaches to estimate the long-run effects of climate on agriculture growth in Sub-Saharan countries, and we prefer the results from the CS-DL approach for the aforementioned reasons.

In this study, the augmented mean group (AMG) estimation by Eberhardt and Teal [24] was also considered as an alternative approach to handle the cross-sectional dependence in the errors. In the AMG approach, the cross-sectional dependence is accounted for by including a “common dynamic process” term explicitly for each cross-section unit. This paper also considers the error correction model (ECM) panel approach in Pesaran et al. [25] to estimate the long-run impacts of climate change on agricultural growth. Furthermore, by the same token of the DCCE estimator, we augment the conventional ECM by cross-sectional averages of the dependent and independent variables to control for unobservable common factors.

To be clear, this paper investigates the overall long-run impact of temperature and precipitation on agricultural growth in 32 Sub-Saharan African countries from 1961 to 2019. We rely on heterogeneous dynamic panel models with a multifactor error structure in our empirical analysis. There are several contributions of our paper to the existing literature. Firstly, we use climate data from Dell, Jones, and Olken [11] covering 32 Sub-Saharan African countries from 1961 to 2019. Compared to previous literature, this dataset covers more countries and a longer time span, providing more accurate measurements of the climate attributes affecting the areas considered. Secondly, different estimations of mean group (MG) estimators from a heterogeneous dynamic panel model with multifactor error structure are considered. We show estimations based on the common correlated effects mean group (CCEMG) approach [20], CS-ARDL and CS-DL approaches [23], the AMG approach [24], the ECM approach [25], and the cross-sectional augmented ECM estimators to prove the consistency of the estimates.

The estimation results suggest that the rising temperatures have significantly developed a negative long-term relationship with the agricultural growth in Sub-Saharan Africa, while the long-run effect of precipitation is less important and not statistically significant in most estimations. According to the preferred CS-DL approach, the negative impact of a 1°C rise in temperature could be as high as a 4.2 to 4.5 percent decrease in the agricultural growth rate. The results indicate that the warming climate has negatively affected the agricultural sector in Sub-Saharan Africa, and adaption measures or appropriate transition of economies from agriculture to other sectors should be under consideration to keep African people from food shortage and economic stagnation.

The rest of the paper is organized in the following way. Section 2 provides the data description and methodology used in this paper; in Section 3, we exhibit the empirical results corresponding to different multifactor modelling methods; we conclude in Section 4.

## 2. Data and Empirical Methodology

Our study focuses on examining the long-run effects of climate (precipitation and temperature) on the agricultural growth rate in Sub-Saharan Africa. We rely on a balanced panel data of annual data for 32 Sub-Saharan African countries covering the period of

1961 to 2019. Our principal source for agricultural variables is the Food and Agriculture Organization's FAOSTAT panel database (FAO 2007). Although FAOSTAT does not offer a data quality grade, it rather provides a combination of official or semi-official aggregates of outputs; it has been considered by a number of studies such as Eberhardt and Teal [26], whereby authors considered annual observations for net agricultural output. Net agricultural output of a sector after adding up all outputs and subtracting intermediate inputs considered for all models. According to FAO (1993), gross output corresponds to overall agricultural output minus the proportion of output used as inputs, such as crop seeds, in its own processing. The proxy for agriculture net output per worker is estimated by dividing the net agricultural output by an economically active labor force in agriculture. The climate data are from Dell, Jones, and Olken [11], which relies on Terrestrial Air Temperature and Precipitation: 1900–2006 Gridded Monthly Time Series, Version 1.01 [19]. Matsuura and Willmott [19] interpolate monthly averages of air temperature and precipitation to a 0.5-by-0.5-degree latitude/longitude grid. Using geospatial software, the data are aggregated by [11] to achieve the country-year level data weighted by population distribution.

As in Lanza et al. [13], there is an upward trend in temperature and a downward trend in precipitation in Sub-Saharan Africa. The average real agricultural net output per worker grows steadily over the whole sample period, except for several sharp decreases in the early 1970s, early 1980s, and early 1990s. These sharp drops in the agricultural sector echo the dramatic decreases in precipitation in these periods. However, as the precipitation recovers from a drought season, the agricultural output surges to grow steadily on its previous path. It is, however, less clear how these agricultural setbacks are related to the warmer climate. The change patterns of temperature are not obviously leading to spontaneous changes in the agriculture sectors.

Therefore, we suspect that for the temperature to have an impact on agricultural activities, it is highly possible that it works through a long-run channel. It is also necessary to investigate the long-run impact of precipitation on agricultural activities even though the short-run effects might be quite significant. Consequently, the main focus of this paper is to study the long-run effect of these two climate measurements on the agricultural output.

#### *Empirical Framework and Estimators*

For empirical analysis, we consider the dynamic heterogeneous panel estimators built on the auto-regressive distributive lag (ARDL) approach. With the panel specification of lag orders  $(p_y, p_x)$ , the ARDL model is specified as follows:

$$y_{i,t} = \omega_i + \sum_{j=1}^{p_y} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{p_x} \beta'_{ij} x_{i,t-j} + u_{i,t}, \quad (1)$$

where the cross-sectional units (countries) are represented as  $i$  ( $i = 1, 2, \dots, N$ ); time series (years) are represented by  $t$  ( $t = 1, 2, \dots, T$ );  $x_{i,t}$  is a  $k$  dimensional vector of explanatory variables;  $\lambda_{ij}$  is a scalar and  $\beta_{ij}$  is a  $k$  dimensional vector of coefficients; and  $\omega_i$  represents group-specific fixed effect. Within this framework, the long-run estimates can be calculated by  $\theta_i = \frac{\sum_{j=0}^{p_x} \beta_{ij}}{1 - \sum_{j=1}^{p_y} \lambda_{ij}}$ .

We specify  $u_{i,t}$  as follows to allow for cross-sectional correlation of the error terms:

$$u_{i,t} = Y'_i f_t + e_{i,t} \quad (2)$$

In the above specification,  $f_t$  represents the unobservable common factors, with unit-specific factor loadings  $Y'_i$ . The error term  $e_{i,t}$  is distributed independently with zero mean and variance  $\sigma^2$ .

As our sample considered is sufficiently large in terms of  $N$  and  $T$ , the heterogeneous panel can be estimated by several approaches differing with reference to the degree of heterogeneity allowed for the parameters. On one side, the pooled mean group (PMG) estimator considers homogeneous slopes and intercepts, and the dynamic fixed effect (DFE)

estimator produces only intercepts to vary across groups. In the case where the effects of the regressors may be completely heterogeneous, these two kinds of estimators may produce unreliable results. Therefore, on the other extreme of the spectrum, the mean group (MG) estimator of Pesaran and Smith [21] fully allows the heterogeneity among slopes and intercepts.

All of these three aforementioned approaches (PMG, MG, and DFE) assume the cross-sectional independence of the residuals in the specification, treating the unobservable factors in a linear trend and neglect the  $Y'_{it}f_{it}$ . Therefore, it may bring biased results in the presence of cross-sectional dependence. A number of studies have addressed the issue of cross-sectional dependence, such as the common correlated effects mean group (CCEMG) estimator of Pesaran [20], the cross-sectionally augmented ARDL (CS-ARDL), the cross-sectionally augmented distributed lag (CS-DL) approach of Chudik, Mohaddes, Pesaran, and Raissi [23], and the augmented mean group (AMG) estimation of [27].

The common correlated effects mean group (CCEMG) estimator resulting from MG estimation of the CCE estimator of Pesaran [20] is as follows:

$$y_{i,t} = \omega_i + \sum_{j=1}^{p_y} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{p_x} \beta'_{ij} x_{i,t-j} + d_{1i} \sum_{j=0}^{p_y} \bar{y}_{t-j} + d_{2i} \sum_{j=0}^{p_x} \bar{x}_{t-j} + u_{i,t}, \quad (3)$$

where  $\bar{y}_t = \sum_{i=1}^N y_{i,t}/N$ , and  $\bar{x}_t = \sum_{i=1}^N x_{i,t}/N$ , denoting the cross-sectional averages. Notice that in the above CCEMG estimation, the lagged dependent variable  $y_{i,t-j}$  is treated as a normal regressor, which may cause inconsistency because of weak exogeneity. The regressions mentioned hereafter are derived from the MG estimator with the consideration of cross-sectional dependence. Though, in general, these estimations do not include the deterministic trend but could be added to capture the omitted idiosyncratic processes evolving in a linear fashion with the passage of time.

For a dynamic panel model with one lagged dependent variable as a regressor, Chudik and Pesaran [22] provide that with the inclusion of  $p_T = \lceil \sqrt[3]{T} \rceil$  lags of the cross-sectional averages, the CCE estimators gain consistency. Similar to the DCCE approach [22], the CS-ARDL approach [23] augments the individual ARDL regressions appropriately with additional lags of cross-sectional averages to control common factors. With the addition of cross-sectional lag terms, the CS-ARDL approach is represented as:

$$y_{i,t} = \omega_i + \sum_{j=1}^{p_y} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{p_x} \beta'_{ij} x_{i,t-j} + \sum_{j=0}^{p_T} \gamma'_{ij} \bar{Z}_{t-j} + u_{i,t}, \quad (4)$$

where  $\bar{Z}_{t-j} = (\bar{y}_{i,t-j}, \bar{x}_{i,t-j})$ , and  $p_T$  is the number of lags of the cross-sectional averages to be included.  $p_T$  is not necessarily equal to  $p_y$  or  $p_x$ . One could choose  $p_T$  according to  $p_T = \lceil \sqrt[3]{T} \rceil$  as in Chudik and Pesaran [22], and one could also allow for different lag orders for  $\bar{y}_{i,t}$  and  $\bar{x}_{i,t}$ . The choice of lags of the cross-sectional averages differentiates the CS-ARDL from the aforementioned CCEMG estimators, in which the lags of the cross-sectional averages are determined by the ARDL lags ( $p_y, p_x$ ).

The long-run unit-specific estimates and the mean group estimates in the CCEMG and the CS-ARDL approach can be calculated as:

$$\hat{\theta}_{CS-ARDL,i} = \frac{\sum_{j=0}^{p_x} \hat{\beta}_{ij}}{1 - \sum_{j=1}^{p_y} \hat{\lambda}_{ij}}, \quad \bar{\theta}_{MG} = \frac{\sum_{i=1}^N \hat{\theta}_i}{N}$$

As mentioned in Chudik, Mohaddes, Pesaran, and Raissi [23], the above CS-ARDL approach relies on the estimation of the short-run estimates  $\hat{\beta}_{ij}$  to get the long-run estimates



$\hat{\theta}_{CS-ARDL,i}$ . When the AR coefficients  $\sum_{j=1}^{p_y} \hat{\lambda}_{ij}$  are close to 1, the calculation of the long-run estimates could be very sensitive to outlier estimates. Furthermore, when the number of lagged terms of the dependent variable is large, a relatively large time dimension is required for satisfactory small sample performance.

To overcome these drawbacks of the CS-ARDL approach, Chudik, Mohaddes, Pesaran, and Raissi [23] propose to transform the ARDL model to a distributed lag model (CS-DL) as follows:

$$y_{i,t} = \omega_i + \theta_i x_{i,t} + \sum_{j=0}^{p_{x-1}} \delta'_{ij} \Delta x_{i,t-j} + \sum_{j=0}^{p_{\bar{y}}} \gamma_{y,ij} \bar{y}_{i,t-j} + \sum_{j=0}^{p_{\bar{x}}} \gamma'_{x,ij} \bar{x}_{i,t-j} + u_{i,t}, \quad (5)$$

where  $p_{\bar{y}}$  and  $p_{\bar{x}}$  are the number of lags of the cross-sectional averages. Through this transformed model, the long-run unit-specific impacts,  $\theta_i$ , are directly estimated, and the mean group estimates are calculated as  $\bar{\theta}_{MG} = \sum_{i=1}^N \hat{\theta}_i / N$ .

As mentioned by Chudik, Mohaddes, Pesaran, and Raissi [23], both CS-DL and CS-ARDL have certain drawbacks. In contrast to the ARDL approach, the long-run effects estimated by CS-DL are only consistent when the feedback effects from the lagged values of the dependent variable to the regressors are absent. Furthermore, the CS-ARDL approach without an appropriate selection of cross-sectional lags provides inconsistent estimates. However, the CS-DL approach remains meritorious in providing the right estimates when the time dimension  $T$  is moderately large. In our empirical analysis, the regressors we consider are temperature and precipitation, considered as exogenous as mentioned by Lanzafoame [13], and therefore, there should be no feedback effects of lagged dependent variable on these regressors. In our CS-ARDL estimation, we choose the cross-sectional lags so that the cross-sectional dependence in the residuals is not statistically significant at 5% significance level, according to the CD test of Pesaran [28].

As per Eberhardt, Teal, and Eberhardt [27], the AMG estimates can be represented as:

$$\Delta y_{i,t} = \sum_{j=1}^{p_y} \lambda_j \Delta y_{i,t-j} + \sum_{j=0}^{p_x} \beta'_j \Delta x_{i,t-j} + \sum_{t=2}^T c_t \Delta D_t + u_{i,t} \Rightarrow \hat{c}_t \equiv \hat{\mu}_t; \quad (6)$$

$$y_{i,t} = \omega_i + \sum_{j=1}^{p_y} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{p_x} \beta'_{ij} x_{i,t-j} + c_i t + d_i \hat{\mu}_t + u_{i,t}. \quad (7)$$

Equation (6) signifies the first stage of this AMG estimation, in which a pooled OLS regression of the first difference model augmented with  $T - 1$  year dummies  $\Delta D_t$  is estimated. The coefficients of the year dummies, denoted as  $\hat{\mu}_t$ , are referred to as a common dynamic process, which represents the estimated cross-group average of the evolution of unobservables with the passage of time. In the second stage, as shown in Equation (7), the country-specific regressions are augmented by this estimated common dynamic process. Alternatively, one can impose unit coefficients on the estimated process by subtracting  $\hat{\mu}_t$  from the dependent variable. Furthermore, we could include a linear trend term to capture truly idiosyncratic time-varying unobservable evolving linearly over time.

All the estimators described above are sufficient to allow for non-linear or non-stationary variables in complex common factor structures, where variables are possibly driven by factors other than  $f_t$ . The AMG estimator uses explicit estimates for  $f_t$  exhibiting a common dynamic process as a meaningful construct. On the contrary, CCEMG, CS-ARDL, and CS-DL estimations do not produce explicit, but rather implicit estimates for unobserved common factors  $f_t$  using cross-sectional averages of regressors.

This paper also considers the error correction approach to estimate the long-run impacts of climate change on agricultural growth. Equation (1) can be transformed as in Pesaran, Shin, and Smith [25] to:

$$\Delta y_{i,t} = \varphi_i [y_{i,t-1} - \theta_i x_{i,t}] + \sum_{j=1}^{p_y-1} \lambda_{ij}^* \Delta y_{i,t-j} + \sum_{j=0}^{p_x-1} \beta_{ij}^{*'} \Delta x_{i,t-j} + \omega_i + u_{i,t}, \quad (8)$$

where  $\varphi_i = -\left(1 - \sum_{j=1}^{p_y} \lambda_{ij}\right)$ ,  $\theta_i = \frac{\sum_{j=0}^{p_x} \beta_{ij}}{1 - \sum_{j=1}^{p_y} \lambda_{ij}}$ ,  $\lambda_{ij}^* = -\sum_{m=j+1}^{p_y} \lambda_{im}$ ,  $j = 1, 2, \dots, p_y - 1$ , and  $\beta_{ij}^{*'} = -\sum_{m=j+1}^{p_x} \beta_{im}$ ,  $j = 1, 2, \dots, p_x - 1$ . We consider standard pooled mean group (PMG), mean group (MG), and dynamic fixed effect (DFE) estimators for the above ECM model to estimate the long-run and short-run effects without considering the cross-sectional dependence in the error term.

As we can see in the error correction model, the group-specific long-run effect,  $\theta_i$ , can be estimated directly as in the CS-DL approach. However, the right-hand side of the ECM model still signifies a lagged dependent variable, which may cause inconsistency in estimation. In this regard, the error correction approach is inferior to the CS-DL approach when the long-run effect is the main interest. More importantly, the above ECM of Pesaran, Shin, and Smith [25] does not take the multifactor error structure into account. By the same token as of the CCE, DCCE, and the CS-ARDL approach, we could augment the ECM in Equation (8) with cross-sectional averages:

$$\Delta y_{i,t} = \varphi_i [y_{i,t-1} - \theta_i x_{i,t}] + \sum_{j=1}^{p_y-1} \lambda_{ij}^* \Delta y_{i,t-j} + \sum_{j=0}^{p_x-1} \beta_{ij}^{*'} \Delta x_{i,t-j} + \sum_{j=0}^{p_T} \gamma_{ij}' \bar{Z}_{i,t} + \omega_i + u_{i,t}. \quad (9)$$

Some may call the above the DCCE-ECM approach, since the inclusion of additional cross-sectional averages is originated from the DCCE estimator. However, by the same token as in Chudik, Mohaddes, Pesaran, and Raissi [23], we prefer to call the above approach the cross-sectional augmented ECM (CS-ECM) model, to differentiate from the conventional ECM model in Pesaran, Shin, and Smith [25] without considering the cross-sectional dependence in the error terms.

### 3. Empirical Analysis

#### 3.1. Summary Statistics, Unit Root Tests, and Lag Selections

Our panel data comprise three variables, namely agricultural net output per worker, temperature, and precipitation for 32 Sub-Saharan African countries from 1961 to 2019. We construct the variable agricultural net output per worker as the natural logarithm of the real agricultural net output (in thousand international dollars) per worker. According to Eberhardt and Teal [26], the real agricultural net output is based on all crops and livestock produced in each country; whereas, the intermediate primary inputs are deducted. As FAO (2007) used 1999–2001 as base years to weigh the average international commodity prices, the same is employed in our study for each commodity and then summed for each year by country. Variables temperature and precipitation are taken from Dell, Jones, and Olken [11], which are population-weighted measurements of climate for each country in each year.

Table 1 provides basic summary statistics for three main variables considered. In the first step of our empirical analysis, we use the augmented Dickey–Fuller (ADF) test [29] to study the stationarity properties of the variables of interest. Table 2 shows ADF unit root test results. Both temperature and precipitation are found stationary at level, whereas variable agricultural net output per worker has been found non-stationary as a process integrated of order one (I(1) hereafter). Therefore, we take the first difference of the I(1) variable to construct the growth rate of net agricultural output per worker, represented by  $\Delta \ln Y$ . In the following empirical estimations, we examine the long-run impacts of

temperature and precipitation (in levels) on the growth rate of net agricultural output per worker ( $\Delta \ln Y$ ) in Sub-Saharan Africa.

**Table 1.** Summary Statistics.

Statistics Summary					
Variable	Observations	Mean	Std. Dev	Min	Max
Year	1888	-	-	1961	2019
Country	1888	1990	17.0339	1	32
Agriculture per worker (log)	1888	-1.109	0.479	-2.49	0.7521
Temperature (°C)	1888	24.594	2.893	18.75	29.583
Precipitation (100 s mm/year)	1888	11.971	5.876	1.588	32.258

Note: Agriculture per worker (log) is the natural logarithm of the real agricultural net output (in thousand international dollars) per worker. According to Eberhardt and Teal [26], the real agricultural net output is based on all crops and livestock products originating in each country, in which the intermediate primary inputs are deducted. Average international commodity prices from 1999 to 2001 are used to weigh the quantities for each commodity and then summed for each year by country.

**Table 2.** Augmented Dickey–Fuller test.

Variables	Agriculture per Worker (log)		Temperature		Precipitation	
	Z-stat	p-Value	Z-stat	p-Value	Z-stat	p-Value
Country						
Angola	1.623	0.947	-5.389	0.000	-2.583	0.005
Benin	0.796	0.213	-2.125	0.017	-3.654	0.001
Botswana	-1.361	0.087	-2.728	0.003	-2.597	0.004
Burkina Faso	-0.585	0.279	-2.922	0.002	-1.817	0.035
Burundi	-1.483	0.069	0.2897	0.614	-1.740	0.041
Cameroon	-0.290	0.386	-4.013	0.000	-2.259	0.012
Central African Republic	0.017	0.507	-3.121	0.001	-1.477	0.070
Chad	-0.143	0.443	-6.034	0.000	-2.268	0.012
Congo, Dem. Rep.	1.035	0.850	-4.027	0.000	-2.934	0.002
Equatorial Guinea	-0.523	0.300	-3.333	0.000	-2.423	0.008
Ethiopia	0.895	0.814	-3.678	0.000	-1.936	0.026
Gabon	-0.858	0.195	-2.194	0.014	-3.499	0.002
Gambia	-2.545	0.005	-4.305	0.000	-3.011	0.001
Ghana	0.980	0.836	-4.131	0.000	-2.706	0.003
Guinea	0.367	0.643	-1.672	0.047	-1.038	0.149
Kenya	-0.846	0.198	-4.235	0.000	-4.355	0.000
Liberia	-1.306	0.095	-3.771	0.001	-1.670	0.047
Madagascar	-0.666	0.252	-3.202	0.001	-1.101	0.135
Malawi	-0.332	0.369	-3.996	0.000	-2.363	0.009
Mali	-2.239	0.013	-3.165	0.001	-1.580	0.057
Mauritania	-1.465	0.071	-4.458	0.000	-2.014	0.022
Mozambique	-0.128	0.449	-3.134	0.001	-3.572	0.001
Niger	-0.144	0.442	-3.788	0.000	-2.047	0.020
Nigeria	0.247	0.597	-3.107	0.000	-2.666	0.038
Rwanda	-1.834	0.033	-0.401	0.344	-2.226	0.013
Senegal	-2.278	0.011	-3.387	0.000	-2.068	0.019
Sierra Leone	-1.168	0.121	-2.487	0.006	-2.105	0.017
Sudan	0.028	0.511	-3.290	0.000	-0.769	0.220
Tanzania	-0.667	0.252	-3.773	0.000	-2.379	0.009
Togo	-0.789	0.214	-2.875	0.002	-4.021	0.000
Uganda	-0.236	0.406	-2.647	0.004	-3.256	0.001
Zimbabwe	-1.751	0.039	-2.922	0.002	-2.163	0.015

Note: All augmented Dickey–Fuller (ADF) regressions include a constant and a deterministic trend.



The second step of the empirical analysis is the lag selection of ARDL specification. Lag selection for the ARDL model can be performed using single-equation estimations for each of the panel units. However, to facilitate the comparison of our long-run estimates from different approaches, we follow Loayza and Ranciere [30] to impose the same lag order for the panel units. According to the Akaike information criterion (AIC), the ARDL (1, 0, 0) model is found appropriate for most of the cross sections in our panel. Consequently, in our following empirical analysis, we base our model on an ARDL (1, 0, 0) specification.

### 3.2. Standard Mean Group Estimators and Cross-Sectional Dependence

The standard pooled mean group (PMG), mean group (MG), and dynamic fixed effect (DFE) are applied to the ECM model given in (8) with  $p_y = 1$  and  $p_x = 0$ . The estimation results are summarised in Table 3.

**Table 3.** Pooled mean group (PMG), mean group (MG), and dynamic fixed effects (DFE) estimator.

Dependent Variable: Agriculture Growth per Worker $\Delta \ln Y$			
	PMG	MG	DFE
Error Correction Term	−1.097 *** (0.0416)	−1.126 *** (0.0405)	−1.261 *** (0.0221)
$\Delta$ Temperature	−0.0220 * (0.0087)	−0.0261 ** (0.0082)	−0.0355 (0.0054)
$\Delta$ Precipitation	0.0128 * (0.0044)	0.0095 ** (0.0038)	0.0056 *** (0.0014)
Intercept	0.0873 *** (0.0054)	−0.201 (0.1206)	0.0193 (0.1001)
Long-Run Coefficients			
Temperature	−0.0038 (0.0022)	−0.00589 (0.0041)	−0.00168 (0.0031)
Precipitation	0.0146 * (0.0006)	0.0068 ** (0.0025)	0.0024 * (0.0012)
CD test statistics	149.07	149.07	149.07
CD ( $p$ values)	0.00	0.00	0.00
N	1824	1824	1824

Note: Coefficients are reported with standard errors in brackets. \*\*\*, \*\*, and \* indicate significance at 1, 5, and 10% levels, respectively.  $\Delta$  defines the first difference. All of the above estimations are based on the error correction model in Equation (8) with  $p_y = 1$  and  $p_x = 0$ . In the pooled mean group (PMG) estimation, no heterogeneity of the slopes and intercepts are assumed; in the mean group (MG) estimation, the estimation is done separately for each cross-sectional unit with full heterogeneity in the slopes and intercepts; in the dynamic fixed effect (DFE) estimation, only intercepts could vary across groups. CD test statistics present the cross section dependence tests of Pesaran [28] on the model residuals with the null of cross-sectional independence.

Exhibited in Table 3, all three estimations point out that an increase in precipitation significantly improves the agriculture per worker in the long run. Exhibiting the results in an increase of 100mm of precipitation, we find it corresponds to a 0.29 to 0.55 percentage point increase in the growth rate of net agricultural output per worker. Nevertheless, temperature, in the long run, has not been found significantly affecting agriculture in Sub-Saharan Africa.

With the consideration of possible cross-sectional dependence that might invalidate the above estimations, we examine the presence of cross-sectional dependence in the error terms using the cross-section dependence (CD) test of Pesaran [28]. This test is based on the mean pairwise correlation coefficients of regression residuals. By conducting the formal test of cross-section dependence, the null of cross-section independence is strongly rejected in all three estimations (check the last two rows of Table 3 for the CD test statistics and the corresponding  $p$  values). The results of the CD tests highlight the non-reliability of standard mean group estimators ignoring the cross-sectional dependence in the residuals.

### 3.3. Common Correlated Mean Group Estimators (CCEMG) and Cross-Sectionally Augmented ARDL (CS-ARDL), Estimators

In this section, we estimate the CCEMG estimator [20] given in Equation (3) and the CS-ARDL estimator [23] given in Equation (4). In the CCEMG estimator, the parameters and standard errors are constructed with an outlier-robust method proposed by Hamilton [31]. We consider the standard no-trend estimations, as well as specifications with country-specific trends, included to control idiosyncratic processes evolving in a linear fashion over time.

In order to address the cross-sectional dependence [20] in Table 4 (columns 1 and 2) by adding cross-sectional averages to control the unobserved common factors. Notice that in the CCEMG method, no lags of cross-sectional averages are added in the estimations. Under this method, the estimates signify the negative association of temperature with the agricultural growth per worker in both the short and long run. We also find that precipitation is significantly positively correlated with agriculture growth per worker in the long run.

**Table 4.** Common correlated effects mean group (CCEMG) and cross-sectionally augmented autoregressive distributed lag (CS-ARDL) estimators.

Dependent Variable: Agricultural Growth per Worker $\Delta \ln Y$				
	CCEMG	CCEMG	CS-ARDL	CS-ARDL
$\Delta \ln Y(t-1)$	−0.185 *** (0.0449)	−0.181 *** (0.0458)	−0.183 *** (0.0481)	−0.151 ** (0.0461)
Temperature	−0.0169 * (0.0103)	−0.0235 * (0.0104)	−0.0182 (0.0134)	−0.0282 * (0.0140)
Precipitation	0.0044 ** (0.0018)	0.0042* (0.0018)	0.0153 * (0.0056)	0.0152 ** (0.0056)
Trend	0.0001 (0.0002)		0.0000 (0.0004)	
Intercept	−0.0096 (0.1796)	−0.0582 (0.1944)	0.0440 (0.6391)	0.0653 (0.2092)
Long-Run Coefficients				
$\Delta \ln Y(t-1)$	−1.848 *** (0.0449)	−1.1808 *** (0.0458)	−1.183 *** (0.0461)	−1.1770 *** (0.0419)
Temperature	−0.0143 * (0.0077)	−0.0199 ** (0.0088)	−0.0157 (0.0097)	−0.0214 * (0.0101)
Precipitation	0.0038 *** (0.0015)	0.0036 *** (0.0016)	0.0117 ** (0.0040)	0.0117 ** (0.0044)
CD test statistics	−1.787	−1.939	−1.8073	−1.9044
CD ( <i>p</i> values)	0.074	0.052	0.0275	0.0274
N	1824	1824	1696	1696

Note: Coefficients are reported with standard errors in brackets. \*\*\*, \*\*, and \* indicate significance at 1, 5 and 10% levels, respectively. Column 1 and 2 present CCEMG estimators in Equation (3) with  $p_y = 1$  and  $p_x = 0$ . The long-run estimates are calculated by  $\hat{\theta}_i = \frac{\sum_{j=0}^{p_x} \hat{\beta}_{ij}}{1 - \sum_{j=1}^{p_y} \hat{\lambda}_{ij}}$ . In the CCEMG estimations, the standard errors are computed via the outlier-robust procedure proposed by Hamilton [31]. Column 3 and 4 depict the CS-ARDL estimates in Equation (4) with  $p_y = 1$ ,  $p_x = 0$ ,  $p_{\bar{y}} = 4$ ,  $p_{\bar{x}} = 1$ . CD test statistics present the cross-section dependence tests [28] on the model residuals with the null of cross-sectional independence.

However, the drawback of this approach is that it does not include cross-sectional lag terms. In a model with lagged dependent variables, the static CCEMG estimator may provide misleading inferences, as mentioned in Chudik and Pesaran [22]. With the inclusion of a lagged dependent variable, endogeneity occurs, and adding simple contemporaneous cross-sectional averages is insufficient to provide consistent results. To address this shortfall, Chudik and Pesaran [22] propose the dynamic CCE (DCCE) estimator, adding a sufficient number of lags of cross-section averages in the estimations.

Chudik, Mohaddes, Pesaran, and Raissi [23] generalize the idea of DCCE to a general ARDL model and describe the estimator as the CS-ARDL estimator.

The last two columns of Table 4 illustrate the results of the CS-ARDL estimations. In the CS-ARDL estimation, we set the cross-sectional average lags as (4, 1, 1) with 4 corresponding to the lag terms of the dependent variable and 1 for the other two climate variables. By comparing the results of the CCEMG with these of the CS-ARDL estimations, we find consistency in the estimates with almost similar coefficients and signs. A one-degree Celsius increase in temperature decreases the agriculture net output growth rate per worker by about 2 percentage points in the long run by both approaches. With the inclusion of additional cross-sectional lags in the CS-ARDL approach, the cross-sectional dependence is alleviated with the  $p$ -values of CD tests statistics increased, exhibiting more cross-section independence as compared to the CCEMG estimations.

### 3.4. Cross-Sectionally Augmented Distributed Lag (CS-DL) Estimators and Cross-Sectional Augmented Error Correction Model (CS-ECM) Estimators

With the focus on the long-run impacts of climate change on agricultural activities, we follow the CS-DL approach by Chudik, Mohaddes, Pesaran, and Raissi [23] given in Equation (5) with  $p_y = 1$  and  $p_x = 0$  to directly estimate the long-run coefficients. As a second approach to estimate the long-run impacts directly with consideration of multifactor error structure, we estimate the CS-ECM given in Equation (9) with  $p_y = 1$ ,  $p_x = 0$ ,  $p_{\bar{y}} = 4$ ,  $p_{\bar{x}} = 1$ . The estimation results are illustrated in Table 5.

**Table 5.** Cross-sectionally augmented distributed lag (CS-DL) and cross-sectionally augmented error correction method (CS-ECM) estimators.

Dependent Variable: Agriculture Growth per Worker(log) $\Delta \ln Y$				
	CS-DL	CS-DL	CS-ECM	CS-ECM
Error Correction Term			−1.145 *** (0.0424)	−1.119 *** (0.0442)
$\Delta$ Temperature	−0.0050 (0.0185)	−0.0035 (0.0167)	−0.0187 (0.0165)	−0.0160 (0.0167)
$\Delta$ Precipitation	0.0175 * (0.0077)	0.0171 * (0.0074)	0.0104 * (0.0042)	0.0110 * (0.0041)
$\Delta$ Temperature (t-1)	0.0173 (0.0230)	0.0157 (0.0216)		
$\Delta$ Precipitation (t-1)	−0.0001 (0.0027)	−0.0002 (0.0029)		
Trend	0.0007 (0.0006)		0.0002 (0.0004)	
Intercept	0.510 (0.517)	0.0336 (0.2812)	0.351 (0.4732)	0.165 (0.2239)
Long-Run Coefficients				
Temperature	−0.0420 * (0.0207)	−0.0474 * (0.0225)	−0.0227 * (0.0112)	−0.0268 * (0.0124)
Precipitation	−0.0032 (0.0065)	−0.0021 (0.0048)	0.0006 (0.0041)	0.0018 (0.0042)
CD test statistics	−1.318	−1.598	−1.547	−1.542
CD ( $p$ values)	0.187	0.110	0.122	0.123
N	1696	1696	1696	1696

Note: Coefficients are reported with standard errors in brackets. \*\*\*, \*\*, and \* indicate significance at 1, 5, and 10% levels, respectively. Column 1 and 2 present CS-DL estimators in Equation (5) with  $p_y = 1$  and  $p_x = 0$ . Column 3 and 4 depict the CS-ECM estimates in Equation (9) with  $p_y = 1$ ,  $p_x = 0$ ,  $p_{\bar{y}} = 4$ ,  $p_{\bar{x}} = 1$ . CD test statistics present the cross-section dependence tests [28] on the model residuals with the null of cross-sectional independence.

Firstly, we compare the CS-ECM estimates in the last two columns of Table 5 with the standard mean group estimates based on the conventional ECM model in Table 3. The results indicate that with the inclusion of cross-sectional lags in the ECM model,

precipitation shows no significant correlation with agricultural growth in the long run, while temperature tends to be mildly negatively correlated with agricultural growth in the long run.

However, the right-hand side of the CS-ECM model still signifies a lagged dependent variable. In the estimation of the CS-ECM model, the estimation is performed with the lagged dependent variable as an independent regressor, and the long-run coefficients are calculated as the ratios of the coefficients of the climate variables over that of the lagged dependent variable (with a minus sign). Consequently, the CS-ECM approach may be treated as a semi-direct way to estimate the long-run effects of the climate variables on agricultural growth.

To directly estimate the long-run effects without a lagged dependent variable on the right-hand side of the equation, the CS-DL estimations provide us with the most reliable estimation results (the first two columns of Table 5). Under the approach, we verify that precipitation may significantly boost agricultural growth in the short run but does not seem to have a long-run impact on agricultural activities. More importantly, the long-run impact of temperature is quite significant with sizable magnitudes. A one Celsius degree increase in temperature will lead to about 4 percentage point decrease in agricultural growth in Sub-Saharan Africa.

The long-run effect of temperature by the CS-DL approach is comparatively high as compared to the estimates in CCEMG, CS-ARDL, and CS-ECM models. Moreover, the CD statistics with their  $p$  values in the CS-DL approach show comparatively higher values of cross-section independence than estimators. This could possibly be the effect of exclusion of lagged dependent variable on the right-hand side of the estimation equation.

### 3.5. Augmented Mean Group (AMG) Estimators

In this section, we estimate the AMG estimator of (Eberhardt and Teal, 2010) given in Equation (7) with  $p_y = 1$  and  $p_x = 0$ . The parameters and standard errors are constructed with the outlier-robust method proposed by Hamilton [31]. The AMG estimates are summarized in Table 6.

As an indirect way to estimate the long-run effects, the AMG estimates in the first two columns of Table 6 are similar to the CCEMG estimates in columns 1 and 2 of Table 4, despite the fact that the AMG approach controls for the multifactor error structure explicitly by the common dynamic process, whereas the CCEMG method handles these factors implicitly by the inclusion of cross-sectional averages. In both of the AMG and the CCEMG approaches, temperature and precipitation are found to have significant short-run as well as long-run impacts on agricultural growth in Sub-Saharan Africa. A one Celsius degree increase in temperature will lead to about 2% points decrease in agricultural growth in Sub-Saharan Africa, while one 100mm increase in precipitation will lead to about 0.3 percentage points increase in agricultural growth in Sub-Saharan Africa.

In columns 1 and 2 of Table 6, we observe that the common dynamic process is highly significant, indicating that common factors over time significantly affect the agricultural growth in Sub-Saharan Africa. With the unit imposition on the coefficients on the common dynamic processes, the last two columns of Table 6 exhibit that one Celsius degree increase in temperature reduces the agricultural growth rate by about 2 to 3 percentage points in the long run. Rainfall exhibits positive long-run effects with a magnitude of about 0.26 percentage points.

**Table 6.** Augmented mean group (AMG) estimators.

Dependent Variable: Agricultural Growth per Worker(log) $\Delta \ln Y$				
	AMG	AMG	AMG(Adj)	AMG(Adj)
$\Delta \ln Y(t-1)$	−0.2059 *** (0.0467)	−0.1954 *** (0.0476)	−0.1991 *** (0.0466)	−0.1882 *** (0.0475)
Temperature	−0.0198 * (0.0082)	−0.0211 ** (0.0060)	−0.0278 *** (0.0078)	−0.0507 *** (0.0049)
Precipitation	0.0050 ** (0.0017)	0.0051 ** (0.0016)	0.0038 (0.0018)	0.0053 (0.0018)
Common Dynamic	0.642 *** (0.116)	0.542 *** (0.1145)		
Process				
Trend	−0.0001 (0.0002)		−0.0006 ** (0.0002)	
Intercept	0.4732 * (0.2063)	0.5153 ** (0.1723)	0.7451 *** (0.1902)	1.2462 *** (0.1251)
Long-Run Coefficients				
$\Delta \ln Y(t-1)$	−1.2059 *** (0.0467)	−1.1954 *** (0.0476)	−1.1991 *** (0.0467)	−1.1882 *** (0.0475)
Temperature	−0.0164 *** (0.0068)	−0.0176 *** (0.0051)	−0.0232 *** (0.0065)	−0.0427 *** (0.0043)
Precipitation	0.0042 *** (0.0014)	0.0043 *** (0.0014)	0.0032 ** (0.0015)	0.0046 ** (0.0016)
CD test statistics	−0.859	−1.062	1.928	2.215
CD ( <i>p</i> values)	0.39	0.288	0.054	0.027
N	1824	1824	1824	1824

Note: Coefficients are reported with standard errors in brackets. \*\*\*, \*\*, and \* indicate significance at 1, 5, and 10% levels, respectively. Column 1 and 2 present AMG estimators given in Equation (7) with  $p_y = 1$  and  $p_x = 0$ .

The long-run estimates are calculated by  $\hat{\theta}_i = \frac{\sum_{j=0}^{p_x} \hat{\beta}_{ij}}{1 - \sum_{j=1}^{p_y} \hat{\lambda}_{ij}}$ . The standard errors are computed via the outlier-robust procedure proposed by Hamilton [31]. In the last two columns, we impose the coefficients of the common dynamics processes to be unit. CD test statistics present the cross-section dependence tests of (Pesaran [28]) on the model residuals with the null of cross-sectional independence.

By calculating the standardized coefficients as in Section 3.3, we can see that one standard deviation change in temperature will have a larger long-run effect on agriculture growth as compared to precipitation. It further proves that temperature has significantly developed a negative relationship with agricultural activities in Sub-Saharan Africa more than the positive effects of precipitation in both the short and long run, endorsing the arguments of Dell, Jones, and Olken [11], Lanzafoame [13], and Abidoye and Odusola [9].

#### 4. Conclusions

Following recent studies on global warming, we estimate the long-run effects of climate change on the agricultural net output growth per worker in Sub-Saharan Africa. Based on a dynamic heterogeneous panel data model with multifactor error structures, we consider different approaches considering the heterogeneity of the parameters and cross-section dependence. With the emphasis on estimating the long-run effects, we estimate the long-run impacts indirectly through the CS-ARDL approach, semi-directly through the CS-ECM method, as well as directly through the CS-DL approach. We also consider the common dynamic process augmented mean group (AMG) to see the consistency of the long-run estimates.

In contrast to the standard mean group estimator (PMG, MG, FE), ignoring the cross-section dependence, all of the estimators we consider (CCEMG, CS-ARDL, CS-DL, CS-ECM, AMG) imply a significant negative long-run correlation between temperature and agricultural growth rates in Sub-Saharan Africa. The positive long-run impact of precipitation has not been found consistently across different estimation methods. The short-run effects of both temperature and precipitation are also not consistent across different estimation methods, indicating that short-run estimates may be sensitive to model and lag specifications.



Conclusively, the study suggests that the rising temperatures have significantly developed a negative relationship with agricultural growth in Sub-Saharan Africa, while the long-run effect of precipitation is less important and not statistically significant in several estimations. The preferred CS-DL approach, which estimates the long-run effects directly, yields the highest magnitude of the negative impact of temperature with a 1 °C rise in temperature leading to a 4.2 to 4.7 percentage point decrease in the agricultural growth rate. It further proposes to take measures for climate change adaptation or appropriate transition of economies from agriculture to other sectors to avoid the negative impacts of surging temperature, especially on the labor market of agricultural-driven Sub-Saharan African countries.

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