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ECONOMIC PERFORMANCE OF WHEAT PRODUCTION AND CLIMATE-BASED YIELD PREDICTION

Climate variability affects wheat production in Northern Kazakhstan, where agricultural enterprises face considerable fluctuations in crop yields and economic performance. This study examines the relationships between climatic conditions, wheat yield, and selected economic indicators in the Kostanay Region, with particular attention to the role of precipitation and temperature in yield formation. The research also aims to develop a regression model for predicting wheat yield under varying climatic conditions. The analysis is based on long-term observations of seasonal precipitation, air temperature, wheat yield, production costs, selling prices, and profitability. Correlation and multiple regression methods were applied to identify relationships between the selected variables. The stationarity of the time series was examined using the augmented Dickey Fuller test to distinguish short-term economic relationships from long-term movements in nominal indicators. The results indicate that July precipitation has the strongest positive association with wheat yield, while higher summer temperatures are generally associated with lower productivity. The economic analysis reveals a close relationship between yield fluctuations and production profitability. Changes in yield are also negatively associated with changes in unit production costs, whereas the relationship with selling prices is less pronounced. The regression model identifies July precipitation as a statistically significant predictor of wheat yield, while the contributions of other climatic variables are less conclusive. The findings suggest that climate-related yield variability is an important consideration in assessing the economic performance of wheat production. The proposed modelling approach can support preliminary yield forecasting and provide additional information for agricultural production planning and climate-related risk assessment.

Keywords: *spring wheat yield, climate change, seasonal precipitation variability, predictive modeling, production profitability, adaptation strategies, economic assessment, risk-prone farming zone*

Кілт сөздер: *жаздық бидайдың өнімділігі, климаттың өзгеруі, жауын-шашынның маусымдық өзгермелілігі, болжамдық модельдеу, өндірістің рентабельділігі, бейімделу стратегиялары, экономикалық бағалау, тәуекелді егіншілік аймағы*

Ключевые слова*: урожайность яровой пшеницы, изменение климата, сезонная изменчивость осадков, прогностическое моделирование, рентабельность производства, стратегии адаптации, экономическая оценка, зона рискованного земледелия*

JEL classification: Q54; Q12; C53

Introduction. Climate change is reshaping the resilience of agriculture across many regions of the world, and the Kostanay Region of Kazakhstan is no exception. As one of the country's leading wheat-producing areas, it combines a favourable annual precipitation total with a highly uneven seasonal distribution, a mismatch that intensifies under global warming: spring and autumn increasingly bring prolonged heavy rainfall, while summer months can pass with almost no precipitation at all. For a region with a short and strictly regulated agrotechnological calendar, this volatility is a direct threat to the timing of sowing and harvest. Delays in sowing push grain maturation closer to the rainy autumn season, when precipitation can disrupt harvesting, while excessive early moisture in the soil creates the opposite problem at the start of the season. Kostanay wheat has long been valued on export markets as a quality enhancer for flour, which makes stable yields not only a regional but a national economic concern. Under these conditions, developing reliable tools to anticipate and manage climate-related risk in wheat cultivation becomes essential.

The purpose of this study is to examine the relationship between climatic factors and wheat yield in the Kostanay Region, develop a regression model for yield prediction, and assess the association between

yield variability and the economic performance of wheat production. The study tests the hypothesis that climatic variability is associated with changes in wheat yield, which, in turn, are related to production costs and profitability. To achieve this purpose, the study addresses three tasks: to identify statistical relationships between precipitation, air temperature, and wheat yield using long-term regional data; to examine the association between yield fluctuations and economic indicators, including unit production costs, selling prices, and profitability; and to develop a multiple regression model for predicting wheat yield based on climatic and production-related variables.

The analysis draws on open-access climate data from NASA POWER and the Food and Agriculture Organization, combined with yield, cost and profitability data from the Bureau of National Statistics of the Republic of Kazakhstan and local archives of experimental farms. Correlation and regression analysis were carried out in Python using standard data-processing libraries. The stationarity of annual time series was examined using the augmented Dickey Fuller (ADF) test. The test results were taken into account when interpreting correlations involving economic indicators, particularly production costs and selling prices, whose non-stationarity required additional analysis of annual changes.

Literature Review. Climate change and its consequences for the agricultural sector have been the subject of active scientific discussion around the world over the past two decades – particularly intensifying in the last five years. Researchers largely agree that while several climatic factors affect the yield of agricultural crops, the most critical are changes in air temperature and variations in the amount of precipitation during the plant growing season [1].

Even earlier scientific studies Porter John R., Semenov M.A., 2005 asserted that the primary natural factors determining the yield of agricultural crops are both the static and dynamic increases in air temperature along with changes in precipitation structure during the stages of plant growth and maturation [2].

The relevance of this issue is confirmed at the level of Kazakhstan's strategic policy documents. The Concept for the Development of the Agro-industrial Complex for 2021-2030 emphasizes the need for adapting agriculture to climate-related challenges and for digital transformation of the agrarian sector. In addition, the National Development Plan of the Republic of Kazakhstan until 2025 sets out objectives for ensuring food security, increasing agricultural profitability, and also reducing climate-related risks. Issues related to the sustainable development of the agricultural sector are also regularly discussed at meetings of the relevant Committee of the Senate of the Parliament of the Republic of Kazakhstan.

Other studies focus on the seasonal and phenological sensitivity of cereal crops to climate variability. These studies have revealed important empirical findings demonstrating that disruptions in the water balance during critical growth phases of wheat - such as stem elongation, tillering, and heading - have a greater impact on yields than the total amount of precipitation over the entire season. The results demonstrate that accounting for the temporal distribution of climatic factors through 10-day periods, phenological development stages and monthly observations improves the ability of forecasting models to identify weather conditions most critical for wheat yield formation. Scientific research and analytical work conducted under the GEOGLAM program also emphasize the significance of climatic factors - particularly temperature and precipitation - for forecasting wheat yields at the global level [3].

From a methodological standpoint, recent years have seen growing interest in the use of predictive models based on machine learning techniques. These include regression methods, correlation analysis, random forests, and neural networks. Notably, Van Klompenburg T., Kassahun A., Catal C. [4] employed highly accurate neural networks to forecast winter wheat yields using both ecological and statistical data. This category also includes the works of Wang J. et al. [5] and the team led by Nevavuori P. [6], which offer interpretations of results derived from various modelling approaches used to assess yield based on climatic inputs-including temperature, precipitation, and soil moisture - by leveraging remote sensing data and machine learning for precision agriculture.

These approaches make it possible to identify both linear and nonlinear relationships between wheat yield and agroclimatic factors by using an integrated dataset: satellite navigation information, agrometeorological data, and production indicators of the agricultural sector. Scientific studies conducted by researchers from the post-Soviet region, Kazakhstan, and Central Asian countries have increasingly focused on assessing the impact of climate change on the efficiency of agricultural production. In particular, the works of Baisholanov S., Baizarov D. [7], as well as research groups led by Romanovska P. et al. [8], along with reports from the Ministry of Agriculture of the Republic of Kazakhstan, point to a growing risk of meteorological hazards in the northern regions of the country, including the Kostanay Region.

Researchers at the Institute for Economic Research of Kazakhstan are conducting experiments to integrate climatic data and sectoral indicators and to macroeconomic models to assess the extent of climate change's impact on social and economic aspects such as income and employment in evaluating the economic consequences of climate influence, studies by Schierhorn et al. Linlin Yao et al. using fixed-effects regressions, CMIP6 models and, panel data analysis, revealed spatial variations in climate impact on yields and economic losses in Kazakhstan and China [9]. The infrastructural and logistical characteristics of Kazakhstan's grain subsector, including issues of innovation and export resilience, have been thoroughly addressed in studies led by G.S Ismuratova and her co-authors [10].

A study published in the journal Agriculture employed the Random Forest model to evaluate the impact of climate change on winter wheat yield in the North China Plain over the period 1980-2020. The findings indicated that climate trends negatively affected winter wheat yields in certain regions, while yield increases were observed in others. The regional differences reported in the study suggest that adaptation measures should be selected with due regard to local conditions. In practical terms, this may require revising sowing dates and choosing crop varieties that are better suited to changing climatic conditions [11].

Guerriero and colleagues from the University of Abruzzo examined the response of wheat production to climatic variability during 1952–2014. Despite the overall upward trend in yields, the results showed that year-to-year fluctuations became increasingly dependent on weather conditions. The authors note that technological improvements alone cannot fully protect wheat production from growing climatic risks. They therefore recommend incorporating climate-based forecasts into agricultural decision-making to ensure the timely selection and implementation of appropriate adaptation measures. Research conducted highlights the importance of yield stability as a critical component of climate change adaptation in agriculture [12].

Survey respondents - including farmers and expert consultants - emphasize that stable yields are more important than maximum yields, particularly under conditions of increasing climate uncertainty. Among the most effective strategies cited a cultivar adaptation, crop rotation within grain-based farming systems, and integrated plant protection. According to Financial Times, extreme precipitation events during the winter of 2023-2024 in the United Kingdom and France severely impacted wheat crops, with yield reductions ranging from 20% to 50% in many regions [13]. These developments reinforce the growing concern over climate instability and its adverse effects on the agricultural sectors of some of the European Union's most productive grain-producing areas.

Studies present valuable scientific findings and methodological approaches that can be applied to develop adaptation strategies for the agricultural sector of the Kostanay Region and the broader area of Northern Kazakhstan under conditions of intensified climate change. Furthermore, the reviewed publications highlight the importance of considering both climatic and economic factors when forecasting grain crop yields and assessing the resilience of the agricultural economy. However, despite the availability of extensive theoretical and empirical data, the topic of multilevel and multifactorial comparison of the climatic and economic consequences of yield variability remains underexplored -particularly for regions classified as risk-prone farming zones. There is also a notable gap in research that combines a global comparative perspective with regional prioritization. (i.e. regionally adapted application of global best practices), which remains highly relevant from both scientific and applied viewpoints.

Main part. The study combines correlation analysis and regression modeling to examine yield wheat variability and its relationship with the economic performance of wheat production. Climatic variables are used to identify the factors associated with yield formation and to develop a predictive model. The economic analysis then examines how fluctuations in wheat yield are associated with changes in unit production costs, selling prices and profitability.

To analyze global climate change, open-access datasets were used, including those from the Food and Agriculture Organization of the United Nations (FAO), the Global Historical Climatology Network – which provides hourly, daily, and aggregated weather observations collected by meteorological services and processed by climate experts worldwide (GHCN, n.d.), – as well as meteorological databases from satellite and ground-based monitoring platforms such as NASA POWER [14]. For the analysis of climatic and environmental indicators in Kazakhstan and Kostanay Region, additional statistical materials were utilized from the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan, Kazhydromet, and Ministry of Agriculture of the Republic of Kazakhstan.

For the analysis of economic indicators, data were obtained from the World Bank, the National Bank of the Republic of Kazakhstan, as well as from local archives of experimental farms Kazakh Grain Union. These sources were selected due to their official and verified nature, strong permutation within the research

community, and the availability of long-term time series. The platforms used are internationally recognized for the high quality, reliability, and regular updates of their datasets. Notional databases provide the necessary regional detail and disaggregation relevant to the Kostanay Region. This approach – from global to regional analysis – allows for a meaningful comparison between global trends and regional patterns, while preserving data comparability and originality. A range of software tools was utilized in the course of this research. For data processing and modelling, Python programming language was employed along with key libraries such as Pandas, Scikit-learn, and Matplotlib. Microsoft Excel was used for preliminary tabular data processing and analysis. Additionally, R packages including ggplot2 and caret were applied for statistical modelling and visualization, while QGIS was used for spatial analysis, geospatial data visualization and cartographic representation of indicators. The selection of these tools was based on their open-source availability, proven scientific reputation, and functionality aligned with the requirements of agroclimatic and economic modelling. The use of Python and R ensured analytical flexibility, whereas QGIS provided robust support for spatial analysis.

To identify the dependencies, a set of indicators in variables was defined (climatic, agrotechnical, and economic).

Climatic variables include: the average monthly air temperature during the growing season (May-August for the Kostanay region); total monthly precipitation during the vegetation period; indices of precipitation irregularity.

Agrotechnical variables include: wheat yield, c/ha - the dependent variable; sown area (hectares); timing of sowing and harvesting campaigns (start date, end date, and duration in days).

Economic variables: cost of wheat production and cultivation, tenge (KZT) per ton; revenue from the sale of marketable wheat grain tenge (KZT) per ton; profitability of wheat production and cultivation (%).

Pearson correlation analysis was employed to evaluate relationships between wheat yield and selected climatic as well as economic variables for the period 1990-2024. Correlations coefficient was calculated for monthly precipitation, air temperature, production costs, wheat sale prices and profitability indicators.

The Pearson correlation coefficient was determined according to the standard statistical expression [15]:

$$r = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\cdot\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}}, \qquad (1)$$

Where x_i and y_i represent paired observations of the analyzed variables, $\bar{x}$ and $\bar{y}$ denote sample means, and n is the number of observations. To assess precipitation variability and temporal irregularity, the coefficient of variation (CV) and precipitation concentration index (PCI) were additionally calculated.

Since the analysis covers long-term time series, their stochastic properties were additionally examined before interpreting the correlation coefficients. Stationarity was tested using the Augmented Dickey-Fuller (ADF) test, with the null hypothesis of a unit root. This procedure was applied to wheat yield, the principal climatic variables, production cost, selling price, and profitability. For non-stationary economic series, correlations in levels were treated with caution, since common trends caused by inflation and structural changes may produce misleading statistical relationships. Where necessary, first differences or appropriately transformed series were considered to separate short-term relationships from long-term nominal trends.

Precipitation variability was assessed using the coefficient of variation (CV) and the precipitation concentration index (PCI). The coefficient of variation (CV) was calculated according to Equation [15]:

$$CV = \left(\frac{\sigma}{\mu}\right) \times 100\%, \qquad (2)$$

Where σ is the standard deviation of monthly precipitation and μ is the corresponding mean precipitation value.

Precipitation Concentration Index (PCI) calculated using the following formula [15]:

$$PCI = \left(\frac{\sum_{i=1}^{12} P_i^2}{\left(\sum_{i=1}^{12} P_i\right)^2}\right)\times 100, \qquad (3)$$

where: P – the amount of precipitation in a given month.

To characterize the regional moisture regime, precipitation variability indices were calculated. These indices reflect both the annual precipitation total and the distribution of rainfall across the main stages of wheat development in the Kostanay Region. This is particularly important under conditions of unstable spring and summer precipitation, where short-term moisture deficits during stem elongation and heading phases may substantially reduce yield formation. For example, heavy rainfall in May can hinder the sowing operations, while a lack of precipitation in July - leading to drought - can destroy the wheat crop. Statistical indices such as CV and PCI provide quantitative assessment of climate risk and integration of these patterns into predictive models for forecasting and evaluating the resilience of wheat production and cultivation. Thus, these indices allow for assessment of both quantitative and qualitative changes in precipitation distribution throughout the year, identify periods of high concentration and deficit, which is of critical important for the agricultural sector.

Based on data from the Kostanay Region for the period 1990 to 2024, a correlation analysis was conducted to examine the relationships between climatic and environmental factors, wheat yield, and key economic indicators of the regional agricultural sector. The analysis, focusing on the impacts of climate change, global warming, and rising cumulative active temperatures during the spring and summer seasons, demonstrated is stable positive correlation between precipitation during the growing period and wheat yield. The primary monthly precipitation data for the period 1990-2024 are presented in Table 1.

The results of the analysis confirmed the high sensitivity of wheat yields to climatic parameters. As previously stated, a strong dependence on weather factors has been observed in recent decades. For example, in 2017-2018, stable yields were recorded due to relatively even precipitation distribution from May to July. In contrast, in 2019 and 2021, yields dropped sharply to 7,2 c/ha and 7,3 c/ha, respectively, amid severe moisture deficits in May and June. The year 2020 illustrates how high precipitation in May can offset insufficient rainfall in June, resulting in an average yield of 10,2 c/ha.

Table – 1

Annual wheat yield and monthly precipitation indicators (1990-2024)

Year	Wheat yield, centners per hectare	March	April	May	June	July	August	September	December	Total annual Precipitation
1990	13,90	39,60	20,72	42,27	37,40	63,71	57,59	24,96	21,17	412,87
1991	3,90	20,97	4,40	1,42	25,32	25,89	41,78	34,73	21,00	233,57
1992	14,70	12,33	12,91	37,85	66,90	73,10	34,70	7,53	11,49	399,62
1993	7,80	27,08	34,58	28,38	62,99	31,18	49,46	34,69	21,40	377,94
1994	9,00	40,23	23,33	65,39	30,89	46,74	47,73	11,30	28,62	377,22
1995	4,20	9,78	6,76	39,34	22,85	16,55	39,93	9,44	56,81	257,17
1996	6,50	4,59	55,24	15,24	34,44	30,70	36,58	19,72	29,13	276,18
1997	9,80	13,33	23,91	55,64	35,07	40,33	32,31	8,97	22,81	348,83
1998	4,00	8,14	27,53	10,52	19,57	17,34	13,94	30,02	35,23	275,07
1999	15,10	19,27	21,12	87,11	66,61	78,01	25,62	48,36	18,34	448,79
2000	10,60	30,37	25,03	48,20	44,74	45,39	34,58	40,16	41,07	388,12
2001	11,80	26,32	17,77	30,55	30,44	44,56	48,18	50,65	15,39	423,97
2002	11,80	35,90	49,30	14,26	33,39	47,71	56,16	12,15	21,40	380,86
2003	11,10	13,12	30,42	79,74	65,68	41,05	18,05	39,47	9,27	379,22
2004	8,00	40,57	48,36	9,00	20,62	31,52	11,89	30,61	42,06	350,30
2005	10,40	47,16	23,54	43,52	37,48	51,56	58,30	24,13	11,74	343,72
2006	13,30	16,35	64,88	38,08	29,58	63,22	21,11	15,81	25,04	394,79
2007	14,90	9,33	36,55	69,89	23,66	73,55	14,05	31,37	10,59	383,39
2008	11,50	45,85	23,23	42,14	33,93	42,99	18,89	21,27	4,24	323,76
2009	11,00	26,06	39,46	67,52	8,74	48,51	57,46	8,73	39,39	375,53
2010	7,30	29,18	7,81	25,16	8,10	26,70	15,91	7,48	29,12	248,52

2011	18,30	33,90	44,61	46,24	95,22	84,99	42,91	55,56	11,13	513,67
2012	6,10	30,68	20,47	42,80	31,11	36,72	59,97	11,22	24,73	324,53
2013	9,60	31,50	51,44	30,41	9,48	50,52	52,32	22,80	28,96	362,17
2014	9,90	20,64	8,06	27,51	37,57	48,22	17,56	21,15	30,10	326,61
2015	11,40	17,93	32,73	96,35	23,27	64,72	22,33	45,75	54,29	462,43
2016	10,50	53,42	36,04	16,52	61,60	46,95	26,75	74,01	35,70	493,88
2017	11,30	17,94	29,75	67,87	63,35	60,72	45,86	10,90	14,59	404,00
2018	11,30	42,15	32,21	68,83	64,34	63,70	68,33	23,82	14,50	449,74
2019	7,30	27,92	26,26	16,87	22,49	40,36	43,55	44,31	27,50	348,20
2020	10,20	23,60	42,92	116,86	32,76	57,13	67,40	42,83	12,22	519,40
2021	7,20	28,99	17,34	9,95	11,21	38,66	4,03	24,96	26,75	278,79
2022	13,70	18,54	10,45	44,22	49,09	58,04	9,51	15,21	16,64	367,25
2023	10,5	23,11	4,79	16,85	62,91	41,82	68,98	47,82	45,59	482,05
2024	14,8	15,99	38,59	36,66	57,82	104,23	84,49	17,69	12,19	484,34

** compiled by the authors using NASA POWER climate data and wheat yield statistics from the Bureau of National Statistics of the Republic of Kazakhstan [14]*

The study uses annual time series for 1990-2024, their stationarity was examined before interpreting the long-term correlations. The Augmented Dickey-Fuller (ADF) test was applied, with the presence of a unit root specified as the null hypothesis. The lag length was selected automatically using the Akaike information criterion (AIC). The results of the stationarity test are presented in Table 2.

Table – 2

Augmented Dickey-Fuller (ADF) stationarity test results for the study variables, 1990–2024

Variable	ADF statistic	p-value	Result at 5%
Wheat yield	-7,342	< 0,001	Stationary
July precipitation	-6,711	< 0,001	Stationary
Summer temperature	-6,956	< 0,001	Stationary
Production cost	-0,828	0,811	Non- stationary
Selling price	0,736	0,991	Non- stationary
Profitability	-6,823	< 0,001	Stationary
Δ Production cost	-13,855	< 0,001	Stationary
Δ Selling price	-8,955	< 0,001	Stationary

** compiled by the authors based on the source [14]*

Wheat yield, July precipitation, summer temperature, and profitability were stationary at the 5% significance level ($p < 0,001$). In contrast, the nominal series of production cost and selling price were non-stationary ($p = 0,811$ and $p = 0,991$, respectively). After first differencing, both economic series became stationary ($p < 0,001$). Therefore, correlations involving the levels of nominal cost and price over the entire 1990-2024 period were interpreted as descriptive rather than evidence of a stable long-term economic relationship.

The ADF test was used as a preliminary diagnostic procedure rather than as a component of the yield prediction equation. Its main purpose was to determine whether correlations involving economic time series could be interpreted in their original levels. Since production costs and selling prices were non-stationary, their annual changes were examined separately. This distinction was necessary to avoid attributing long-term movements in nominal economic indicators directly to variations in wheat yield. Temperature conditions exhibit a more complex relationship with yield formation than precipitation. The corresponding data on accumulated active temperatures for the study period (1990–2024) are presented in Table 3.

Table – 3

Annual wheat yield and monthly precipitation characteristics in Kostanay Region during 1990-2024

Year	Wheat yield, centners per hectare	Autumn Active Temperatures, C	Winter Active Temperatures. C	Spring Active Temperatures. C	Summer Accumulated daily active temperatures C	Cost of growing 1 centner of wheat, tenge (KZT)	Selling price of 1 centner of wheat, tenge (KZT)	Profit per 1 centner of wheat, tenge (KZT)	Profitability of wheat cultivation, %
1990	13,90	3,3	-13,0	6,3	20,8	550	1050	500	90,91
1991	3,90	5,8	-15,0	6,0	21,6	1050	1100	50	4,76
1992	14,70	2,3	-13,7	3,4	18,2	760	1370	610	80,26
1993	7,80	-1,1	-14,1	2,2	20,3	1430	1580	150	10,49
1994	9,00	4,7	-17,1	3,0	19,1	1220	1670	450	36,89
1995	4,20	5,0	-13,9	7,6	22,0	1770	1900	130	7,34
1996	6,50	2,8	-16,5	2,2	21,5	1685	1860	175	10,39
1997	9,80	5,4	-14,7	7,3	20,5	1289	1760	471	36,54
1998	4,00	2,9	-16,0	2,4	24,8	1930	1990	60	3,11
1999	15,10	3,8	-11,7	2,3	20,0	980	1870	890	90,82
2000	10,60	2,1	-11,8	5,0	21,6	1550	2290	740	47,74
2001	11,80	3,6	-13,5	7,1	19,5	1590	2180	590	37,11
2002	11,80	4,9	-11,1	4,5	19,1	1660	2490	830	50,00
2003	11,10	4,1	-17,4	3,4	20,6	2430	4020	1590	65,43
2004	8,00	5,6	-12,2	5,1	21,9	3450	4130	680	19,71
2005	10,40	5,6	-16,6	5,0	20,7	2740	4330	1590	58,03
2006	13,30	4,2	-14,6	6,2	20,7	2210	4120	1910	86,43
2007	14,90	4,7	-11,3	4,0	20,6	2450	4780	2330	95,10
2008	11,50	5,3	-16,6	6,3	22,1	3450	4890	1440	41,74
2009	11,00	4,6	-13,1	4,2	20,2	3780	4870	1090	28,84
2010	7,30	5,9	-19,6	4,4	23,0	4570	5310	740	16,19
2011	18,30	3,5	-18,1	3,9	19,7	2720	4890	2170	79,78
2012	6,10	4,5	-18,6	6,5	22,7	4800	5230	430	8,96
2013	9,60	5,4	-16,9	4,6	20,2	3990	5060	1070	26,82
2014	9,90	2,2	-15,6	5,7	20,4	3890	5120	1230	31,62
2015	11,40	2,5	-14,5	4,3	20,6	3780	5020	1240	32,80
2016	10,50	0,8	-12,6	5,6	20,6	3900	5110	1210	31,03
2017	11,30	3,9	-14,7	3,6	19,8	3890	5570	1680	43,19
2018	11,30	4,0	-16,5	1,6	19,3	4210	5560	1350	32,07
2019	7,30	2,3	-16,5	5,2	20,7	5500	6310	810	14,73
2020	10,20	3,2	-10,9	6,2	20,2	4120	6020	1900	46,12
2021	7,20	2,8	-15,6	5,1	22,0	6700	7200	500	7,46
2022	13,70	2,7	-13,0	4,7	20,6	4100	6700	2600	63,41
2023	10,5	0,9	-12,7	5,4	19,1	5600	8000	2400	42,86
2024	14,8	2,9	-11,3	6,1	20,6	4800	8200	3400	70,83

** compiled by the authors using NASA POWER climate data and wheat yield statistics from the Bureau of National Statistics of the Republic of Kazakhstan [14]*

Moderate temperatures ranging from 24 – 27 °C in June and July are associated with more stable wheat yields of approximately 12-14 centners per hectare. In contrast, temperatures exceeding 30 °C combined with low soil moisture correlate with a sharp decline in yield, dropping below 7 centners per hectare. This relationship is reflected in the scatter plot constructed NASA POWER satellite observations and meteorological records obtained from Kazhydromet (Figure 1). The relationship between accumulated summer active temperatures and wheat yield indicates that thermal conditions remained relatively stable throughout the study period. Annual variations in accumulated active temperatures were limited, with values fluctuating only slightly around the long-term mean. Over the study period, however, the estimated

trend was not statistically significant. Therefore, the accumulated active temperatures cannot be considered to have increased or decreased systematically between 1990 and 2024. In contrast, wheat yield showed substantial year-to-year variability. The observed fluctuations reflect the combined influence of weather conditions, soil moisture availability, and agronomic factors on crop productivity. Years with favorable environmental conditions were associated with relatively high yields, whereas less favorable seasons resulted in noticeable yield reductions, which is consistent with the characteristics of crop production in the risk-prone agricultural zone of Northern Kazakhstan.

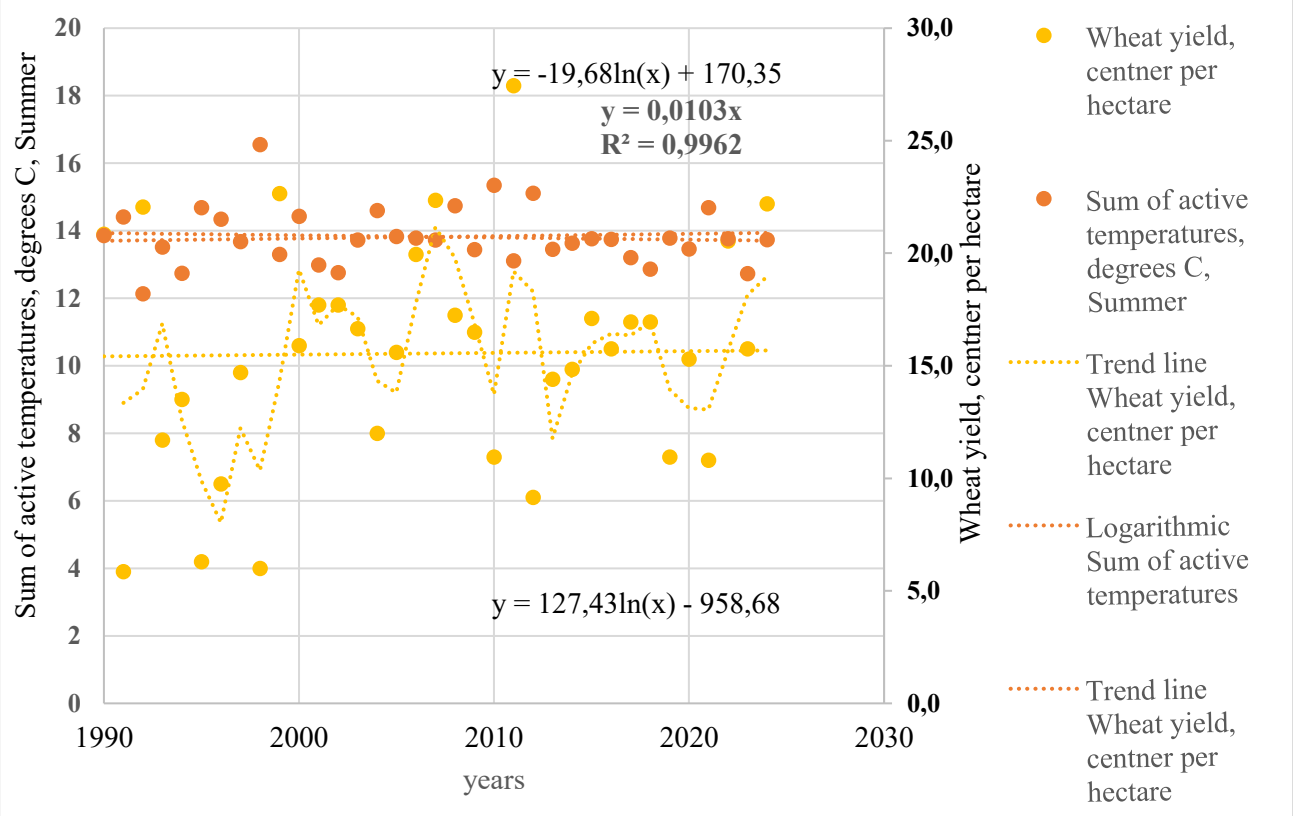


Figure –1. **Graphical representation of the relationship between summer air temperatures and wheat yield dynamics from 1990 to 2024**

** compiled by the authors using NASA POWER climate data and wheat yield statistics from the Bureau of National Statistics of the Republic of Kazakhstan [14]*

Logarithmic Sum of active temperatures. The application of a moving average allows smoothing short-term fluctuations and reveals a slight tendency toward gradual yield stabilization over time. This may partly reflect improvements in agricultural technologies, crop management practices, and the introduction of more productive wheat varieties. Taken together, these results show that changes in temperature alone do not account for the observed variation in wheat yield. A more reliable forecast requires the joint consideration of precipitation distribution, temperature, and other relevant climatic variables. This approach also provides a better basis for estimating production losses and the associated economic risks under changing climatic conditions. A negative relationship was found between wheat yield and the sum of active temperatures during the summer months (r=- 0,62), which corresponds to a moderately strong correlation. This suggests that as summer temperatures increase, wheat yield tends to decline. As illustrated in Figure 2, the regression line exhibits a negative slope, supporting the conclusion that under conditions of low precipitation, higher cumulative summer temperatures lead to reduced yields.

The green dots on the graph represent actual yield values corresponding to different levels of accumulated summer temperatures from 1990 to 2024. The red line represents the line of best fit derived from the linear regression model.

As a result, we obtained the following equation:

$$y = -1{,}6x + 43{,}6$$

The coefficient of determination R2 = 0,38

The results of the linear regression between wheat yield and the cumulative active temperatures during the summer months, with a slope coefficient of -1,60, indicate an inverse proportional relationship: for every 1 °C increase in cumulative summer temperatures, wheat yield decreases on average by 1,6 centners per hectare.

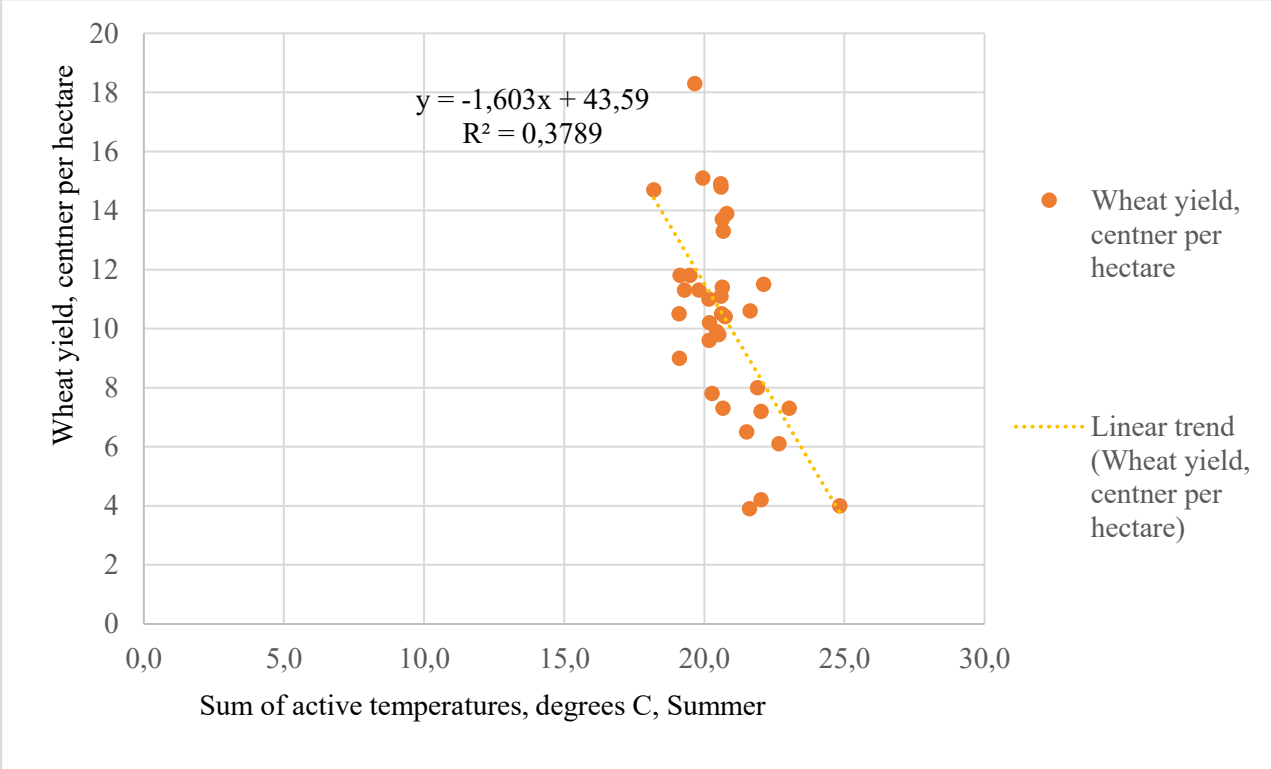


Figure – 2. **Correlation between wheat yield and the sum of active temperatures during the summer months; linear regression**

** compiled by the authors based on the source [14]*

The intercept of the regression equation, equal to 43,59, theoretically implies that yield would reach this value if the cumulative active temperature were zero, which is practically impossible during the summer months; however, this is how the mathematical model behaves. The coefficient of determination R2 = 0,3789, indicating that summer air temperature is an important- but not the sole-factor influencing wheat yield in the Kostanay Region. The remaining variation in yield approximately 62% is explained by other variables (factors), such as precipitation, soil moisture, cumulative active temperatures in autumn, winter, and spring, agrotechnical practices, etc. A negative correlation was also observed between July temperatures and wheat yield, reaching r= -0,51 (p <0,05). The relationship between climatic conditions and wheat yield also has economic implications for agricultural producers. Variations in yield are associated with changes in unit production costs and profitability, while selling prices are influenced by additional market factors. To examine these relationships, the analysis compares wheat yield with the economic indicators of wheat production over the study period. The corresponding dynamics are presented in Figure 3.

Figure 3 clearly illustrates the relationship between wheat yield, production cost, and selling price based on specific periods.

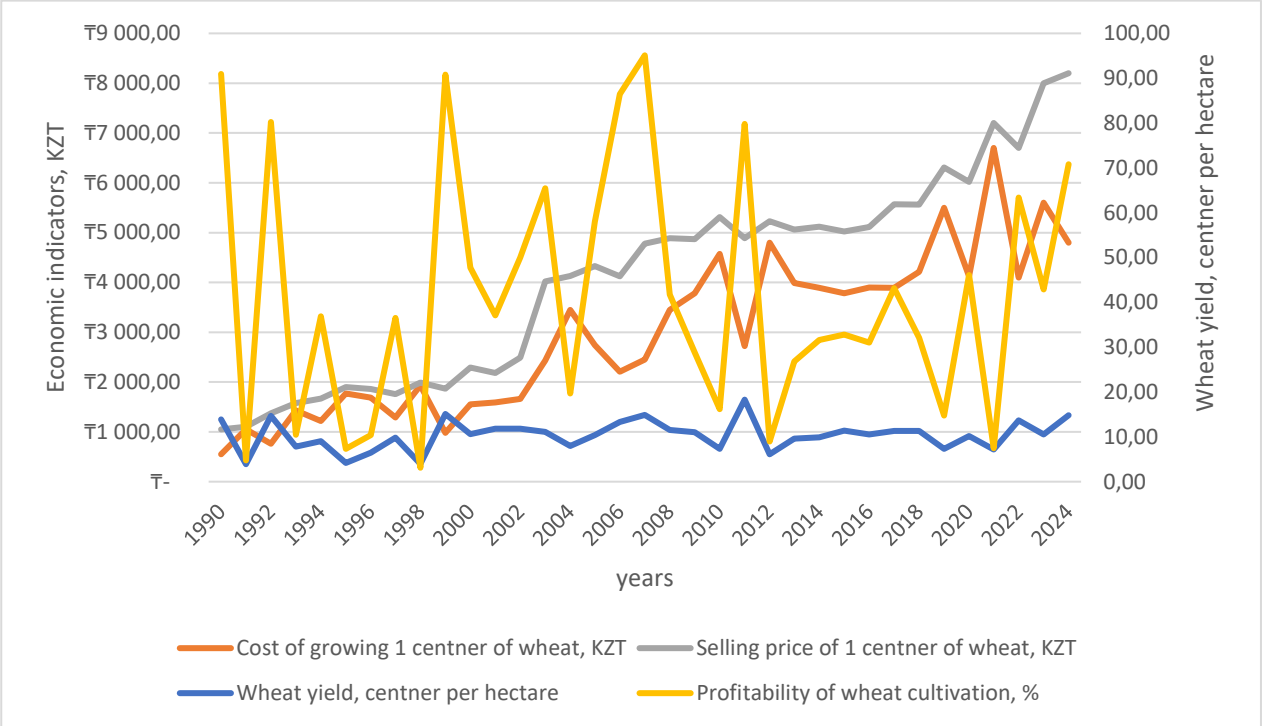


Figure – 3. **Graph of the relationship between wheat yield and economic indicators**
**compiled by the authors*

The economic assessment shows that the relationship between wheat yield and production performance should be interpreted differently for nominal monetary indicators and relative efficiency measures. Since production cost and selling price were found to be non-stationary in levels, their long-term correlations with yield cannot be regarded as evidence of a stable economic relationship. The analysis was therefore supplemented by correlations based on annual changes in these variables. The correlation between annual changes in wheat yield and production cost was negative and relatively strong (r=-0,766). Thus, an increase in yield relative to the previous year was generally associated with a decrease or a smaller increase in production cost per unit of output, whereas a decline in yield tended to increase the cost burden per unit produced. The weaker correlation between annual changes in wheat yield and selling price (r=-0,393), suggests that regional yield fluctuations alone do not fully explain changes in selling prices. A different result was obtained for profitability, which was stationary over the study period. The correlation between wheat yield and profitability reached (r=0,900), indicating a strong positive association between production results and economic efficiency. Taken together, these results suggest that climatic variability may be associated with the economic performance of wheat reproduction through fluctuations in yield and unit production costs, while selling prices are less closely related to annual changes in regional yield. Consequently, adverse climatic conditions may affect the economic performance of wheat production not only through physical yield losses but also through higher production costs per unit of output and lower profitability.

The research hypothesis assumed that climatic variability affects the economic performance of wheat production primarily through changes in yield. The empirical results provide support for this hypothesis. July precipitation showed the strongest positive relationship with wheat yield (r=0,89), (p<0,01), while mean summer air temperature was negatively associated with yield. The economic analysis further showed a strong positive relationship between yield and profitability (r=0,90) and a negative relationship between annual changes in yield and production cost (r=-0,766). At the same time, the relationship between changes in yield and selling price was weaker (r=-0,393), indicating that market price dynamics cannot be explained by regional yield fluctuations alone. Thus, the hypothesis is supported with respect to the climate–yield relationship and the transmission of yield variability to production cost and profitability, but not as a direct relationship between climatic variables and all nominal economic indicators.

To construct a predictive model for forecasting wheat yield in the Kostanay region, the following key variables were selected (based on correlation values ≥0.4).

The structure of the predictive model includes variables, logical relationships, and output data, all interpreted within the context of yield forecasting. This study proposes an original specification of a multiple linear regression model for wheat yield. Although the regression framework is standard, the methodological contribution lies in the joint consideration of July precipitation, accumulated active temperatures, precipitation irregularity, and the use of adaptive agricultural technologies:

$$Y = \beta_0 + \beta_1 \cdot P_{july} + \beta_2 \cdot T_{summer} + \beta_3 \cdot I_{precip} + \beta_4 \cdot C + \varepsilon \quad (4)$$

Where: Y – predicted wheat yield, (centners per hectare); β_0 – Intercept term, model constant; β_1 – Coefficient for July precipitation; P_{july} – Total precipitation in July (mm); β_2 – Coefficient for summer temperature; T_{summer} – Sum of active summer temperatures, °C; β_3 – Coefficient for precipitation irregularity; I_{precip} – Irregularity index (calculated separately); β_4 – Coefficient accounting for agricultural technologies; C - a binary or index variable reflecting the application of technologies (such as water saving practices or improved high-yield crop varieties); ε – Random error term representing the influence of unobserved factors (Table 4).

Table – 4

Results of Multiple Regression Analysis of Wheat Yield, 1990–2023

Variable	Coefficient-β	Standard Error	t-statistic	p-value
Intercept	4,883	5,002	0,976	0,337
July precipitation	+0,152	0,018	8,571	<0,001
Average summer air temperature	-0,108	0,210	-0,515	0,611
Precipitation irregularity (*CV*)	-1,021	1,531	-0,667	0,510
Conditional indicator *C*	+1,517	0,507	2,992	0,006

** compiled by the authors based on the source [14]*

The results of the multiple regression analysis for 1990–2023 indicate that the model is statistically significant overall ($F = 56,65$; $p < 0,001$). The coefficient of determination (R^2) is 0,887, while the adjusted R^2 is 0,871. July precipitation exhibits the strongest and most statistically robust positive association with wheat yield ($\beta = 0,152$; $p < 0,001$). The coefficients for average summer air temperature and precipitation irregularity are negative but statistically insignificant ($p > 0,05$). The conditional indicator C is positively associated with wheat yield ($\beta = 1,517$; $p = 0,006$); however, its interpretation is limited by the fact that it was constructed using production profitability as a reference.

The estimated coefficients show how wheat yield is expected to change when one of the explanatory variables changes and the remaining factors are held constant. This makes it possible to use the model for the following purposes:

1.The regression results can be used to illustrate the potential economic implications of yield differences under alternative production conditions. For example, the coefficient of the conditional indicator C is 1,517 centners per hectare. At an assumed selling price of KZT 5000 per centner, this difference corresponds to KZT 7585 per hectare in gross revenue. This calculation is illustrative and does not represent a confirmed economic effect of adopting agricultural technologies, since the indicator C was constructed with reference to profitability.

2.The estimated coefficients for summer temperature and precipitation irregularity are negative but statistically insignificant. Therefore, their individual effects should not be used to calculate reliable monetary losses. These variables remain relevant to the interpretation of climatic risks, while July precipitation provides the strongest statistically supported contribution to the estimated yield model.

3. Practical application enables:

-Estimate wheat yield under alternative climatic conditions and use the resulting predictions, together with independently specified selling prices and production costs, as inputs for preliminary economic planning;

-Plan investment allocations: If high precipitation is expected, the sown area can be expanded accordingly. In the event of a forecast for high temperatures, the area under fallow can be increased, along with other measures aimed at mitigating the risks of moisture deficit during the growing season.

These assessments make it possible to manage agricultural risk and to plan appropriate agrotechnical and agrotechnological measures. (Various agrotechnical strategies for mitigating the risks associated with dryland farming in the Kostanay region - based on predictive modelling forecasts - will be discussed in the next article).

The developed model has high practical value under intensifying climate change and can serve as a decision-support tool for technical and technological planning in regions of risk-prone agriculture, particularly within the agricultural sector of the Kostanay region. The model helps reduce uncertainty in production planning and minimize economic losses resulting from adverse weather scenarios.

Conclusions. The study identified significant relationships between climatic conditions, wheat yield including the economic performance of wheat production, In the Kostanay Region, July precipitation showed the strongest positive association with yield, while higher summer temperatures were generally associated with lower productivity.

The economic analysis revealed a strong positive correlation between wheat yield and profitability and a negative relationship between annual changes in yield and unit production costs. The association with selling prices was weaker, indicating that market factors also influence the economic results of wheat production. The stationarity analysis provided a basis for interpreting these relationships while accounting for the non-stationarity of nominal economic indicators.

The multiple regression model confirmed the statistical significance of July precipitation in predicting wheat yield. The effects of summer temperature and precipitation irregularity were less conclusive. The findings demonstrate the relevance of combining climate-based yield prediction with economic analysis to support production planning and climate related risk assessment in wheat cultivation.

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БИДАЙ ӨНДІРІСІНІҢ ЭКОНОМИКАЛЫҚ ТИІМДІЛІГІ ЖӘНЕ КЛИМАТТЫҚ ФАКТОРЛАР НЕГІЗІНДЕ ОНЫҢ ӨНІМДІЛІГІН БОЛЖАУ

Аңдатпа

Климаттың өзгермелілігі Солтүстік Қазақстандағы бидай өндірісіне әсер етеді, ал өңірдегі ауыл шаруашылығы кәсіпорындары өнімділік пен экономикалық нәтижелердің елеулі ауытқуларына тап болады. Мақалада Қостанай облысындағы климаттық жағдайлар, бидай өнімділігі және өндірістің жекелеген экономикалық көрсеткіштері арасындағы өзара байланыстар зерттеледі. Өнімділіктің қалыптасуындағы атмосфералық жауын-шашын мен ауа температурасының рөліне ерекше назар аударылған. Зерттеудің мақсаты әртүрлі климаттық жағдайларда бидай өнімділігін болжауға арналған регрессиялық модель әзірлеуді де қамтиды. Зерттеу маусымдық жауын-шашын мөлшері, ауа температурасы, бидай өнімділігі, өнімнің өзіндік құны, өткізу бағалары және рентабельділік бойынша көпжылдық бақылау деректеріне негізделген. Қарастырылып отырған айнымалылар арасындағы өзара байланыстарды анықтау үшін корреляциялық талдау және көптік регрессия әдістері қолданылды. Уақыт қатарларының стационарлығы кеңейтілген Дики-Фуллер тесті арқылы тексерілді, бұл қысқа мерзімді экономикалық өзара байланыстарды номиналды көрсеткіштердің ұзақ мерзімді өзгерістерінен ажыратуға мүмкіндік берді. Зерттеу нәтижелері бидай өнімділігімен ең айқын оң байланыс шілде айындағы жауын-шашын мөлшеріне тән екенін көрсетті, ал жазғы ауа температурасының жоғарылауы жалпы алғанда, өнімділіктің төмендеуімен қатар жүрді. Экономикалық талдау өнімділіктің ауытқуы мен өндіріс рентабельділігі арасында тығыз өзара байланыс бар екенін анықтады. Өнімділіктің өзгерістері мен өнім бірлігінің өзіндік құнының өзгерістері арасында да теріс корреляциялық байланыс байқалды, ал өткізу бағаларымен байланыс әлсіздеу болды. Регрессиялық модель шілде айындағы жауын-шашын мөлшерін өнімділікті болжаудың статистикалық тұрғыдан мәнді факторы ретінде айқындады, ал қалған климаттық айнымалылардың ықпалы онша айқын болмады. Алынған нәтижелер бидай өндірісінің экономикалық тиімділігін бағалау кезінде климаттық жағдайларға байланысты өнімділіктің өзгермелілігін ескеру қажеттігін көрсетеді. Ұсынылған модельдеу тәсілін өнімділікті алдын ала болжауға, өндірістік жоспарлауды ақпаратпен қамтамасыз етуге және ауыл шаруашылығындағы климаттық тәуекелдерді бағалауға пайдалануға болады. Зерттеу нәтижелері бидай өнімділігі мен шілде айындағы жауын-шашын мөлшері арасында ең айқын оң байланыс байқалатынын, ал жазғы ауа температурасының жоғарылауы жалпы алғанда өнімділіктің төмендеуімен қатар жүретінін көрсетті.

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ЭКОНОМИЧЕСКАЯ ЭФФЕКТИВНОСТЬ ПРОИЗВОДСТВА ПШЕНИЦЫ И ПРОГНОЗИРОВАНИЕ ЕЁ УРОЖАЙНОСТИ НА ОСНОВЕ КЛИМАТИЧЕСКИХ ФАКТОРОВ

Аннотация

Климатическая изменчивость оказывает влияние на производство пшеницы в Северном Казахстане, где сельскохозяйственные предприятия сталкиваются со значительными колебаниями урожайности зерновых культур и экономических результатов. В статье исследуются взаимосвязи между климатическими изменениями, урожайностью пшеницы и экономическими показателями производства и выращивания зерна пшеницы в Костанайской области. Особое внимание уделено роли атмосферных осадков и температуры воздуха в формировании урожайности. Данное исследования также предусматривает разработку регрессионной модели прогнозирования урожайности пшеницы при различных климатических условиях. Исследование основано на многолетних наблюдениях за сезонными осадками, температурой воздуха, урожайностью пшеницы, себестоимостью её производства, ценами реализации и рентабельностью. Для выявления взаимосвязей между рассматриваемыми переменными применены корреляционный анализ и

множественная регрессия. Стационарность временных рядов проверялась с использованием расширенного теста Дики-Фуллера, что позволило разграничить краткосрочные экономические взаимосвязи и долгосрочные изменения номинальных показателей. Результаты исследования показали, что наиболее выраженная положительная связь с урожайностью пшеницы наблюдается для июльских осадков, тогда как повышение летних температур в целом сопровождается её снижением. Экономический анализ выявил тесную взаимосвязь между колебаниями урожайности и рентабельностью производства. Изменения урожайности также имеют отрицательную корреляционную связь с изменениями себестоимости единицы продукции, в то время как взаимосвязь с ценами реализации выражена слабее. Регрессионная модель определила июльские осадки как статистически значимый фактор прогнозирования урожайности, тогда как влияние остальных климатических переменных оказалось менее определённым. Полученные результаты свидетельствуют о необходимости учитывать климатически обусловленную изменчивость урожайности при оценке экономической эффективности производства пшеницы. Предложенный подход к моделированию может использоваться для предварительного прогнозирования урожайности, информационного обеспечения производственного планирования и оценки климатических рисков в сельском хозяйстве.