

Agricultural productivity in Latin America and the Caribbean in the presence of unobserved heterogeneity and climatic effects

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Abstract Total factor productivity (TFP) analysis has been the focus of a large number of methodological and empirical studies over the past several decades. One remarkable gap in this literature is the omission of climatic variables as regressors in the models used to derive TFP measures. The purpose of this paper is to narrow this gap by developing climate-adjusted (CA) TFP measures. We combine information from the Climatic Research Unit with Food and Agriculture Organization data for 28 Latin American and Caribbean countries over a 52-year period (1961–2012) to estimate random parameter stochastic production frontier (SPF) models. The goal is to investigate the impact of climatic variability on TFP. The estimated coefficients from the SPF models are used to construct a climatic effects index across countries and over time. The average annual variation in climatic conditions is stronger at the end of the 2000s compared to earlier periods. Climatic variability has a negative effect on production in 20 of the 28 LAC countries analyzed, and this is more severe over Central America and the Caribbean. The average reduction in output across the region attributable to climatic variables is between 0.02 and 22.7% over the last decade compared to the period 1961–1999. The estimated average annual growth rate of CATFP (0.69%) is consistently lower than TFP (1.08%), confirming the adverse impact of climatic variability on agricultural output and

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productivity in LAC. The results show considerable variability across countries, and this points to the importance of accounting for climatic effects in analyzing TFP.

1 Introduction

Agriculture plays an important role in the overall economic growth in Latin American and Caribbean (LAC) countries (World Bank 2003). However, Chomitz and Buys (2007) and FAO (2010), among others, point out that agricultural productivity in LAC faces a rising challenge imposed by climate change. FAO (2015) reveals that South America and Africa had the largest net loss of forests between 1990 and 2015 worldwide, with much of that loss in South America probably related to the transformation of tropical forests into pasture land for cattle ranching (Geist and Lambin 2002).

The adverse impact of climatic variability on agricultural production is gaining more attention, with an increasing number of studies focusing on the interrelation between climatic variability, agriculture, the food system, and adaptation (e.g., Mendelsohn and Dinar 2003; Mukherjee et al. 2013; Tol 2013; Qi et al. 2015; Burke and Emerick 2016). Several studies have shown that agricultural productivity in least developed countries is vulnerable to climatic variability (e.g., Müller et al. 2010; Lobell et al. 2011). The World Bank (2012) indicates that the LAC region is expected to suffer severe consequences as a result of rising global temperatures. The historical data seems to corroborate this concern. Figure 1 depicts the region's maximum temperature anomaly, defined as the deviation from the region's long-term mean (1901–2012), and shows that the overall temperature in LAC has risen steadily, since the mid-1970s. In addition, according to Wani et al. (2009), almost 90% of the farmland in LAC is rain-fed, which makes agricultural production very sensitive to changes in precipitation patterns.

Various studies for Latin American countries focusing on the economic impact of future climate conditions have analyzed the changes in crop and livestock productivity due to variations in temperature and precipitation (e.g., ECLAC 2013; IADB and ECLAC 2014). Nevertheless,

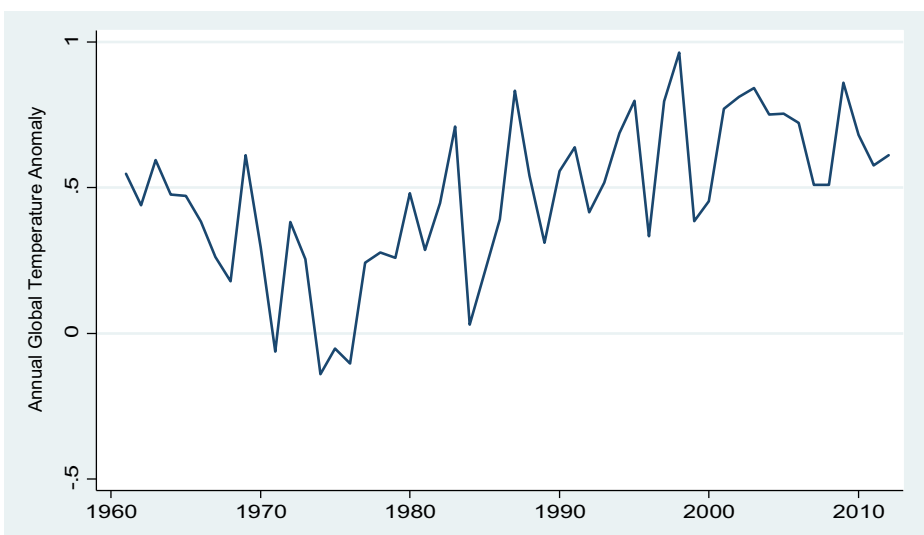


Fig. 1 Maximum temperature anomaly in LAC (1961–2012)

these studies do not present a theoretical framework to capture the impact of year-to-year variation in climatic conditions on production and total factor productivity, which is an element of growing importance with clear implications to output and productivity growth (Dell et al. 2014).

A better understanding of how climatic variables affect production and productivity across countries, accounting for country unobserved heterogeneity (e.g., soil type, average managerial ability), is critical to formulate effective policies. To this end, this article takes advantage of recent methodological contributions, namely the true fixed effect and true random effects stochastic production frontier (SPF) panel data estimators, proposed by Greene (2005a, b), along with the random parameter or random coefficients model (Wooldridge 2002; Greene 2012).

Our work contributes to the literature by addressing the failure to incorporate climatic variability directly when estimating total factor productivity (TFP). The study examines the effects of climatic variables on output and TFP by developing a climate-adjusted TFP (CATFP) measure. Several studies focusing on agricultural productivity in LAC have computed TFP and its components based on traditional inputs (i.e., land, labor, capital, fertilizers, etc.) while excluding climatic variables from the production function. Other authors investigate the role of climatic variability in agricultural productivity (e.g., Mullen 2007; Villavicencio et al. 2013), but to our knowledge, the only published study that incorporates climatic variables directly and explicitly in TFP decomposition is Hughes et al. (2011).

The remainder of this paper is structured as follows: Section 2 presents the analytical framework, Section 3 focuses on the data and the empirical model, Section 4 presents the results, and Section 5 devotes to conclusions and policy implications.

2 Analytical framework

We investigate the impact of climatic variability on production and productivity using panel data SPF specifications. Greene (2005a, b) introduced the true random and true fixed effects (TRE and TFE) models to deal with time-invariant unobserved heterogeneity within stochastic frontier specifications. Here, we use the random parameter or random coefficients model (RPM or RCM) in conjunction with Greene's TRE model. We discard the fixed effects option a priori because it typically yields imprecise estimates when the model includes regressors that are time invariant or that vary slowly across time, as is the case with climatic variables (Wooldridge 2002).

The RPM along with the TRE has the ability to capture heterogeneity for both the intercept and slope parameters in the model (Greene 2008). Hereafter, we refer to the combined TRE, RPM, and SPF frameworks as the true random parameter SPF or TRP-SPF. The rationale for adopting this model rests on the importance of accounting for cross-country heterogeneity given that LAC countries are quite diverse in terms of input quality and technology. In addition, the TRP-SPF approach makes it possible to identify separately time-variant inefficiency from time-invariant country-specific unobserved heterogeneity, such as land quality and environmental conditions that are not captured explicitly in the data and potentially affect the production process. The TRP-SPF estimates are then used to calculate the O'Donnell (2016) TFP index that allows for a consistent comparison of TFP change across countries and time and for decomposing such change into relative measures of technological progress, scale efficiency, technical efficiency, and production environment. We then undertake a detailed analysis of TFP adjusted by climatic effects or CATFP.

2.1 Panel data stochastic production frontiers

Our TRP-SPF model can be expressed as:

$$Y_{it} = \alpha_i + \sum_{k=1}^K \beta_{ik} X_{kit} + \tau_i T_i + \sum_{j=1}^J \eta_j Z_{jit} + \sum_{g=1}^G \omega_g W_{git} + v_{it} - u_{it} \quad (1)$$

where Y_{it} denotes the natural logarithm (log) of agricultural production for the i -th country in the t -th year; X_{kit} is a vector of inputs (expressed in logs) including land, labor, machinery, fertilizers, animal stock, and feed; T is a time trend reflecting technological progress; Z_{jit} are climatic variables expressed in levels (Jones and Olken 2010) that comprise average maximum temperature and monthly average precipitation; W_{jit} captures measures of climatic stability and includes maximum temperature anomaly, monthly standard deviation of maximum temperature, precipitation anomaly, monthly standard deviation of precipitation, and monthly number of rainy days (all in levels); α_i is a random country-specific intercept parameter that accounts for time-invariant unobserved heterogeneity; β_{ik} is an $(i \times k)$ matrix of random slope parameters that follow a predetermined distribution (Greene 2005b, 2008) and account for the unobserved heterogeneity in the covariates across countries (e.g., soil quality); and η_j are parameters to be estimated. The term v_{it} is a random error assumed to follow a normal distribution with mean zero and constant variance ($v_{it} \sim iid N(0, \sigma_v^2)$), and u_{it} is a nonnegative unobservable random term, which captures the technical inefficiency of the i -th country in period t . The inefficiency term u_{it} is assumed to follow a half-normal distribution. The specification of the climatic variables in Eq. 1 follows the growing body of related literature, which is based on the year-to-year variation of these variables and has a strong causative interpretation that allows for the identification of the net climatic effect on agricultural production and productivity (Dell et al. 2014).

We use the Cobb-Douglas (CD) functional form to approximate the technology underlying the TRP-SPF model in Eq. 2; thus, the estimated parameters of the conventional inputs can be interpreted as partial elasticities of production. The CD is chosen because, as argued by O'Donnell (2016), it satisfies nonnegativity and monotonicity globally, while the Translog, a commonly used alternative, does not. More importantly, TFP measures derived from the Translog functional form fail to fulfill the transitivity property, which is a significant violation of the index number theory (O'Donnell 2016). The TRP-SPF models are estimated by simulated maximum likelihood using N-logit 4 (Greene 2012).

2.2 Climatic effects index and CATFP decomposition

Based on Eq. 1 and following Hughes et al. (2011), the expression for the term that captures the climatic variability effect (\hat{C}_{it}) can be written as¹:

$$\hat{C}_{it} = \sum_{g=1}^g \hat{\omega}_g W_{git} \quad (2)$$

¹ We exclude mean values because they do not capture variability.

The climatic effect index, CEI_{it} , is then calculated as $\exp(\hat{C}_{it})$, and this term is used to assess the impact of changes in climatic variables on production across countries and over time.

We now turn to the TFP index methodology proposed by O’Donnell (2016), which we modify to accommodate the random parameters included in our TRP-SPF specification. TFP can be expressed as the ratio of aggregate (ag) output to aggregate input as follows:

$$TFP_{it} = \frac{Y_{it}^{ag}}{X_{it}^{ag}} \tag{3}$$

where the numerator and denominator represent aggregate output and aggregate input, respectively, and both are assumed to be nondecreasing, nonnegative, and linearly homogeneous functions. The index that compares TFP of country i at time t with that of country m in period s is as follows:

$$TFPI_{msit} = \frac{TFP_{it}}{TFP_{ms}} = \frac{Y_{it}^{ag}/X_{it}^{ag}}{Y_{ms}^{ag}/X_{ms}^{ag}} \tag{4}$$

Given a single-output CD technology, the TRP-SPF, a vector of inputs, and substituting Eq. 1 into Eq. 4, $TFPI_{msit}$ can be rewritten as (O’Donnell 2017):

$$\begin{aligned} TFPI_{msit} = & [\exp(\alpha_i - \alpha_m)] \times \left[\prod_{k=1}^K \frac{X_{kit}^{\beta_k}}{X_{kms}^{\beta_k}} \times \left(\frac{X_{kms}}{X_{kit}} \right)^{\frac{\beta_k}{r}} \right] \times [\exp(\tau_i T_i - \tau_m T_m)] \\ & \times \exp \left[\sum_{j=1}^J \eta_j (Z_{jit} - Z_{jms}) \right] \times \exp \left[\sum_{g=1}^G \omega_g (W_{git} - W_{gms}) \right] \times \left[\frac{\exp(v_{it})}{\exp(v_{ms})} \right] \\ & \times \left[\frac{\exp(-u_{it})}{\exp(-u_{ms})} \right] \end{aligned} \tag{5}$$

The components of the TFP index in Eq. 5 are as follows: The first right-hand term (square brackets) captures time-invariant differences in country unobserved heterogeneity (UH); the second term is an index for relative change in scale efficiency (SE), where $r = \sum_{k=1}^K \beta_k$ is an overall measure of returns to scale for the full sample and β_k is the average estimated coefficient for input k (Table 2); the third is the relative change in technological progress (TP); the fourth and fifth terms are changes in climatic effects (CE); the sixth component measures relative change in technical efficiency (TE) calculated according to Jondrow et al. (1982); and the last term captures functional form error and other statistical noise (SN). All Greek parameters are as defined above. We underscore that the transitivity property allows indirect and consistent comparisons of two countries across time and space by choosing any country and any year as the reference point. Equation 1 with and without climatic variables is used to derive CATFP and TFP measures, respectively.

3 Data and empirical model

3.1 Conventional production inputs/output

We use a FAO input-output dataset which is a balanced panel covering the 52-year period going from 1961 to 2012 for 28 LAC countries for a total of 1456 observations (Table 1).² This dataset, or earlier versions of it, has been used in several empirical studies (e.g., Bharati and Fulginiti 2007; Fuglie et al. 2012). Output is expressed as the gross value of agricultural production assessed at constant 2004–2006 global-average prices in international 2005 US dollars. There are six conventional inputs: Land (LAN), Labor (LAB), Machinery (MAC), Fertilizer (FER), Animal Stock (ANS), and Animal Feed (FED). The definition of all these variables can be found in Fuglie et al. (2012) and in the online [Supplementary material](#).

3.2 Climatic variables and data

According to the climatic literature, agricultural production is sensitive to extreme values as well as the frequency or distribution of both precipitation and temperature (Kumar et al. 2011). Therefore, in our model, climatic variability and the intrayear distribution of climatic effects are captured by including the annual maximum temperature anomaly (TMX_A) measured as the deviation of each annual observation from the long-term mean (1901–2012), the annual average temperature (TMX), the intrayear standard deviation of temperature (TMX_{SD}) defined as the monthly standard deviation, the annual precipitation anomaly (PRE_A) measured as the deviation of each annual observation from the long-term mean (1901–2012), the intrayear standard deviation of precipitation (PRE_{SD}), the monthly average (PRE_{AV}) given by the average across 12 months, and the monthly precipitation frequency (RAD_{AV}) measured as the average number of rainy days across 12 months (Fishman 2011).

Our definition of anomaly is similar to that used in Barrios et al. (2010). An advantage of using anomaly, as opposed to average absolute values of temperature and precipitation, is that factors such as station location and elevation are less critical.³ Moreover, agricultural decisions are based on expected weather behavior, so weather deviating from expectations is likely to affect production. Thus, the use of anomalies is a reasonable way to incorporate these unanticipated negative shocks. In addition, the evidence indicates that climate change causes variations in the frequency and intensity of precipitation (Chou et al. 2012). Consequently, the variables often used to quantify these variations are the number of rainy days and precipitation quantity, respectively (Kumar et al. 2011). Finally, instead of using the coefficient of variation to capture the effect of potential extreme events on production, as done by Chen et al. (2004) and Cabas et al. (2010), we employ the intrayear standard deviation and average climatic variables separately. This choice is predicated on our interest in capturing climatic conditions and variability separately as measures of intrayear distribution.

To construct the climatic variables, we use the well-known dataset from the Climatic Research Unit (CRU) of the University of East Anglia covering the period from 1961 to 2012, which has been employed in several studies (e.g., Schlenker and Lobell 2010). This

² The 28 countries in LAC include (1) Caribbean: The Bahamas, Cuba, Dominican Republic, Haiti, Jamaica, Puerto Rico, and Trinidad and Tobago; (2) Mexico and Central America: Mexico, Belize, Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua, and Panama; and (3) South America: Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, French Guiana, Guyana, Paraguay, Peru, Suriname, Uruguay, and Venezuela.

³ See <https://www.ncdc.noaa.gov/monitoring-references/dyk/anomalies-vs-temperature> for more details.

Table 1 Descriptive statistics for 28 LAC countries for the 1961–2012 period (sample size = 1456)

Variables	Mean	Std. dev.	Min	Max
Production	5.75	15.00	0.00	150
Machinery	47.33	131.71	0.02	1000
Fertilizer	300.80	1068.28	0.07	13,000
Animal stock	14.53	34.64	0.00	258.80
Feed	2983.33	7916.65	0.02	71,000
Land	5874.06	13,183.23	1.79	86,656.10
Labor	1474.39	2907.82	5.00	16,345
Max temp	28.74	3.38	12.86	31.77
Max temp _{SD}	0.51	0.24	0.10	1.87
Precipitation	1833.48	705.87	436.10	3686.70
Precipitation _{SD}	53.44	30.04	5.46	270.34
Rainy days	156.02	47.47	50.10	259.40

SD: intrayear standard deviation, *temp*: temperature

dataset contains monthly and yearly time series for the number of rainy days (RAD) which includes all days with >0.1 mm of precipitation, quantity of precipitation (PRE) in millimeters, and maximum temperature (TMX) measured in degree Celsius (°C). The RAD, PRE, and TMX data are based on monthly climatic observations and weather station anomalies that are interpolated into high-resolution grids (0.5° × 0.5° latitude/longitude). Although agricultural seasons vary widely across LAC countries, it is not possible to estimate our models using more disaggregated climatic variables. Thus, the climatic data used in the analysis are 12-month averages, adjusted for seasonality as explained below, in order to match with the annual input-output data available.⁴ This approach is consistent with Yang and Shumway (2016) who argue that using aggregate climatic data does not capture substantial climatic variation within a decision-making unit, but makes empirical estimation possible.

First, monthly climatic variables are adjusted for seasonality using the seasonal trend decomposition (STL) approach based on the local regression (LOESS) procedure (Cleveland et al. 1990). Adjusting weather data for seasonality has been shown to provide a better fit in regression analyses (Craigmile and Guttorp 2011). As indicated, agricultural seasons vary across LAC and this makes it difficult to include seasonal climatic variables when using annual panel data from several countries. An advantage of the STL approach over the classical moving-average decomposition is that one can handle any type of seasonality while allowing the seasonal component to change over time (Cleveland et al. 1990); therefore, this approach is well suited for our purposes. Climatic variables across all LAC show a seasonal effect; thus, the STL approach is used to deseasonalize temperature, precipitation, and rainy days for each of the countries in the sample (see online [Supplementary material](#)).

4 Results

We estimated a number of Cobb-Douglas specifications including alternative climatic variables and different assumptions regarding which conventional input parameters should be random or fixed.⁵ These different model specifications were compared using likelihood ratio tests.⁶ We

⁴ For more details about the construction of the climatic variables, see Harris et al. (2013).

⁵ We perform multicollinearity tests for all conventional inputs and climatic variables using the “rmcoll” syntax in Stata 14 (Cameron and Trivedi 2005). The evidence does not support the presence of multicollinearity.

⁶ We did not find evidence to support the inclusion of quadratic terms for climatic variability.

retained the preferred random parameter production frontier model including the five climatic variables discussed earlier (TRPc). For comparison purposes, we also estimated the same model but excluding the climatic variables (TRPnc). In both the TRPc and TRPnc models, the parameters for land, machinery, feed, labor, and time trend are random, i.e., are allowed to vary across countries, while the parameters for the other inputs are nonrandom. In other words, the models incorporate unobserved heterogeneity associated with land, machinery, feed, and labor and differences in technologies across countries. Any distribution may be used for any parameter depending on the nature of the data (Greene 2008). In our context, the random parameters for the variables land, feed, labor, and technology follow a normal distribution. However, a log-normal distribution is used for the variable machinery to ensure consistency with regularity conditions across all country-specific parameters. Table 2 reports the average estimated parameters for all variables, fixed and random, and the country-specific estimated parameters are reported in the online [Supplementary material](#).

All parameters for the variables that capture traditional inputs across models are statistically significant at the 1% level, and regularity conditions from production economic theory (i.e., partial output elasticities should be nonnegative and less than 1) are satisfied (Table 2). In addition, average technological progress, captured by the time trend parameters, is significant at the 1% level with slight variations across the two models. The parameters for the climatic variables are statistically significant with the exception of the intrayear standard deviation of precipitation. As expected, we fail to accept the TRPnc specification without climatic variables at the 1% level of significance; thus, TRPc outperforms TRPnc. This implies that excluding the climatic variables leads to an omitted variables problem and thus to biased estimates. Moreover, the signal-to-noise ratio (λ) is highly significant revealing the importance of technical inefficiency in output variability. The estimated parameters of the TRPc frontier, reported in the fourth column of Table 2, reveal that agricultural production in LAC is most responsive to land, followed by animal stock and feed.⁷

4.1 Climatic effects index

Maximum temperature and annual and monthly precipitation all have a significant impact on production. Temperature (TMX_{λ}) and precipitation anomalies (PRE_{λ}) both have a negative and significant impact on production. Intra-year deviation (TMX_{SD}) from the current mean of maximum temperature (28.7 °C) has an adverse significant impact on output, while intra-year deviation in precipitation (PRE_{SD}) has a positive but nonsignificant effect on production. The results also reveal that monthly precipitation frequency (RAD_{AV}) has a significant negative effect on production.

Figure 2 exhibits mean CEI values that capture climatic variability across countries over time. The CEI is normalized by the average climatic conditions for the period 1961–1999 as in Hughes et al. (2011). These values are computed from the estimated coefficients for the TRPc model from Eq. 2. These values suggest that CEI has had an increasingly negative effect on production over time.

⁷ Over the 1961–2012 period, fertilizer use grew at the fastest annual rate (5.8%) relative to all other inputs, while land increased at 1.3% per year. Figure C in the online Supplementary material (Section E) shows the trends for all inputs used in our models.

Table 2 Estimates for the true random parameter stochastic production frontier models without (TRPnc) and with climate (TRPc) ($N = 1456$)

Models	Model TRPnc		Model TRPc	
	Coeff.	SE	Coeff.	SE
Constant	13.870***	0.003	12.873***	0.061
Machinery	0.090***	0.002	0.044***	0.004
Fertilizer	0.044***	0.002	0.066***	0.004
Animal stock	0.338***	0.004	0.257***	0.006
Feed	0.036***	0.002	0.116***	0.003
Land	0.303***	0.005	0.427***	0.009
Labor	0.148***	0.004	0.017*	0.009
Time trend	0.007***	0.000	0.005***	0.000
TMX _A			-0.023***	0.008
TMX			0.008***	0.002
TMX _{SD}			0.049***	0.013
PRE _A			-0.0006***	0.000
PRE _{AV}			0.008***	0.000
PRE _{SD}			0.0001	0.000
RD _{AV}			-0.008***	0.003
λ	3.067***	0.120	1.843***	0.277
σ	0.14***	0.002	0.137***	0.004
σ_u	0.148	n/a	0.120	n/a
σ_v	0.048	n/a	0.065	n/a
RTS	0.96		0.93	
TE				
Mean	0.889		0.911	
SD	0.067		0.048	
Min	0.597		0.668	
Max	0.986		0.983	
Log-likelihood	1168.7		1218.7	

Variables are measured in natural log

SE standard error, n/a not available

***, **, and * are 1%, 5%, and 10% level of significance, respectively

Using the mean CEI, we compute the percent change in production over the period 2000–2012 relative to 1961–1999 holding inputs constant at their mean values. Figure 3 reveals that the average negative effect of climatic variability on output in the last decade compared to the earlier period ranges from 0.02% (Dominican Republic) to 22.7% (Guatemala). Furthermore, the results suggest that the effects of climatic variability fluctuate significantly across LAC subregions and countries with a tendency to be more detrimental in Central American and Caribbean countries. Significant negative effects are also evident for Brazil (15.7%), Venezuela (10.6%), and Uruguay (6.4%). In fact, the climatic effect in all countries in our sample is negative except for eight countries: Bolivia, Chile, Colombia, Ecuador, Suriname, Panama, Puerto Rico, and Haiti. We do not have data on investments in irrigation infrastructure or in other adaptation strategies that might have been implemented in various countries to help farmers cope with climatic variability. Likewise, we do not have detailed data on hurricanes across countries over the period studied (1961–2012). Hurricane events are likely to affect agricultural infrastructures and thus agricultural production and productivity in Caribbean countries. Therefore, results for certain countries in the Caribbean (e.g., Haiti, Puerto Rico) should be interpreted with caution.

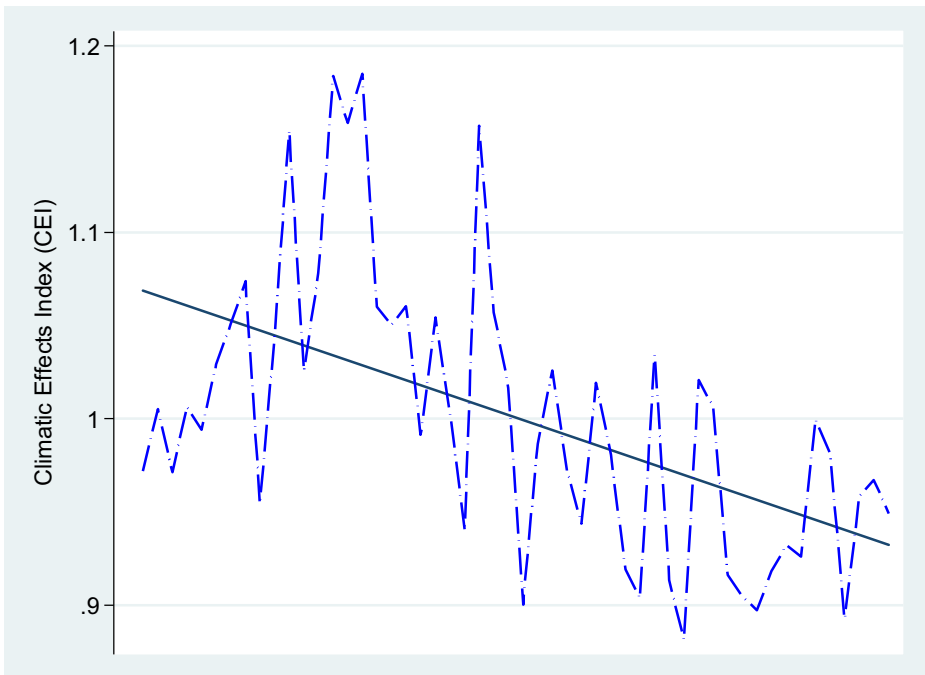


Fig. 2 Mean climatic effects index (CEI) across LAC countries, 1961–2012

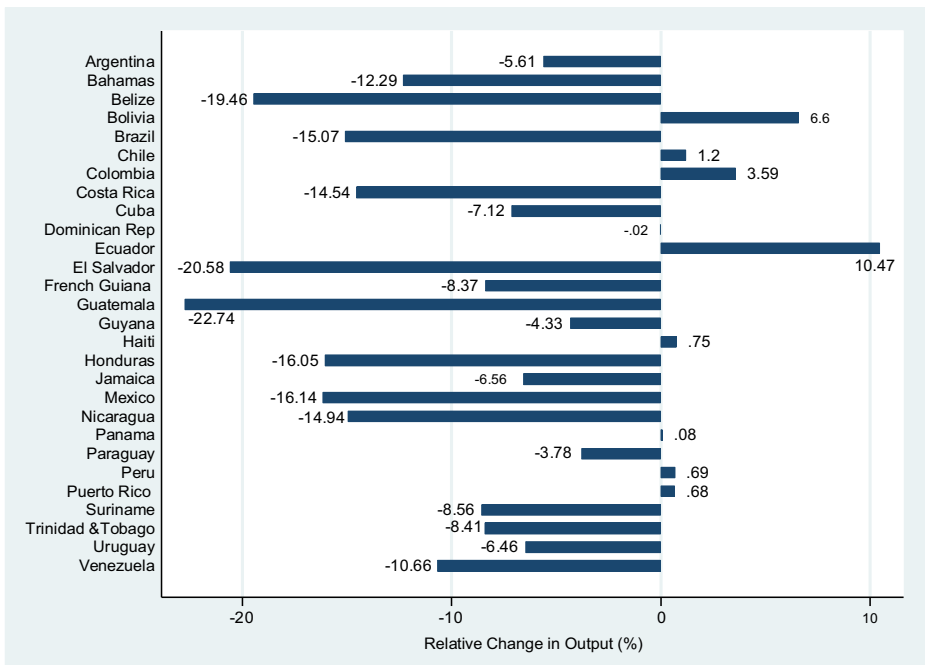


Fig. 3 Relative change in output across countries in LAC due to climatic variability (1961–1999 vs 2000–2012) (%)

4.2 Total factor productivity and its components

We now turn our discussion to TFP and analyze the difference between TFP and CATFP. As depicted in Table 3, the (simple) average TFP growth in the region for the period is 1.08% per year. By contrast, the simple average CATFP growth rate in the region is 0.69% per year. At the country level, 25 out of the 28 countries exhibit a lower CATFP than TFP, showing the negative impact of climatic variability on agricultural productivity growth. The largest percentage point differences between TFP and CATFP are in Paraguay (1.3%), Nicaragua (1.2%), and Guatemala (1.0%). Also, several Caribbean countries show consistently lower rates of CATFP, which may be due to extreme events such as hurricanes. Investigating how hurricanes or other extreme events might affect CATFP would be worth considering in future research (e.g., Pielke et al. 2003).

Figure 4 depicts average TFP and CATFP levels across LAC countries. Both measures follow similar trends with significant variation over the years. However, the gap between the two indexes widens which underscores the rising adverse impact of climatic variability on TFP over time. In addition, CATFP is always lower than TFP corroborating the adverse impact of climatic variability on agricultural output in LAC.

The decomposition of average CATFP shows that Panama has the highest average TE at 0.934 for the 1961–2012 period while Nicaragua (TE = 0.85) and French Guiana (TE = 0.87)

Table 3 Average annual TFP and CATFP growth rates and percentage point difference (%Diff) in LAC, 1961–2012

Country	TFP	CATFP	% point diff
Argentina	1.03	0.56	0.47
The Bahamas	1.53	1.43	0.10
Bolivia	1.18	0.45	0.73
Brazil	2.06	1.54	0.52
Belize	1.94	1.49	0.46
Chile	2.44	1.82	0.62
Colombia	1.85	1.36	0.49
Costa Rica	1.48	1.65	-0.17
Cuba	-0.24	-0.43	0.19
Dominican Republic	0.57	0.25	0.32
Ecuador	1.35	0.89	0.46
El Salvador	0.41	0.52	-0.11
French Guiana	0.41	-0.20	0.61
Guatemala	1.98	0.94	1.04
Guyana	0.66	0.59	0.07
Haiti	0.00	-0.33	0.33
Honduras	1.98	1.41	0.56
Jamaica	0.52	0.61	-0.09
Mexico	1.60	1.08	0.52
Nicaragua	1.13	-0.08	1.21
Panama	0.12	-0.32	0.45
Paraguay	1.15	-0.14	1.29
Peru	1.47	1.13	0.34
Puerto Rico	0.02	0.52	-0.50
Suriname	1.01	0.34	0.67
Trinidad and Tobago	-0.66	-0.23	-0.43
Uruguay	1.22	1.03	0.18
Venezuela	1.96	1.37	0.59
LAC	1.08	0.69	0.39

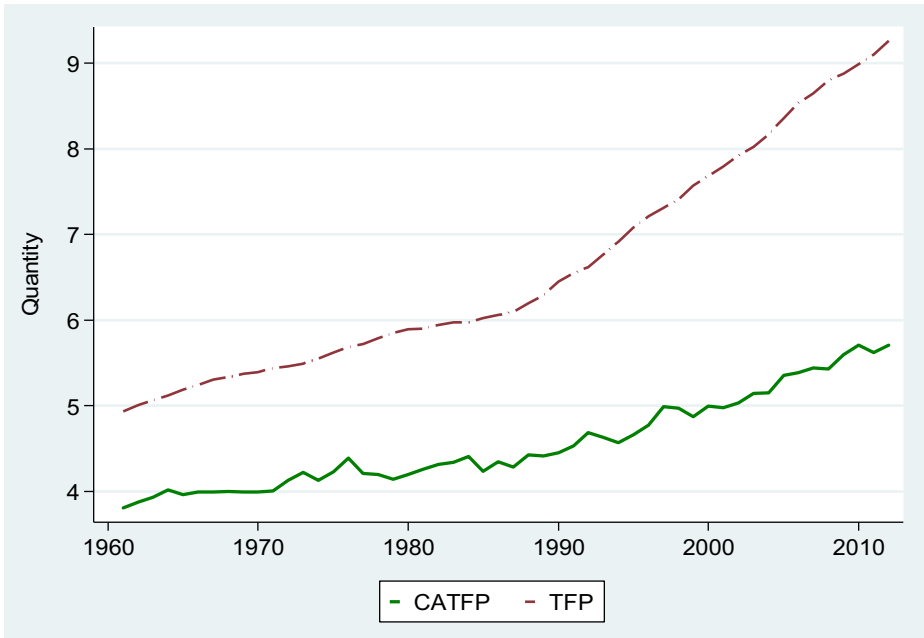


Fig. 4 Annual average TFP and CATFP for Latin America and the Caribbean, 1961–2012

have the lowest (Table 4). It is worth noting that TE provides a measure of the gap between what is produced and what could be produced given inputs, technology, and the environment

Table 4 Annual average growth rates in CATFP and its components (%) and level of TE in LAC, 1961–2012

Countries	CATFP	CE	TP	SE	TE	UH	SN	TE level
Argentina	0.56	-0.01	0.62	-0.02	-0.05	0.02	0.000	0.919
Bahamas	1.43	0.05	0.79	0.09	0.36	0.13	0.006	0.895
Bolivia	0.45	-0.03	0.48	-0.07	0.04	0.03	0.000	0.921
Brazil	1.54	-0.02	1.61	-0.04	-0.03	0.03	-0.001	0.915
Belize	1.49	0.02	1.52	0.04	-0.17	0.07	-0.001	0.910
Chile	1.82	0.02	1.74	0.04	-0.02	0.04	0.001	0.917
Colombia	1.36	0.03	1.08	0.05	0.16	0.04	0.003	0.897
Costa Rica	1.65	-0.09	2.06	-0.18	-0.19	0.06	-0.008	0.919
Cuba	-0.43	0.02	-0.42	0.03	-0.08	0.02	0.000	0.919
Dominican Rep	0.25	0.01	0.12	0.03	0.00	0.08	0.000	0.922
Ecuador	0.89	0.03	0.82	0.06	-0.05	0.03	0.001	0.883
El Salvador	0.52	0.07	0.20	0.15	0.05	0.06	0.001	0.922
French Guiana	-0.20	0.05	-0.11	0.10	-0.32	0.07	0.000	0.879
Guatemala	0.94	0.04	0.71	0.08	0.06	0.05	0.002	0.924
Guyana	0.59	-0.01	0.62	-0.02	-0.03	0.03	0.000	0.911
Haiti	-0.33	0.04	-0.48	0.06	0.05	0.00	-0.001	0.908
Honduras	1.41	0.06	1.16	0.12	0.02	0.05	0.003	0.908
Jamaica	0.61	-0.08	0.75	-0.14	0.02	0.06	-0.001	0.917
Mexico	1.08	-0.04	1.04	-0.07	0.11	0.04	0.000	0.921
Nicaragua	-0.08	0.00	-0.36	0.00	0.23	0.04	-0.001	0.857
Panama	-0.32	-0.06	-0.12	-0.11	-0.07	0.03	0.000	0.934
Paraguay	-0.14	-0.01	-0.29	-0.02	0.14	0.04	0.000	0.916
Peru	1.13	0.04	0.98	0.06	0.02	0.03	0.002	0.909
Puerto Rico	0.52	0.00	0.54	0.02	-0.06	0.03	0.000	0.931
Suriname	0.34	-0.02	0.06	-0.03	0.30	0.04	0.000	0.916
Trinidad and Tobago	-0.23	0.06	-0.41	0.12	-0.02	0.03	-0.001	0.910
Uruguay	1.03	0.01	1.01	0.02	-0.02	0.02	0.000	0.919
Venezuela	1.37	-0.01	1.27	-0.02	0.08	0.05	0.001	0.912
LAC	0.69	0.01	0.61	0.01	0.02	0.04	0.000	0.91

in a given country. The average returns to scale (RTS) measure is estimated at 0.91 (see Table 2) implying that overall the technology exhibits decreasing returns to scale. Using Eq. 5, the percentage rate of growth in CATFP can be decomposed as follows: $\% \Delta \text{CATFP} = \% \Delta \text{UH} + \% \Delta \text{TE} + \% \Delta \text{SE} + \% \Delta \text{TP} + \% \Delta \text{CE} + \% \Delta \text{SN}$, where the components are as previously defined. The average estimated parameter for the time trend (τ) reveals that LAC countries, as a whole, experienced technological progress at a 0.61% annual rate over the sample period (Table 4). However, given the random coefficient specification used, country-specific rates of technological progress can be computed. As displayed in Table 4, Costa Rica (2.06%), Chile (1.74%), and Brazil (1.61%) exhibit the highest average annual rates of TP, whereas Haiti (−0.48%), Cuba (−0.42%), and Trinidad and Tobago (−0.41%) have the lowest.

Figure 5 shows that TP has been the key driver of agricultural productivity in the region, which is consistent with other studies (e.g., Bharati and Fulginiti 2007; Nin-Pratt et al. 2015). The scale efficiency has remained quite flat, decreasing by 0.01% annually without much of an effect on overall productivity (Table 4). This result is not surprising given the nature of decreasing returns to scale of the technology. Finally, TE for all countries combined was more or less constant during the first two decades followed by a decline and then a slight increase in the last decade averaging 0.02% per year over the period.

Our TFP growth estimates are difficult to compare with what is reported by other authors, because of differences in model specifications (e.g., definition of inputs and outputs, time periods, countries, estimation methodology, etc). Notwithstanding, our results are similar to those of Fuglie et al. (2012) who covered the same time period as in this study though they used a different methodology. Our estimates are lower than those of Nin-Pratt et al. (2015) who found an average annual growth of 1.2% for 26 LAC countries for the 1981–2012 period. The CATFP estimates are not comparable with other studies because no such measures have been reported.

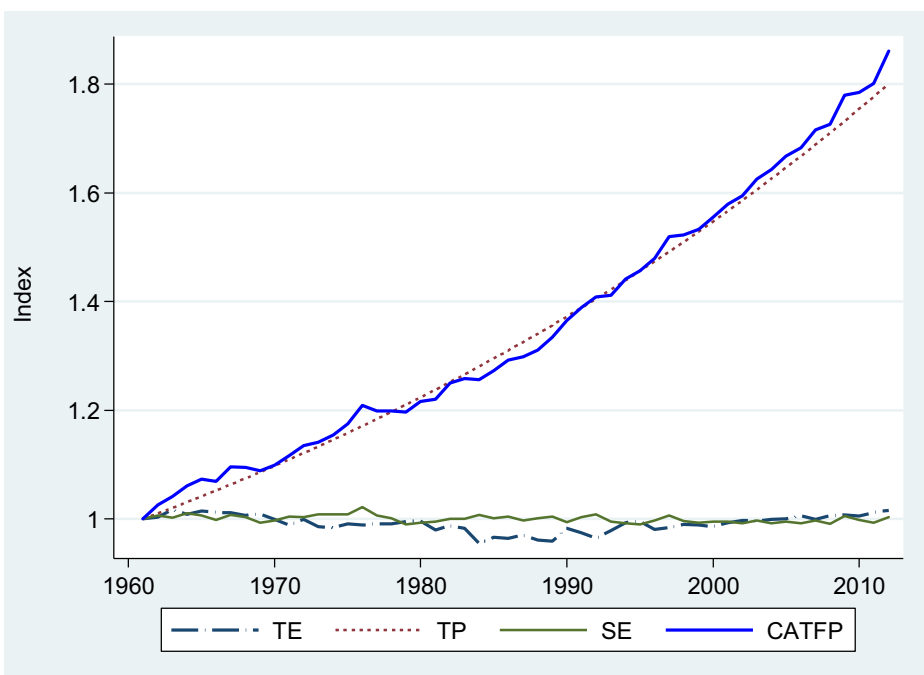


Fig. 5 Cumulative CATFP and components (TE, TP, and SE) in LAC, 1961–2012 (1961 = 1)

5 Concluding remarks

The impact of climatic variability on agricultural production and productivity is an unfolding area of study and debate among researchers, policymakers, and international institutions. Despite the significance of this issue, previous studies related to agricultural productivity in LAC countries have neglected the climatic variability component.

The results of our analysis indicate that the combined effect of changes in temperature and precipitation patterns has had an adverse impact on output in LAC. In addition, the evolution of the CEI suggests an increasingly negative impact on production over time, reducing output during the 2000–2012 period compared to 1961–1999. These results along with the projections for future climate change (IPCC 2014) suggest that agricultural production can be expected to undergo severe pressure, *ceteris paribus*. The *ceteris paribus* assumption is likely to be too strong, and we expect that technological progress and adaptation by farmers and governments would moderate the adverse effects of climatic variability. Nevertheless, these results highlight the importance of undertaking adequate and effective measures to mitigate the impacts of climatic variability on agricultural production and to promote suitable adaptation strategies.

Mean annual TFP growth rates adjusted for climatic variability (CATFP) are lower than traditional estimates, revealing negative climatic effects on productivity growth during the 1961–2012 period. In addition, there is considerable variability in CATFP across countries and over time within countries. Climatic variability affects production unevenly across time and space, and these effects have been particularly negative in most Central American and several Caribbean countries.

Technological progress has been the key driver of agricultural productivity growth in LAC. Therefore, investment in R&D to facilitate access to the best available technologies is critical in the region. In addition, investments in training and education to reinforce the absorptive capacity of existing and of new technologies are also critical. For example, governments should consider policies that promote investing in new climate-resilient technologies while reorienting agricultural systems to reinforce resilience, climate-adaptive capacity, and technical efficiency (Lipper et al. 2014). Such implementation should reflect specific country conditions, as climatic variability impacts are heterogeneous.

The impact of climatic variability on agricultural productivity is a global issue with potential worldwide consequences on food security, particularly for people who are most vulnerable and least able to cope with this adversity. Promoting climate adaptation programs in agriculture and providing technical and financial assistance to local governments could help reduce the negative impacts of climatic variability. More investment and coordination among stakeholders is needed in the agricultural sector to encourage sustainable and climate-resilient production technologies and crop varieties that can better withstand climatic variability.

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