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Decomposing Total Factor Productivity Growth in Iran's Agriculture Sector with Consideration of Climatic Variables

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Abstract

Climatic conditions are key determinants of agricultural productivity, affecting both production levels and food security. This study aims to decompose total factor productivity growth in Iran's agricultural sector by explicitly incorporating climatic variables. True Random Parameters Stochastic Production Frontier (TRP-SPF) model and the Maximum Likelihood method were used to estimate parameters in two scenarios, with and without climate variables which are evaluated by TRP_c and TRP_{nc} models, respectively. The results showed that the variables of cultivated area, tractors, and technology have a positive and significant impact on production in both models, and the highest effect observed for cultivated area. In the TRP_c model, the variables of temperature and precipitation also made significant contributions to higher production. The average technical efficiency in the TRP_{nc} model was estimated at 56.5%, and in the model with climatic variables, it decreased to 43.3%. These results confirmed the significant impact of climatic variables on production and suggested that agricultural output could be increased by more than 50% with the same resources and technology, minimizing inefficiency factors and the adverse effects of climatic variables. Decomposition of the Climatic Adjusted Total Factor Productivity (CATFP) index into four components, including climatic effects, scale effects, technical efficiency, and technological progress, revealed that climatic effects have the greatest impact, accounting for 26.4%, while the other three components contributed almost equally to improving productivity. Given the significant impact of climatic variables on agricultural productivity, this study recommends strategies adapting better with climatic conditions of different regions.

Keywords: Agriculture, Climatic effects, Scale effects, Technical efficiency, Total factor productivity

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Introduction

Agriculture is a cornerstone of a nation's economy and a prerequisite for the development of secondary industries. Ensuring stability and prosperity in the agricultural sector is crucial for a country to achieve economic growth and improve living standards. In 2023, the agricultural sector accounted for approximately 4.12% of global GDP. For Iran, this share was 12.8% in the same year, while for some other developing countries, it was reported to be as high as 25% (World Bank, 2024). However, due to the vulnerability of agriculture and its dependence on climatic conditions, agricultural production is significantly influenced by climate change. To sustain dynamism and further development in the agricultural sector, analyzing the impact of climate change on agricultural production has become a critical task for farmers and policymakers alike. In fact, agriculture, as a vital component of the global economy particularly in developing countries faces numerous challenges driven by a variety of factors. One of the most significant of these factors is climate change, which has profound implications for crop production and food security. Over the past few decades, climatic trends in many agricultural regions of the world have been relatively rapid (Lobell & Gourdji, 2012), and climate change is increasingly recognized as the most severe environmental challenge facing humanity. These climatic shifts are expected to continue in the coming decades (Chen *et al*., 2016; Duffy *et al*., 2021). Particularly, changes related to rising temperatures and altered precipitation patterns could lead to significant reductions in agricultural products. Moreover, extreme weather events such as heatwaves and heavy rainfall leading to flooding have been on the rise in recent decades.

According to World Bank data, Fig. 1 and 2 depict the trends in average temperature (in degrees Celsius) and precipitation (in millimeters) for Iran over the past five decades, respectively. A closer inspection of these two critical climatic variables reveals considerable fluctuations throughout the period, suggesting a complex and volatile climate pattern that likely exerts significant pressure on agricultural productivity. While both temperature and precipitation have shown considerable variation, a striking observation is the upward trajectory of average temperature, which has risen from approximately 16°C in 1972 to over 19°C in 2022. This increase in temperature is indicative of a broader global warming trend that may accelerate over time, with potential long-term consequences for agricultural systems, particularly in a region like Iran, where agriculture is highly sensitive to temperature changes. In contrast, precipitation levels have followed a more erratic path. The highest recorded rainfall was 335.79 mm in 1982, whereas the lowest was a dramatic 128.9 mm in 2021. The sharp reduction in precipitation in recent years raises serious concerns, as it signals a potential shift toward more frequent and severe droughts, along with increasingly erratic rainfall patterns. These climatic changes could significantly impact agricultural production and limit the availability of water for irrigation. The combination of rising temperatures and decreasing precipitation over the last five decades poses a significant threat to agricultural production in Iran. The warming climate may increase the frequency and intensity of heatwaves, further stressing crops and reducing yields. At the same time, lower and more erratic rainfall exacerbates water scarcity, making it more difficult for farmers to maintain consistent crop output. Additionally, the variability in these climatic factors introduces a high degree of uncertainty, which can destabilize agricultural planning and long-term sustainability. The interplay between these changing climatic conditions is likely to disrupt traditional farming practices and requires urgent adaptation strategies to safeguard food security and agricultural livelihoods.

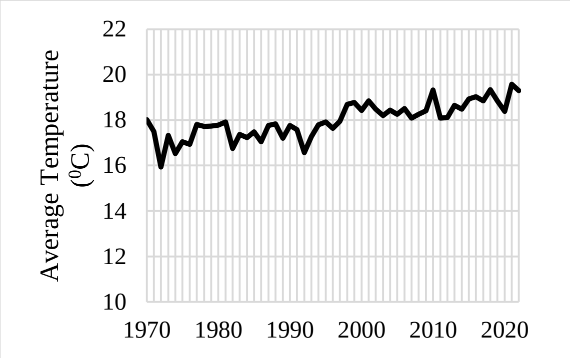

Figure 1- Long-term trend of average temperature

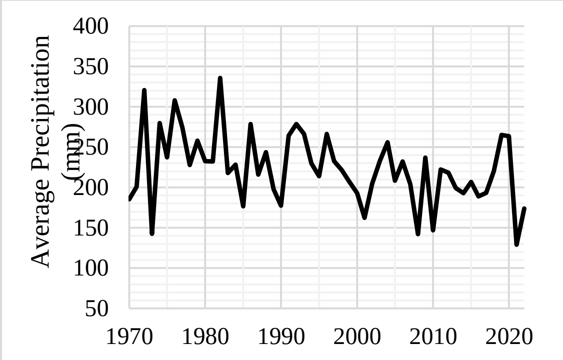

Figure 2- Long-term trend of average precipitation

Increasing agricultural production to meet the growing demands of a rising global population, in the face of climate change threats, remains a formidable challenge (Mall *et al.*, 2017). Consequently, climate change particularly temperature and precipitation fluctuations affects the efficiency of agricultural production, which can result in higher food prices and, in addition to impacting food availability, also affects economic access to food (Hosseinzad *et al.*, 2023). Furthermore, it can influence the income of agricultural producers (Calzadilla *et al.*, 2013). In less developed countries, vulnerability to climate change is more pronounced, exacerbated by low investment in agricultural research (Heisey, 2001). Climate change primarily affects Total Factor Productivity (TFP) in agriculture through two main channels (O'Donnell, 2022). On the one hand, it impacts TFP by altering the availability and allocation of resources, such as changes in rainfall, which serve as additional input variables. On the other hand, it affects TFP by modifying the levels of output variables. It is important to note that the impact of climate change varies across different agricultural regions, as its effects on climatic resources are unique to each specific area. Therefore, measuring the impact of climate change on agricultural productivity is essential for a comprehensive analysis of its effects on agricultural production. According to existing literature, assessments of climate change impacts on agricultural productivity have predominantly focused on very large or small regions and countries. There is a need for further analyses in different parts of the world, such as Iran, to better understand the effects of climatic variables on agricultural production and productivity. This would enable the application of innovative technologies for agricultural adaptation, and the development of effective policies and targeted strategies to address climate change and enhance agricultural resilience. This issue, in addition to improving food security, is critical for guiding farmers in adjusting cropping structures. Awareness of these impacts will significantly influence the experience and outlook of farmers (Rippke *et al.*, 2016; Karki *et al.*, 2020), and ultimately, global trade will also benefit from a reduction in the impacts of climate change on agricultural production (Njuki *et al.*, 2019).

Due to the importance of the topic, various studies have been conducted on the impact of climate change on the agricultural productivity, naturally leading to a comprehensive review by Praveen & Sharma (2019) of reports, articles, and documents evaluating the impacts of climate change on agricultural production. By integrating existing research, they analyzed how climate change influences agriculture, particularly in developing countries, and explored the potential role of agriculture in addressing climate change through sustainable practices. Naturally, researchers, depending on the objectives of their study, utilize different methods to assess the impact of climate variables on productivity. For instance, Liang *et al.* (2017) used a multivariate regression model and estimated that temperature and precipitation factors explained about 70% of the agricultural productivity variation in the United States. Similarly, Ozdemir (2022) analyzed the impacts of climate change on agricultural productivity in the Asia region using autoregressive distributed lag (ARDL) models. Ahmed *et al.* (2023) investigated the effects of temperature increases and political crises on crop yields, focusing on wheat, rice, maize, and soybeans, through simulation analyses. In this study, they identified adaptation measures, such as improved farming practices and technology adoption, as strategies that can enhance productivity. Bouteska *et al.* (2024) employed two modeling approaches, the productivity function and the Ricardian approach, to investigate the impact of climate change on agricultural productivity and food security in Ethiopia. Their findings highlighted the vulnerability of agriculture to climate change and the importance of considering adaptation strategies. It is also important to note that some researchers have used stochastic production frontier (SPF) models and various TFP indexes to analyze the impact of climate variables. For example, Salim & Islam (2010) utilized the Törnqvist index, Sabasi & Shumway (2018) applied the Lowe index, and Njuki *et al.* (2018) employed the multiplicative index. These approaches help in refining the measurement of productivity changes due to climate factors. Moreover, several researchers have conducted predictive studies on the impact of climate change on productivity. In this context, Habib-ur-Rahman *et al.* (2022) predicted the effects of climate change on the yields of rice and wheat, the two main crops in Pakistan. They highlighted that adopting appropriate climate adaptation technologies, such as adjusting planting times and improving irrigation management, could enhance productivity and profitability under changing climate conditions. In line with this, Zhou *et al.* (2024) analyzed the impact of climate change on agricultural total factor productivity in China before making a 30-year prediction, from 2031 to 2060. The study underscores the importance of considering climate change when developing agricultural adaptation strategies.

A review of the studies highlights that all research emphasizes the importance of understanding the impact of climate change on agricultural productivity and food security, and underscores the need for appropriate measures to adapt to climate change, particularly for Asian countries and developing nations. Consequently, the aim of this study is to decompose the growth of total factor productivity in Iran's agriculture sector, with a particular emphasis on climatic variables over the period from 1970 to 2022. This research aims not only to quantify the impact of climate change but also to critically assess the contributions of various factors to the overall productivity growth, providing a comprehensive understanding of the dynamic interplay between climate and agricultural productivity. The methodologies and findings presented in this paper provide a valuable reference for advancing agricultural production under the influence of climate change.

Materials and Methods

TRP-SPF Model

This research applies a True Random Parameters Stochastic Production Frontier (TRP-SPF) approach to model the agricultural production frontier. The TRP-SPF framework is particularly useful for capturing unobserved heterogeneity within the data. It achieves this by introducing observation-specific intercept and slope parameters, which reflect underlying factors such as technological advances, environmental conditions, and variations in input quality that influence agricultural output but are not directly measured in the dataset. These unobserved factors are likely to affect production processes, and the model allows for their implicit inclusion, enhancing the accuracy of the estimated production frontier. In addition to accounting for unobserved heterogeneity, the TRP-SPF model is capable of isolating time-varying technical efficiency, thus providing a dynamic view of how efficiency evolves over time (Greene, 2008). This characteristic is particularly relevant for understanding the long-term agricultural productivity under varying conditions, such as shifts in technology or climate. The model specification adopted here follows a similar structure to the Random Parameter (RP) model, as discussed by Wooldridge (2005), and is conceptually aligned with approaches outlined by Tsionas (2002) and Greene (2008). However, unlike traditional models that analyze cross-country variation, this analysis is confined to a single country. Thus, it focuses on estimating the production frontier within a specific national context, without considering inter-country disparities. The results generated by the TRP-SPF model are then utilized to estimate and decompose Climatic Adjusted Total Factor Productivity (CATFP), offering insights into the productivity changes while adjusting for climatic variations. This decomposition allows for a more refined understanding of productivity growth and its drivers over time. The following TRP-SPF model is employed in this study:

$$y_t = \mu + \sum_{k=1}^{K} B_k x_{kt} + \lambda T + \sum_{j=1}^{J} \eta_j z_{jt} + v_t - u_t \quad (1)$$

where y_t is agricultural production in the t-th time period; x_{kt} is a vector of input variables, which includes factors such as land, labor, machinery, fertilizer, and pesticide; T represents a time trend capturing technological progress over time. It is worth noting that, due to the lack of time-series data on technological progress in the agricultural sector, a time trend variable is used in this study (Ortega & Lederman, 2004; Hosseini & Dashti, 2014; Lachaud & Bravo-Ureta, 2021). z_{jt} denotes a set of climatic variables. μ is a random intercept parameter that accounts for unobserved, time-invariant heterogeneity. B_k is a vector of random slope parameters for the input variables, allowing for variation in how different inputs affect agricultural production across observations. v_t is the error term, assumed to follow a normal distribution with a mean of zero and constant variance. u_t represents a non-negative random term, capturing the inefficiency of agricultural production in time period t, and this inefficiency term follows a half-normal distribution.

The Cobb-Douglas functional form is employed in this study, based on its widespread application in research, as highlighted by Ghoshal & Goswami (2017), Zhang *et al.* (2020), Vasyl'Yeva (2021), Wang *et al.* (2021), and Akbari *et al.* (2022), and due to the consistency of the obtained results with theoretical expectations. Therefore, the empirical model of the present study can be expressed in the form of a Cobb-Douglas specification, as shown in Equation 2. It is worth noting that the labor variable was excluded from the empirical model due to the insignificance of its coefficient.

$$\mathrm{Ln}y_t = \mu + \beta_1 \mathrm{LnX}_{\mathrm{lan\,t}} + \beta_2 \mathrm{LnX}_{\mathrm{tra\,t}} + \beta_3 \mathrm{LnX}_{\mathrm{fer\,t}} + \beta_4 \mathrm{LnX}_{\mathrm{pes\,t}} + \lambda T + \eta_5 \mathrm{LnZ}_{\mathrm{tem\,t}} + \eta_6 \mathrm{LnZ}_{\mathrm{pre\,t}} + \eta_7 \mathrm{LnZ}_{\mathrm{temd\,t}} + \eta_8 \mathrm{LnZ}_{\mathrm{pred\,t}} + v_t - u_t \quad (2)$$

where, y_t represents the value of agricultural production in thousands of dollars for different years. $\mathrm{X}_{\mathrm{lan\,t}}$ denotes the cultivated land area in thousands of hectares, while $\mathrm{X}_{\mathrm{tra\,t}}$ refers to the number of tractors (machinery) in thousands. $\mathrm{X}_{\mathrm{fer\,t}}$ indicates the amount of chemical fertilizer used, measured in tons, and $\mathrm{X}_{\mathrm{pes\,t}}$ represents the pesticide usage, also in tons. The variable T symbolizes technological progress over time, while $\mathrm{Z}_{\mathrm{tem\,t}}$ refers to the average temperature, measured in degrees Celsius, and $\mathrm{Z}_{\mathrm{pre\,t}}$ denotes the average precipitation, measured in millimeters. The variables $\mathrm{Z}_{\mathrm{temd\,t}}$ and $\mathrm{Z}_{\mathrm{pred\,t}}$ represent deviations of temperature and precipitation, respectively, from their long-term averages to capture climatic variability. Additionally, Ln denotes the natural logarithm.

The model can be estimated by Maximum Likelihood (ML) method, allowing for a robust estimation of the parameters and the calculation of productivity indices. The CATFP index, as described by O'Donnell (2018), is then used to measure and decompose CATFP. The CATFP index for time t relative to a base period s is expressed as Equation 3.

$$CATFPI_{st} = \frac{CATFPI_t}{CATFPI_s} = \frac{Y_t(X_t)}{Y_s(X_s)} \quad (3)$$

where Y_t and X_t represent the aggregate output and aggregate input at time t, respectively. Y_s and X_s represent the aggregate output and aggregate input at the base period s. In the context of this study, the aggregate output Y_t and aggregate input X_t are derived from the results of the TRP-SPF model. These functions are assumed to be non-decreasing, non-negative, and linearly homogeneous. By utilizing the coefficients resulting from the estimation of the TRP-SPF model, the decomposition of CATFP into various components can be expressed as Equation 4 (Lachaud & Bravo-Ureta, 2021).

$$\mathrm{CATFPI}_{st} = [\prod_{k=1}^{K}\left(\frac{x_{kt}}{x_{ks}}\right)^{\beta_k - b_k}] \times [\prod_{j=1}^{J}\left(\frac{z_{jt}}{z_{js}}\right)^{\eta_j}] \times [(\frac{T_t}{T_s})^{\xi}T] \times [\frac{\exp(-u_t)}{\exp(-u_s)}] \quad (4)$$

The components of the productivity function, as represented by Equation (4), are as follows: The first term on the right-hand side of the equation indicates the relative changes in scale effects (SE). The second term reflects the changes in climatic effects (CE), which are influenced by weather conditions. The third term represents the relative change in technological progress (TP). The fourth term captures the relative changes in technical efficiency (TE).

Data

The data used in the present study consists of time series from 1970 to 2022 (53 years) for Iran, including the value of agricultural production in constant 2014 US dollars, cultivated area, number of tractors, labor force, chemical fertilizers, and pesticides. These data were sourced from the FAO website for the study period. It is important to note that the agricultural sector in this research does not include the livestock and poultry subsectors. Additionally, two key climatic variables, precipitation and temperature, were considered, with data for these variables extracted from the World Bank.

Results and Discussion

In this section, initially, the descriptive statistics of the key variables studied in the research, including the mean, minimum, maximum, and standard deviation for all the considered variables, are presented in Table 1. Subsequently, the results obtained from the model estimations will be analyzed.

Table 1- Descriptive statistics (T = 53 years)

Variable	Unit	Mean	Max. (year)	Min. (year)	Standard Deviation
Value of Agricultural Production	Billion USD	20.27	34.57 (2016)	6.51 (1971)	8.64
Land	Million hectares	16.90	18.70 (1995)	13.71 (1980)	1.13
Tractors (Machinery)	1000 No	210.74	352.11 (2022)	20.00 (1970)	107.52
Labor	1000 No	1329.49	4082.6 (2019)	318.14 (1970)	1513.912
Fertilizer	1000 Tone	1608.46	2478.96 (2022)	895.26 (1976)	430.78
Pesticide	1000 Tone	29.52	74.58 (2021)	3.01 (1988)	28.82
Temperature	^{0}C	17.99	19.57 (2021)	15.93 (1972)	0.78
Precipitation	Millimeters	223.45	335.79 (1982)	128.95 (2021)	44.01

Based on Table 1, the value of agricultural production has shown significant fluctuations, with a peak of 34.57 billion USD in 2016 and a low of 6.51 billion USD in 1971. These variations are likely due to factors such as global price changes, domestic agricultural policies, and economic conditions during different periods. The substantial increase in production for recent years, particularly in 2016, may reflect improvements in productivity, technology, or government support. The cultivated land area has also experienced changes, with an average of 16.90 million hectares. The peak of 18.70 million hectares was recorded in 1995, while the lowest value of 13.71 million hectares occurred in 1980. Despite this fluctuation, the overall area has remained relatively stable, indicating structural limitations in agricultural sector. Machinery use (tractors) has grown steadily, with the number of tractors rising from 20,000 in 1970 to 352.11 thousand in 2022. This growth highlights the increasing mechanization of Iranian agriculture, which has become more reliant on technology to boost productivity. This trend suggests the government's focus on mechanization to enhance agricultural efficiency. Labor in agriculture has shown significant variation, with a peak of 4,082.6 thousand workers in 2019 and a low of 318.14 thousand in 1970. These fluctuations may reflect changes in the agricultural labor market, migration, or structural shifts within the sector. The increase in recent years could be related to a rise in agricultural activities or a greater dependence on agricultural employment. Fertilizer use has seen a significant increase over the period, with an average of 1,608.46 thousand tons used annually. The highest use of 2,478.96 thousand tons occurred in 2022, signaling more intensive agricultural practices. However, this also raises concerns about the growing reliance on chemical inputs, which could have long-term environmental implications. Pesticide use has followed a similar pattern, with a sharp rise from 3.01 thousand tons in 1988 to 74.58 thousand tons in 2021. This increase may be driven by higher pest pressures or the expansion of agricultural production, particularly in recent years. Regarding temperature and precipitation, the average temperature during the period was 17.99°C, with a peak of 19.57°C in 2021, reflecting a trend of rising temperatures. Precipitation averaged 223.45 mm annually, with fluctuations throughout the period, including a low of 128.95 mm in 2021. These climatic changes suggest the potential impacts of climate change, which could affect agricultural patterns, water availability, and crop yields. Overall, the data in Table 1 highlights the dynamic nature of Iran's agricultural sector, influenced by changes in production, resource use, and climatic conditions. The observed fluctuations indicate both the challenges and opportunities in adapting to environmental changes, and they underscore the need for effective policy measures to support sustainable agricultural practices and better manage resources in the face of evolving climatic and economic conditions.

In this study, the impact of various factors on agricultural production in Iran is analyzed using the TRP-SPF model, with the results estimated using the Maximum Likelihood Estimation method and reported in Table 2. The model was estimated in two scenarios: one with climatic variables and one without them, to assess the role of climate in shaping agricultural productivity. The factors considered include cultivated area, machinery, chemical fertilizers, pesticides, and climatic variables such as temperature, precipitation, and deviations from long-term averages of temperature and precipitation. The results from both models are compared to better understand the significance of climatic factors in determining agricultural output. Based on this table, the cultivated area is a significant and positive contributor to agricultural output in both models. This indicates that an increase in cultivated area leads to a proportional increase in agricultural production. Specifically, a 1% increase in cultivated area results in an approximate 0.61% increase in production. The inclusion of climatic variables does not significantly alter this relationship, suggesting that increasing the area under cultivation remains a key driver of agricultural production in Iran, regardless of climatic conditions. Machinery has a crucial role in enhancing production. The coefficient for machinery increases from 0.115 (TRP_{nc}) to 0.220 (TRP_c), showing that the effect of machinery becomes even more pronounced when climatic variables are included. The higher coefficient in the model with climatic variables suggests that machinery usage compensates for the negative effects of climate variability, likely by improving efficiency in farming practices. A 1% increase in machinery usage results in approximately a 0.22% increase in agricultural output, reinforcing the importance of technological advancements in boosting agricultural production.

Another point to note regarding Table 2 is that chemical fertilizers (X_{fer}) exhibit a statistically significant impact on agricultural production in the model without climatic variables, but are not statistically significant in the model that includes climatic variables. In the model without climatic variables, the coefficient of chemical fertilizers is negative, indicating that increased use of chemical fertilizers may result in diminishing returns or potentially harmful effects on agricultural output. However, the model with climatic variables suggests that the inclusion of climate factors may alter the relationship between fertilizer use and agricultural production. This indicates that the negative impact of fertilizers may be confounded by climatic variables and may not be as pronounced when the effects of climate are accounted for. It is important to focus on the efficient and sustainable use of fertilizers, particularly in the context of climate variability, to avoid environmental degradation and improve overall agricultural output.

Table 2- Estimates for the TRP-SPF Models without (TRP_{nc}) and with climatic variables (TRP_c)

	Model TRP_{nc}		**Model TRP_c**	
Variable	**Coefficients**	**t- statistic**	**Coefficients**	**t- statistic**
Constant	1.664	0.70	-5.221*	-1.78
X_{lan}	0.607***	4.28	0.613***	5.40
X_{tra}	0.115***	18.61	0.220***	15.96
X_{fer}	-0.027**	-2.40	-0.032	-1.63
X_{pes}	-0.022***	-5.72	0.031***	4.85
T	0.036**	2.1	0.024***	3.401
Z_{tem}			0.089**	2.37
Z_{pre}			0.331***	2.97
Z_{temd}			0.006	0.65
Z_{pred}			-0.039**	-2.35
σ_u^2	0.162		0.169	
σ_v^2	0.141		0.112	
γ	0.535		0.601	
RTS	0.673		0.864	
TE				
Mean	56.597		43.376	
SD	16.076		11.898	
Min	30.342		25.47	
Max	84.358		68.77	
Log-likelihood	573		693	

Note: ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Pesticides have a significant and positive effect on agricultural production, especially in the model with climatic variables. The coefficient for pesticides is negative (-0.022) in the model without climatic variables but turns positive (0.031) in the model with climatic variables. This change suggests that pesticides play a key role in mitigating the adverse effects of environmental factors such as pests and diseases, especially in climates where weather conditions may exacerbate pest problems. A 10% increase in pesticide use leads to a 0.3% increase in production, reflecting the importance of pest control in maintaining agricultural yields. The variable T, representing technology or technological progress, shows a positive and statistically significant effect on agricultural production in both models, indicating that technological advancements contribute positively to agricultural production in both scenarios.

In terms of climatic variables, temperature has a positive and statistically significant effect on agricultural production, with a coefficient of 0.089, suggesting that warmer temperatures may provide certain advantages, such as extended growing seasons. However, the overall effect is relatively small. Precipitation, on the other hand, has a highly significant and positive effect on agricultural output, with a coefficient of 0.331. This indicates that an increase in rainfall improves agricultural production, as it directly benefits crop growth. This finding aligns with the study by Barikani *et al.* (2024), as their research also identified rainfall as a statistically significant factor with a positive impact on the production of rain-fed wheat in Iran. The deviation of temperature from the long-term average shows a minimal and statistically insignificant impact.

The average technical efficiency (TE) in the model without climatic variables is 56.6%, with a standard deviation of 16.1%. In the model with climatic variables, the average TE drops to 43.4%, with a standard deviation of 11.9%. The results suggest significant variation in technical efficiency across the two models. In the model TRP_{nc}, the technical efficiency shows a relatively wide range, with the minimum and maximum TE values being 30.3% and 84.35%, respectively. This indicates that, in the absence of climate factors, the technical efficiency varies substantially, with some regions or periods achieving relatively high efficiency in utilizing inputs. In contrast, in the model that includes climatic variables, the minimum and maximum TE values narrow, ranging from 25.4% to 68.7%. The inclusion of climatic factors appears to reduce the overall efficiency, as evidenced by the lower range of TE. This suggests that climatic factors might introduce additional challenges that negatively affect agricultural production, leading to a decrease in the sector's efficiency. To better analyze technical efficiency in both scenarios from 1970 to 2022, the results are illustrated in Fig. 3. The inclusion of climatic variables reduces the technical efficiency, highlighting that environmental factors such as temperature and precipitation introduce additional challenges and uncertainties that lower the efficiency of agricultural producers. Furthermore, as shown in Fig. 3, it appears that the gap in technical efficiency between the models with and without climatic variables increases over time, suggesting that the impact of climate variability on technical efficiency becomes more pronounced as time progresses.

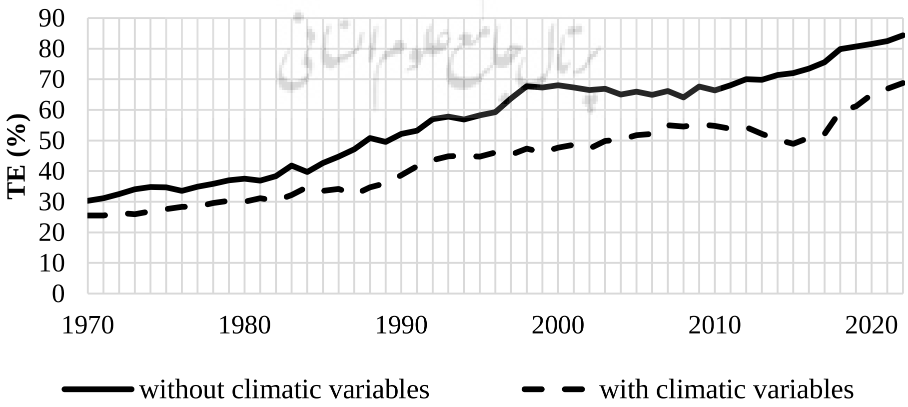

Figure 3- Trends of technical efficiency with and without climatic variables

The results from the TRP-SPF models with and without climatic variables demonstrate that both environmental and non-environmental factors significantly influence technical efficiency in Iran. While factors like cultivated area, machinery, and pesticides continue to show significant positive effects on production, climatic variables introduce substantial risks. Temperature, precipitation, and the deviation of precipitation from the long-term average, significantly affect agricultural output. Temperature shows a slight positive effect, while precipitation has a strong positive influence. However, deviations from normal climatic conditions in precipitation, have a negative impact for production. The reduction in technical efficiency when climatic variables are included highlights the vulnerability of agriculture to climate change. Therefore, agricultural policies must focus on both technological improvements and strategies for adapting to climatic variability to ensure sustainable productivity growth.

Table 3 illustrates the fluctuations in the CATFP index for Iran's agricultural sector from 1970 to 2022, highlighting an overall upward trend. Starting from the base year of 1970, the CATFP reached its highest value of 2.69 in 2022. The average annual growth rate of CATFP during this period was 1.70, indicating that the overall growth rate of agricultural total factor productivity during the study period, compared to the base year, has been 70%. It is important to note that these upward fluctuations are also observed within each decade. For example, by the end of the 1970-1980 decade, Iran had experienced a 7% growth in CATFP compared to 1970. On the other hand, the highest growth in CATFP occurred during the 2010-2020 decade. In addition, the highest fluctuations in the CATFP index occurred during this decade, particularly in the latter half of the decade, ranging from 1.91 in 2015 to approximately 2.4 in 2019, representing a variation of 0.47. Following this, the period from 1990 to 2000 experienced the next largest fluctuations. Overall, while Iran's agricultural productivity has steadily increased over the past five decades, the growth rate was not uniform across all periods. The most substantial advancements occurred in the last two decades, which can be attributed to policy shifts, technological innovation, and improvements in agricultural management. However, challenges related to climate variability and resource limitations can impact the consistency of growth over the years.

The contributions of climate effects, scale effects, technological progress, and technical efficiency to the variability of cumulative CATFP were estimated, and the results are presented in Table 4. According to the findings, the average contribution of climate effects is approximately 26.43%, which is higher than that of other factors. This highlights the significant impact of climatic conditions on the variability of the CATFP index. Following this, technological progress ranks as the second most influential factor, with an average contribution of 24.97%. This indicates that nearly 25% of the variation in the productivity index is attributable to technological progress. Technical efficiency explains 24.55% of CATFP variability, while scale effects contribute the least, accounting for approximately 24% of the productivity variation over the study period.

To provide a more detailed analysis, Fig. 4 illustrates the contributions of these four factors to CATFP from 1970 to 2022. Based on the results in Table 4 and the trends observed in Fig. 4, it can be concluded that scale effects not only had the lowest contribution to CATFP on average during the period under review, but its share in determining agricultural productivity in Iran has also declined over time. In contrast, the contribution of technological progress to CATFP has shown a consistent upward trend. This result is similar to the findings of Lachaud & Bravo-Ureta, (2021).

Table 3- CATFP, average CATFP by decade, and annual growth rate in Iran, 1970–2022

Year	CATFP	Year	CATFP	Year	CATFP	Year	CATFP	Year	CATFP	Year	CATFP
1970**	1.00	1980	1.18	1990	1.51	2000	1.86	2010	2.14	2020	2.55
1971	1.00	1981	1.22	1991	1.63	2001	1.90	2011	2.11	2021	2.62
1972	1.03	1982	1.19	1992	1.71	2002	1.85	2012	2.13	2022	2.69
1973	1.01	1983	1.26	1993	1.76	2003	1.95	2013	2.04		
1974	1.05	1984	1.36	1994	1.76	2004	1.97	2014	1.97		
1975	1.08	1985	1.31	1995	1.75	2005	2.03	2015	1.91		
1976	1.11	1986	1.34	1996	1.80	2006	2.04	2016	1.99		
1977	1.11	1987	1.26	1997	1.78	2007	2.15	2017	2.04		
1978	1.16	1988	1.36	1998	1.85	2008	2.13	2018	2.33		
1979	1.19	1989	1.41	1999	1.80	2009	2.16	2019	2.39		
Average CATFP by decade, and annual growth rate (1970-2022)											
Decade 1970-1980	1.07	1980-1990	1.28	1990-2000	1.73	2000-2010	2.00	2010-2020	2.10	1970-2022	1.70

Note: ** indicates base year. (1970 = 1)

Table 4- Contribution of climate effects, scale effects, technological progress, and technical efficiency in cumulative CATFP

	1970-1980	1980-1990	1990-2000	2000-2010	2010-2020	Average Share
Climatic Effects (CE)	26.97	24.34	26.48	27.39	26.77	26.43
Scale Effects (SE)	25.82	26.62	23.37	22.83	22.64	24.03
Technological Progress (TP)	22.77	24.43	25.71	25.3	26.04	24.97
Technical Efficiency (TE)	24.44	24.61	24.44	24.48	24.55	24.55

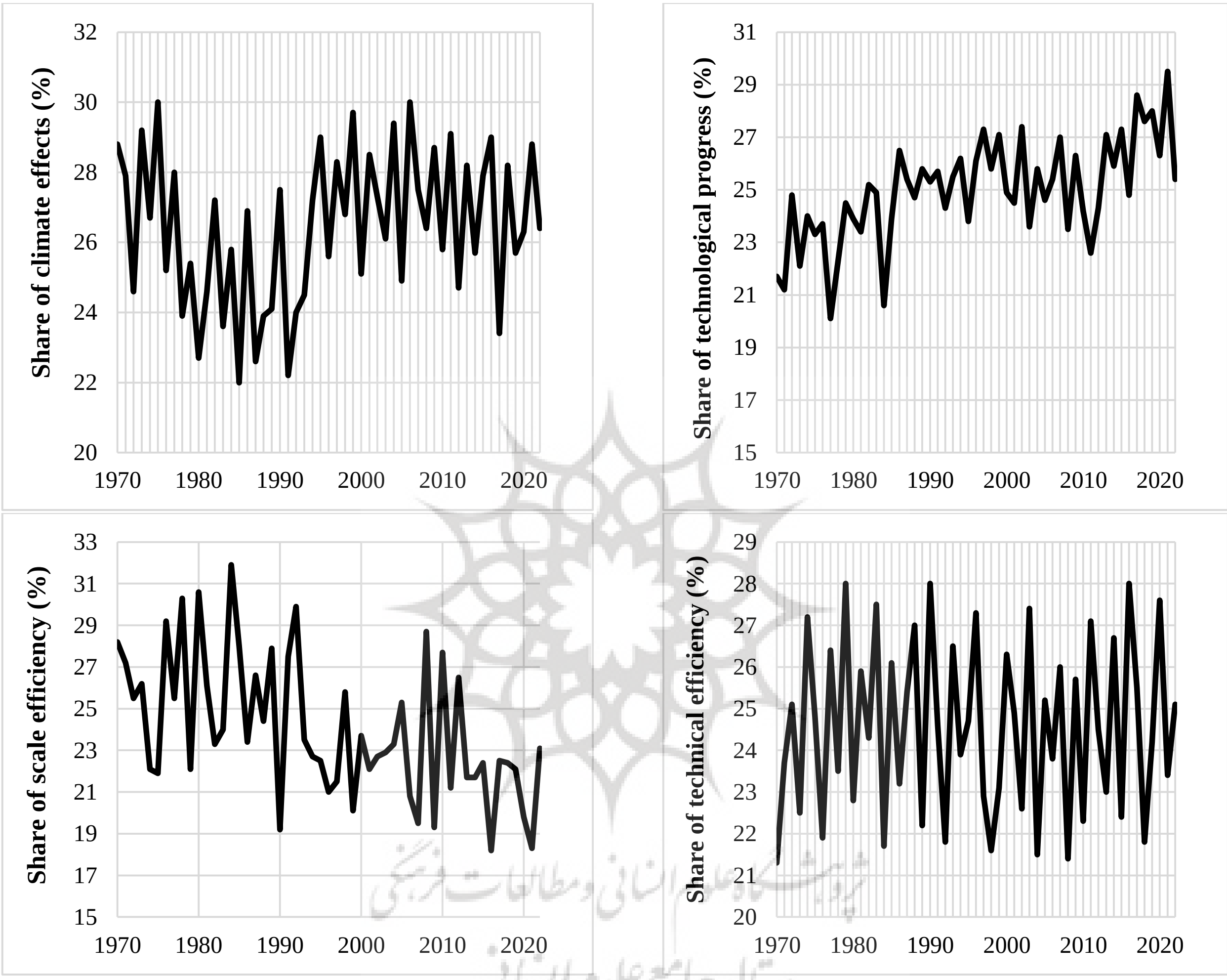

Fig 4- Contribution of technical efficiency, technological progress, scale effects and climate effects in cumulative CATFP

The shares of technical efficiency and climate effects, however, have exhibited fluctuations without a specific pattern over the same period. Notably, the variability of climate effects has been at higher levels in the past two decades.

Conclusion

This study provides an in-depth analysis of the factors influencing agricultural productivity in Iran from 1970 to 2022, with a particular focus on the role of climatic variables. By employing the TRP-SPF model under two scenarios, with and without climatic factors, the findings highlight the critical interplay between environmental conditions and agricultural efficiency. The results underscore several key insights and provide a basis for policy implementation. The findings indicate that increasing cultivated land has consistently contributed to production, but this approach by itself may not deal with meet future challenges. Investment in machinery and advanced farming techniques showed a potential enhancement in output, particularly under conditions of climatic variability. For example, the role of machinery in improving resilience to adverse weather highlights the importance of promoting technological adoption. Climatic factors, while beneficial in optimal conditions, reveal the sector's vulnerability to deviations from historical norms. Temperature and precipitation variability pose substantial risks, with erratic rainfall patterns leading to significant efficiency losses. This underscores the need for targeted adaptation strategies, such as improving irrigation systems and adopting climate-resilient crops. Similarly, inefficiencies in input utilization, such as over-reliance on chemical fertilizers, indicate a pressing need to adopt sustainable farming practices. Addressing these inefficiencies will require both education and incentives to guide farmers toward optimal resource management.

The result showed that the average of CATFP index is 1.7. Despite the general fluctuations in CATFP throughout the study period, the highest fluctuations occurred in the last two decades, which could be attributed to changes and improvements in technology. It is important to note that the contributions of the components of the CATFP have not been constant or uniform over study period. According to the decomposition results of the index into four components, including climatic effects, technical efficiency, scale effects, and technological progress, the contribution of climatic effects has been greater than the other components and has remained at higher levels during the period from 1990 to 2022. It seems that climate change has intensified during this period, a point that is confirmed by many studies. In this regard, according to the results obtained, it was observed that on average, 26.43% of the growth in total factor productivity is attributed to climatic variables. In other words, improvements in precipitation and temperature conditions provide a favorable environment for enhancing productivity, as the high yield of certain modern technologies such as certificated seeds or fertilizers is contingent upon favorable rainfall and temperature conditions. While climatic variables have a prominent effect on productivity growth, the impacts of the other three components, i.e., scale effects and technical efficiency are almost at the same level, with only slight differences. Therefore, in order to improve productivity, considering climatic variables is of significant importance. Replacing more Climate-resilient crops can also contribute to productivity enhancement. In other words, considering weather determinants such as temperature and precipitation, alongside economic factors, will ultimately lead to improved efficiency and increased productivity in the agricultural sector. In addition, given the positive impact of technology and the increasing share of technological progress in productivity growth, the role of modern technology in enhancing the productivity of economic units, especially in agriculture, is undeniable. The use of modern technological practices, such as drip irrigation and certificated seeds, results in higher outputs from a given amount of inputs, which signifies the enhancement and growth of factor productivity

Technical inefficiency is also required to be considered for improving agricultural productivity. In this regard, the technical efficiency of the agricultural sector, even without considering climatic variables, was estimated at approximately 56.6%, indicating the potential for at least a 40% increase in production with the same available resources and inputs. The observed decrease in technical efficiency when accounting for climatic variables suggests that environmental uncertainties hinder optimal resource utilization. Increasing the efficiency of producers by identifying and eliminating the factors causing inefficiency should also be a priority for policymakers in the agricultural sector. Improving efficiency essentially means increasing production with the same resources and technology in order to achieve higher output without incurring additional costs, thus enhancing profitability and the productivity.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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مقاله پژوهشی
جلد ۳۹، شماره ٤، زمستان ١٤٠٤، ص. ٣٤٤-٣٢٩

تجزیه رشد بهره‌وری کل عوامل تولید بخش کشاورزی ایران با تأکید بر متغیرهای آب و هوایی

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چکیده

شرایط اقلیمی از عوامل تعیین‌کننده بهره‌وری تولید محصولات کشاورزی است که ضمن تأثیر بر سطح تولید، بر امنیت غذایی نیز مؤثر می‌باشد. بنابراین هدف مطالعه حاضر تجزیه رشد بهره‌وری کل عوامل تولید بخش کشاورزی در ایران با لحاظ متغیرهای آب و هوایی است. برای این منظور، از مدل TRP-SPF و روش حداکثر درست‌نمایی برای برآورد پارامترها در دو سناریو با لحاظ متغیرهای آب و هوایی (TRP_c) و بدون آن (TRP_{nc}) بهره گرفته شد. نتایج نشان می‌دهند که در هر دو مدل، متغیرهای سطح زیرکشت، تراکتور و فناوری تأثیر مثبت و معناداری بر تولید دارند که بیشترین تأثیر مربوط به متغیر سطح زیرکشت است. همچنین در مدل TRP_c، متغیرهای دما و بارش نیز به‌طور معناداری اثر مثبت بر تولید دارند. میانگین کارایی فنی در مدل TRP_{nc} برابر با ۵۶/۵ درصد برآورد شد و در مدل با متغیرهای اقلیمی به ۴۳/۳ درصد کاهش یافت که ضمن تأیید تأثیر قابل‌توجه متغیرهای اقلیمی بر تولید، موید امکان افزایش تولیدات بخش کشاورزی با همان منابع و تکنولوژی به میزان بالغ بر ۵۰ درصد می‌باشد، درصورتی‌که عوامل عدم کارایی و تأثیر سوء متغیرهای اقلیمی به کمترین مقدار خود تقلیل داده شوند. تجزیه شاخص CATFP به چهار جزء، اثرات اقلیمی، اثرات مقیاس، کارایی فنی و پیشرفت فناوری، نشان داد که اثرات اقلیمی با سهم ۲۶/۴ درصدی بیشترین تاثیر و سه جزء دیگر سهم تقریبا یکسانی در ارتقای بهره‌وری عوامل تولید داشته‌اند. نظر به تأثیر قابل توجه متغیرهای آب و هوایی بر عملکرد بخش کشاورزی، اتخاذ تدابیری که انطباق بیشتری با شرایط اقلیمی مناطق مختلف داشته باشد، توصیه می‌گردد.

واژه‌های کلیدی: بهره‌وری کل عوامل تولید، تأثیرات آب و هوایی، کارایی فنی، کارایی مقیاس، کشاورزی

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