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Analyzing the Impact of Climate and Economic Factors on Crop Production: Evidence from the U.S.

Zeynab Giyasova[1*], Ilhama Mahmudova[1], Mustafa Kemal Oktem[2], Khatira Maharramova[3], Tamilla Abbasova[1]

[1] Department of Economy, Azerbaijan State University of Economics (UNEC), AZ1001 Baku, Azerbaijan
[2] Department of Business Administration, Hacettepe University, 06800 Ankara, Turkey
[3] Department of Public Administration and Social Innovations, Azerbaijan State University of Economics (UNEC), AZ1001 Baku, Azerbaijan

[*] Correspondence: Zeynab Giyasova (zeynab.giyasova@unec.edu.az)

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Abstract: This study investigates the joint influence of climatic and economic determinants on agricultural productivity in the United States over the period 1961–2022. The analysis employs the Crop Production Index (CPI) as the dependent variable, alongside average annual temperature (AAT), GDP growth (GDPG), and gross fixed capital formation (GFCF) as explanatory variables, to assess the interactions between environmental conditions, economic dynamics, and crop output. Preliminary descriptive statistics affirmed the suitability of the dataset for parametric modeling, while the Augmented Dickey-Fuller (ADF) test confirmed the stationarity of all series at level (I(0)). Results from Ordinary Least Squares (OLS) regression indicate that AAT positively and significantly influences CPI, with a one-degree Celsius increase corresponding to a 7.70-unit rise ($p < 0.01$). In contrast, GDPG and GFCF exhibit negative impacts on CPI, decreasing it by 1.96 units ($p < 0.05$) and 2.93 units ($p < 0.05$), respectively. Granger causality tests reveal unidirectional causality from CPI to AAT ($F = 7.075$, $p = 0.001$), from AAT to GDPG ($F = 3.202$, $p = 0.048$), and from GDPG to GFCF ($F = 4.618$, $p = 0.014$), highlighting the temporal interdependencies among agricultural and economic indicators. Structural break analysis identifies four significant regime shifts during 1961–2022, reflecting the compounded effects of climatic fluctuations and economic transformations on agricultural output. These findings emphasize the pivotal role of temperature in shaping crop productivity, while also demonstrating that macroeconomic expansion can inadvertently constrain agricultural performance. The study offers empirical insights for designing integrated climate and economic policies aimed at sustaining agricultural productivity amid evolving environmental and economic conditions.

Keywords: Crop Production Index; Climate change; Economic growth; Environment; Time-series analysis; United States

1 Introduction

Climate change exerts a profound influence on both human well-being and ecosystem balance, affecting water availability for essential activities such as drinking, irrigation, and industrial use [1]. In 2024, the contiguous United States recorded an average annual temperature (AAT) of 55.5 °F (13 °C), marking a historical high that exceeded the 20th-century average by approximately 3.5 °F, consistent with a long-term warming trend of roughly 0.17 °F per decade since 1901 [2]. Variations in rainfall, snowfall, and snowmelt timing significantly shape the distribution of surface and groundwater resources across regions. Globally, precipitation levels vary widely—from less than 0.1 inch annually in arid deserts to over 900 inches in tropical areas—while the conterminous United States receives an average annual depth of approximately 30 inches, equivalent to about 1,430 cubic miles of water. The fate of this precipitation is determined by several interrelated factors, including rainfall intensity, topography, soil properties, vegetation cover, temperature, and urban development [3].

In recent years, scientific initiatives such as the National Forest Climate Change Maps project, developed by the Rocky Mountain Research Station (RMRS) and the Office of Sustainability and Climate, have advanced understanding of climate dynamics. These maps integrate historical (1975–2005) and projected (2071–2090) datasets on temperature, precipitation, snow, and stream flow, derived from the Coupled Model Intercomparison Project Phase 5 (CMIP5) global climate models downscaled to a 4 km grid, offering critical insights for climate-adaptive resource management and policy planning [4]. The contiguous United States demonstrates diverse precipitation regimes resulting from variations in latitude, altitude, and physiographic conditions. Typically, rainfall patterns follow a negative exponential distribution, indicating that small precipitation events occur far more frequently than large ones; cumulatively, a small number of heavy-rain days contribute the majority of total precipitation [5].

The U.S. experienced notable fluctuations in GDP growth (GDPG) between 2020 and 2023. Following a sharp contraction of approximately -2% in 2020 due to the pandemic, GDP rebounded strongly by 6% in 2021. Growth slowed to 2.5% in 2022, before slightly accelerating to approximately 3% in 2023, reflecting ongoing economic recovery and moderate expansion in domestic output [6]. Beyond environmental implications, climate variability also interacts with economic systems and productivity levels. In the United States, productivity is particularly vital in sectors such as housing, where it shapes affordability and influences broader patterns of wealth accumulation [7]. Similarly, in agriculture, climate factors such as temperature play a defining role in determining crop yields, resource efficiency, and long-term sustainability. The Crop Production Index (CPI) provides a key indicator for assessing changes in agricultural output over time, measuring production relative to a base period and reflecting the physical and chemical characteristics of soils as well as environmental constraints such as flooding or ponding [8, 9].

Given these interconnections, analyzing the combined impact of climate and economic factors on crop production is essential for understanding agricultural resilience and policy formulation in the face of environmental change. This study, therefore, examines the relationship between climatic variables—particularly precipitation and temperature—and economic determinants influencing crop productivity in the United States, drawing on empirical data and econometric analysis to provide evidence-based insights into sustainable agricultural development.

2 Literature Review

A substantial body of research has examined the complex and region-specific impacts of climate change on agricultural systems, addressing both environmental and economic dimensions. Schlenker and Roberts [10] investigated analyzed the temperature sensitivity of U.S. corn, soybean, and cotton yields using county-level panel data combined with high-resolution daily weather observations. Their findings indicate that crop yields rise until reaching species-specific temperature thresholds (29 °C for corn, 30 °C for soybeans, and 32 °C for cotton), beyond which yields decline sharply, reflecting limited historical adaptation. Projections further suggest that, under existing cultivation regions, average yields could decrease by 30%–46% under gradual warming and 63%–82% under accelerated warming by the end of the century, underscoring substantial risks associated with future temperature increases.

Kukal and Irmak [11] assessed the influence of climate variability on maize, sorghum, and soybean yields in the U.S. Great Plains over the period 1968 to 2013, employing comprehensive historical crop and climate datasets. They found that temperature and precipitation affected yields differently depending on crop type and location, while irrigation substantially mitigated negative climatic effects, enhancing resilience and informing adaptive management and resource allocation strategies.

Hossain et al. [12] evaluated the economic impacts of climate change on crop production in Bangladesh using a Ricardian modeling approach linking net crop income with climate variables. Their results indicated that both temperature and rainfall significantly affected agricultural income, with higher temperatures benefiting irrigated farms, and projections suggested potential increases in net crop income per hectare, albeit with notable spatial and seasonal variations.

Skrypnyk et al. [13] examined the effects of climate change on the yields of major export-oriented crops—corn, sunflower, and wheat—across Ukraine's agro-climatic zones from 2000 to 2018. Their findings confirmed northward shifts in cultivation areas, stable wheat yields, and significant expansion of corn and sunflower acreage, underscoring the need for adaptive strategies to address heightened climate risks, particularly in the Steppe zone, which exhibited greater vulnerability to climatic variability.

Osei-Kusi et al. [14] explored the long-term determinants of carbon emissions in Europe and Central Asia, Sub-Saharan Africa, and the Middle East and North Africa between 1990 and 2020, utilizing advanced econometric methods including the Regularized Common Correlated Effects (rCCE), Common Correlated Effects (CCE), and Mean-Group (MG) estimators. The study highlighted region-specific interactions among emissions, crop production, energy consumption, and economic growth, emphasizing the importance of green technology adoption, energy efficiency improvements, and tailored mitigation policies to achieve sustainable agricultural and environmental outcomes.

Additional studies [15–18] have demonstrated that climate change, driven by shifts in temperature, CO_2 concentrations, and precipitation, presents significant global challenges for agriculture. Although elevated CO_2 may enhance plant growth, rising temperatures and associated yield reductions are projected to generate substantial economic consequences, including multi-billion-dollar crop income losses in Pakistan and increased revenue volatility for U.S. corn and soybean production under extreme weather events and projected future climate variability.

Collectively, these studies illustrate the multifaceted impacts of climate change on agriculture, emphasizing the necessity of integrating environmental, technological, and economic perspectives in research and policy development to enhance resilience and ensure sustainable crop production under changing climatic conditions.

3 Data and Methodology

The study employs annual time-series data spanning 1961–2022, sourced from the World Bank [19], U.S. Bureau of Labor Statistics [20] and the Federal Reserve Economic Data [21]. The dataset includes four key variables: the CPI, AAT, GDPG (annual %), and gross fixed capital formation (GFCF, % of GDP). These variables were selected to capture the interplay between agricultural output, climatic conditions, and economic dynamics. Descriptive statistics and preliminary data analysis were conducted to assess central tendencies, dispersion, and distributional properties, ensuring suitability for subsequent econometric modeling.

The chart in Figure 1 demonstrates a clear long-term upward trend in the CPI, indicating sustained increases in agricultural output likely driven by productivity improvements, technological adoption, or expanded cultivation. AAT remains relatively stable, showing only a slight upward drift with minor short-term fluctuations around a gradually increasing mean. In contrast, GFCF as a percentage of GDP exhibits long-term stability with minimal variation, reflecting steady investment patterns. GDPG, however, is highly volatile, displaying pronounced short-term peaks and troughs typical of annual business cycle fluctuations around a stable long-term average.

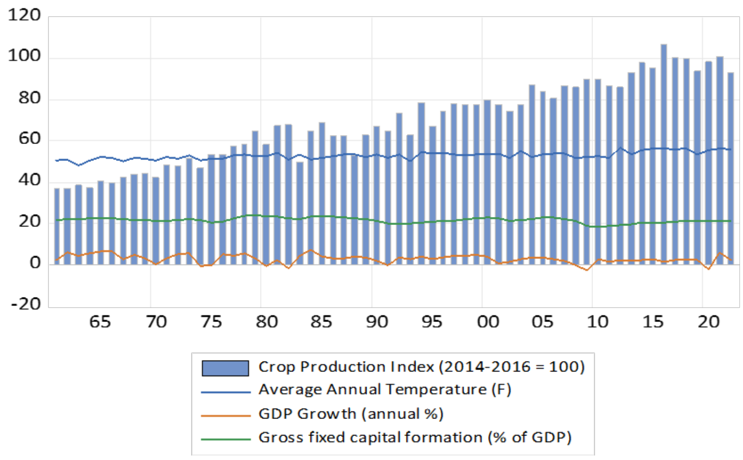

Figure 1. Visual trend of the dataset

The descriptive statistics in Table 1 reveal that the CPI demonstrates the greatest variability, with a standard deviation of 19.67 relative to a mean of 69.28, whereas AAT is the most stable variable, showing minimal dispersion (std. dev. = 1.79). Across all four variables, the high Jarque-Bera probabilities (all > 0.05) indicate that the null hypothesis of normality cannot be rejected, confirming that the distributions do not significantly deviate from normality. These results suggest that the dataset is appropriate for parametric analyses that rely on the assumption of normally distributed variables.

Table 1. Descriptive statistics summary

Statistic	CPI	AAT	GDPG	GFCF
Mean	69.279	52.974	3.033	21.720
Median	67.750	52.9000	3.044	21.910
Std. Dev.	19.666	1.789	2.122	1.278
Maximum	106.710	56.600	7.236	24.426
Minimum	36.930	48.300	-2.576	18.313
Jarque-Bera Prob.	0.208	0.803	0.198	0.291
Observations	62	62	62	62

Note: CPI, Crop Production Index; AAT, average annual temperature; GDPG, GDP growth; GFCF, gross fixed capital formation.

The analysis proceeded in several steps to ensure robust and reliable results. Initially, correlation analysis was performed to examine the linear relationships between variables and to identify potential multicollinearity issues.

Stationarity properties of the series were assessed using the Augmented Dickey-Fuller (ADF) [22] test to determine their integration order, which is a prerequisite for valid regression analysis and to avoid spurious results.

Following confirmation of stationarity, the Ordinary Least Squares (OLS) regression model was employed to estimate the impact of AAT, GDPG, and GFCF on the CPI. The following equation represents the multiple OLS regression model:

$$Y_t = \beta_o + \beta_1 X_{1t} + \beta_2 X_{2t} + \ldots + \beta_k X_{kt} + \varepsilon_t \tag{1}$$

where, Y_t represents the dependent variable, X_{lt} to X_{kt} are the independent variables, β_0 is the intercept, β_1 to β_k are the slope coefficients showing the effect of each independent variable, and ε_t denotes the error term capturing unexplained variations.

Diagnostic tests, including checks for homoskedasticity, were conducted to validate the classical assumptions of the OLS framework and to ensure that the estimated coefficients are efficient, unbiased, and reliable for inference.

Additionally, Granger causality tests [23] were applied to explore the directionality of relationships among the variables, while structural break analysis using the Bai–Perron procedure identified potential shifts in the underlying dynamics of agricultural productivity over time. This comprehensive methodological approach ensures that the findings reflect both the statistical and economic significance of the relationships under study.

4 Results and Discussion

All variables in Table 2 demonstrate ADF test statistics exceeding the 5% critical value in absolute terms, leading to the rejection of the null hypothesis of a unit root. This outcome verifies that each series is stationary at level, classified as I(0). Therefore, the dataset satisfies the stationarity requirement necessary for the application of the OLS regression model, ensuring the validity and reliability of the estimation results.

Table 2. Unit root test results

Variable	Augmented Dickey-Fuller (ADF) Test Statistic	Stationarity Status	Integration Order
CPI	-6.916	Stationary at level	I(0)
AAT	-4.087	Stationary at level	I(0)
GDPG	-6.688	Stationary at level	I(0)
GFCF	-4.353	Stationary at level	I(0)

Note: CPI, Crop Production Index; AAT, average annual temperature; GDPG, GDP growth; GFCF, gross fixed capital formation.

The correlation analysis in Table 3 indicates a strong positive relationship between the CPI and AAT (r = 0.743), suggesting that higher temperatures are closely associated with increased crop production. In contrast, the CPI exhibits negative correlations with GDPG Annual (r = -0.315) and GFCF (r = -0.383), implying that periods of higher agricultural output tend to coincide with lower economic growth and investment levels. Additionally, GDPG Annual and GFCF are moderately positively correlated (r = 0.358), while AAT shows negligible associations with these economic indicators, highlighting that temperature primarily influences agricultural productivity rather than broader economic activity.

Table 3. Correlation test

Variable	CPI	AAT	GDPG	GFCF
CPI	1.000	0.743	-0.315	-0.383
AAT	0.743	1.000	-0.051	-0.167
GDPG	-0.315	-0.051	1.000	0.358
GFCF	-0.383	-0.167	0.358	1.000

Note: CPI, Crop Production Index; AAT, average annual temperature; GDPG, GDP growth; GFCF, gross fixed capital formation.

The regression findings in Table 4 reveal that AAT exerts a positive and statistically significant influence on the CPI. A one-degree Celsius increase in AAT is associated with an estimated 7.70-unit rise in the CPI, assuming other factors remain constant. Conversely, GDPG (annual %) displays a negative and significant relationship with crop production, indicating that a one-percentage-point increase in GDPG reduces the CPI by approximately 1.96 units. This suggests that economic expansion may reallocate resources or labor toward non-agricultural sectors. In addition, a one-unit increase in GFCF (% of GDP) decreases the CPI by around 2.93 units, implying that rising investment levels may predominantly benefit industrial or service-oriented activities rather than agriculture. The overall model fit

(R^2 = 0.66, $p < 0.01$) indicates robust explanatory capacity, confirming that the selected variables collectively and significantly determine variations in agricultural productivity (Table 5).

Table 4. Ordinary Least Squares (OLS) regression results

Variable	Coefficient	Std. Error	t-Statistic	Prob.	Significance
AAT	7.699	0.853	9.027	0.000	***
GDPG	-1.959	0.759	-2.579	0.012	**
GFCF	-2.931	1.277	-2.296	0.025	**
Constant (C)	-268.992	56.318	-4.776	0.000	***

Note: *** $p < 0.01$, ** $p < 0.05$. AAT, average annual temperature; GDPG, GDP growth; GFCF, gross fixed capital formation.

Table 5. Ordinary Least Squares (OLS) overall model fit results

Statistic	Value
R-squared	0.660
Adjusted R-squared	0.643
F-statistic (Prob.)	37.61 (0.000)
Durbin–Watson	1.39

The overall model fit (R^2 = 0.660, $p < 0.01$) indicates robust explanatory capacity, confirming that the selected variables collectively and significantly determine variations in agricultural productivity (Table 5).

As all probability values exceed the 0.05 significance level, the null hypothesis of homoskedasticity cannot be rejected. This outcome indicates that the residuals from the OLS regression exhibit constant variance, confirming the absence of heteroskedasticity (Table 6). Consequently, the model meets one of the fundamental assumptions of classical OLS estimation, ensuring that the coefficient estimates are both efficient and reliable for statistical inference.

Table 6. Heteroskedasticity test result

Test Statistic	Value	Prob.	Decision
F-statistic	1.1837	0.3239	Fail to reject H_0
Obs*R-squared	3.5769	0.3109	Fail to reject H_0
Scaled explained SS	1.7624	0.6232	Fail to reject H_0

The Bai–Perron multiple structural break tests (Table 7 and Table 8) reveal four statistically significant breakpoints in the relationship between crop production and its key determinants—temperature, GDPG, and capital formation—during the period 1961–2022. The significant F-statistics identify regime shifts occurring in 1977, 1988, 1997, and 2013, indicating that major economic or environmental transformations during these years altered the underlying dynamics of agricultural productivity. These structural changes imply that the model parameters vary over time, reflecting the influence of policy interventions or climatic fluctuations on the evolution of the agricultural production system.

Table 7. The Bai–Perron multiple structural break test A

Break Test	F-Statistic	Scaled F-Statistic	Critical Value (5%)	Decision
0 vs. 1	17.299	69.198	16.19	Significant
1 vs. 2	11.845	47.380	18.11	Significant
2 vs. 3	5.569	22.276	18.93	Significant
3 vs. 4	5.689	22.760	19.64	Significant
4 vs. 5	0.000	0.000	20.19	Not Significant

Table 8. The Bai–Perron multiple structural break test B

Identified Break Dates	Sequential	Repartition
Break 1	1997	1975
Break 2	1977	1988
Break 3	2013	1997
Break 4	1988	2013

In addition to this econometrical approach, The Granger causality analysis (Table 9) indicates that the null hypothesis that the CPI does not Granger-cause AAT is rejected, suggesting a significant historical effect of crop production on temperature. Additionally, a one-way Granger causality exists from AAT to GDPG Annual (p = 0.048), whereas the reverse relationship is not significant. Furthermore, GDPG Annual Granger-causes GFCF (p = 0.014), implying that past GDPG provides predictive information for future investment levels. All other examined relationships, including the effects of GDP or GFCF on the CPI, do not exhibit statistically significant Granger causality at the 5% significance level.

Table 9. Granger causality test results

Null Hypothesis (Does Not Granger–Cause)	F-Statistic	Probability (p-Value)	Decision
AAT–CPI	0.515	0.600	Do Not Reject
CPI–AAT	7.075	0.001	Reject
GDPG–CPI	0.119	0.887	Do Not Reject
CPI–GDPG	2.952	0.060	Do Not Reject
GFCF–CPI	1.420	0.250	Do Not Reject
CPI–GFCF	1.815	0.172	Do Not Reject
GDPG–AAT	1.431	0.247	Do Not Reject
AAT–GDPG	3.202	0.048	Reject
GFCF–AAT	2.717	0.074	Do Not Reject
AAT–GFCF	1.330	0.272	Do Not Reject
GFCF–GDPG	0.206	0.815	Do Not Reject
GDPG–GFCF	4.618	0.014	Reject

Note: The test is performed at the 5% significance level (alpha = 0.05). Rejection occurs when the Probability (p-value) is less than 0.05. CPI, Crop Production Index; AAT, average annual temperature; GDPG, GDP growth; GFCF, gross fixed capital formation.

The interaction between climatic conditions and economic factors constitutes a fundamental determinant of agricultural productivity, with implications that propagate along the value chain, influencing both the physical characteristics of crops and the sustainability performance of agro-processing industries [24, 25]. The findings of this study demonstrate that AAT positively influences the CPI, with moderate increases in temperature historically supporting higher crop production. This aligns with Schlenker and Roberts [26], who found that U.S. crop yields are highly sensitive to temperature, though extreme heat beyond optimal thresholds reduces productivity. Negative relationships between GDPG and CPI, as well as between GFCF and CPI, indicate that economic expansion and investment may divert resources away from agriculture, complementing Henseler and Schumacher's [27] observation that climate impacts influence economic productivity through capital, labor, and total factor productivity. Our results also correspond with Lobell et al. [28], who reported that historical temperature trends have already affected global crop yields, particularly maize and wheat. Granger causality analysis highlights a bidirectional relationship between crop production and temperature, reinforcing the role of climate as a key driver of agricultural performance. Furthermore, GDPG Granger-causing investment suggests that macroeconomic dynamics indirectly shape agricultural productivity by influencing resource allocation. Overall, these findings emphasize that sustainable crop production in the U.S. requires strategies integrating both climate variability and economic factors to mitigate risks and maintain long-term agricultural resilience.

5 Conclusion

The empirical analysis highlights that agricultural productivity in the United States is intricately influenced by both climatic and economic variables. Temperature emerges as a key determinant, with historical data indicating that moderate increases have supported higher crop production, while extreme deviations may pose risks. In contrast, periods of heightened GDPG and capital formation appear to redirect resources away from agriculture, suggesting potential trade-offs between industrial expansion and crop output. The Granger causality results reveal directional interactions, showing that past crop production can predict temperature patterns, and that economic performance influences investment behavior, illustrating complex feedback mechanisms within the agricultural–economic system. Structural break tests further demonstrate that these relationships are not constant, with significant shifts corresponding to major environmental or economic events over the 1961–2022 period. These findings underscore the necessity for context-specific policies that account for the dynamic interplay between climate and economic forces, rather than assuming uniform effects across time. To ensure sustainable growth in the agricultural sector, strategic planning must incorporate adaptive measures that mitigate climate risks while balancing economic priorities. Overall, the study provides actionable insights for decision-makers aiming to enhance agricultural resilience and maintain stable crop production under evolving environmental and economic conditions.

Author Contributions

Conceptualization, Z.G. and I.M.; methodology, Z.G. and M.K.O.; software, Z.G.; validation, M.K.O., K.M., and T.A.; formal analysis, I.M.; investigation, Z.G.; resources, I.M. and K.M.; data curation, Z.G.; writing—original draft preparation, Z.G. and I.M.; writing—review and editing, M.K.O., K.M., and T.A.; visualization, Z.G.; supervision, I.M. and M.K.O.; project administration, Z.G.; funding acquisition, K.M. and T.A. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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