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# The Impact of Climatic Factors on Grain Crop Yields in Uzbekistan

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**ABSTRACT**

This article is dedicated to analyzing the impact of climate change on grain crop yields in Uzbekistan between 1991 and 2023. The main objective of the work is to establish how temperature fluctuations and precipitation affect the short-term and long-term yield dynamics. The study used the ARDL econometric model, which allows us not only to identify short-term changes but also to track how yield indicators adjust over time. To determine the reliability of the model results, stability tests were conducted using the Augmented Dickey-Fuller and P-P tests, which allowed for the use of both source and transformed data. The model results indicate that temperature has a positive effect on yield both in the short and long term. The impact of precipitation in the short term is not statistically significant; however, its lagged effect is negative. That is, a high level of precipitation in the previous year may adversely affect yield in the following year. In the model (ARDL 1,0,1) selected by the BIC criterion, the delayed temperature value is not included, but the main effect is retained. The model selected under the AIC criterion (ARDL 1,1,1) gives a more accurate result as it also includes the delayed temperature effect, although it is shown not to be statistically significant. This study contributes to the existing body of literature by using this model which analyse the short-run and long-run relationships between different time series variables. The originality lies in that the results of the ARDL model based on two different scenarios in studying the impact of climatic factors on grain crop yields in our country, as well as their validation using a number of diagnostic tests, fully meet all requirements for all criteria. On this basis, it is possible to fully utilise this model. The findings of this study hold significant practical value for policymakers ANF agricultural economists in Uzbekistan. Under the conditions of global climatic changes, the wide use of econometric research methods in the study of agricultural production processes will contribute to decision-making on sustainable development of the agriculture and achievement of high efficiency.

**Keywords:** Climate Factors, Grain Crop Yields, ARDL Model, Short-Run Effect, Long-Run Effect, Uzbekistan
**JEL Classifications:** Q10, Q54, O13, C32

## 1. INTRODUCTION

Today, climate change is one of the global challenges that have a serious impact on agricultural production. In particular, grain yields are sensitive to changes in climatic conditions – rising temperatures, changes in precipitation patterns and frequent extreme weather events can lead to significant reductions. This, in turn, negatively affects food security, the agricultural economy and, in general, global economic stability.

Global climate change has led to an increase in the global average temperature of 0.8-1.2°C compared to pre-industrial times. According to the Intergovernmental Panel on Climate Change's 2018 projections, the global average temperature could increase by 0.2°C every decade, which scientific research has shown could negatively affect crop yields (IPCC, 2022).

In addition, studies using world crop models and economic models predict that grain prices could increase by 23% by 2050 (IPCC, 2022).

The geographical location of Central Asian countries, lack of forests, lack of access to open seas and limited freshwater resources increase the region's vulnerability to climate change. Irrigated areas depend on the availability of fresh water supplied to the country by melt water from the Tien Shan and Pamir Mountains. Water use limits for each country are as follows: 0.4 $km^3$ is allocated from the Amu Darya for Kyrgyzstan, 7.44 $km^3$ for Afghanistan, 9.8 $km^3$ for Tajikistan, 21.73 $km^3$ for Turkmenistan and 38.91 $km^3$ for Uzbekistan. The Syr Darya distributes 2.46 $km^3$ for Tajikistan, 4.03 $km^3$ for Kyrgyzstan, 12.29 $km^3$ for Kazakhstan and 17.28 $km^3$ for Uzbekistan (Rudenko et al., 2012). The withdrawal of huge amounts of water from the main rivers Amu Darya and Syr Darya for agriculture has led to the disappearance of the Aral Sea. Water resources are lost due to poor channel flow, evaporation and inappropriate use, resulting in water scarcity in the lake. In recent decades, due to climate warming, excess water resources have melted into rivers that yielded less water (Punkari et al., 2014).

Projections show that "by the end of this century, average temperatures across the region could rise to 6.5°C above pre-industrial levels" (Reyer et al., 2017). In Central Asia, "the location of the Pamir and Tien Shan mountain systems, inaccessible water resources, poor infrastructure and continental climate exacerbate the situation" (Xenarios et al., 2019).

Globally, climate change is impacting economies through various sectors, affecting almost all areas of human activity (Rustamova and Babadjanova, 2023). Climate models predict that wheat and rice yields could decline by 17% by 2050 (Song et al., 2022).

The analysis shows that the negative effects of climate change affect not only crop yields, but also have a direct impact on economic stability (Farooq et al., 2023).

In this regard, scientific analyses of this problem, the study of its economic consequences and the development of adaptation strategies are among the most actual tasks today.

To understand the impact of climatic factors on grain crop yield in the country, this study applies the Autoregressive Distributed Lag (ARDL) model to analyze the impacts of temperature and precipitation. Using time series data covering the period from 1991 to 2023, the research explores both short-run and long-run relationships among these variables.

## 2. LITERATURE REVIEW

There are a number of economists who have studied the impact of climate change on grain yields using econometric models. The following are examples of some of the scientists who have conducted research in this area.

The works of researchers such as Chunxiao Song, Xiao Huang, Les Oxley, Hengyun Ma and Ruifeng Liu have examined the economic impact of climate change on wheat and maize yields in the North China Plain. Their results show that extreme weather events such as drought and floods significantly reduce the yields of these crops (Song et al., 2022).

A study on the impact of climate change on wheat yields in Central Asia (Sommer et al., 2013) analysed the impacts of climate change using crop models. The authors found that increasing temperatures and changing precipitation patterns lead to a shorter growing season and increased water stress, which negatively affects wheat productivity. In addition, changing climatic conditions contribute to increased salinisation of soils and water resources, which is particularly noticeable in the Amu Darya river basin, one of the two main rivers flowing into the Aral Sea. These findings emphasise the importance of developing adaptation measures to support agricultural resilience in the face of climate change.

Wenjie Dong, Jimin Zhou and Guolin Feng developed a new economic indicator to assess the impact of climate change on grain yields. Their methodology makes it possible to determine the long-term impact of climate change on agriculture (Dong et al., 2007).

In the studies of Ioanna G. Gkiza, Stefanos A. Nastis, Basil D. Manos and Efthichios S. Sartzetakis, a geographically weighted regression (GWR) method was applied to analyse the economic impact of climate change on cereal yields in Greece. Their work showed that the impact of climate on yields has regional differences (Gkiza et al., 2021).

Scientists Rangarairai Roy Shoko, Abenet Belete and Petronella Chaminuka analysed the impact of climate change on maize yields in South Africa using data from 1970-2016. The results showed that rainfall and temperature have a significant effect on yields, but excessive increases can have negative impacts (Shoko et al., 2019).

Other researchers – Abbas Ali Chandio, Waqar Akram, Fayyaz Ahmad, Ilhan Ozturk, Avik Sinha and Yuansheng Jiang – investigated the impact of climate change on wheat and maize yields in Pakistan using data from 1986 to 2015. Their results showed that average rainfall has a positive effect on yield, whereas maximum temperature has a negative effect in the long term (Chandio et al., 2022).

In the study by Bolodurina I.P., Parfyonov D.I. and Pivovarova K.V., devoted to the specifics of the impact of changing climatic conditions on grain crop yields in the dry-steppe zone of Russia, a comprehensive analysis of the impact of weather factors on agricultural productivity was carried out. The authors used methods of singular spectrum analysis (SSA) and econometric models, including models with multifrequency data (MIDAS) and panel data, to assess both linear and non-linear relationships between climatic variables and grain yields. The results of the study showed that climate has a significant impact on crop yields, with both seasonal and long-term components identified, which has important implications for agricultural adaptation strategies and food security (Bolodurina et al., 2018).

The article by B. Porfiriev and V. Kattsov presents a comprehensive assessment of the impact of climate change on Russia's macroeconomy up to 2030, including original estimates and forecasts developed by the authors. The work analyses in detail the consequences of changes in weather and climate conditions on the dynamics and quality of work of various production complexes in the country. The study examines the main directions and measures aimed at adapting the economy to climate impacts and reducing associated risks. The authors emphasise the need for an integrated consideration of the climate factor in the development of modernisation and efficiency improvement programmes in such sectors as energy, housing and utilities, transport, construction, agriculture and industry. Special attention is paid to the role of the scientific community and research organisations, which play a key role in adapting the Russian economy and society to changing climatic conditions (Porfiriev and Kattsov, 2011).

Indian scientists Amit Kumar, S.N. Mishra, S.K. Sinha and P.K. Joshi used an autoregressive distributed lag (ARDL) model to study the impact of climate change on grain crops, particularly on grain production in India. Their results indicate that both climatic and non-climatic factors have a significant impact on grain production (Kumar and Singh, 2014).

Thus, the totality of the conducted research demonstrates that grain crop yields significantly depend on climatic changes, and the use of modern econometric models and methods of temporal analysis allows not only to assess the current impact, but also to forecast future trends in agricultural production.

Our study also used an ARDL model, selected based on AIC and BIC criteria, to analyse the short- and long-term effects of climate variables on grain crop yields. The study is based on 33 years of data, which allows for a more in-depth analysis of climate change factors affecting total grain yields.

## 3. METHODOLOGY

### 3.1. Data

This study examines the relationship between grain yield, temperature and precipitation in Uzbekistan. Furthermore, it aims to assess the impact of main climatic factors such as temperature and precipitation on grain crop yields in the country. To achieve this objective, the study analyzed time series data covering the period from 1991 to 2023 and performed several statistical tests to confirm the accuracy and validity of the data. The research adopted the Autoregressive Distributed Lag (ARDL) cointegration approach by Pesaran et al. (1999). In the model, grain yield served as the dependent variable, while temperature and precipitation were included as explanatory variables. The logarithmic transformation of the data was applied to verify normal distribution. Table 1 presents the variables and their corresponding measurement units.

**Table 1: Variables description**

| Variable | Symbol | Definition | Source |
|---|---|---|---|
| Grain crops yield | lnY | Average yield of grain crops, qt/ha | Data from the National Statistics Committee of the Republic of Uzbekistan (1991-2024) |
| Temperature | lnTemp | Average annual temperature (Celsius degree (°C)) | Trading Economics website information (https://tradingeconomics.com ) |
| Precipitation | lnPre | Average annual precipitation (mm) | Trading Economics website information (https://tradingeconomics.com ) |

### 3.2. Econometric Methodology

#### *3.2.1. Unit root test*

Unit root tests are important because they help determine whether a time series is stationary or non-stationary (Kwiatkowski et al., 1992). Stationarity means the statistical properties of the series such as mean and variance remain constant over time, which is a key assumption for many time series models. If a series has a unit root, it is non-stationary and may follow a random walk, meaning shocks to the series have permanent effects. Identifying a unit root ensures the data is properly transformed (e.g., differenced) before modeling to avoid misleading or spurious regression results. This enhances forecasting accuracy, ensures valid statistical inference, and allows for more reliable economic and policy analysis. Additionally, unit root tests are fundamental for cointegration analysis, which helps understand long-run relationships between economic variables.

In scientific articles, unit root tests are widely used to assess the stationarity of time series data, which is a fundamental step in econometric and statistical research. In this study, two different unit root tests were used: The Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) and the Phillips-Perron (P-P) test. These tests were applied to ensure that no variable in the regression had a higher integration order than expected and to demonstrate the advantage of using ARDL instead of traditional cointegration methods.

#### *3.2.2. ARDL model*

The ARDL model developed by Pesaran et al. (2001) was used in this study as a robust estimation method to examine the short- and long-run relationships between the variables in the model. The ARDL bound test, a widely used econometric method, was used to examine the long-run relationship between time series variables. Cointegration analysis allows for the coexistence of short- and long-run dynamics in the data. Compared to traditional cointegration methods, the ARDL bound test offers a number of advantages, Borhan et al. (2023). It includes various data structures, including I(0) and I(1) variables, deterministic terms and lags. Unlike other cointegration tests, the ARDL bound test can be applied when some variables are I(0) and others are I(1). This flexibility is crucial because most real-world data are not perfectly stationary. This feature makes it a flexible tool for modeling a variety of economic dependencies. In addition, the ARDL bound test provides more accurate estimates than other cointegration methods, especially when the number of lags is large. In addition, the ARDL bound test can identify the causal direction between variables that is difficult to detect in traditional cointegration approaches. Finally, the ARDL bound test also includes model selection criteria, such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), which help determine the optimal number of lags for the cointegration relationship. The ARDL bound test is important in cointegration analysis because of its flexibility, efficiency, ability to test causality and inclusion of model selection criteria. Equation (1) shows the ARDL long-run estimation.

$$lnY_t = \omega_0 + \omega_1 lnTemp_{t-1} + \omega_2 lnPre_{t-1} + \sum_{i=1}^{\omega} \varphi_1 \Delta lnTemp_{t-i} + \sum_{i=1}^{\omega} \varphi_2 \Delta lnPre_{t-i} + \epsilon_t \quad (1)$$

By comparing the T-statistic obtained in the ADF and P-P test with the critical values, if the T-statistic is <1%, 5%, or 10% of the critical value (i.e., larger on the negative side), the null hypothesis ($H_0$: The series is not stationary) is rejected and the variable is considered stationary; such a variable is accepted for the ARDL model. If the T-statistic is greater than the critical value, the series is not-stationary and a differentiation must be taken to be I(1).

In the ARDL (Auto Regressive Distributed Lag) model, determining the optimal number of delays (lag) is of great importance because it affects the accuracy of the model and the reliability of the results. The importance of choosing the optimal number of lags correctly can be explained by the following aspects:

#### 3.2.2.1. Model accuracy

The optimal number of delays ensures that the dynamic relationship between variables is fully and accurately captured. If the number of delays is insufficient, the model may ignore important information. If there are too many delays, the model may become overly complex, leading to overfitting problems.

#### 3.2.2.2. Reliability of statistical results

Choosing the right number of delays improves the statistical performance of the model (e.g., measures such as $R^2$, AIC, BIC). This improves the reliability of the results and reduces errors.

#### 3.2.2.3. Proper estimation of the relationship between variables

The ARDL model is used to examine both short-run and long-run relationship between variables. If the optimal number of delays is not chosen, the short-run or long-run relationship may not be estimated correctly.

#### 3.2.2.4. Model stability

The correct number of delays ensures the stability of the model. If the number of delays is chosen incorrectly, the model may be unstable and the results will be incorrect.

In ARDL model, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are mainly used to determine the optimal number of variable delays. The Akaike Information Criterion (AIC) works on the basis of selecting the model with the smallest value. This method considers the balance between the accuracy of the model and its complexity. The Bayesian Information Criterion (BIC) is similar to AIC, but it places more stringent requirements on model complexity.

#### *3.2.3. Diagnostic test*

In order to ensure the reliability of the data, several diagnostic methods were used in the study. Tests such as the Breush-Pagan-Godfrey test to identify heteroscedasticity, Breusch and Pagan (1979), the Ramsey Reset test to evaluate specification error, Ramsey (1969) and the Breusch-Godfrey LM test for serial correlation (Breusch, 1978; Godfrey, 1978) were used in our research. Information about the results obtained from these tests is presented in Table 6.

## 4. RESULTS

### 4.1. Unit Root Test Results

In this study, the stationarity of the variables was examined using both the ADF and P-P unit root tests to determine their order of integration and the suitability of cointegration analysis. As shown in the Table 2, lnTemp and lnPre are stationary at level, indicating significance under both intercept and intercept+trend specifications, whereas lnY becomes stationary only after first differencing. These mixed results from the unit root tests suggest that some variables are integrated of I(0), while others are integrated of I(1). Therefore, the ARDL approach is appropriate, as it can effectively handle variables with different integration orders and estimate both short-run and long-run relationships within the model.

### 4.2. Model Results

In our study, using the capabilities of Stata software, we realised the results through two different scenarios, choosing the optimal number of delays according to these two criteria.

The first scenario is based on the Akaike Information Criterion (AIC), which selected the ARDL (1,1,1) model with appropriate indicators as the optimal model for the variables.

**Table 2: Unit root test results**

| Variable | ADF unit root test | | | |
|---|---|---|---|---|
| | Intercept | | Intercept-trend | |
| | Level | 1st difference | Level | 1st difference |
| lnY | −1.25 (0) | −4.95 (0)*** | −1.288 (0) | −4.912 (0)*** |
| lnTemp | −3.303 (0)** | −10.246 (0)*** | −5.453 (0)*** | −10.093 (0)*** |
| lnPre | −4.11 (0)*** | −6.063 (0)*** | −4.119 (0)** | −5.951 (0)*** |
| **Variable** | **P-P unit root test** | | | |
| | **Intercept** | | **Intercept-trend** | |
| | **Level** | **1st difference** | **Level** | **1st difference** |
| lnY | −1.254 (3) | −4.913 (3)*** | −1.292 (3) | −4.838 (3)*** |
| lnTemp | −3.293 (3)** | −13.545 (3)*** | −5.531 (3)*** | −13.189 (3)*** |
| lnPre | −3.91 (3)*** | −6.969 (3)*** | −3.925 (3)** | −6.786 (3)*** |

***, ** and * denote significance at 1%, 5% and 10%, respectively

According to the results of the ARDL (1,1,1) model, the $R^2$ value is 0.9659, which means the model explains 96.59% of the data. This indicates a very good model fit. The adjusted $R^2$ is also high (0.9588), indicating that the model is accurate without unnecessary variables. The value of F-statistic is 136.12, indicating that the overall statistics of the model are significant (Table 3).

The results for the variables show that the coefficient of the lagged variable yield (L1.yield) is 0.8449984 (P = 0.000), which is significant. This means that the value of the previous year's yield has a strong positive effect on the current yield. That is, if the yield was high last year, the probability that the yield will be high this year is also high.

Current temperature has a positive effect on yield, with a 1 unit increase in temperature leading to a 1.587 unit increase in yield. Lag coefficient of precipitation (L1.precipitation) is −0.0238933 (P = 0.016) which is also significant. This means that the value of precipitation in the previous year has a negative effect on the current yield. That is, if there was a lot of precipitation last year, this year's yield may decrease slightly.

The ARDL model uses the LRM (Long-Run Multiplier) formula in the Equation 2 to determine the long-run effect:

$$LRM = \frac{\beta}{1-\alpha} \quad (2)$$

Where $LRM$ is long-run effect coefficient, $\beta$ is short-run effect coefficient of the variable, $\alpha$ is AR coefficient of the dependent variable.

Next, we calculate the long-term effects of temperature and precipitation on yield and proceed with the analysis.

$$LRM_{temperature} = \frac{1,587262}{1-0,8449984} = \frac{1,587262}{0,1550016} \approx 10,24 \quad (3)$$

$$LRM_{precipitation} = \frac{0,0156557}{1-0,8449984} = \frac{0,0156557}{0,1550016} \approx 0,1 \quad (4)$$

This implies that the long-term effect of temperature on yield is significant and can increase yield by 10.24 units. The long term effect of precipitation is insignificant (0.1) and it plays a minor role in determining yield.

The second scenario: the optimal order of delaying variables in the ARDL (1,0,1) model was selected by Bayesian criterion (BIC).

Based on the results of the ARDL (1,0,1) model, the $R^2$ is 0.9632, which means that the model explains 96.32% of the data. This indicates an excellent model fit. The adjusted $R^2$ is also high (0.9574), indicating a balance between the simplicity of the model and its ability to explain the data. The F-value is 163.75, which confirms the statistical significance of the model (Table 4).

The results related to the variables show the following:
The coefficient of lagged yield (L1.yield) is 0.8764391 (P = 0.000) which is significant and positive. This means that the value of yield in the previous year has a strong positive effect on the current yield. That is, the effect of yield value in previous years on the current year's yield remains stable.

Current temperature has a positive and significant effect on yield, which means that an increase in temperature by 1 unit increases yield by 1.61 units. This indicates a direct relationship between yield and current temperature. The coefficient of lagged precipitation (L1.precipitation) is −0.0258487 (P = 0.009) which is also significant. This indicates that last year's precipitation has a negative and significant effect on the current year's yield. That is, if last year's precipitation was 1 unit higher, the current year's yield may slightly decrease.

We now proceed to calculate and analyze the long-term effects of temperature and precipitation on yield in the context of this model.

$$LRM_{temperature} = \frac{1,611655}{1-0,8764391} = \frac{1,611655}{0,1235609} \approx 13,04 \quad (5)$$

$$LRM_{precipitation} = \frac{0,0141791}{1-0,8764391} = \frac{0,0141791}{0,1235609} \approx 0,11 \quad (6)$$

**Table 3: Analysis of the results of the ARDL (1,1,1) model**

| Overall model indicators | | | | | |
|---|---|---|---|---|---|
| **Indicator** | **Value** | **Interpretation** | | | |
| $R^2$ | 0.9659 | The model explains 96.59% of the data. | | | |
| Adj $R^2$ | 0.9588 | The adjusted $R^2$ is also high, indicating the accuracy of the model. | | | |
| F-statistic | 136,12 (P=0,000) | The model demonstrates the significance of the overall statistic. | | | |
| Root MSE | 1.8767 | The model's error level (i.e., deviation of forecasts from actual values) is 1.8767 units. | | | |
| **Model results table** | | | | | |
| **Variable** | **Coefficient** | **Standard Error** | **t-value** | **P-value** | **Interpretation** |
| L1. yield | 0.8449984 | 0.0455334 | 18.56 | 0.000 | The yield value for the previous year has a strong positive effect on the current yield. |
| temperature | 1.587262 | 0.5492189 | 2.89 | 0.008 | The current temperature has a positive effect on yield. |
| L1. temperature | 0.820677 | 0.5946999 | 1.38 | 0.18 | The temperature from the previous year has no significant effect on current yield. |
| precipitation | 0.0156557 | 0.0096031 | 1.63 | 0.116 | Current precipitation has no significant effect on yield. |
| L1. precipitation | −-0.0238933 | 0.0092496 | −2.58 | 0.016 | Precipitation from the previous year has a negative effect on current yield. |
| _const (constant) | −25.1299 | 10.85276 | −2.32 | 0.029 | The constant coefficient reflects the base value of the model. |

**Table 4: Analysis of the results of the ARDL (1,0,1) model**

| Overall model indicators | | | | | |
|---|---|---|---|---|---|
| **Indicator** | **Value** | **Interpretation** | | | |
| $R^2$ | 0.9632 | The model explains 96.32% of the data. | | | |
| Adj $R^2$ | 0.9574 | The adjusted $R^2$ is also high, indicating the model's accuracy. | | | |
| F-statistic | 163.75 (P=0.000) | The model demonstrates the significance of the overall statistic. | | | |
| Root MSE | 1.9104 | The model's error level (i.e., difference between predicted and actual values) is 1.9104 units. | | | |
| **Model results table** | | | | | |
| **Variable** | **Coefficient** | **Standard Error** | **t-value** | **P-value** | **Interpretation** |
| L1. yield | 0.8764391 | 0.0401302 | 21.84 | 0.000 | The yield value from the previous year has a strong positive effect on the current yield. |
| temperature | 1.611655 | 0.5587749 | 2.88 | 0.008 | Current temperature has a positive effect on yield. |
| precipitation | 0.0141791 | 0.0097144 | 1.46 | 0.157 | Current precipitation has no significant effect on yield. |
| L1. precipitation | −0.0258487 | 0.0093043 | −2.78 | 0.01 | Precipitation from the previous year has a negative effect on current yield. |
| _cons (constant) | −14.5268 | 7.802018 | −1.86 | 0.074 | The constant coefficient is not significant (P>0.05). |

**Table 5: ECM model results**

| Model | ECT coefficient (L1. yield) | P-value | The rate of return to equilibrium (%) |
|---|---|---|---|
| ARDL (1,1,1) (at AIC) | −0.155 | 0.002 | 15.5 |
| ARDL (1,0,1) (at BIC) | −0.12357 | 0.005 | 12.36 |

ARDL: Autoregressive distributed lag

This means that the long-term effect of temperature on yield is significant and can increase yield by 13.04 units. The long-term effect of precipitation is insignificant (0.11) and is not a direct but an indirect effect.

Based on the model results from the two scenarios, it can be stated that in terms of short-term impact, temperature has an immediate positive effect on yields, while excessive precipitation in previous years may have a negative effect on yields. In the long term, temperature has a strong impact on yields, while the long-term impact of precipitation is very small (about 0.1), which means that it does not cause significant changes in the long term.

ECM model results were also calculated based on models using AIC and BIC criteria (Harris and Sollis, 2003). The ECM model is based on the ARDL approach and is used to estimate long-run and short-run relationships in time series. This model determines how short-run changes return to long-run equilibrium if there is a long-run relationship. The following Table 5 summarizes the Error Correction Term (ECT) (Table 5).

In both models, the ECT coefficient (L1. yield) is negative and statistically significant, indicating the existence of a long-run relationship. In general, the ECT coefficient is the main element of the Error Correction model derived from the ARDL model and determines how and at what speed the economic variables return to equilibrium if a deviation from this equilibrium has occurred. The ECT coefficient should always be negative because it expresses the mechanism of return to equilibrium and this is a positive result. If it is positive, the system is moving away from equilibrium, and this may indicate an incorrect result. The ECM model means that if yields deviate from the long-term trend, they will gradually return to equilibrium year after year. This determines how quickly changes in agriculture return to their natural equilibrium.

According to the data in Table 5, in the ARDL (1,1,1) model (under the AIC criterion), yields return to their long-term equilibrium at a rate of 15.5% each year. For example, if yields are suddenly 10 units above the long-run trend, they will fall by 1.55 units the following year, i.e. the process of returning to equilibrium is faster. In the ARDL (1,0,1) model defined by the BIC criterion, yields recover 12.36% of the deviation from equilibrium each year. This model returns to equilibrium slightly slower than the model based on the AIC criterion. As an example, if yields are suddenly 10 units below the long-term trend, the yield will increase by 1.23 units in subsequent years.

### 4.3. Diagnostic Test Results

After estimating the ARDL model under the two scenarios, tests such as autocorrelation test (Breusch-Godfrey LM), heteroscedasticity test (Breusch-Pagan), and model specification test (Ramsey RESET) are conducted to determine the adequacy of the selected model.

As can be seen from Table 6, according to the results of Breusch-Godfrey autocorrelation test, there is no autocorrelation of residuals in both models, i.e. errors of previous periods do not affect subsequent periods. According to the results of Breusch-Pagan heteroscedasticity test, the models have no heteroscedasticity problem, that is, the distribution of residuals remains stable. The results of the Ramsey RESET test show that there are no missing important variables in the models, i.e. the models are constructed correctly.

In general, the results of the models defined by the AIC and BIC criteria are robust and reliable, as the main diagnostic tests did not reveal any problems.

## 5. DISCUSSION

The main objective of this study was to investigate the complex relationships between yields and climatic factors in grain crops in Uzbekistan from 1991 to 2023. The study aimed to answer two important questions.

First, can the threat of climate change approaching the country's agriculture have a negative impact on yields in grain crops?

**Table 6: The results of the tests conducted to assess the compliance of the model**

| Test name | Purpose | Condition | First model (AIC) | Second model (BIC) | Conclusion |
|---|---|---|---|---|---|
| Autocorrelation test (Breusch-Godfrey LM) | Check for autocorrelation in residuals | P>0.05 | P=0.5419 | P=0.9195 | No autocorrelation in residuals |
| The heteroscedasticity test (Breusch-Pagan) | Check for constant variance of residuals | P>0.05 | P=0.5301 | P=0.7947 | Residual variance is constant (homoskedasticity) |
| Model specification test (Ramsey RESET) | Check for omitted variables in the model | P>0.05 | P=0.4681 | P=0.5663 | Model is correctly specified |

Second, what are the short- and long-term effects of these factors on crop yields?

The work was carried out in order to answer these questions and to provide a comprehensive assessment of the long-term perspective of the impact of climatic factors on yield growth as a key element in improving the efficiency of grain crop production. In addition, the results of tests conducted using the ARDL model confirmed the existence of cointegration relationship between the variables, which ensured the validity and reliability of the findings.

## 6. CONCLUSION

The model results indicate that temperature has a positive effect on yield both in the short and long term. The impact of precipitation in the short term is not statistically significant; however, its lagged effect is negative. That is, a high level of precipitation in the previous year may adversely affect yield in the following year.

In the model (ARDL 1,0,1) selected by the BIC criterion, the delayed temperature value is not included, but the main effect is retained. The model selected under the AIC criterion (ARDL 1,1,1) gives a more accurate result as it also includes the delayed temperature effect, although it is shown not to be statistically significant.

Based on the above analytical results, it is advisable to consider the following aspects:

- Climate change can have a significant impact on agriculture; therefore, it is necessary to determine the optimal temperature range, develop appropriate adaptation strategies, and implement adaptive measures in grain crop cultivation
- An increase in precipitation may have a negative effect, thus it is essential to improve drainage systems in cultivated areas and to optimize and systematize the use of water resources.

Based on the results of the analysis, it can be emphasised that the results of the ARDL model based on two different scenarios in studying the impact of climatic factors on grain crop yields in our country, as well as their validation using a number of diagnostic tests, fully meet all requirements for all criteria. On this basis, it is possible to fully utilise this model. Under the conditions of global climatic changes, the wide use of econometric research methods in the study of agricultural production processes will contribute to decision-making on sustainable development of the agriculture and achievement of high efficiency.

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