Climate Change and Agricultural Productivity: A Case Study of Wheat in Visegrad Countries

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Abstract: - The paper analyses impact of climate change on wheat production in the Visegrad 4 (V4) countries. The main goal of this paper is to analyse the long-term impact of climatic variables, such as temperature and precipitation on wheat production in V4 countries. By providing empirical evidence, the study offers insights that may contribute to the policy discussions that aim at improving the resilience od wheat production to climate change. The analysis is based on the Just and Pope stochastic production function using data from 2003 to 2023. The model parameters were estimated using GRETL software. Due to the characteristics of panel data, only the fixed effects model was suitable for this study. This approach requires a unique interpretation for each cross-sectional unit, particularly for V4 countries. It suggests that the slope coefficients are consistent across all V4 countries, but the functions differ in intercepts. The literature frequently denotes this as the LSDV model. Results indicate that both economic and environmental factors play a significant role in determining wheat yields. The impact of temperature and precipitation is specific to each month and exhibits a markedly nonlinear nature, with climate changes tending to influence wheat yield negatively.

Key-Words: - climate change, wheat, yield, temperature, precipitation, price, production function

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1 Introduction

Over the last century, global climate change has led to elevated temperatures, resulting in heatwaves and droughts and an increased risk of precipitation, storms, and floods, [1]. These natural and human-induced alterations pose significant challenges to achieving sustainability by depleting natural resources. Furthermore, they can potentially exacerbate the vulnerability of agricultural yields, [2], [3]. Global warming is documentable on a worldwide scale, including regions such as the Slovak Republic, Czech Republic [4], Poland [5], Austria [6] and Europe [7]. [8] mentions that the impact of rising temperatures on agricultural yields can be both positive and negative, with the outcome contingent on the specific characteristics of a given country.

Overall, each climate change component produces multiple effects, the relative importance of which depends on soil conditions, species and plant type.

In their study, [9] systematically examined the impacts of climate change on agricultural production, placing particular emphasis on production variability. Employing the established production function developed by Just and Pope, they evaluated the effects of climate fluctuations on the output of dry wheat spanning the years 1991 to 2016.

[10] explored how increasing temperature and CO2, along with changes in precipitation, could manifest in potential yields for different historical pedoclimatic conditions at high latitudes. The APSIM (Agricultural Production Systems Simulator) crop model was employed to simulate the productivity of four annual crops - barley, forage maize, oats, and spring wheat - across five locations in Sweden.

For the period 1980–2003, [11] analysed the relationship between crop yields and three climatic variables - minimum temperature, maximum temperature, and precipitation - across 12 major California crops. They used months and the most important climatic variables for each crop to create regressions related to yield and climatic conditions.

The article by [12] aimed to identify a climatic signal in the actual yields of maize, sorghum, and peanuts in SSA (Sub-Saharan Africa). They investigated the relationship between crop yields and spatially compatible climate data over the period 1962–2014 using the Random Forest method, a diagnostic machine-learning approach.

The V4 countries - Czechia, Poland, Hungary, and Slovakia - face shared agricultural challenges, particularly in addressing the impacts of climate change. Over time, climatic variability, particularly rising temperatures and irregular precipitation have significantly influenced agricultural output, with wheat yields proving especially sensitive, [13]. Wheat production is highly sensitive to weather conditions, which requires adjustment of farming practices and adoption of innovative technologies to mitigate the impacts of climate change, [14]. Research [15] highlights the negative effects of increasing temperature extremes on wheat yields in the Czech Republic, highlighting the need for an adaptive agricultural strategy. Similar patterns have been observed in Poland as [16] examines how climate variability affects soil conditions and crop productivity. Study [17] reports a significant decline in summer rainfall in Hungary, which poses risks to wheat production. In a related study, [18] analyses historical climate records to assess how such changes have affected wheat yields over time.

Building on these findings, our study focuses on the long-term effects of climatic factors, especially temperature and precipitation on wheat production in the V4 countries.

Based on the reviewed literature and the identified research gap, the following hypotheses are formulated:

H1: Higher average temperatures during the growing season are associated with lower wheat yields in the V4 countries.

H2: Variability in growing-season precipitation significantly affects wheat yields, with insufficient rainfall leading to reduced production.

H3: Temperature and precipitation interact significantly in determining wheat yields

H4: Wheat yield response to climatic factors differs across V4 countries due to variations in agricultural practices and local conditions.

By testing these hypotheses, the study contributes to discussions on climate change and agricultural production. It also focuses on identifying measures that may help mitigate the adverse effects on agriculture. In addition, the analysis helps to address the limited empirical evidence on the relationship between climate change and wheat production in V4 countries.

2 Methodology

The production function is a central concept in production theory, representing the relationship between output (total wheat production) and various inputs. In this study, the explanatory variables include precipitation, temperature, and price, while wheat yield per hectare represents the output variable. This framework helps to explain how different combinations of these inputs result in varying levels of wheat output. In this study, wheat yield refers to production per hectare (tons/ha), while wheat production denotes total output.

A basic production function, in this case, can be represented as:

$$Y = f(P, T, C) \quad (1)$$

- Y is hectare yield (measured in tons per hectare),
- P is precipitation (measured in millimeters),
- T is temperature (measured in degrees Celsius),
- C is price (measured in euros per ton).

Including price variables in the production function analysis is inconsistent with traditional production theory because production functions typically focus on physical relationships between inputs and outputs. Prices are better suited for cost functions or profit functions rather than production functions. However, we included price variables in our study to provide economic context, acknowledging this limitation. The analysis used the wheat market prices that reflect prevailing market conditions. Data is obtained from official agricultural statistics and databases of the V4 countries for the period from 2003 to 2023. Figure 1 shows the conceptual framework of the empirical analysis, highlighting the relationship between the key independent variables and the dependent variable.

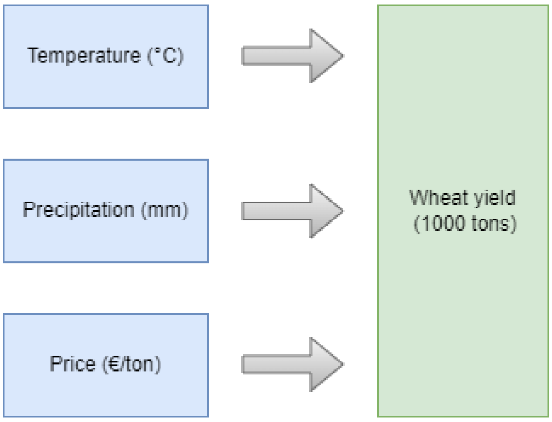

Fig. 1: Variable relationship
Source: Own processing

Variable selection was also based on the results of previous studies [19], [20], [21], [22], [23], [24], [25].

The time series for V4 countries were combined into a panel data set, which was further processed and analysed by appropriate panel techniques and further developed methodology conducted by [26]. The authors conducted a similar analysis in the Czech Republic using regional data. The proposed paper focuses on the situation in V4 countries and is based on data collected from individual countries.

2.1 Model Specification

In this subsection, we discuss the selected functional forms for the empirical implementation of the theoretical production model. The choice of functional form is critical for correctly interpreting results and understanding the relationships between inputs and output. In empirical analyses of agricultural crop production, such as wheat, selecting an appropriate production function form is essential. This study considers two principal production function specifications: the Cobb-Douglas and Translog forms. Each specification has different advantages and limitations that must be taken into account when selecting the appropriate model.

2.1.1 Cobb-Douglas Production Function

The Cobb-Douglas production function is widely used due to its simplicity and transparency. Its popularity largely stems from the ease of result interpretation, and it is relatively simple to compute. However, the model assumes constant elasticities of substitution between inputs, which may not be realistic in all cases, [27]. This assumption can be limited if there are significant differences in substitution possibilities among different inputs. A key limitation of the model is its inability to account for nonlinearities and interaction effects among inputs, thereby restricting its use in more complex context, [28]. As consequences, the model may yield incorrect inferences when variable relationships are more complex.

2.1.2 Translog Production Function

The Translog production function provides greater flexibility than the Cobb-Douglas function, as it allows for variable elasticities of substitution and does not impose constant returns to scale. Consequently, it is better suited to modelling complex relationships between inputs and output. This model is particularly useful in analyzing situations where relationships between variables are nonlinear and where interaction effects among inputs exist, [29].

2.1.3 Choice of Functional Forms

The selection between Cobb-Douglas and Translog production function depends on the characteristics of the data we used. Translog production function was chosen because it allows more flexible representation of the relationships between climatic and economic variables. This choice enables us to capture better nonlinear effects and interactions among variables, which is particularly important in the context of climate change and its impact on agricultural production.

The yield function formulation in this study is based on the stochastic production function proposed by [30]. This model allows for flexibility in analyzing production risks and variabilities, which is particularly important when examining the impacts of climate change on agricultural production.

$$y = f(X) + h(X)^{\frac{1}{2}}\varepsilon \qquad (2)$$

where $h(X)^{\frac{1}{2}}$ is a function of predictors in X, y denotes the yield, and ε represents the residual term, assumed to be independently and identically distributed (i.i.d.) N (0, $\delta^2\varepsilon$) The Just and Pope specification, particularly with the inclusion of the term. The estimation process of equation (2) involves three sequential steps. Initially, y undergoes regression on X utilizing the ordinary least squares (OLS) method (Ordinary Least Squares). Subsequently, the squared residuals from the first step are employed in a regression on X using OLS in the second step. Finally, in the third step, y is regressed on X along with the square root of the predictions obtained from the second step. In the latter scenario, the trend variable is utilised in conjunction with temperature and precipitation variables to capture alterations in the first-order parameters stemming from the impacts of climate change. The empirical model is expressed as:

$$y = \alpha'x + \beta'y + \delta'z + h(X)^{\frac{1}{2}}\,\varepsilon \qquad (3)$$

Estimation of the parameter vectors α, β, and δ relies on three groups of regressors, grouped into three vectors: x, y, and z. The x vector includes variables related to production efficiency and input–output ratios (wheat price in euros per ton) and average winter precipitation (November–March). The y vector captures climatic conditions during the growing season through mean monthly temperatures and precipitation from April to July. The z vector incorporates climate change indicators (interactions of temperature and precipitation with time) and a time trend (t, t^2) representing technological progress. Model parameters were estimated in GRETL using a fixed effects (LSDV) panel model with robust standard errors, covering data for the V4 countries from 2003–2023 obtained from national statistical and meteorological sources. Table 1 shows an overview of data used in the analysis such descriptions of the model variables, their symbols, and summary statistics.

3 Results

Table 2 shows the estimated parameters of the panel model. Insignificant variables were removed from the model by a backward elimination process. The significant model achieved an R-squared value of 0.73. The table reports estimated coefficients along with their standard errors, t-ratios, and p-values for various variables in the model. The explanatory variables include wheat price (Price), average monthly precipitation (Mo), monthly average temperatures (t4, t5, t6, t7) and average precipitation for specific months (p4, p7). In addition, interaction terms and quadratic specifications are incorporated through combined variables (t5t, t6t, t7t, p4t, p5t, p6t, p7t), including squared terms (t5t_2, t6t_2, t7t_2, p4t_2, p7t_2) to capture nonlinear temperature-precipitation effects.

Table 1. Summary Statistics of Model Variables

Variable	Symbol	Mean	Std Dev	Min	Max	Source	Role	Unit
Wheat yield	Y	4.78	0.84	2.64	6.51	CZSO, GUS, KSH, VÚEPP	Dependent	1.000 tons
Price	Price	179.95	60.56	87.76	379.71	SZIF, IMGW PIB, HungaroMet, GUS, KSH	Independent	€/ton
Average precipitation (Nov.-Mar.)	Mo	41.85	14.10	19.44	80.60	CHMI, SHMU, IMGW-PIB, HungaroMet	Independent	mm/year
Temperature April	t4	10.61	2.19	5.40	16.00		Independent	°C
Temperature May	t5	15.21	2.71	10.60	30.80		Independent	°C
Temperature June	t6	19.12	2.89	2.00	25.90		Independent	°C
Temperature July	t7	20.62	3.58	2.11	26.50		Independent	°C
Precipitation April	p4	38.29	20.95	0.00	101.80		Independent	mm/year
Precipitation May	p5	79.76	41.85	17.40	227.00		Independent	mm/year
Precipitation June	p6	77.93	38.08	13.50	210.90		Independent	mm/year
Precipitation July	p7	81.72	40.15	13.80	168.60		Independent	mm/year

Source: Own processing

The last two rows present the estimated coefficients for the time vector (t, t_2), which captures technological progress over time. The p-value indicates the statistical significance of each coefficient. These parentheses indicate significance levels, where *** for α=0.01, ** for α=0.05, * for α=0.1. Coefficients significant at these levels are marked with the corresponding number of stars. The table provides the results of studying the impact of climate change (temperature, precipitation) on wheat production and production variability

The model met all required assumptions. In interpreting model results, it should be considered that values are generalized for the whole central European region. Estimated values could be interpreted as average trends for all V4 countries.

One of the important findings of our article is that wheat price is an important factor. The analysis suggests a significant correlation between wheat prices and yields. Higher prices in previous periods may motivate farmers to produce more in response to favourable market conditions. The relationship between wheat prices and yields is complex, as evidenced [31]. Results show that high production in previous years can lead to lower prices, which in turn affects the economic profitability of wheat cultivation.

Table 2. Estimated parameters of stochastic production function – mean equation

	coefficient	std. error	t-ratio	p-value
const	9.878	3.253	3.037	0.004 ***
Price	-0.192	0.088	-2.174	0.035 **
Mo	0.104	0.060	1.723	0.092 *
t4	-0.709	0.205	-3.462	0.001 ***
t5	5.524	2.441	2.263	0.029 **
t6	-4.049	2.351	-1.722	0.092 *
t7	-2.710	1.253	-2.162	0.036 **
p4	0.412	0.119	3.473	0.001 ***
p7	-0.698	0.289	-2.410	0.020 **
t5t	-0.926	0.403	-2.298	0.026 **
t6t	0.785	0.442	1.775	0.083 *
t7t	0.433	0.195	2.213	0.032 **
p4t	-0.100	0.030	-3.339	0.002 ***
p5t	0.010	0.005	2.071	0.044 **
p6t	-0.014	0.005	-2.576	0.013 **
p7t	0.155	0.056	2.776	0.008 ***
t5t_2	0.037	0.016	2.369	0.022 **
t6t_2	-0.034	0.019	-1.832	0.074 *
t7t_2	-0.017	0.008	-2.150	0.037 **
p4t_2	0.004	0.001	2.849	0.007 ***
p7t_2	-0.007	0.002	-2.841	0.007 ***
t	-1.358	0.697	-1.949	0.058 *
t_2	0.064	0.032	2.000	0.052 *
R^2	0.73		Significance	0.0003

*** significant at α=0.01 ** at α=0.05 * at α=0.1
Source: Own processing

Another result complying with the expectations is the significant effect of moisture. Its impact was significant at level of α=0.1. Precipitation was found to be statistically significant only in April (0.412), which is consistent with the study, [32], and in July (-0.698). The result is that higher precipitation in April supports wheat growth and yield, while excessive precipitation in July may have an adverse effect. Other months were significant only in interaction with climate change variables. Estimated coefficients for time variables, which were used as the approximation of technological change, were negative in contrast with expectations. This could be caused by different levels of technological change in V4 countries over time and, therefore, different trends in wheat yields.

The production function estimation suggested by Just and Pope also includes the influence of explanatory factors on the variability of the dependent variable. In this case, it means influence on the variability of wheat yield. All variables were included in Table 2 to estimate the variability function, but insignificant variables were removed using backward elimination. Results show that wheat yield variability is influenced primarily by temperature and precipitation in the summer months.

We also employed the backward elimination method to systematically remove statistically insignificant variables from our model, thereby enhancing its explanatory power. The initial analysis began with a comprehensive model that included all potential variables listed in Table 2. As these variables may affect the variability in wheat yield, we fit the model and assess the statistical significance of each variable by examining their p-values. In the next step, we set the significance level (α) to 0.05. This step ensured that variables with p-values greater than 0.05 were considered statistically insignificant. In each iteration of backward elimination, we removed the variable with the highest p-value from the model and then re-estimated the model. This process was repeated until all remaining variables exhibited p-values below the 0.05 threshold. Consequently, the final model retained only those variables with the strongest impact on wheat yield variability

Table 3. Estimated parameters of variability function

	coefficient	std. error	t-ratio	p-value
const	0.064	0.036	1.807	0.075 *
t6	-0.041	0.016	−2.591	0.0116 **
p6	0.006	0.003	2.097	0.0395 **
p7	0.011	0.006	1.77	0.0809 *
t6t	0.005	0.002	2.839	0.0059 ***
p7t	-0.003	0.001	−2.880	0.0052 ***
p7t_2	0.000	0.000	2.807	0.0064 ***
t^2	-0.001	0.000	−2.838	0.0059***
R^2	0.17		Significance	0.038

*** significant at α=0.01 ** at α=0.05 * at α=0.1
Source: Own processing

An important conclusion based on a comparison of results in Table 2 and Table 3 is that the average yield value is influenced by temperate and precipitation over a more extended period. A crucial role in influencing the variability of final wheat harvest conditions in the summer months, which are harvesting periods. The model estimated for yield variability was significant with an R squared value equal to 0.17, much smaller than the equation for the mean (0.73). However, despite its small value, the coefficient remains statistically significant (p= 0.03), which indicates that average yields are influenced by climate change and are more robust than yield variability. Regarding variability, the extent of climate change impacts is lesser but still significant.

Based on the results, the answers to the hypotheses are as follows:

• Hypothesis 1, which states that an increase in average temperature during the growing season will negatively affect wheat yields in the V4 countries, was confirmed.

• Hypothesis 2 suggests that precipitation variability during the growing season significantly affects wheat yields and deserves further investigation. Precipitation was significant only in certain months (April and July), and its impact on overall yields is limited.

• Hypothesis 3 assumes that there is a significant interaction between temperature and precipitation, and this affects wheat yields.

Our findings support this hypothesis, as we recorded a positive effect of higher temperatures on yields in months with adequate rainfall, particularly in May.

• Hypothesis 4 states that different V4 countries exhibit varying responses of wheat yields to climatic factors. While our analyses focused on average trends across the entire group, the implications of variability in agricultural practices and local conditions suggest that regional analyses are needed for a deeper understanding of these differences.

4 Conclusion

This study aimed to examine the long-term impact of temperature, precipitation, and agricultural area on wheat production in the context of V4 countries. The formulation of the yield function was derived from the stochastic production model proposed by Just and Pope in 1979, a standard method for investigating the impact of climate change on agricultural production. The most significant impact on wheat yield was noted in relation to temperature. The first-order temperature parameter indicated its negative effect in April, June, and July and positive in May. An increase in wheat yield is expected in May, as the coefficient for temperature in this month (t5) is positive (5.524). On the other hand, a decrease in wheat yield is expected in April, June, and July as the coefficients for temperature in these months (t4, t6, t7) are negative (-0.709, -4.049, -2.710).

Although the claims suggest potential relationships between temperature and wheat yield, empirical evidence does not support their impact on yield. However, based on literature, temperature in different months may have different effects on wheat growth stages and disease and pest incidence. Although the relationships have not been empirically confirmed, these assumptions could be the subject of further research. The significance of interactions with the time trend indicates the substantial influence of climate change on wheat yield, suggesting a nonlinear relationship between wheat yields and temperature.

This study offers several significant contributions. The findings highlight the importance of understanding the interactions between climatic variables and agricultural production. Results provide a valuable basis for policy formulation and stakeholder decision-making process aimed at enhancing agricultural resilience to climate change.

Building on these findings, future research could focus on regional differences and the assessment of the impact of climate on wheat production. It is also important to focus on assessing the effectiveness of different agricultural policies and practices to increase resilience.

Overall, the analysis confirms that climate change influences the production of wheat. It has both positive and negative consequences for crop production. The effect of climate change also depends on the specific characteristics of each country and its regions. Based on the findings, this study holds significance for shaping the future agricultural policy of V4 countries. To our knowledge, this study is the first to validate these findings for V4 countries. Furthermore, our findings provide a new perspective on the relationship between climate change and wheat production in Central Europe.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

- Zuzana Bajusová developed the overall research concept and coordinated the research process, revised the manuscript critically for content and coherence, and ensured its academic quality and submission readiness.
- Viktória Benďáková developed the overall research concept and designed the methodology.
- Andrea Janíčeková conducted the literature review, contributed to structuring the manuscript.
- Jozef Palkovič supervised the research project.

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