Agricultural Water Management 324 (2026) 110114

Contents lists available at ScienceDirect

Agricultural Water Management

journal homepage: www.elsevier.com/locate/agwat

# Impact of climate change on agricultural production efficiency in leading agriculture-producing economies: A DEA Malmquist Productivity Index

Junid Ahmad [a], Yunchen Wang [a], Liguang Zhang [a], Wasi Ul Hassan Shah [b,*], Rizwana Yasmeen [c], Heshan Sameera Kankanam Pathiranage [d]

[a] College of Management, Sichuan Agricultural University, No.211, Huimin Road, Wenjiang District, Chengdu City, Sichuan Province, China
[b] School of Economics and Management, Zhejiang Shuren University, Hangzhou 310015, China
[c] School of Economics and Management, Panzhihua University, Panzhihua, Sichuan 617000, China
[d] Department of Business Management, Sri Lanka Institute of Information Technology, Malabe, Sri Lanka

ARTICLE INFO

Handling Editor-Dr. Brent Clothier

*Keywords:*
Agricultural efficiency
DEA–Malmquist
Climate change
Technology change
Regional heterogeneity
Non-parametric tests

ABSTRACT

Climate change significantly impacts global agricultural productivity, making it essential to examine its precise influence on production efficiency. This study evaluates the impact of climate change on agricultural production efficiency among the global leading agriculture-producing economies from 1990 to 2021. Using a DEA–Malmquist Productivity Index, the study estimates total factor productivity change (TFPC) and decomposes it into efficiency change (EC) and technological change (TC), both without and with explicit climate variables (temperature, precipitation). Average TFPC without climate factors is 1.0428, indicating 4.28 % productivity growth over the period, primarily driven by technological change. When climate variables are incorporated, the average TFPC is 1.0409; the mean difference of −0.0019 (≈ −0.18 %) shows a small but non-negligible climate impact on productivity growth. Regional variations are heterogeneous: South America and Africa exhibit diverse climate impacts, while Oceania shows the least climate effect. Mann-Whitney U and Kruskal-Wallis tests confirm significant differences in TFPC (and components) between climate and non-climate specifications and across regions. The findings underscore technology's key role in sustaining productivity under climate stress and highlight the need for region-specific adaptation policies to complement technological diffusion.

## 1. Introduction

Agriculture is a cornerstone of the global economy and food security, supporting the livelihoods of billions, particularly in developing nations (Pingali, 2012; World Bank, 2025). However, as a sector fundamentally dependent on climate-sensitive natural resources, it is acutely vulnerable to the escalating impacts of climate change (Foley et al., 2011). Altered temperature and precipitation regimes directly threaten crop yields, economic stability, and the resilience of food systems, with impacts most severe in regions like sub-Saharan Africa, South Asia, and Latin America (Schlenker and Letters, 2010; Charles et al., 2010; Tilman et al., 2011).

To effectively adapt, it is crucial to move beyond assessing impacts on single outputs and instead evaluate climate change's effect on agricultural total factor productivity (TFP). The overall efficiency with which all inputs (land, labor, capital) are converted into output. A decline in TFP represents a more systemic and economically critical challenge than a simple yield reduction. Numerous research studies explore the impact of climate change on a single factor of production decline without incorporating the comprehensive inputs (Chandio et al., 2025a; Chandio et al., 2025b).

Most studies investigating climate-agriculture linkages are localized, focusing on single countries, specific crops, or short timeframes, which limits the derivation of generalizable, global insights (Hussain et al., 2020; Gul et al., 2022). More critically, few analyses decompose aggregate TFP change into its core drivers: technological progress (shifts in the production frontier) and efficiency improvements (movement towards the frontier). Even fewer explicitly integrate climatic variables directly into the productivity measurement framework (Sheng and Modelling, 2019). Consequently, the existing literature fails to provide robust, comparative evidence quantifying the precise marginal loss in productivity growth attributable to climate change the "climate drag."

* Corresponding author.
*E-mail addresses:* junidswufe@gamil.com (J. Ahmad), wangyc8684@qq.com (Y. Wang), zlg1990zlg@163.com (L. Zhang), wasiulhassanshah@zjsru.edu.cn (W.U.H. Shah), rizwanayasmeen@pzhu.edu.cn (R. Yasmeen), heshan.s@sliit.lk (H.S.K. Pathiranage).

https://doi.org/10.1016/j.agwat.2025.110114
Received 24 October 2025; Received in revised form 23 December 2025; Accepted 25 December 2025
Available online 6 January 2026
0378-3774/

Moreover, it cannot discern whether this drag primarily hinders technological innovation or impedes the efficient adoption of existing technologies.

This study bridges these gaps by conducting a long-term (1990–2021), multi-regional analysis of the world's 31 largest agricultural-producing economies. The study employed a Data Envelopment Analysis (DEA) based Malmquist Productivity Index to decompose Total Factor Productivity Change (TFPC) into Efficiency Change (EC) and Technological Change (TC). The core methodological contribution is the explicit integration of climate variables (temperature, precipitation) to construct a "with-climate" productivity frontier, which is directly compared to a traditional "without-climate" frontier. This comparative design uniquely allows us to isolate the marginal effect of climate on productivity and its components. This study further apply non-parametric statistical tests (Mann-Whitney U, Kruskal-Wallis) to validate the significance of observed differences across models and regions.

This innovative approach generates novel, policy-relevant insights. First, it provides a global estimate of the climate-induced drag on agricultural productivity growth. Second, it reveals whether technological change or efficiency improvement has been the primary buffer against climate stress. Third, it uncovers significant heterogeneity in climate impacts across different geographic regions. Collectively, these findings offer a rigorous, empirical basis for designing targeted and effective climate adaptation strategies in the agricultural sector.

The paper is structured as follows: Section 2 reviews the relevant literature, Section 3 details the methods and data, Section 4 presents the results, and Section 5 discusses the findings. The conclusion, policy implications and future research directions are illustrated in Section 6.

## 2. Literature review

To place the current study into the context of the overall scholarly conversation, this review is organized into three thematically interconnected clusters: (1) the well-known impacts of climate change on agricultural Productivity, (2) the most common methodological approaches to quantifying agricultural Productivity and efficiency, and (3) the gaps in the knowledge that remain at present, especially as far as the integration of climatic variables into efficiency analyses is concerned.

### *2.1. Agricultural productivity and the effects of climate change*

The current opinion in the literature confirms that anthropogenic climate change, in terms of heat rays, disrupted precipitation values, and greater occurrence of extreme weather phenomena, is an inherent threat to global agricultural economies (Lobell and physiology, 2012; Lesk et al., 2016). The association is characterized by a high level of heterogeneity on the regional level. Although there are short-term positive effects, especially in susceptible rain-fed agricultural systems of sub-Saharan Africa, South Asia, and Latin America, the bulk of the evidence points to significant adverse effects even in some of the more favorable, higher-latitude regions (Schlenker and Roberts, 2007; Hussain et al., 2020; Chen et al., 2018).

These impacts have biophysical processes that are well documented. The heat stress hastens the growth of crops thus reducing the duration of the important growth stages and decreasing the yield potential (Lobell and Field, 2007). Enhanced variability of climates increases the intensity and occurrence of droughts and floods that trigger direct losses of crops and soil erosion (Yumul et al., 2011; Easterling et al., 2023). Besides, changing weather patterns may change the geographical distribution and severity of pests and diseases, presenting new biotic stressors (Chakraborty et al., 2015). These immediate effects are transmitted into larger socioeconomic effects, threatening the livelihoods of rural populations, economic sustainability and eventually local and global food security (Wheeler and Von Braun, 2013; Bates et al., 2008).

To address these challenges, there has been a lot of research based on adaptation and mitigation measures. It includes the production and popularization of climate-resistant crop cultivars, accurate farming technologies to maximize the amount of input used, water management solutions, and the integrative structure of Climate Smart Agriculture (CSA) (Tey and Brindal, 2022; Lipper et al., 2014). It is a well-known fact among scholars that the implementation of such strategies is most affected by favorable policy frameworks and institutional incentives (Fischer et al., 2002; Gordeev et al., 2018).

### *2.2. Techniques of measuring agricultural productivity and efficiency*

The effectiveness of adaptation strategies and the assessment of the performance of agriculture requires the effective measurement of productivity. A broad range of methodologies has been used by researchers, with some having their own strengths and weaknesses. Conventional methods, such as growth accounting and aggregate production functions, approximate total output in relation to aggregate inputs but often do not take into consideration the issue of inefficiency (Chen et al., 2021).

Frontier analysis methods are used in order to explicitly model inefficiency. Stochastic Frontier Analysis (SFA) is a parametric model that separates both random error and systematic inefficiency by assuming a functional expression of the production frontier (Madau, 2012). Data Envelopment Analysis (DEA), on the other hand, is a non-parametric, linear programming model, which forms a piece-wise frontier based on the best-performing decision-making units (DMUs) in a dataset (Charnes et al., 1978). One of the salient strengths of DEA in climate-impact studies is its flexibility, which does not need a priori functional specifications and can effectively accommodate various inputs and outputs, which makes it suitable for measuring efficiency in various and non-standard conditions, including climatic shocks (Kumar et al., 2009; Burney et al., 2010).

The Malmquist Productivity Index (MPI), which is frequently used together with DEA, is a significant instrument for studying change in productivity over time. The main strength of it is that it breaks down Total Factor Productivity Change (TFPC) into two core bases, Efficiency Change (EC), which reflects the advancement to the existing frontier (through better management and resource allocation) and Technological Change (TC), which is an indicator of the change of frontier itself (through innovation and implementation of new technologies) (Färe et al., 1994).This dismantling is essential in policy-making because it helps differentiate between the better practices with the current technology and the need to have a great technological improvement.

Empirical use of such frontier techniques has shown a strong spatial and time difference in agricultural efficiency, often associated with varying degrees of technology adoption, input use, and institutional service (Headey, economics, 2008). Research that utilizes such methods has reported the impacts of climate on efficiency across different countries, such as Pakistan, Vietnam, Australia, and China (Hussain et al., 2020; Duffy et al., 2021; Chen et al., 2021).

### *2.3. Gaps and the role that this study plays*

A critical analysis of the literature, however, reveals persistent and interrelated gaps that this research directly addresses.

To begin with, there is lack of empirical scope. The existing literature is still characterized by localized and single-country case-studies or looking at the specific type of crops (e.g., (Gul et al., 2022; Dawadi et al., 2022). Nevertheless, this patchwork approach limits the ability to draw generalizable, comparative conclusions regarding global trends and the relative vulnerability of different agricultural systems.

Second, and more methodologically important, climate variables and frontier efficiency models are not integrated. Numerous studies find a relationship between climate measures and efficiency that is measured, and yet most studies do not directly include temperature and precipitation as part of the productivity measure (e.g., in the DEA model). This exclusion restricts the capability to devise a counterfactual a climate-adjusted frontier against which the edge effect of climate can be accurately measured.

Third, connected to the former, a lack of studies determining the systematic decomposition of productivity to isolate the differential impact of climate on its drivers is found. The knowledge of whether climatic stress stands as the main barrier to the adoption of new technology (modifying TC) or is the constraint to the efficient utilization of the available resources (modifying EC) is essential in designing specific interventions. The existing literature does not a provide a good source of evidence on these fronts.

To this end, this research will fill these particular gaps. This multi-regional (1990 2021), long-term (31 largest agricultural producers in the world) analysis of the world breaks the single-country analysis fragmentation. We are also innovating with explicit inclusion of the climate variables into a DEA-Malmquist model so that one can directly compare the productivity frontiers and their constituents with and without climatic factors. This method alone allows us to: (1) to measure the marginal climate drag on the growth of world agricultural productivity, (2) to examine whether this drag is concentrated on technological or technical efficiency, and (3) to examine the heterogeneity of these impacts in large geographic regions, in a way that provides an integrated and empirical foundation on the development of world and regional policy.

## 3. Methods

### 3.1. Analytical framework & rationale

This paper uses a multi-stage analytic model to examine how the climate variables affect agricultural Total Factor Productivity (TFP). The process, as represented in Fig. 1, is aimed at eliminating the confounding effect of climatic factors. The first step is the process of choosing the key agricultural-producing economies and the collection of a panel dataset, covering 1990–2021, which includes classic inputs, outputs, and climate factors. A Data Envelopment Analysis (DEA)-based Malmquist Productivity Index is employed to gauge the total factor agricultural productivity change at two core analytical stages, i.e., with the baseline model specification consisting of the use of conventional economic inputs, and with the augmented model specification that incorporates temperature and precipitation as non-discretionary environmental inputs. The comparative design enables the direct evaluation of the effect of climate considerations on productivity measurements. This last step exposes the by-products of the efficiency and productivity scores to non-parametric statistical tests (Mann-Whitney U and Kruskal-Wallis) to confirm the relevance of the identified differences amongst models, as well as between geographical regions. This is a sequential process of measurement, comparative analysis and statistical inference that guarantees robust findings on the influence of climate on agriculture productivity changes.

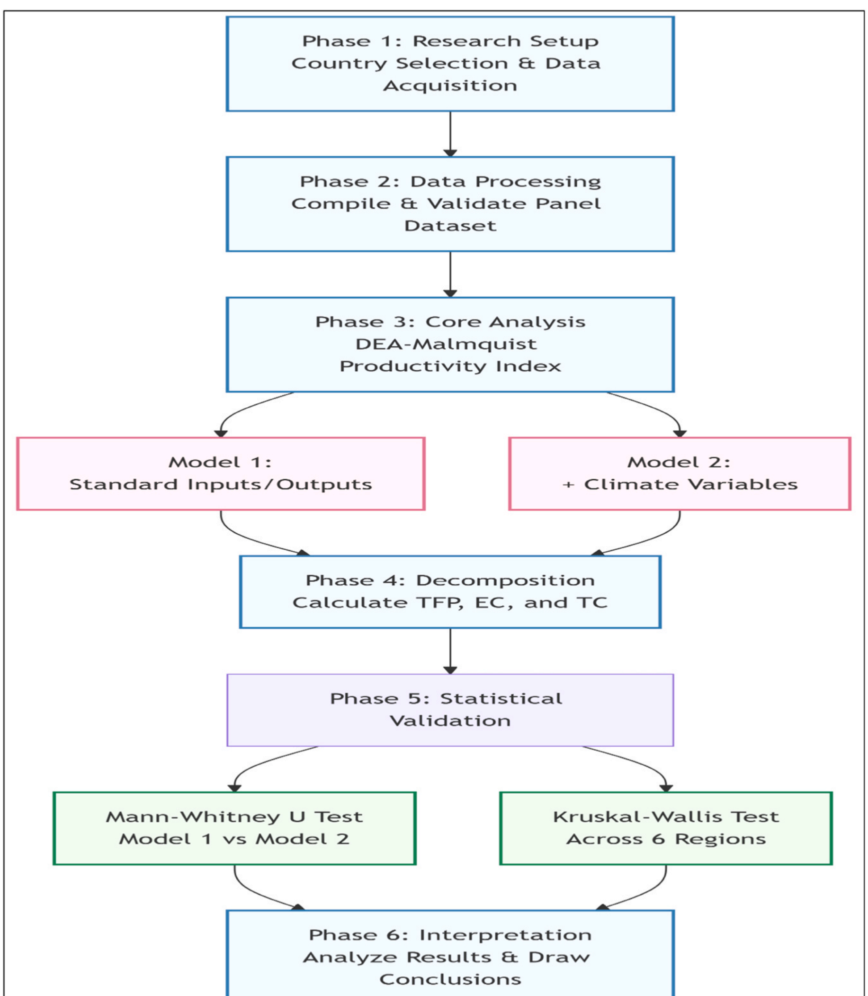


**Fig. 1.** Methodology Flowchart.

### 3.2. Empirical Model: DEA-Malmquist formulation

#### 3.2.1. Integration of model orientation and climate variables

An input-based DEA model is used to measure productivity, assuming Variable Returns to Scale (VRS). The choice of the input orientation is based on the fact that it is relevant to the central problem in agriculture, that is, how to achieve maximum production with a given number of resources (land, labor, capital) instead of increasing the inputs to reach a predetermined output level (Coelli et al., 2005). The VRS assumption is essential because it recognizes the fact that the countries in our sample do not always work at an optimal level, which gives an opportunity to measure pure technical efficiency.

The non-discretionary input variables of the DEA are climate variables (annual mean temperature and total precipitation). This intervention, which is in line with the practice of O'donnell, (2020) in environmental productivity models, acknowledged that the aspects are fundamental in agricultural production, but they are not managed directly by producers in the short run. Their presence enables the production frontier to capture the difference between the environmental settings of the different countries.

#### 3.2.2. Malmquist TFP Index: Mathematical model

The Malmquist index, which was proposed by Caves et al. (1982) and generalized by Fare et al. (1994), is a measure of Total Factor Productivity Change (TFPCH) between two time periods. It is characterized by distance functions. Let inputs be denoted by $x^t \in R_+^N$ and outputs by $y^t \in R_+^M$ at time $t$. The production technology set is:

$$S^t = \{(x^t, y^t) : x^t \text{ can produce } y^t\}.$$

The output distance function for the period $t$ 's technology is:

$$D_o^t(x^t, y^t) = \inf\{\theta : (x^t, y^t/\theta) \in S^t\}.$$

The Malmquist TFP index between period $t$ (base) and period $t+1$ is calculated as the geometric mean of two period-specific indices:

$$M_o(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\left(\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)}\right)\left(\frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)}\right)\right]^{\frac{1}{2}} \tag{1}$$

This index can be decomposed into two mutually exclusive components:

$$M_o = \underbrace{\frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)}}_{\text{Efficiency Change (EFFCH)}} \times \underbrace{\left[\left(\frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)}\right)\left(\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})}\right)\right]^{\frac{1}{2}}}_{\text{Technological Change (TECHCH)}} \tag{2}$$

A value in the EFFCH that is above 1 signifies that technical efficiency (catching up to the frontier) has been improved, and a TECHCH value that is above 1 signifies that there has been technological advancement (an outward shift of the frontier). TECHCH and EFFCH are the factors of the overall TPFCH.

### 3.3. Variable selection and data

#### 3.3.1. Variables and justification

The choice of variables is based on the classical theory of agricultural production and the tradition of the previous research on the DEA-based productivity (Bai et al., 2020). The model used three discretionary inputs, two climate inputs and two outputs as indicated in Table 1.

#### 3.3.2. Data Processing

The analysis utilizes an unbalanced panel dataset for 31 major agricultural countries from 1990 to 2021. Financial data (Gross Agricultural Production Value) are reported in constant 2014–2016 US dollars. National-level climate variables (Mean Temperature, Total Precipitation) were constructed from high-resolution gridded data (CRU TS) using area-weighted averaging. For the economic variables, minor data gaps (affecting less than 2 % of observations) were filled via moving average interpolation.

### 3.4. Sample choice and classification of regions

The sample will include the 31 leading agricultural-producing countries in 2021, as per the Food and Agriculture Organization (FAOSTAT). The countries are combined to cover more than 85 % of the world's agricultural production, which makes them globally representative. This list is given in the manuscript (initially Table 2).

To conduct regional analysis, the countries were categorized into six geographic regions following the United Nations standard classification scheme M49, which was Africa, Asia, Europe, North America, Oceania and South America. The manuscript demonstrates the regional groupings (initially Table 3). Geographic heterogeneity in climate-productivity links can be analyzed in this classification.

### 3.5. Statistical validation

The hypothesis test was based on the comparison of the DEA model results through the non-parametric tests because efficiency scores are not normally distributed.

Mann Whitney U Test: Wilcoxon presented the Mann-Whitney $U$ test in 1945, and Mann and Whitney implemented further adjustments in 1947. The widely used non-parametric test is frequently applied to compare two groups with distinct hypotheses. The Wilcoxon Rank Sum Test is also known as the Mann-Whitney Wilcoxon Test. It assesses whether the two samples originate from the same underlying population by evaluating the distributions of the two populations. This analysis involves comparing the medians of the two groups. Both the null hypothesis (H _0: 1 =2) and the alternative hypothesis (H _1: 1 =2) compare the means of two unrelated groups.

**Table 1**
Definitions of the variables, reasons and sources of data.

| Category | Variable | Unit | Justification | Data Source |
|---|---|---|---|---|
| Discretionary Input | Arable Land | 1000 ha | Primary physical resource for crop production. | (Food and Agriculture Organization of the United Nations, 2025) |
| Discretionary Input | Agricultural Labor | % of total employment | Measures human capital allocation to the sector. | World Bank WDI / ILOSTAT (2023) |
| Discretionary Input | Fertilizer Use | kg per hectare | Key technological input directly influencing yield. | (Food and Agriculture Organization of the United Nations, 2025) |
| Climate Input | Mean Temperature | °C | Critical determinant of crop growth cycles, phenology, and heat stress. | (Ian et al., 2020) |
| Climate Input | Total Precipitation | mm/year | The principal source of water for rain-fed agriculture; extremes affect yield. | (Ian et al., 2020) |
| Output | Gross Agricultural Production Value | Million USD (constant 2014–2016) | Comprehensive, standardized measure of total sectoral economic output. | (Food and Agriculture Organization of the United Nations, 2025) |
| Output | Per Capita Production Index | Index (2014–2016 =100) | Controls for population size, enabling more equitable cross-country comparison of productive performance. | (Food and Agriculture Organization of the United Nations, 2025) |

**Table 2**
Top 31 countries in terms of Gross Production (Agricultural) 2021.

| No | Country | Value (1000 USD) |
|---|---|---|
| 1 | China | 1573853399 |
| 2 | India | 448214033 |
| 3 | USA | 341880825 |
| 4 | Brazil | 157538175 |
| 5 | Iran | 122702354 |
| 6 | Indonesia | 106539815 |
| 7 | Russia | 97898045 |
| 8 | France | 79606343 |
| 9 | Japan | 64078760 |
| 10 | Colombia | 58634861 |
| 11 | Mexico | 57791897 |
| 12 | Türkiye | 57290440 |
| 13 | Spain | 56764091 |
| 14 | Germany | 50896282 |
| 15 | Australia | 49505978 |
| 16 | Viet Nam | 49183750 |
| 17 | Ukraine | 46063815 |
| 18 | Egypt | 42939289 |
| 19 | Italy | 42863577 |
| 20 | Thailand | 38202141 |
| 21 | Pakistan | 37496930 |
| 22 | Republic of Korea | 36860182 |
| 23 | Nigeria | 35654965 |
| 24 | Bangladesh | 35501213 |
| 25 | Canada | 35067234 |
| 26 | Philippines | 33863587 |
| 27 | United Kingdom | 30790182 |
| 28 | Malaysia | 28391070 |
| 29 | South Africa | 24758091 |
| 30 | Poland | 24728121 |
| 31 | Argentina | 23617534 |

**Table 3**
Different global regions.

| Region | Selected Countries |
|---|---|
| Africa | Egypt, Nigeria, South Africa, |
| Asia | Bangladesh, China, Democratic People's Republic of Korea, India, Indonesia, Iran (Islamic Republic of), Japan, Malaysia, Pakistan, Philippines, Thailand, Türkiye, Vietnam |
| Europe | France, Germany, Italy, Poland, the Russian Federation, Spain, Ukraine, the United Kingdom of Great Britain and Northern Ireland |
| North America | Canada, Mexico, and the United States of America |
| Oceania | Australia |
| South America | Argentina, Brazil, Colombia |

This test was applied to compare the distributions of the Malmquist index scores—Total Factor Productivity Change (TFPCH), Efficiency Change (EFFCH), and Technological Change (TECHCH)—obtained from the model with climate variables against those from the model without climate variables. It formally tests the following hypotheses:

**$H_{01}$.** The distribution of TFPCH is identical between the models with and without climate factors.

**$H_{02}$.** The distribution of EFFCH is identical between the models with and without climate factors.

**$H_{03}$.** The distribution of TECHCH is identical between the models with and without climate factors.

A significant result ($p < 0.05$) would lead to the rejection of the null hypothesis, indicating that the inclusion of climate variables significantly alters the measured productivity component.

Kruskal-Wallis Test: The Kruskal-Walli's test is one of the statistical tools employed in ranking the degree of statistical significance especially when there are more than two unique groups (Theodorsson-Norheim, 1986). his test was used to determine if there were statistically significant differences in the median scores of TFPCH, EFFCH, and TECHCH across the six geographic regions (Africa, Asia, Europe, North America, Oceania, South America) as defined in Section 3.4. It tests the hypotheses:

**$H_{04}$.** The distribution of TFPCH is the same across all six regions.

**$H_{05}$.** The distribution of EFFCH is the same across all six regions.

**$H_{06}$.** The distribution of TECHCH is the same across all six regions.

A significant result ($p < 0.05$) indicates significant regional heterogeneity in productivity dynamics. All statistical tests were performed at a 5 % significance level using SPSS version 27.

## 4. Results

This research investigates the impact of climate change on total factor agricultural productivity (MI) and its decomposing factors: efficiency change and technology change (EC and TC) in the top 31 agricultural producer Countries from 1990 to 2021. The DEA Malmquist Productivity Index was employed to assess productivity growth with and without considering climate factors.

### *4.1. Overall factor productivity change in the absence of climate (1990–2021)*

The Table 4 and Fig. 2 show Malmquist Index (MI), Efficiency Change (EC), and Technological Change (TC) of the 31 leading agricultural producing countries between 1990 and 2021, which are estimated without the consideration of the climate variables in the DEA model. When the value is higher than 1 it is an indication of improvement and when it is lower than 1 it shows a decline. The mean Malmquist Index in the 31-year period was 1.0428 which represents an

**Table 4**
MI, EC, and TC without Climate factors.

| **Year** | **MI** | **EC** | **TC** |
|---|---|---|---|
| 1990–1991 | 1.0574 | 1.015 | 1.0416 |
| 1991–1992 | 1.0366 | 1.009 | 1.029 |
| 1992–1993 | 1.0026 | 1.0467 | 0.9581 |
| 1993–1994 | 1.0689 | 0.9591 | 1.1122 |
| 1994–1995 | 1.0729 | 1.0548 | 1.0279 |
| 1995–1996 | 1.0762 | 0.9614 | 1.1262 |
| 1996–1997 | 0.9401 | 1.0563 | 0.9009 |
| 1997–1998 | 1.013 | 1.0536 | 0.9703 |
| 1998–1999 | 1.0257 | 0.9275 | 1.1138 |
| 1999–2000 | 0.9839 | 1.0241 | 0.961 |
| **Avg. 1990–2000** | **1.0277** | **1.0107** | **1.0241** |
| 2000–2001 | 1.0012 | 1.0353 | 0.9727 |
| 2001–2002 | 1.0098 | 1.023 | 0.9849 |
| 2002–2003 | 1.1064 | 1.0655 | 1.0402 |
| 2003–2004 | 1.1246 | 0.9508 | 1.1825 |
| 2004–2005 | 1.0489 | 1.0397 | 1.0136 |
| 2005–2006 | 1.1208 | 1.0494 | 1.0703 |
| 2006–2007 | 1.098 | 0.9797 | 1.125 |
| 2007–2008 | 1.1292 | 1.0051 | 1.1245 |
| 2008–2009 | 0.9539 | 1.0734 | 0.8921 |
| 2009–2010 | 1.073 | 0.9596 | 1.1258 |
| **Avg. 2000–2010** | **1.0666** | **1.0182** | **1.0532** |
| 2010–2011 | 1.1245 | 1.0186 | 1.1082 |
| 2011–2012 | 1.023 | 1.0552 | 0.9752 |
| 2012–2013 | 1.0349 | 1.0021 | 1.0412 |
| 2013–2014 | 0.9885 | 1.0573 | 0.9352 |
| 2014–2015 | 0.9469 | 1.0003 | 0.9505 |
| 2015–2016 | 1.0081 | 0.9597 | 1.0523 |
| 2016–2017 | 1.0378 | 1.0218 | 1.0168 |
| s2017–2018 | 1.0515 | 0.9869 | 1.0657 |
| 2018–2019 | 1.0112 | 1.017 | 0.9928 |
| 1999–2020 | 1.1108 | 0.9901 | 1.1209 |
| 2020–2021 | 1.0468 | 1.0599 | 0.9942 |
| **Avg. 2010–2021** | **1.0349** | **1.0154** | **1.023** |
| **Avg. 1990–2021** | **1.0428** | **1.0148** | **1.0331** |

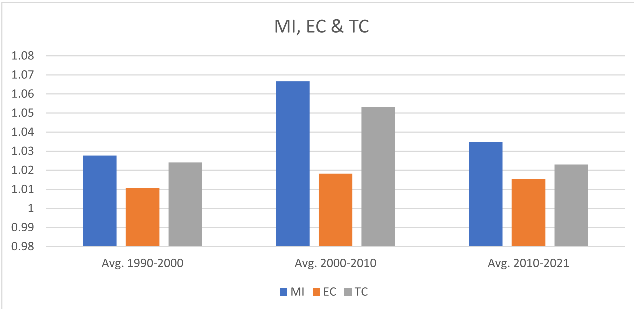


**Fig. 2.** MI, EC, and TC change during the study period (1990–2021).

average productivity growth of 4.28 per annum. This total growth was due to average Efficiency Change of 1.0148 and average Technological Change of 1.0331. Decadal analysis indicates that there are distinct periods, 1990–2000 was associated with an average MI of 1.0277 (EC=1.0107, TC=1.0241) and the 2000–2010 with 1.0666 (EC=1.0182, TC=1.0532) and 2010–2021 with 1.0349 (EC=1.0154, TC=1 There was an annual fluctuation in values with maximum MI of 1.1292 in 2007–2008 and minimum MI of 0.9401 in 1996–1997.

### 4.2. *Regional averages of MI, EC, and TC without climate factors*

The results in Table 5 and Fig. 3, illustrated the average Malmquist Index (MI), efficiency Change (EC), and Technological Change (TC) per region of the world as well as the individual countries are provided without considering climate factors. The highest level of productivity increase in the region was in Asia with an average MI= 1.0485 mostly due to Technological Change (TC=1.0376). China had the highest national MI of 1.1257 which was nearly all because of technological improvement (TC=1.1246). The North America was at 1.0567 and the United States headed the list with 1.0754 (MI=1.0754, TC=1.0754). Europe had moderate growth (MI=1.0382) that was contributed by both efficiency and technology, which was also the case with the Russian Federation (MI=1.0750, TC=1.0747). Africa had an average growth which was lower (MI=1.0236) with Egypt performing the best (MI=1.0645) in terms of a combination of efficiency and technological benefits. The average in South America was 1.0324 with the improvement made by Brazil (MI=1.0590), and Argentina remained unchanged in all the indices. Oceania, which is the case of Australia, also showed strong growth (MI=1.0534) powered by technological change. Nigeria persisted in the index values of 1.000, which means that the productivity, efficiency, and technology remained at the same level during the time.

**Table 5**
Average MI, EC, and TC without Climate factors in different regions and countries.

| Region | Country | MI | EC | TC |
|---|---|---|---|---|
| Africa | Egypt | 1.0645 | 1.0537 | 1.0274 |
| Africa | Nigeria | 1 | 1 | 1 |
| Africa | South Africa | 1.0062 | 1.0081 | 1.0026 |
| **Avg. Africa** | | **1.0236** | **1.0206** | **1.01** |
| Asia | Bangladesh | 1.0207 | 1.0251 | 1.0026 |
| Asia | China | 1.1257 | 1.0002 | 1.1246 |
| Asia | South Korea | 1.0503 | 1.019 | 1.0303 |
| Asia | India | 1.0576 | 0.994 | 1.0712 |
| Asia | Indonesia | 1.0466 | 1.0168 | 1.028 |
| Asia | Iran | 1.0658 | 1.0352 | 1.0346 |
| Asia | Japan | 1.0638 | 1 | 1.0638 |
| Asia | Malaysia | 1.0625 | 1.0212 | 1.0449 |
| Asia | Pakistan | 1.0024 | 1.0005 | 1.0002 |
| Asia | Philippines | 1.032 | 1.0325 | 1.0085 |
| Asia | Thailand | 1.0269 | 1.0192 | 1.023 |
| Asia | Türkiye | 1.0309 | 0.9893 | 1.046 |
| Asia | Vietnam | 1.045 | 1.0402 | 1.011 |
| **Avg. Asia** | | **1.0485** | **1.0149** | **1.0376** |
| Europe | France | 1.0249 | 1.0135 | 1.0096 |
| Europe | Germany | 1.0585 | 1.0012 | 1.0573 |
| Europe | Italy | 1.0051 | 1.0026 | 1.0023 |
| Europe | Poland | 1.0104 | 1.023 | 0.9979 |
| Europe | Russian Federation | 1.075 | 1.0001 | 1.0747 |
| Europe | Spain | 1.0526 | 1.0144 | 1.0364 |
| Europe | Ukraine | 1.0445 | 1.0156 | 1.0385 |
| Europe | UK | 1.0344 | 1.0021 | 1.031 |
| **Avg. Europe** | | **1.0382** | **1.0091** | **1.0309** |
| North America | Canada | 1.0585 | 1.0212 | 1.0374 |
| North America | Mexico | 1.0361 | 1.0169 | 1.0479 |
| North America | USA | 1.0754 | 1 | 1.0754 |
| **Avg. North America** | | **1.0567** | **1.0127** | **1.0536** |
| Oceania | Australia | 1.0534 | 1.0032 | 1.0511 |
| South America | Argentina | 1 | 1 | 1 |
| South America | Brazil | 1.059 | 1.0489 | 1.0416 |
| South America | Colombia | 1.0381 | 1.0402 | 1.0057 |
| **Avg. South America** | | **1.0324** | **1.0297** | **1.0158** |

### 4.3. *Total Factor Productivity Change with Climate Factors (1990–2021)*

Table 6 and Fig. 4 show the Malmquist Index (MI), Efficiency Change (EC) and Technological Change (TC) 1990–2021, which were calculated using climate factors in the DEA model. The total average Malmquist Index per year the period was 1.0409 stating that the productivity increased by 4.09 %. This has been obtained using an average Efficiency Change of 1.0146 and an average Technological Change of 1.0295. The decadal averages including climatic factors were: the average MI was 1.0248 (EC=1.0087, TC=1.0208) in the 1990–2000 period, 1.0646 (EC=1.0243, TC=1.0426) in the 2000–2010 period and 1.0341 (EC=1.0113, TC=1.0255) in the Three were annual variations and the maximum MI of 1.1512 was seen in the year 2010–2011 and the minimum MI of 0.9387 was found in 1996–1997.

### 4.4. *Section 4.4: Regional Averages of MI, EC, and TC with Climate Factors*

Table 7 and Fig. 5 show the average Malmquist Index (MI), Efficiency Change (EC) and Technological Change (TC) as a result by region and country with climate factors integrated into the model. Once climate is put into consideration, Asia has the highest regional productivity growth with an average MI of 1.0491 which is still mainly influenced by Technological Change (TC=1.0351). In Asia, India has a significant MI of 1.1002, especially because of technological advancement (TC= 1.1200), whereas China has a MI those moderates to 1.0061. The North America comes as the second in terms of average MI of 1.0516 with the highest national MI in the region of 1.0884 in Canada. The average MI in Europe is 1.0344 and Germany is performing well (MI=1.0851, TC=1.0837) and Italy has been falling (MI=0.9671). The average MI in Africa stands at 1.0179, and Egypt (MI=1.0494) is the best performer. Oceania (Australia) registers MI of 1.0738. The average of South America is 1.0247 with Brazil having 1.0394 with no change in Argentina. Like in the model where there are no climate factors, the indices of Nigeria stand at 1.000 in all measures.

### 4.5. *Impact of climate factors on MI, EC, and TC (1990–2021)*

Table 8 describes the change in the Malmquist Index (MI) per year due to climate factors in the form of the difference between the values of MI with and without climate variables. The average change in MI due to climate factors was negative over the whole time of the study period (1990–2021) at −0.0019 (-0.18 %). The effect was quite different in each year. There are significant adverse changes of −9.04 % and −7.55 % in 2012–2013 and 1997–1998 respectively. On the other hand, the positive changes were noted in the years 2001–2002 (+5.96) and 2013–2014 (+5.21). The 1990s have a slight negative impact (−0.28 %), and so does the 2000s (−0.19 %), as well as 2010s (−0.08 %).

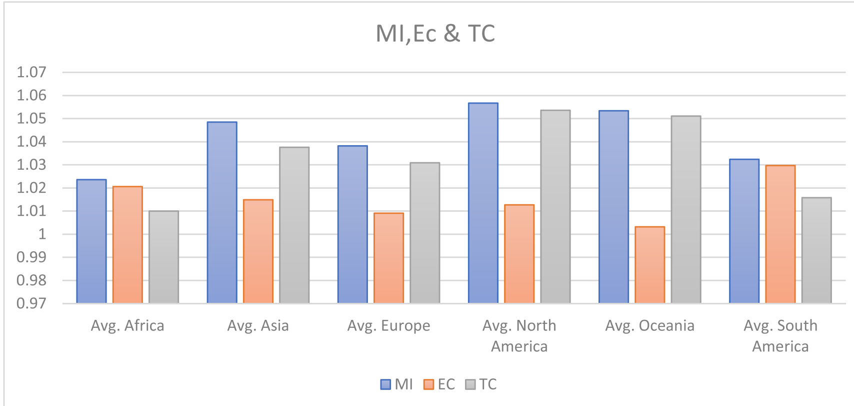


**Fig. 3.** MI, EC, and TC across different regions of the Globe.

**Table 6**
MI, EC, and TC with Climate factor.

| Year | MI | EC | TC |
|---|---|---|---|
| 1990–1991 | 1.0271 | 0.9742 | 1.0523 |
| 1991–1992 | 1.0677 | 1.0015 | 1.0686 |
| 1992–1993 | 0.9773 | 1.055 | 0.9242 |
| 1993–1994 | 1.0595 | 0.9644 | 1.1 |
| 1994–1995 | 1.0707 | 1.0594 | 1.0176 |
| 1995–1996 | 1.1124 | 0.978 | 1.137 |
| 1996–1997 | 0.9387 | 1.0981 | 0.8576 |
| 1997–1998 | 0.9419 | 0.9964 | 0.9527 |
| 1998–1999 | 1.0337 | 0.9415 | 1.0999 |
| 1999–2000 | 1.019 | 1.019 | 0.9986 |
| **Avg. 1990–2000** | **1.0248** | **1.0087** | **1.0208** |
| 2000–2001 | 0.9686 | 1.0478 | 0.93 |
| 2001–2002 | 1.0738 | 1.0635 | 1.0011 |
| 2002–2003 | 1.0561 | 1.0089 | 1.0459 |
| 2003–2004 | 1.1205 | 0.994 | 1.1288 |
| 2004–2005 | 1.0296 | 1.0263 | 1.0063 |
| 2005–2006 | 1.071 | 1.0693 | 1.0037 |
| 2006–2007 | 1.129 | 0.9787 | 1.153 |
| 2007–2008 | 1.1104 | 1.0049 | 1.1086 |
| 2008–2009 | 0.9651 | 1.0568 | 0.9189 |
| 2009–2010 | 1.122 | 0.9926 | 1.1294 |
| **Avg. 2000–2010** | **1.0646** | **1.0243** | **1.0426** |
| 2010–2011 | 1.1512 | 1.0062 | 1.1432 |
| 2011–2012 | 1.0439 | 1.0489 | 1.002 |
| 2012–2013 | 0.9491 | 0.9866 | 0.9617 |
| 2013–2014 | 1.0428 | 1.0847 | 0.9631 |
| 2014–2015 | 0.9505 | 0.9853 | 0.9684 |
| 2015–2016 | 1.0133 | 0.9829 | 1.0286 |
| 2016–2017 | 1.0231 | 1.0323 | 0.9964 |
| 2017–2018 | 1.0492 | 0.945 | 1.111 |
| 2018–2019 | 0.9631 | 1.047 | 0.9149 |
| 1999–2020 | 1.1026 | 0.977 | 1.1282 |
| 2020–2021 | 1.0869 | 1.0281 | 1.0635 |
| **Avg. 2010–2021** | **1.0341** | **1.0113** | **1.0255** |
| **Avg. 1990–2021** | **1.0409** | **1.0146** | **1.0295** |

Table 9 illustrates the effects of the climate factors on Efficiency Change (EC). On the balance of 1990–2021 the total average impact was insignificant (-0.0002 or −0.02 %). The annual effects were not only positive but also not only negative with a high positive impact of + 4.35 in 2003–2004 and a high negative impact of −5.74 in 1997–1998.

The influence on Technological Change (TC) is provided in Table 10. The average impact of climate factors on TC during the entire period was small negative (−0.0036 or −0.35 %). This impact was the strongest in the 2000s (-1.02 % in average) but became a bit positive in the 2010s + 0.24 %). There were major annual changes including a −8.27 % effect in 2012–2013 and a + 6.52 % effect in 2020–2021.

### 4.6. *Regional heterogeneity in climatic impact on productivity components*

Table 11, Table 12, and Table 13 are the quantification of regional and national heterogeneity in the impact of climate factors on MI, EC, and TC respectively. There was a significant difference in the effect on MI (Table 11) by region. Asia had a low average impact, + 0.06 % which hides significant country-specific impacts: China has a MI that fell by −10.62, and India by + 4.03. The average MI of North America fell by a small margin (-0.48 %), which was caused by a decrease in the USA by −5.25 % and an increase by + 2.82 % in Canada. The average MI in Europe declined by −0.37, Africa by −0.56 and South America by −0.75. Australia (Oceania) experienced an increment of + 1.94 %.

The EC (Table 12) impact was largely dampened at the regional level. South America had the largest average regional change of a −1.79 % drop, which was majorly caused by a −4.69 % drop in Brazil. Other areas exhibited less than average changes of less than −0.5 %.

Trends on TC (Table 13) were more regional. When climate was put into consideration, Africa (-0.64), Asia (-0.24), Europe (-0.39), and North America (-1.42) recorded some of the averages in TC. In North America, the USA (-5.25 %) had the greatest negative effect. South America (+0.07 %) and Oceania (+1.54 %) recorded moderately average gains in TC.

### 4.7. *Mann-Whitney U and Kruskal-Wallis Test's results*

The results presented in Sections 4.1–4.4 suggest observable differences in Total Factor Productivity Change (MI), Efficiency Change (EC), and Technological Change (TC) when measured with and without climate factors. To determine whether these differences are statistically significant and thereby ensure the reliability of the findings, non-parametric statistical tests were employed. The Mann-Whitney *U* test was applied to compare the average values of TFPC, EC, and TC between the models with and without climate factors. The results, corresponding to hypotheses 1–3 in Table 14 and illustrated in Figs. A1 to A3, show significance values (p-values) below the 0.05 threshold. We therefore reject the null hypotheses and conclude that there are statistically significant differences in TFPC, EC, and TC when climate variables are incorporated. This result statistically validates that climate factors exert a significant and measurable impact on agricultural productivity, reinforcing the core methodological approach of this study. Similarly, the Kruskal-Wallis test was used to evaluate whether the distributions of TFPC, EC, and TC differ significantly across the five global regions. The results for hypotheses 4–6, also presented in Table 14 and supported by Figs. A4 to A6, indicate p-values less than 0.05. Thus, we reject the null hypotheses and conclude that there are statistically significant regional disparities in agricultural productivity metrics. This finding provides robust statistical evidence for the regional variations discussed qualitatively in Sections 4.2 and 4.4, confirming that the drivers of

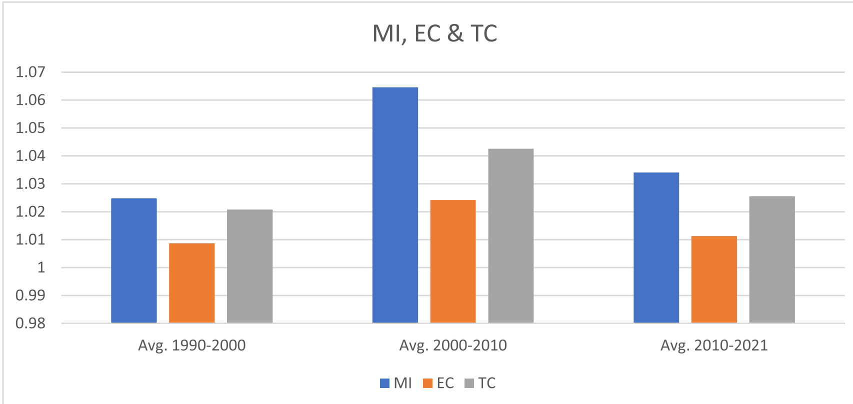


**Fig. 4.** Average MI, EC, and TC from 1990 to 2021.

**Table 7**
Average MI, EC, and TC with Climate factors in different regions and countries.

| Region | Country | MI | EC | TC |
|---|---|---|---|---|
| Africa | Egypt | 1.0494 | 1.0553 | 1.0121 |
| Africa | Nigeria | 1 | 1 | 1 |
| Africa | South Africa | 1.0042 | 1.0145 | 0.9985 |
| **Avg. Africa** | | **1.0179** | **1.0233** | **1.0035** |
| Asia | Bangladesh | 1.0321 | 1.0316 | 1.0061 |
| Asia | China | 1.0061 | 1 | 1.0061 |
| Asia | South Korea | 1.0593 | 1.019 | 1.0377 |
| Asia | India | 1.1002 | 0.9902 | 1.12 |
| Asia | Indonesia | 1.0729 | 1.0192 | 1.0513 |
| Asia | Iran | 1.0752 | 1.0421 | 1.0356 |
| Asia | Japan | 1.0114 | 1 | 1.0114 |
| Asia | Malaysia | 1.0818 | 1.0213 | 1.0636 |
| Asia | Pakistan | 1.0061 | 1.0106 | 0.9992 |
| Asia | Philippines | 1.0626 | 1.0428 | 1.0189 |
| Asia | Thailand | 1.0271 | 1.0229 | 1.0214 |
| Asia | Türkiye | 1.049 | 0.9914 | 1.0588 |
| Asia | Vietnam | 1.054 | 1.0306 | 1.0268 |
| **Avg. Asia** | | **1.0491** | **1.0171** | **1.0351** |
| Europe | France | 1.0105 | 1 | 1.0105 |
| Europe | Germany | 1.0851 | 1.0009 | 1.0837 |
| Europe | Italy | 0.9671 | 1.0039 | 0.9657 |
| Europe | Poland | 1.028 | 1.035 | 0.9993 |
| Europe | Russian Federation | 1.0463 | 1 | 1.0463 |
| Europe | Spain | 1.0519 | 1.0108 | 1.0405 |
| Europe | Ukraine | 1.0679 | 1.0222 | 1.0519 |
| Europe | UK | 1.0184 | 1.003 | 1.0172 |
| **Avg. Europe** | | **1.0344** | **1.0095** | **1.0269** |
| North America | Canada | 1.0884 | 1.0242 | 1.0638 |
| North America | Mexico | 1.0476 | 1.0272 | 1.0331 |
| North America | USA | 1.0189 | 1 | 1.0189 |
| **Avg. North America** | | **1.0516** | **1.0171** | **1.0386** |
| Oceania | Australia | 1.0738 | 1.0018 | 1.0673 |
| South America | Argentina | 1 | 1 | 1 |
| South America | Brazil | 1.0394 | 0.9997 | 1.0404 |
| South America | Colombia | 1.0347 | 1.0342 | 1.009 |
| **Avg. South America** | | **1.0247** | **1.0113** | **1.0165** |

productivity are not uniform across the globe.

The implications of these results are critical for policy formulation: a uniform, one-size-fits-all policy approach is statistically unjustified. For instance, the significant differences in TC suggest that technologically advanced regions such as Asia and North America may benefit from policies promoting next-generation innovations (e.g., digital agriculture), whereas regions like Africa, where efficiency change (EC) plays a more dominant role, may require policies aimed at improving access to existing technologies and strengthening infrastructure. These insights underscore the necessity of the targeted, region-specific policy recommendations proposed in this study.

## 5. Discussions

The statistical confirmation that climate factors significantly alter the measurement of agricultural Total Factor Productivity Change (TFPC) and its components (Table 14) validates the core premise of this study. Beyond this general confirmation, the decomposition of impacts reveals a more precise mechanism: climate variability exerts its primary influence by disrupting Technological Change (TC), with a comparatively muted effect on Efficiency Change (EC) (Tables 9, 10). It means that it is droughts, heatwaves, and irregular rainfall that impact significantly the actual yield of output of the current technologies (high-yield seed varieties or precise irrigation systems) instead of the management potential to efficiently utilize inputs (Fei et al., 2023). To illustrate, a severe drought may counter the yield potential of a drought-tolerant type of maize that is modeled as a negative contribution of climate to TC. This puts to test the perception of technology as an exogenous driver and its susceptibility to environmental conditions.

The extensive regional heterogeneity of this climate-technology interaction is a crucial observation. The comparison between China (TC: −10.5) and India (TC: +4.6) in terms of climate, when climate is considered (Table 13) indicates that there are different adaptive capacities and technological directions. The negative influence of China can demonstrate the system that optimizes high-productivity technologies according to the norms of historical climatic conditions and exposes them to growing volatility (Tilman et al., 2011). On the other hand, the positive outcome of India may represent effective spread of climate-adjusted practices/varieties over the study time, or the positive impact of the positive monsoonal patterns. In the same way, the huge negative effect on TC in the United States (-5.3 %) as compared to the positive effect in Canada (+2.5) indicates that despite the technological background development, local climate pattern and policy on climate adaptation still demonstrate varying impacts. These are the regional differences, which are statistically verified by the Kruskal-Wallis test (Table 14), and the reason why a universal history of productivity cannot be applied.

These results combine with and build on regionally dominant paradigms of agricultural development. The Green Revolution technologies have over the years contributed to the growth of productivity in Asia (Evenson and Gollin, 2003). According to our findings, the further development of its direction will be based on the implementation of climate-resilience in this technological core, such as the promotion of flood-tolerant rice or Bt crops against climate-induced pest epidemics (Ahmed et al., 2021). The adverse climate effect on TC in the Americas is consistent with the fact that GM and precision agriculture systems, though transformative not exempt to weather shocks of extreme magnitude (Qaim, 2020). The balance in growth values indicates a more balanced but less rapid increase in Africa, which is more of adaptation than absolute yield maximization as seen in Africa where foundational

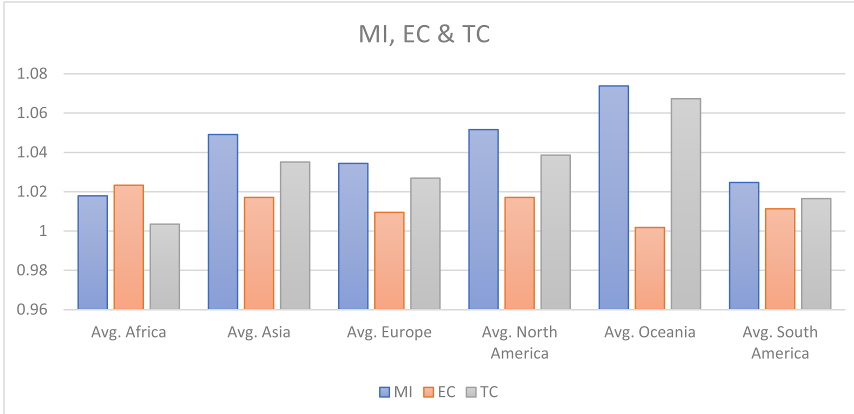


**Fig. 5.** MI, EC, and TC in different regions around the Globe.

**Table 8**
Change in the MI due to climate factors over the study period 1990–2021.

| Year | MI Without CF | MI With CF | Change in MI | % of Change |
|---|---|---|---|---|
| 1990–1991 | 1.0574 | 1.0271 | -0.0303 | -2.95 |
| 1991–1992 | 1.0366 | 1.0677 | 0.0311 | 2.91 |
| 1992–1993 | 1.0026 | 0.9773 | -0.0253 | -2.59 |
| 1993–1994 | 1.0689 | 1.0595 | -0.0094 | -0.89 |
| 1994–1995 | 1.0729 | 1.0707 | -0.0022 | -0.21 |
| 1995–1996 | 1.0762 | 1.1124 | 0.0362 | 3.25 |
| 1996–1997 | 0.9401 | 0.9387 | -0.0014 | -0.15 |
| 1997–1998 | 1.013 | 0.9419 | -0.0711 | -7.55 |
| 1998–1999 | 1.0257 | 1.0337 | 0.008 | 0.77 |
| 1999–2000 | 0.9839 | 1.019 | 0.0351 | 3.44 |
| **Avg. 1990–2000** | **1.0277** | **1.0248** | **-0.0029** | **-0.28** |
| 2000–2001 | 1.0012 | 0.9686 | -0.0326 | -3.37 |
| 2001–2002 | 1.0098 | 1.0738 | 0.064 | 5.96 |
| 2002–2003 | 1.1064 | 1.0561 | -0.0503 | -4.76 |
| 2003–2004 | 1.1246 | 1.1205 | -0.0041 | -0.37 |
| 2004–2005 | 1.0489 | 1.0296 | -0.0193 | -1.87 |
| 2005–2006 | 1.1208 | 1.071 | -0.0498 | -4.65 |
| 2006–2007 | 1.098 | 1.129 | 0.031 | 2.75 |
| 2007–2008 | 1.1292 | 1.1104 | -0.0188 | -1.69 |
| 2008–2009 | 0.9539 | 0.9651 | 0.0112 | 1.16 |
| 2009–2010 | 1.073 | 1.122 | 0.049 | 4.37 |
| **Avg. 2000–2010** | **1.0666** | **1.0646** | **-0.002** | **-0.19** |
| 2010–2011 | 1.1245 | 1.1512 | 0.0267 | 2.32 |
| 2011–2012 | 1.023 | 1.0439 | 0.0209 | 2 |
| 2012–2013 | 1.0349 | 0.9491 | -0.0858 | -9.04 |
| 2013–2014 | 0.9885 | 1.0428 | 0.0543 | 5.21 |
| 2014–2015 | 0.9469 | 0.9505 | 0.0036 | 0.38 |
| 2015–2016 | 1.0081 | 1.0133 | 0.0052 | 0.51 |
| 2016–2017 | 1.0378 | 1.0231 | -0.0147 | -1.44 |
| s2017–2018 | 1.0515 | 1.0492 | -0.0023 | -0.22 |
| 2018–2019 | 1.0112 | 0.9631 | -0.0481 | -4.99 |
| 1999–2020 | 1.1108 | 1.1026 | -0.0082 | -0.74 |
| 2020–2021 | 1.0468 | 1.0869 | 0.0401 | 3.69 |
| **Avg. 2010–2021** | **1.0349** | **1.0341** | **-0.0008** | **-0.08** |
| **Avg. 1990–2021** | **1.0428** | **1.0409** | **-0.0019** | **-0.18** |

**Table 9**
Change in the EC due to climate factors over the study period 1990–2021.

| Year | EC Without CF | EC With CF | Change in EC | % of Change |
|---|---|---|---|---|
| 1990–1991 | 1.015 | 0.9742 | -0.0408 | -4.19 |
| 1991–1992 | 1.009 | 1.0015 | -0.0075 | -0.75 |
| 1992–1993 | 1.0467 | 1.055 | 0.0083 | 0.79 |
| 1993–1994 | 0.9591 | 0.9644 | 0.0053 | 0.55 |
| 1994–1995 | 1.0548 | 1.0594 | 0.0046 | 0.43 |
| 1995–1996 | 0.9614 | 0.978 | 0.0166 | 1.7 |
| 1996–1997 | 1.0563 | 1.0981 | 0.0418 | 3.81 |
| 1997–1998 | 1.0536 | 0.9964 | -0.0572 | -5.74 |
| 1998–1999 | 0.9275 | 0.9415 | 0.014 | 1.49 |
| 1999–2000 | 1.0241 | 1.019 | -0.0051 | -0.5 |
| **Avg. 1990–2000** | **1.0107** | **1.0087** | **-0.002** | **-0.2** |
| 2000–2001 | 1.0353 | 1.0478 | 0.0125 | 1.19 |
| 2001–2002 | 1.023 | 1.0635 | 0.0405 | 3.81 |
| 2002–2003 | 1.0655 | 1.0089 | -0.0566 | -5.61 |
| 2003–2004 | 0.9508 | 0.994 | 0.0432 | 4.35 |
| 2004–2005 | 1.0397 | 1.0263 | -0.0134 | -1.31 |
| 2005–2006 | 1.0494 | 1.0693 | 0.0199 | 1.86 |
| 2006–2007 | 0.9797 | 0.9787 | -0.001 | -0.1 |
| 2007–2008 | 1.0051 | 1.0049 | -0.0002 | -0.02 |
| 2008–2009 | 1.0734 | 1.0568 | -0.0166 | -1.57 |
| 2009–2010 | 0.9596 | 0.9926 | 0.033 | 3.32 |
| **Avg. 2000–2010** | **1.0182** | **1.0243** | **0.0061** | **0.6** |
| 2010–2011 | 1.0186 | 1.0062 | -0.0124 | -1.23 |
| 2011–2012 | 1.0552 | 1.0489 | -0.0063 | -0.6 |
| 2012–2013 | 1.0021 | 0.9866 | -0.0155 | -1.57 |
| 2013–2014 | 1.0573 | 1.0847 | 0.0274 | 2.53 |
| 2014–2015 | 1.0003 | 0.9853 | -0.015 | -1.52 |
| 2015–2016 | 0.9597 | 0.9829 | 0.0232 | 2.36 |
| 2016–2017 | 1.0218 | 1.0323 | 0.0105 | 1.02 |
| s2017–2018 | 0.9869 | 0.945 | -0.0419 | -4.43 |
| 2018–2019 | 1.017 | 1.047 | 0.03 | 2.87 |
| 1999–2020 | 0.9901 | 0.977 | -0.0131 | -1.34 |
| 2020–2021 | 1.0599 | 1.0281 | -0.0318 | -3.09 |
| **Avg. 2010–2021** | **1.0154** | **1.0113** | **-0.0041** | **-0.41** |
| Avg. 1990–2021 | 1.0148 | 1.0146 | -0.0002 | -0.02 |

resilience technologies, such as drought tolerant maize are indispensable (Kassie et al., 2015; Mekonnen et al., 2021). In North America, productivity growth has been intricately associated with frontier biotechnologies and resource-efficient methodologies. For example, the widespread adoption of genetically modified (GM) crops in the United States, such as Bt cotton and herbicide-tolerant soybeans, has been a cornerstone of productivity gains, reducing pesticide use and increasing yields (Qaim, 2020). This has been complemented by precision agriculture technologies. In Europe, progress is driven by precision and sustainability-focused practices, heavily supported by policy frameworks like the European Union's Common Agricultural Policy (CAP), which incentivizes eco-schemes and integrated crop-livestock systems (Finger et al., 2019). The model of sustainable intensification in Europe (Finger et al., 2019) seems to be less affected by the climate on the average, which can be explained by the presence of more risk-diversifying practices. The primary weakness of this study has is that it utilizes data at the national level and this might obscure the sub-national differences in climate exposure and technological uptake. Moreover, the DEA structure reflects the achieved productivity; it does

**Table 10**
Change in the TC due to climate factors over the study period 1990–2021.

| Year | TC Without CF | TC With CF | Change in TC | % of Change |
|---|---|---|---|---|
| 1990–1991 | 1.0416 | 1.0523 | 0.0107 | 1.0168 |
| 1991–1992 | 1.029 | 1.0686 | 0.0396 | 3.7058 |
| 1992–1993 | 0.9581 | 0.9242 | -0.0339 | -3.668 |
| 1993–1994 | 1.1122 | 1.1 | -0.0122 | -1.1091 |
| 1994–1995 | 1.0279 | 1.0176 | -0.0103 | -1.0122 |
| 1995–1996 | 1.1262 | 1.137 | 0.0108 | 0.9499 |
| 1996–1997 | 0.9009 | 0.8576 | -0.0433 | -5.049 |
| 1997–1998 | 0.9703 | 0.9527 | -0.0176 | -1.8474 |
| 1998–1999 | 1.1138 | 1.0999 | -0.0139 | -1.2638 |
| 1999–2000 | 0.961 | 0.9986 | 0.0376 | 3.7653 |
| **Avg. 1990–2000** | **1.0241** | **1.0208** | **-0.0033** | **-0.3233** |
| 2000–2001 | 0.9727 | 0.93 | -0.0427 | -4.5914 |
| 2001–2002 | 0.9849 | 1.0011 | 0.0162 | 1.6182 |
| 2002–2003 | 1.0402 | 1.0459 | 0.0057 | 0.545 |
| 2003–2004 | 1.1825 | 1.1288 | -0.0537 | -4.7573 |
| 2004–2005 | 1.0136 | 1.0063 | -0.0073 | -0.7254 |
| 2005–2006 | 1.0703 | 1.0037 | -0.0666 | -6.6354 |
| 2006–2007 | 1.125 | 1.153 | 0.028 | 2.4284 |
| 2007–2008 | 1.1245 | 1.1086 | -0.0159 | -1.4342 |
| 2008–2009 | 0.8921 | 0.9189 | 0.0268 | 2.9165 |
| 2009–2010 | 1.1258 | 1.1294 | 0.0036 | 0.3188 |
| **Avg. 2000–2010** | **1.0532** | **1.0426** | **-0.0106** | **-1.0167** |
| 2010–2011 | 1.1082 | 1.1432 | 0.035 | 3.0616 |
| 2011–2012 | 0.9752 | 1.002 | 0.0268 | 2.6747 |
| 2012–2013 | 1.0412 | 0.9617 | -0.0795 | -8.2666 |
| 2013–2014 | 0.9352 | 0.9631 | 0.0279 | 2.8969 |
| 2014–2015 | 0.9505 | 0.9684 | 0.0179 | 1.8484 |
| 2015–2016 | 1.0523 | 1.0286 | -0.0237 | -2.3041 |
| 2016–2017 | 1.0168 | 0.9964 | -0.0204 | -2.0474 |
| s2017–2018 | 1.0657 | 1.111 | 0.0453 | 4.0774 |
| 2018–2019 | 0.9928 | 0.9149 | -0.0779 | -8.5146 |
| 1999–2020 | 1.1209 | 1.1282 | 0.0073 | 0.647 |
| 2020–2021 | 0.9942 | 1.0635 | 0.0693 | 6.5162 |
| **Avg. 2010–2021** | **1.023** | **1.0255** | **0.0025** | **0.2438** |
| **Avg. 1990–2021** | **1.0331** | **1.0295** | **-0.0036** | **-0.3497** |

**Table 11**
Impact of Climate change on MI in different regions of the world.

| Region | Country | MI Without CF | MI With CF | Change in MI | % of Change |
|---|---|---|---|---|---|
| Africa | Egypt | 1.0645 | 1.0494 | -0.0151 | -1.4185 |
| Africa | Nigeria | 1 | 1 | 0 | 0 |
| Africa | South Africa | 1.0062 | 1.0042 | -0.002 | -0.1988 |
| **Avg. Africa** | | **1.0236** | **1.0179** | **-0.0057** | **-0.5569** |
| Asia | Bangladesh | 1.0207 | 1.0321 | 0.0114 | 1.1169 |
| Asia | China | 1.1257 | 1.0061 | -0.1196 | -10.6245 |
| Asia | South Korea | 1.0503 | 1.0593 | 0.009 | 0.8569 |
| Asia | India | 1.0576 | 1.1002 | 0.0426 | 4.028 |
| Asia | Indonesia | 1.0466 | 1.0729 | 0.0263 | 2.5129 |
| Asia | Iran | 1.0658 | 1.0752 | 0.0094 | 0.882 |
| Asia | Japan | 1.0638 | 1.0114 | -0.0524 | -4.9257 |
| Asia | Malaysia | 1.0625 | 1.0818 | 0.0193 | 1.8165 |
| Asia | Pakistan | 1.0024 | 1.0061 | 0.0037 | 0.3691 |
| Asia | Philippines | 1.032 | 1.0626 | 0.0306 | 2.9651 |
| Asia | Thailand | 1.0269 | 1.0271 | 0.0002 | 0.0195 |
| Asia | Türkiye | 1.0309 | 1.049 | 0.0181 | 1.7557 |
| Asia | Vietnam | 1.045 | 1.054 | 0.009 | 0.8612 |
| **Avg. Asia** | | **1.0485** | **1.0491** | **0.0006** | **0.0572** |
| Europe | France | 1.0249 | 1.0105 | -0.0144 | -1.405 |
| Europe | Germany | 1.0585 | 1.0851 | 0.0266 | 2.513 |
| Europe | Italy | 1.0051 | 0.9671 | -0.038 | -3.7807 |
| Europe | Poland | 1.0104 | 1.028 | 0.0176 | 1.7419 |
| Europe | Russian Federation | 1.075 | 1.0463 | -0.0287 | -2.6698 |
| Europe | Spain | 1.0526 | 1.0519 | -0.0007 | -0.0665 |
| Europe | Ukraine | 1.0445 | 1.0679 | 0.0234 | 2.2403 |
| Europe | UK | 1.0344 | 1.0184 | -0.016 | -1.5468 |
| **Avg. Europe** | | **1.0382** | **1.0344** | **-0.0038** | **-0.366** |
| North America | Canada | 1.0585 | 1.0884 | 0.0299 | 2.8248 |
| North America | Mexico | 1.0361 | 1.0476 | 0.0115 | 1.1099 |
| North America | USA | 1.0754 | 1.0189 | -0.0565 | -5.2539 |
| **Avg. North America** | | **1.0567** | **1.0516** | **-0.0051** | **-0.4826** |
| **Oceania** | **Australia** | **1.0534** | **1.0738** | **0.0204** | **1.9366** |
| South America | Argentina | 1 | 1 | 0 | 0 |
| South America | Brazil | 1.059 | 1.0394 | -0.0196 | -1.8508 |
| South America | Colombia | 1.0381 | 1.0347 | -0.0034 | -0.3275 |
| **Avg. South America** | | **1.0324** | **1.0247** | **-0.0077** | **-0.7458** |

not directly link weather events of a particular type to the quantifiable shifts. Further studies based on sub-national data and that incorporates process-based crop models and productivity studies would yield a better analysis of the mechanisms of impact of climate change.

## 6. Conclusion and Policy Recommendations

This study examines total factor productivity, compares the impact of climate factors on agricultural productivity, and examines how climate factors influence total factor productivity in selected 31 top agricultural-producing countries between 1990 and 2021. The study's results reveal that climate change presents a significant risk to agricultural productivity, and its effects differ across various geographical areas and countries. The DEA Malmquist Productivity Index test was employed to assess productivity growth and compared total factor productivity (TFP), efficiency change (EC), and technical change (TC) across agricultural regions worldwide, with and without taking into account climate factors. Without climate factors the average Malmquist Index was 1.0428, indicating an average increase of 4.28 % in total agricultural productivity. During 2003–2004 and 2010–2011 high levels of productivity were observed, suggesting significant advancements.

The MI values varied from 0.9401 to 1.0762, with an average value of 1.0277 this indicates that there was a modest rise in production. The TC values varied from 0.9009 to 1.1262, with an average of 1.0241, indicating a moderate level of technical advancement. The EC values varied from 0.9508 to 1.0734, with an average of 1.0182, indicating a consistent enhancement in efficiency. All these trends depict a progressive rise in productivity, efficiency, and technology adoption within a study period, suggesting considerable progress in the long run. The findings further show that the increased productivity in terms of the Malmquist Index has been primarily influenced by efficiency gains and technological enhancements. When considering the climate factors, the (MI) average value −0.0019 is (-0.18 %), was which caused by climate conditions from 1990 to 2021 indicating a minor adverse impact on productivity growth during the whole study period the results indicate that the climate factors generally lead to decrease in overall productivity, especially in MI. There have been significant changes in TC influenced by climate conditions, including a notable fall of −0.0795 (-8.2666 %) in 2012–2013 and a significant increase of 0.0693 (6.5162 %) in 2020–2021. Overall, the average change in TC caused by climate conditions between 1990 and 2021 is −0.0036 (-0.3497 %), suggesting a small detrimental effect on overall TC. The average change in EC brought about by climate circumstances between 1990 and 2021 is −0.0002 (-0.02 %), indicating that efficiency fluctuations over the whole period of the study had a minor effect overall.

The results indicate that the climate factors generally lead to a minor decrease in overall productivity, especially in MI, TC, and EC. Climate change has led to some problems, however, overall output, efficiency, and technology have all gotten more effective over the study period.

**Table 12**
Impact of Climate change on EC in different regions of the world.

| Region | Country | EC Without CF | EC With CF | Change in EC | % of Change |
|---|---|---|---|---|---|
| Africa | Egypt | 1.0537 | 1.0553 | 0.0016 | 0.1518 |
| Africa | Nigeria | 1 | 1 | 0 | 0 |
| Africa | South Africa | 1.0081 | 1.0145 | 0.0064 | 0.6349 |
| **Avg. Africa** | | **1.0206** | **1.0233** | **0.0027** | **0.2646** |
| Asia | Bangladesh | 1.0251 | 1.0316 | 0.0065 | 0.6341 |
| Asia | China | 1.0002 | 1 | -0.0002 | -0.02 |
| Asia | South Korea | 1.019 | 1.019 | 0 | 0 |
| Asia | India | 0.994 | 0.9902 | -0.0038 | -0.3823 |
| Asia | Indonesia | 1.0168 | 1.0192 | 0.0024 | 0.236 |
| Asia | Iran | 1.0352 | 1.0421 | 0.0069 | 0.6665 |
| Asia | Japan | 1 | 1 | 0 | 0 |
| Asia | Malaysia | 1.0212 | 1.0213 | 0.0001 | 0.0098 |
| Asia | Pakistan | 1.0005 | 1.0106 | 0.0101 | 1.0095 |
| Asia | Philippines | 1.0325 | 1.0428 | 0.0103 | 0.9976 |
| Asia | Thailand | 1.0192 | 1.0229 | 0.0037 | 0.363 |
| Asia | Türkiye | 0.9893 | 0.9914 | 0.0021 | 0.2123 |
| Asia | Vietnam | 1.0402 | 1.0306 | -0.0096 | -0.9229 |
| **Avg. Asia** | | **1.0149** | **1.0171** | **0.0022** | **0.2168** |
| Europe | France | 1.0135 | 1 | -0.0135 | -1.332 |
| Europe | Germany | 1.0012 | 1.0009 | -0.0003 | -0.03 |
| Europe | Italy | 1.0026 | 1.0039 | 0.0013 | 0.1297 |
| Europe | Poland | 1.023 | 1.035 | 0.012 | 1.173 |
| Europe | Russian Federation | 1.0001 | 1 | -0.0001 | -0.01 |
| Europe | Spain | 1.0144 | 1.0108 | -0.0036 | -0.3549 |
| Europe | Ukraine | 1.0156 | 1.0222 | 0.0066 | 0.6499 |
| Europe | UK | 1.0021 | 1.003 | 0.0009 | 0.0898 |
| **Avg. Europe** | | **1.0091** | **1.0095** | **0.0004** | **0.0396** |
| North America | Canada | 1.0212 | 1.0242 | 0.003 | 0.2938 |
| North America | Mexico | 1.0169 | 1.0272 | 0.0103 | 1.0129 |
| North America | USA | 1 | 1 | 0 | 0 |
| **Avg. North America** | | **1.0127** | **1.0171** | **0.0044** | **0.4345** |
| **Oceania** | **Australia** | **1.0032** | **1.0018** | **-0.0014** | **-0.1396** |
| South America | Argentina | 1 | 1 | 0 | 0 |
| South America | Brazil | 1.0489 | 0.9997 | -0.0492 | -4.6906 |
| South America | Colombia | 1.0402 | 1.0342 | -0.006 | -0.5768 |
| **Avg. South America** | | **1.0297** | **1.0113** | **-0.0184** | **-1.7869** |

**Table 13**
Impact of Climate change on TC in different regions of the world.

| Region | Country | TC Without CF | TC With CF | Change in TC | % of Change |
|---|---|---|---|---|---|
| Africa | Egypt | 1.0274 | 1.0121 | -0.0153 | -1.4892 |
| Africa | Nigeria | 1 | 1 | 0 | 0 |
| Africa | South Africa | 1.0026 | 0.9985 | -0.0041 | -0.4089 |
| **Avg. Africa** | | **1.01** | **1.0035** | **-0.0065** | **-0.6436** |
| Asia | Bangladesh | 1.0026 | 1.0061 | 0.0035 | 0.3491 |
| Asia | China | 1.1246 | 1.0061 | -0.1185 | -10.5371 |
| Asia | South Korea | 1.0303 | 1.0377 | 0.0074 | 0.7182 |
| Asia | India | 1.0712 | 1.12 | 0.0488 | 4.5556 |
| Asia | Indonesia | 1.028 | 1.0513 | 0.0233 | 2.2665 |
| Asia | Iran | 1.0346 | 1.0356 | 0.001 | 0.0967 |
| Asia | Japan | 1.0638 | 1.0114 | -0.0524 | -4.9257 |
| Asia | Malaysia | 1.0449 | 1.0636 | 0.0187 | 1.7896 |
| Asia | Pakistan | 1.0002 | 0.9992 | -0.001 | -0.1 |
| Asia | Philippines | 1.0085 | 1.0189 | 0.0104 | 1.0312 |
| Asia | Thailand | 1.023 | 1.0214 | -0.0016 | -0.1564 |
| Asia | Türkiye | 1.046 | 1.0588 | 0.0128 | 1.2237 |
| Asia | Vietnam | 1.011 | 1.0268 | 0.0158 | 1.5628 |
| **Avg. Asia** | | **1.0376** | **1.0351** | **-0.0025** | **-0.2409** |
| Europe | France | 1.0096 | 1.0105 | 0.0009 | 0.0891 |
| Europe | Germany | 1.0573 | 1.0837 | 0.0264 | 2.4969 |
| Europe | Italy | 1.0023 | 0.9657 | -0.0366 | -3.6516 |
| Europe | Poland | 0.9979 | 0.9993 | 0.0014 | 0.1403 |
| Europe | Russian Federation | 1.0747 | 1.0463 | -0.0284 | -2.6426 |
| Europe | Spain | 1.0364 | 1.0405 | 0.0041 | 0.3956 |
| Europe | Ukraine | 1.0385 | 1.0519 | 0.0134 | 1.2903 |
| Europe | UK | 1.031 | 1.0172 | -0.0138 | -1.3385 |
| **Avg. Europe** | | **1.0309** | **1.0269** | **-0.004** | **-0.388** |
| North America | Canada | 1.0374 | 1.0638 | 0.0264 | 2.5448 |
| North America | Mexico | 1.0479 | 1.0331 | -0.0148 | -1.4123 |
| North America | USA | 1.0754 | 1.0189 | -0.0565 | -5.2539 |
| **Avg. North America** | | **1.0536** | **1.0386** | **-0.015** | **-1.4237** |
| **Oceania** | **Australia** | **1.0511** | **1.0673** | **0.0162** | **1.5412** |
| South America | Argentina | 1 | 1 | 0 | 0 |
| South America | Brazil | 1.0416 | 1.0404 | -0.0012 | -0.1152 |
| South America | Colombia | 1.0057 | 1.009 | 0.0033 | 0.3281 |
| **Avg. South America** | | **1.0158** | **1.0165** | **0.0007** | **0.0689** |

Subsequently has previously shown that technological progress has a significant impact on the rise in output, especially in recent years. The research indicates that climate elements exert a multifaceted influence on total factor productivity (TFP), efficiency change (EC), and technological change (TC). The study illustrates that technological advancement and EC played a crucial role in boosting productivity. The costs associated with agricultural production have been reduced as a result of advancements in technological development (TC) and a reduction in the use of traditional agricultural inputs. Overall, the effect on technological advancement was positive. Technological advancements are the main catalyst for the growth and development of the agricultural sector. Thus, enhancing agricultural technological proficiency helps to mitigate the adverse consequences caused by climate change. The agricultural productivity of the selected countries has experienced a rise, indicating a significant increase in global agricultural production in these years. When considering climate factors, there has been an overall decrease in the average change in agricultural productivity.

By including climate parameters as a resource for analyzing the impact of climate change on agricultural output, the estimation of productivity becomes more precise, resulting to a more practical analysis compared to the actual environment. The influence of climatic conditions on advances in technology was more substantial compared to its effect on efficiency change. The impact of technology on productivity varied across regions. Egypt and South Africa experience a boost in production due to technological progress while, Nigeria does not experience an increase in TFP. In Asia, although there is a slight decline in productivity due to climate factors in China, while, India has seen improved productivity as a result of the advancement in technology despite a slight decline in efficiency. In Europe Germany and Ukraine increased productivity due to technological progress, while, Italy decreased it. Regarding North America, the US was reported to notable decline in productivity while Canada recorded a boost in productivity. In Oceania, Australia had the highest increase in productivity due to technology, and in South America, Brazil was the country that had a moderate increase in productivity. The effects of climate change vary across various agricultural regions and nations. The study demonstrates when climate factors were considered, the (MI) showed a slight reduction, indicating that climate change hurt productivity growth. Examining the variations between agricultural regions reveals that certain regions are less impacted by climate change and exhibit little changes in the indicators when climatic considerations are taken into account. These countries' governments must consider the possibility of suitably

**Table 14**
Mann- Whitney U and Kruskal Wallis test results.

| Hypothesis Test Summary | | | | |
|---|---|---|---|---|
| | Null Hypothesis | Test | Sig | Decision |
| 1 | The average TFPC gauged with and without climate factors are identical. | Independent-Samples Mann-Whitney U Test | .034 | Reject |
| 2 | The average EC gauged with and without climate factors are identical. | | .023 | Reject |
| 3 | The average TC gauged with and without climate factors are identical. | | .000 | Reject |
| 4 | The distribution of average TFPC is the same across categories of five different regions. | Independent-Samples Kruskal Wallis Test | .013 | Reject |
| 5 | The distribution of average EC is the same across categories of five different regions. | | .001 | Reject |
| 6 | The distribution of average TC is the same across categories of five different regions. | | .039 | Reject |

enlarging the scope of agriculture. In contrast, nations such as East Asia and Central Asia, which experience more adverse impacts from climate change, may explore transitioning to agricultural practices that are less reliant on climate conditions to mitigate losses caused by climate change. The agricultural sector, which relies heavily on climate-sensitive resources, is highly susceptible to adverse climatic conditions. To mitigate these impacts, farmers can adopt climate-smart agricultural practices and sustainable farm management techniques. This will help enhance resilience and reduce systemic disruptions within agricultural production systems caused by climate change.

According to the above analysis it is recommended to tackle these issues the crucial steps should be taken, firstly, the effective policies and initiatives created that are to be adopted in each region of the world. To tackle the post-harvest losses and enhance market access, there is a need for Africa to develop rural infrastructures such as roads, storage facilities, and irrigation systems for agriculture investments. In Asia, efficient irrigation techniques such as drip and sprinkler systems can be employed to combat water constraints and improve water use efficiency. In Europe, the implementation of cutting-edge technology such as robots, artificial intelligence (AI), and the Internet of Things (IoT) in precision farming and automated operations can significantly enhance productivity and crop yields. Countries should implement climate-smart agricultural techniques, employ genetic engineering, and adopt sustainable farming methods such as organic farming and minimizing chemical usage have the potential to alleviate the effects of climate change and safeguard the environment. Climate change's effect on agricultural technology advancements points to the need for more focus on technological development. Innovative agricultural technology should be enhanced, and technologies should be better suited to the changing environment. Climate change has the potential to impede technology advancement; hence regional management offices ought to focus more on raising technical standards. This may be achieved via developing agricultural scientific research expertise and boosting capital investment in technological development. When technological advancement is at an impasse, we might think about how to use the technology already in place more effectively in the agricultural sector to increase technical efficiency. In conclusion, as evident from this report highlighting agriculture innovation, agriculture can adapt to a changing climate globally using regional methods that harness technical advancements to deal with the effects of climate change appropriately.

For vulnerable regions in Africa and parts of Asia, this means prioritizing and subsidizing climate-resilient technologies such as drought-tolerant crop varieties, efficient irrigation (drip, solar pumps), and climate-smart practices like conservation agriculture. For high-tech regions like North America and Europe, policy should create incentives for the adoption of precision agriculture technologies (e.g., AI, IoT sensors) that optimize input use and reduce the environmental footprint, making growth more sustainable. Governments and agricultural extension services must develop early warning systems and response protocols tied to climatic forecasts. Policies should promote crop insurance schemes and flexible planting strategies that allow farmers to adapt to predicted adverse conditions (e.g., drought associated with El Niño), thereby mitigating losses and stabilizing national productivity. The stark regional disparities in technical change (TC) highlight a critical need for policies aimed at bridging the technology gap. This involves strengthening international cooperation for technology transfer and, more importantly, investing in local capacity building and education to ensure farmers possess the skills to effectively implement new technologies and adapt to a changing climate.

## Funding

Zhejiang Provincial Philosophy and Social Sciences Planning Project (25NDJC091YB).

## CRediT authorship contribution statement

**Yunchen Wang:** Supervision, Software, Methodology, Investigation, Conceptualization. **Heshan Sameera Kankanam Pathiranage:** Writing – original draft, Methodology, Investigation, Formal analysis. **Rizwana Yasmeen:** Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Wasi Ul Hassan Shah:** Writing – review & editing, Writing – original draft, Investigation, Data curation, Conceptualization. **Liguang Zhang:** Writing – review & editing, Supervision, Software, Conceptualization. **Junaid Ahmad:** Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix

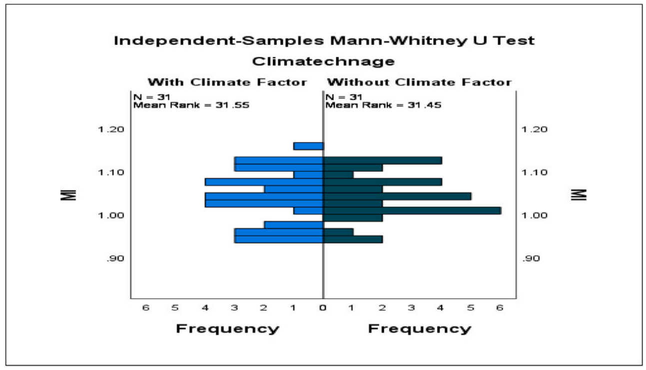


**Figure A1.** MI distribution with and without climate impact

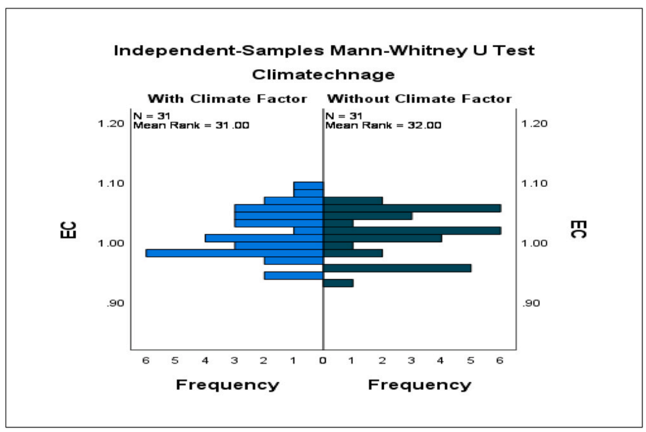


**Figure A2.** EC distribution with and without climate impact

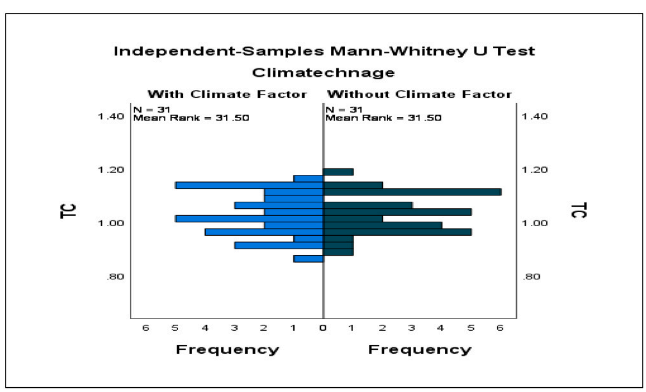


**Figure A3.** TC distribution with and without climate impact

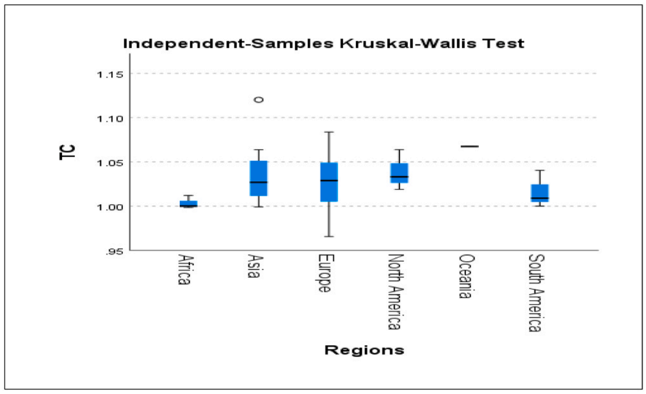


**Figure A4.** TC distribution across the global region

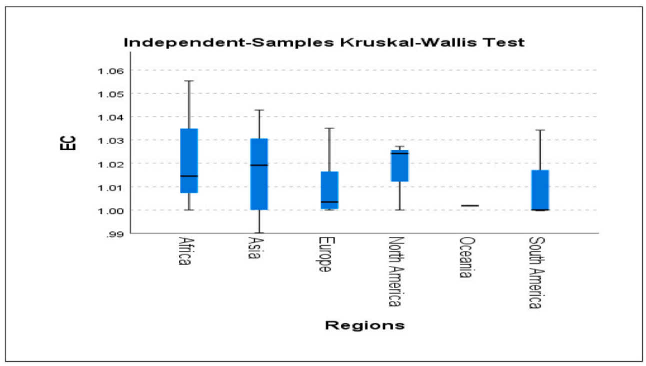


**Figure A5.** EC distribution across the global region

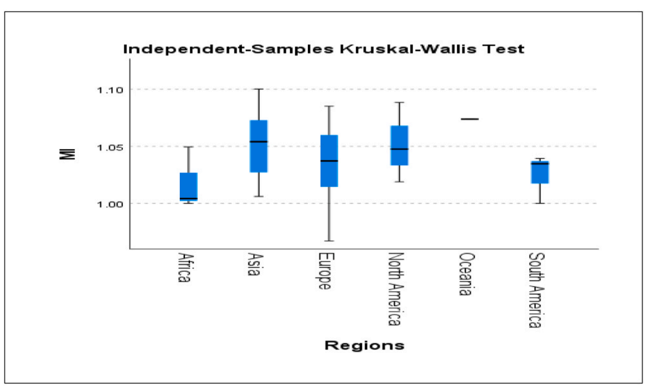


**Figure A6.** MI distribution across the global region

## Data availability

Data will be made available on request.

## References


Ahmed, A. U., Hoddinott, J., Abedin, N., & Hossain, N. (2021). The impacts of GM foods: results from a randomized controlled trial of Bt eggplant in Bangladesh. *Wiley Online LibraryAU* Ahmed, J Hoddinott, N Abedin, *N HossainAmerican Journal of Agricultural Economics, 2021•Wiley Online Library*, *103*(4), 1186–1206.

Bai, X., Zhang, T., Tian, S., 2020. Evaluating Fertilizer Use Efficiency and Spatial Correlation of Its Determinants in China: A Geographically Weighted Regression Approach. International Journal of Environmental Research and Public Health 17 (23), 8830. https://doi.org/10.3390/IJERPH17238830.

Bates, B., Wu, S., Kundzewicz, Z., Palutikof, J., 2008. Climate change and water. Intergov. Panel Clim. Change (IPCC). http://41.73.194.134/handle/123456789/552.

Burney, J., Woltering, L., Burke, M., Naylor, R., Pasternak, D., 2010. Solar-powered drip irrigation enhances food security in the Sudano–Sahel. In: pnas.orgJ Burney, L Woltering, M Burke, R Naylor, D PasternakProceedings of the National Academy of Sciences, 107. pnas.org, pp. 1848–1853. https://doi.org/10.1073/PNAS.0909678107.

Caves, D., Christensen, L., the, W.D.-E. journal of, 1982. The economic theory of index numbers and the measurement of input, output, and productivity, 1982, undefined. JSTOR.

Chakraborty, D., Wang, T., Andre, K., Konnert, M., Lexer, M.J., Matulla, C., Schueler, S., 2015. Selecting populations for non-analogous climate conditions using universal response functions: the case of douglas-fir in central Europe. PLoS One 10. https://doi.org/10.1371/JOURNAL.PONE.0136357.

Chandio, A.A., Akram, W., Min Du, A., Ahmad, F., Tang, X., 2025a. Agricultural transformation: Exploring the impact of digitalization, technological innovation and climate change on food production. Res. Int. Bus. Financ. 75, 102755. https://doi.org/10.1016/J.RIBAF.2025.102755.

Chandio, A.A., Zhang, H., Ahmad, F., 2025. Climate change and crop production nexus: assessing the role of technological development for sustainable agriculture in Vietnam 16, 177–200. https://doi.org/10.1108/IJCCSM-11-2022-0138.

Charles, H., Godfray, J., Beddington, J.R., Crute, I.R., Haddad, L., Lawrence, D., Muir, J. F., Pretty, J., Robinson, S., Thomas, S.M., Toulmin, C., 2010. Food security: the challenge of feeding 9 billion people. In: science.orgHCJ Godfray, JR Beddington, IR Crute, L Haddad, D Lawrence, JF Muir, J Prettyscience, 2010. science.org.

Charnes, A., Cooper, W., operational, E.R.-E. journal of, 1978. Charnes, A., Cooper, W., operational, E.R.-E. journal of, 1978, , 1978. Measuring the efficiency of decision making units. Elsevier 2, 429–444.

Chen, W., Chen, J., Production, Y.M.-J. of C., 2021. Renewable energy investment and carbon emissions under cap-and-trade mechanisms, 2021, undefined. In: ElsevierW Chen, J Chen, Y MaJournal of Cleaner Production, 2021. Elsevier.

Chen, Y., Zhang, Z., Dynamics, F.T.-E.S., 2018, undefined, 2018. Impacts of climate change and climate extremes on major crops productivity in China at a global warming of 1.5 and 2.0C. esd.copernicus.org.

Coelli, T., Rao, D.P., O'donnell, C., Battese, G., 2005. An introduction to efficiency and productivity analysis.

Dawadi, B., Shrestha, A., Acharya, R., Y.D.-R, 2022. undefined, 2022. Impact of climate change on agricultural production: A case of Rasuwa District, Nepal. In: ElsevierB Dawadi, A Shrestha, RH Acharya, YP Dhital, R DevkotaRegional Sustainability, 2022. Elsevier.

Duffy, C., Pede, V., Toth, G., Kilcline, K., O'Donoghue, C., Ryan, M., Spillane, C., 2021. Drivers of household and agricultural adaptation to climate change in Vietnam. Clim. Dev. 13, 242–255. https://doi.org/10.1080/17565529.2020.1757397.

Easterling, et al., 2023. Incorporating non-stationarity from climate change into rainfall frequency and intensity-duration-frequency (IDF) curves. Elsevier.

Evenson, R.E., Gollin, D., 2003. Assessing the impact of the Green Revolution, 1960 to 2000. Science. https://doi.org/10.1126/science.1078710.

Fare, R., Grosskopf, S., Lovell, C., 1994. Prod. Front.

Färe, R., Grosskopf, S., Norris, M., review, Z.Z.-T.A. economic, 1994. Productivity growth, technical progress, and efficiency change in industrialized countries, 1994, undefined. In: JSTORR Färe, S Grosskopf, M Norris, Z ZhangThe American economic review, 84. JSTOR, pp. 66–83, 1994, undefined.

Fei, C., Jägermeyr, J., McCarl, B., Contreras, E.M., Mutter, C., Phillips, M., Ruane, A.C., Sarofim, M.C., Schultz, P., Vargo, A., 2023. Future climate change impacts on U.S. agricultural yields, production, and market. Anthropocene. https://doi.org/10.1016/j.ancene.2023.100386.

Finger, R., Swinton, S.M., El Benni, N., Walter, A., 2019. Precision farming at the nexus of agricultural production and the environment. Annualreviews.Org 11, 313–335. https://doi.org/10.1146/ANNUREV-RESOURCE-100518-093929.

Fischer, G., Shah, M., Velthuizen, H.Van, 2002. Climate change and agricultural vulnerability.

Foley, J., Ramankutty, N., Brauman, K., Nature, E.C.-, 2011. Solutions for a cultivated planet. & 2011, undefined Nature.ComJA Foley, N Ramankutty, KA Brauman, ES Cassidy, JS Gerber, M Johnston, ND MuellerNature. nature.Com. https://doi.org/10.1038/nature10452.

Food and Agriculture Organization of the United Nations, 2025. FAOSTAT. URL https://www.fao.org/faostat/en/#data (accessed 26 January 2025).

Gordeev, R., Pyzhev, A., Sustainability, E.Z.-, 2018. Does climate change influence Russian agriculture?, 2022, undefined Evidence from panel data analysis. mdpi.com.

Gul, A., Chandio, A., Siyal, S., A.R, S, P, 2022. How climate change is impacting the major yield crops of Pakistan? an exploration from long-and short-run estimation, 2022, undefined. In: Springer, 29, pp. 26660–26674. https://doi.org/10.1007/s11356-021-17579-z, 2022, undefined.

Headey, D., economics, S.F.-A., 2008. Anatomy of a crisis: the causes and consequences of surging food prices, 2008, undefined Wiley Online LibraryD Headey, S FanAgricultural economics. Wiley Online Library.

Hussain, M., Butt, A.R., Uzma, F., Ahmed, R., Irshad, S., Rehman, A., Yousaf, B., 2020. A comprehensive review of climate change impacts, adaptation, and mitigation on environmental and natural calamities in Pakistan. Environ. Monit. Assess. 192. https://doi.org/10.1007/S10661-019-7956-4.

Ian, H., Osborn, T.J., Phil, J., Lis, D. Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset 1–18. https://doi.org/10.1038/s41597-020-0453-3.

Kassie, M., Teklewold, H., Jaleta, M., Marenya, P., Erenstein, O., 2015. Understanding the adoption of a portfolio of sustainable intensification practices in eastern and southern Africa. Land Use Policy 42, 400–411. https://doi.org/10.1016/J.LANDUSEPOL.2014.08.016.

Kumar, S., Economics, M.K.-E., D, 2009. Measurement of environmental efficiency and productivity: a cross-country analysis, 2009, undefined cambridge.orgS Kumar, M KhannaEnvironment and Development Economics. cambridge.org.

Lesk, C., Rowhani, P., Nature, N.R.-, 2016. Influence of extreme weather disasters on global crop production. nature.comC Lesk, P Rowhani, N RamankuttyNature, 2016•nature.com 529, 84–87. https://doi.org/10.1038/NATURE16467+(ARCHIVE.CISER.CORNELL.EDU).

Lipper, L., Thornton, P., Campbell, B., change, T.B.-, climate, 2014. Climate-smart agriculture for food security, 2014, undefined. In: nature.comL Lipper, P Thornton, BM Campbell, T Baedeker, A Braimoh, M Bwalya, P Caron, A CattaneoNature climate change, 4. nature.com. https://doi.org/10.1038/NCLIMATE2437.

Lobell, D.B., Field, C.B., 2007. Global scale climate-crop yield relationships and the impacts of recent warming. Environ. Res. Lett. 2. https://doi.org/10.1088/1748-9326/2/1/014002.

Lobell, D., physiology, S.G.-P., 2012. The influence of climate change on global crop productivity, 2012, undefined academic.oup.comDB Lobell, SM GourdjiPlant physiology. academic.oup.com.

Madau, F.A., 2012. Tech. Scale Effic. Ital. Citrus Farming. A Comp. Stoch. Front. Anal. (SFA) data Envel. Anal. (DEA) Models.

Mekonnen, A., Tessema, A., Ganewo, Z., Haile, A., 2021. Climate change impacts on household food security and adaptation strategies in southern Ethiopia. Food and Energy Security. https://doi.org/10.1002/fes3.266.

O'donnell, C.J., 2020. Estim. Eff. Weather Clim. Change Agric. Product. Presente.

Pingali, P.L., 2012. Green Revolution: Impacts, limits, and the path ahead. https://doi.org/10.1073/pnas.0912953109.

Qaim, 2020. Role of new plant breeding technologies for food security and sustainable agricultural development. Wiley Online LibraryM QaimApplied Economic Perspectives and Policy. 2020•Wiley Online Library, pp. 129–150. https://doi.org/10.1002/AEPP.13044.

Schlenker, W., Letters, D.L.-E.R., 2010. Robust negative impacts of climate change on African agriculture, 2010, undefined iopscience.iop.orgW Schlenker, DB LobellEnvironmental Research Letters. iopscience.iop.org.

Schlenker, Roberts, 2007. Nonlinear Effects of Weather on US Crop Yields, Implications for Climate Change, and Why These Effects Matter for Developing Countries. books.google.com.

Sheng, Y., Modelling, X.X.-E., 2019. undefined, 2019. The productivity impact of climate change: Evidence from Australia's Millennium drought. In: ElsevierY Sheng, X XuEconomic Modelling, 76. Elsevier, pp. 182–191. https://doi.org/10.1016/j.econmod.2018.07.031.

Tey, Y.S., Brindal, M., 2022. A meta-analysis of factors driving the adoption of precision agriculture. Precis Agric. 23, 353–372. https://doi.org/10.1007/S11119-021-09840-9.

Theodorsson-Norheim, E., 1986. Kruskal-Wallis test: BASIC computer program to perform nonparametric one-way analysis of variance and multiple comparisons on ranks of several independent samples. Computer Methods and Programs in Biomedicine. https://doi.org/10.1016/0169-2607(86)90081-7.

Tilman, D., Balzer, C., Hill, J., Befort, B.L., 2011. Global food demand and the sustainable intensification of agriculture. In: pnas.orgD Tilman, C Balzer, J Hill, BL BefortProceedings of the national academy of sciences, 108. pnas.org, pp. 20260–20264. https://doi.org/10.1073/PNAS.1116437108.

Wheeler, T., Von Braun, J., 2013. Climate change impacts on global food security. Science 341 (1979), 508–513. https://doi.org/10.1126/SCIENCE.1239402.

World Bank, 2025. Agriculture Overview: Development news, research, data | World Bank [WWW Document]. URL ⟨https://www.worldbank.org/en/topic/agriculture/overview?utm⟩ (accessed 11.30.25).

Yumul, G.P., Cruz, N.A., Servando, N.T., Dimalanta, C.B., 2011. Extreme weather events and related disasters in the Philippines, 2004-08: a sign of what climate change will mean? Disasters 35, 362–382. https://doi.org/10.1111/J.1467-7717.2010.01216.X.