Volume XVII Number 2, 2025

Economic Analysis of Grain Product Metrics

Valentin Uteulin[1], Gulnar Lukhmanova[2], Olessya Lemechshenko[2], Kulzhamal Bleutayeva[2], Baglan Murzabekova[3]

[1] Akhmet Baitursynuly Kostanay Regional University, Republic of Kazakhstan

[2] Zhetysu University named after I. Zhansugurov, Taldykorgan, Republic of Kazakhstan

[3] Almaty Technological University, Republic of Kazakhstan

Abstract

The study aims to analyse the key factors affecting grain production in Kazakhstan to develop recommendations for improving the efficiency and sustainability of the agricultural sector. Statistical methods and econometric modelling techniques were used, including the least squares method with heteroscedasticity and autocorrelation robust errors and autoregression with external factors for time series analysis. These methods were used to estimate the impact of various internal and external factors on the gross grain harvest. The analysis demonstrated that grain yields depend on a variety of factors, such as innovations in agricultural technology, climatic conditions and economic policy. The identified factors were grouped with measurable indicators for each, which became the basis for building models. The study determined that the autoregressive model is more suitable for describing the impact on the dependent variable – grain harvest. The most influential indicators are yields and research and development costs. The results of the study can be used to adjust agricultural policy and strategies for agricultural development in Kazakhstan. Proposals for optimising land use and integrating modern agricultural technologies will increase productivity and reduce the impact of negative factors.

Keywords

Yield, sown area, gross harvest, fertiliser, multiple regression model, food security.

Uteulin, V., Lukhmanova, G., Lemechshenko, O., Bleutayeva, K. and Murzabekova, B. (2025) "Economic Analysis of Grain Product Metrics", *AGRIS on-line Papers in Economics and Informatics*, Vol. 17, No. 2, pp. 109-123. ISSN 1804-1930. DOI 10.7160/aol.2025.170208.

Introduction

In recent years, the issues of food security and sustainability in the agricultural sector have gained increased significance at both national and global levels, particularly in emerging economies where agriculture plays a critical role in economic and social development. This is especially true for the Republic of Kazakhstan, which possesses substantial potential for increasing the production and export of grain crops, thereby strengthening its economy and enhancing its position in the global market. However, a noticeable knowledge gap exists regarding the specific economic indicators and factors influencing grain production efficiency within the country (Marmul et al., 2020; Serhiienko et al., 2023). As global climate change continues to pose challenges, there is an urgent need to develop adaptive agricultural strategies that mitigate risks and minimize yield losses, particularly concerning grain production. Furthermore, global economic trends, such as food price volatility and changing trade regulations, necessitate that Kazakhstan adopt flexible and innovative approaches to agricultural production (Lukhmanova et al., 2019a). Despite existing resources, the grain sector faces numerous challenges, including yield fluctuations and technological inadequacies (Kalenska, 2022).

Baidybekova et al. (2022) examined the economic development of Kazakhstan's agricultural sector, asserting that food security is achieved through self-sufficiency in domestic food production, complemented by imports. Their analysis for 2017-2021 underscored the necessity of measures to enhance agricultural sector efficiency and sustainability. While Kazakhstan is a major supplier in the global grain market (Lukhmanova et al., 2019b), the industry encounters various challenges that necessitate comprehensive analysis and strategic solutions. Wang et al. (2021a) emphasized the role of grain exports in maintaining the global food balance and national food security, discussing the impacts of global factors, including

COVID-19, on food prices and Kazakhstani grain export potential.

The exploration of economic aspects related to grain production in Kazakhstan is particularly pertinent amidst the globalization of food markets and the climatic changes affecting agriculture. Although Kazakhstani agriculture is a fundamental element of the national economy, providing food security and significant export opportunities, it still faces challenges like yield variability and the necessity for technological advancement. Zhanaltay (2023) identified pressing issues within the agricultural sector through an analysis of national key indicators, noting significant progress but also unresolved challenges, such as low investment levels and outdated agricultural technologies. Furthermore, Namazova and Wei (2020) highlighted Kazakhstan's status as a producer and exporter of high-quality wheat, investigating the causes of issues such as low productivity and the adverse effects of weather on grain yields. Their findings stressed the need for reforms, investment attraction, and the application of advanced technologies to bolster productivity and competitiveness in the global grain market. Yuksel et al. (2023) evaluated the economic efficiency of Kazakhstan's agro-industrial complex using econometric tools to assess the industry's impact on economic development and public investment in agriculture.

The research seeks to address the current state of grain production in Kazakhstan by identifying key factors influencing its efficiency and proposing strategies to enhance competitiveness. It is crucial to understand the interplay of internal and external factors affecting crop production and distribution, as well as to explore innovative solutions that can be implemented to improve the situation. While existing studies on the economics of grain production in various countries cover a range of topics, including sustainability and global economic impacts, Kazakhstan's unique natural and economic conditions necessitate a targeted analysis that incorporates both local specifics and broader challenges. This study aims to fill that gap by providing a comprehensive analysis of the key factors affecting grain production in Kazakhstan.

Materials and methods

In this study, two econometric models were employed to analyze grain production indicators in Kazakhstan. The selection of the Least Squares Regression (LSR) and Autoregressive Moving Average with Exogenous Variables (ARMAX) models was driven by their suitability for analyzing grain production trends. LSR provides a straightforward assessment of relationships between variables, while ARMAX accounts for time dependencies and external influences, making it more robust for forecasting. Key variables were chosen based on their relevance to grain production: gross grain harvest, yields, R&D expenditures, precipitation, fertilizer consumption, and pesticide use. These indicators capture economic, environmental, and technological factors affecting agriculture. Limitations include LSR's assumption of linearity and independence, which may not fully reflect real-world complexities, and ARMAX's requirement for stationarity, necessitating data transformations. Additionally, data constraints and the exclusion of some relevant factors, such as soil quality and extreme weather events, may impact results. Alternative approaches could include panel data models to account for regional variations or machine learning techniques to capture nonlinear interactions. Structural equation modeling might offer insights into causal relationships, while Bayesian methods could provide probabilistic forecasts. These approaches could enhance the robustness of future agricultural analyses.

Data for this analysis were collected from various reputable sources, including national agricultural statistics, government reports, and research publications. The dataset covered the period from 2004 to 2022, providing a comprehensive view of grain production trends in Kazakhstan. Key variables included the amount of arable land, grain yields, research and development costs, and environmental factors such as average annual precipitation and fertilizer consumption. Prior to analysis, the data underwent preprocessing to ensure quality and consistency. This involved handling missing values, normalizing data ranges, and conducting preliminary statistical tests to assess the suitability of the dataset for the chosen econometric models. The preprocessing steps were essential to eliminate noise and enhance the reliability of the model outcomes, thus allowing for a more accurate interpretation of the factors affecting grain production in the Republic of Kazakhstan.

The modelling used indicators reflecting the dynamics of environmental indicators of environmental monitoring and assessment, statistics on agriculture, forestry, hunting and fishing for 2004-2022. according to the Bureau of National

Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (2024a; 2024b):

- gross harvest of cereals, including rice, and legumes (in weight after cultivation);
- yields of cereals, including rice, and pulses;
- internal expenditures on research and development (R&D) by industry (agricultural sciences);
- average annual rainfall;
- volume of mineral fertiliser consumption per unit of sown area of agricultural land;
- consumption of organic fertilisers per unit of sown area of agricultural land;
- pesticide consumption per unit area of agricultural land.

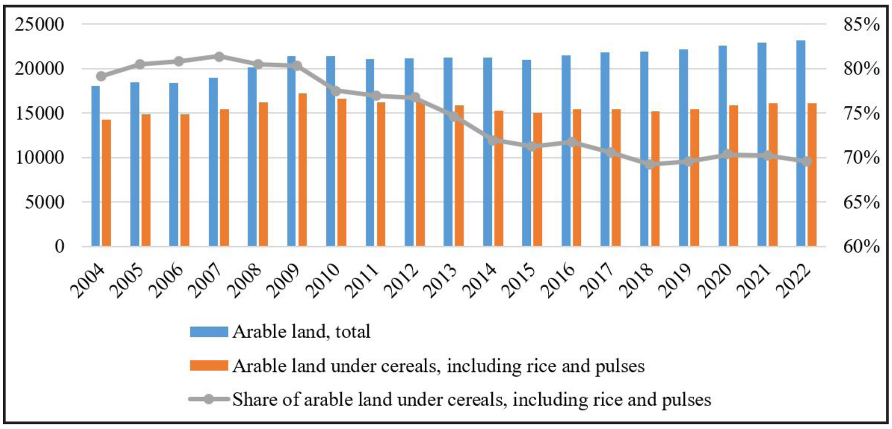
The limitation of the empirical data used for the modelling to 2022 is due to the lack of publicly available information on the values of environmental indicators of environmental monitoring and assessment. The complex methods employed in the study were used to form a sequence of actions necessary for the economic analysis of grain production indicators and to justify the expediency of choosing a model to explain the observed changes and forecasting.

Results and discussion

Assessment of individual indicators and grouping of factors affecting grain production in the Republic of Kazakhstan

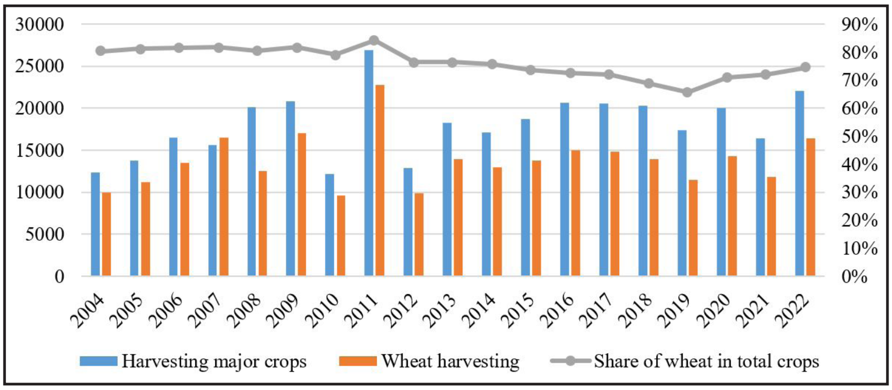
The economic analysis of grain production indicators involves the assessment of key indicators related to the amount of arable land, including both the total amount and the share of land under grain crops, which is important for studying the potential for grain production. The results of the analysis for 2004-2022 are shown in Figure 1.

The data shown in Figure 1 demonstrates that during 2004-2022, the share of arable land for grain in the total volume of grain production decreased by 9.59%. Figure 2 shows the growth rates of the harvest of major crops, including wheat, for 2004-2022, which was used to assess



Source: compiled by the authors based on the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (2024a)

Figure 1: Ratio of arable land under grain to total arable land in the Republic of Kazakhstan.



Source: compiled by the authors based on the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (2024a)

Figure 2: The ratio of wheat harvested to total crops harvested in the Republic of Kazakhstan.

the dynamics and efficiency of the agricultural sector of the Republic of Kazakhstan in the context of changing internal and external conditions.

According to the data presented, the share of wheat in the total crop harvest in the period from 2004 to 2022 ranged from 65.71% (in 2019) to 84.32% (in 2011). The information provided will form the basis for further analysis, where the interrelationships between the identified factors and grain production results will be assessed using modelling. This will not only determine the current state of the industry but also formulate reasonable proposals for optimisation and development. Table 1 shows the growth rates of indicators reflecting changes in the amount of arable land, harvested volume of major crops and wheat.

The dynamics of changes in the indicators characterising the volume of arable land compared to the base year 2004 shows an increase of 28.42% and 12.86% (for all arable land and arable land under grain, respectively). Every year during 2004-2022, the growth was positive compared to the base. At the same time, the total amount of arable land decreased in 2006, 2011, 2014 and 2015 (provided that the previous year was used as a comparison base), while for arable land metrics for grain, these years were 2006, 2010-2011, 2013-2015 and 2018. Thus, it is possible to draw an interim conclusion that the increase in arable land for grain, with the total growth from 14278 million hectares to 16114.4 million hectares, was 12.86%, which is significantly less than the change in arable land – 28.42%. Assessing the growth rates of the metrics reflecting the harvest of the main types of agricultural products and wheat harvest, significant fluctuations were noted. At the same time, in 2014, there was a decrease in metrics characterising both the size of arable land and the volume of harvested crops, which may indicate the presence of a correlation between the aforementioned indicators. The most significant changes in the growth rates of indicators characterising harvesting in general for the main types of agricultural products and for wheat were in 2008, 2010 and 2012. The absence of significant changes in the volume of cultivated land in these years suggests the need to address factors that have influenced the deterioration in overall performance. The economic analysis of grain product indicators was used to identify factors that affect the gross grain harvest, yields

Year	Growth rate of total arable land		The growth rate of arable land under cereals, including rice and pulses		Growth rate of harvest of major crops		Growth rate of wheat harvest	
	The chain method	Baseline method (2004 base)	The chain method	Baseline method (2004 base)	The chain method	Baseline method (2004 base)	The chain method	Baseline method (2004 base)
2005	102.27	102.27	103.95	103.95	111.37	111.37	112.69	112.69
2006	99.59	101.84	99.99	103.93	119.81	133.43	120.20	135.46
2007	103.19	105.09	103.96	108.05	121.96	162.74	122.33	165.71
2008	106.14	111.55	104.94	113.39	77.36	125.89	76.14	126.18
2009	106.49	118.79	106.28	120.51	133.72	168.34	136	171.60
2010	100.06	118.86	96.58	116.40	58.50	98.47	56.52	97
2011	98.34	116.89	97.59	113.60	221.26	217.88	235.85	228.76
2012	100.51	117.49	100.23	113.86	47.72	103.96	43.29	99.03
2013	100.38	117.93	97.67	111.20	141.71	147.33	141.66	140.29
2014	99.88	117.79	96.31	107.10	94.14	138.69	93.23	130.79
2015	98.96	116.56	97.98	104.93	108.80	150.90	105.77	138.34
2016	102.14	119.06	102.81	107.88	110.51	166.75	109.01	150.80
2017	101.71	121.09	100.01	107.90	99.76	166.35	98.78	148.97
2018	100.27	121.42	98.34	106.11	98.49	163.84	94.20	140.33
2019	101.08	122.73	101.63	107.83	85.97	140.85	82.13	115.24
2020	102.02	125.2	103.13	111.21	115.13	162.15	124.51	143.48
2021	101.52	127.11	101.45	112.82	81.61	132.34	82.86	118.89
2022	101.03	128.42	100.04	112.86	134.53	178.04	138.85	165.08

Source: compiled by the authors based on the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (2024a)

Table 1: Results of the analysis of indicators reflecting changes in the amount of arable land, harvested volume of major crops and wheat, %.

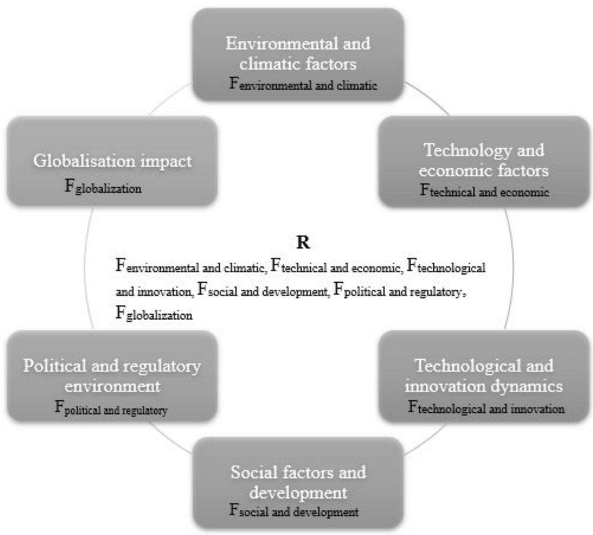
and other metrics. Table 2 summarises the groups of factors that are most relevant in the analysis of grain product performance. Notably, the list of factors and indicators can be expanded depending on the research objectives, but the presented grouping of factors provided a comprehensive image of the need to address a wide range of indicators for the parameter being assessed.

Table 2 provides a clearer picture of the measurable indicators associated with each factor, facilitating a more accurate quantitative analysis of their impact on grain production in Kazakhstan. It can be used as a basis for the development of econometric models that will allow for analysis, forecasting results and justification of policy decisions by including specific measurable variables. The interrelation of factors affecting grain production in Kazakhstan is shown in Figure 3,

Group of factors	Factor	Indicator	Unit of measurement
Environmental and climatic factors	Temperature fluctuations	Average annual temperature change	°C
	Precipitation	Average annual precipitation	mm
	Extreme weather events	Frequency of extreme weather events	Quantity/year
	Soil quality	Organic matter content	%
		Soil pH level	pH
		Degree of erosion	1000 ha
Technology and economic factors	Resource costs	Average cost of mineral fertilisers per hectare	Tenge/ha
		Average cost of organic fertilisers per hectare	Tenge/ha
	R&D investments	Domestic R&D expenses in the agricultural sciences	million tenge
Technological and innovation dynamics	New technologies	Percentage of land used for precision farming	%
	Innovations	Share of use of GM seeds	%
Social factors and development	Access to resources	Share of the population with access to education and healthcare services	%
Political and regulatory environment	Government support and subsidies	Amount of subsidies in the agricultural sector	million tenge
Globalisation impact	Global market trends	World grain/cereal price index	Index
	Currency fluctuations	National currency exchange rate against USD	Tenge/USD

Source: compiled by the authors

Table 2: Grouping of factors influencing the grain market of Kazakhstan.



Note: R – resultant indicator reflecting the dependence of grain production on a set of factors.
Source: compiled by the authors

Figure 3: Modelling logic of the external factor dependence of grain production.

including the dependence of the resulting indicator R for each of the groups shown in Table 2.

Following the objectives of the study, the identification of key productivity drivers and the development of recommendations for improving the efficiency of grain production in the Republic of Kazakhstan necessitates the construction of a model that, based on indicators reflecting the impact of previously identified factors, will allow to assess each of the parameters included in the model.

Modelling as a tool for analysing grain product performance

In the process of studying the indicators of grain products of the Republic of Kazakhstan, modelling allows not only to analyse current data and time series but also to predict future changes and assess the impact of various factors on economic efficiency. In the context of grain production, the models identify key drivers affecting gross yields, analyse profitability and formulate strategies for sustainable development. Two models were built in this study:

1. LSR-error-based HAC, which addresses distortions in the data caused by heteroscedasticity and autocorrelation. This regression model provides a more accurate assessment of the impact of various variables on the dependent variable, gross grain harvest (Gross_harvest).
2. The ARMAX model, integrating both autoregressive and external variables, is a powerful tool for analysing time series in grain production. The use of this model is appropriate when analysing relationships in data where time dependencies and external influences have a significant impact on the resulting indicator.

The LSR model was built in Gretlusing observations for 2004-2022. (T=19) (Tables 3 and 4).

	Coefficient	Statistical error	z	p-value
const	-4823.19	10532.8	-0.4579	0.647
Productivity_of_grains	1683.42	39.4184	42.71	<0.0001***
Internal_R_D_costs_by_industry	0.0645573	0.0278887	2.315	0.0206**
Average_annual_precipitation	-0.400898	2.60307	-0.154	0.8776
Volume_of_consumption_of_mineral_fertilizers	37.7981	93.8673	0.4027	0.6872
Consumption_of_organic_fertilizers	-36.4074	41.6326	-0.8745	0.3818
Consumption_of_pesticides	-161.773	1429.04	-0.1132	0.9099
Combined_water_and_wind_erosion	14.8686	54.2984	0.2738	0.7842

Source: compiled by the authors using the Gretltoolkit based on the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (2024a; 2024b)

Table 3: Results of the LSR regression model for the analysis of grain harvest in the Republic of Kazakhstan.

Indicator	Value
Average dependant Variable	18035.98
Square sum Remainder	8345247
R-square	0.967149
F (7.11)	438.2468
Log Plausibility	-150.3911
Crit. of Schwartz	324.3377
Parameter rho	0.55927
Statistical Deviation of Dependent Variable	3756.712
Statistical Model Error	871.0102
Correction R-square	0.946244
P-value (F)	1.46e-12
Crit. Akaike	316.7822
Crit. Hannan-Quinn	318.0609
Statistical Durbin-Watson	0.866984

Source: compiled by the authors using the Gretltoolkit based on the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (2024a; 2024b)

Table 4: Statistical indicators and quality assessments of the LSR model.

According to Table 3, the constant is statistically insignificant (p>0.05), which indicates that when all independent variables are zero, the predicted value of the dependent variable Gross_harvest is not statistically different from zero. The variable Productivity_of_grains is statistically significant and has a positive effect on the variable Gross_harvest. Its increase by one unit will result in an increase in Gross_harvest by 1683.42 units. Research and development costs (Internal_R_D_costs_by_industry) also have a statistically significant positive impact on Gross_harvest. The remaining variables (Average_annual_precipitation, Volume_of_consumption_of_mineral_fertilisers, Consumption_of_organic_fertilisers, Consumption_of_pesticides, Combined_water_and_wind_erosion) are not statistically significant (p>0.05), which indicates that they have no statistically significant effect on Gross_harvest in this model. To conclude on the quality of the model, the next step is to conduct a heteroscedasticity assessment. The results of White's test for heteroscedasticity assessed whether the model has an uneven scatter of residuals depending on the values of the independent variables (Table 5). For this purpose, the squares of the residuals u2 are used as the dependent variable.

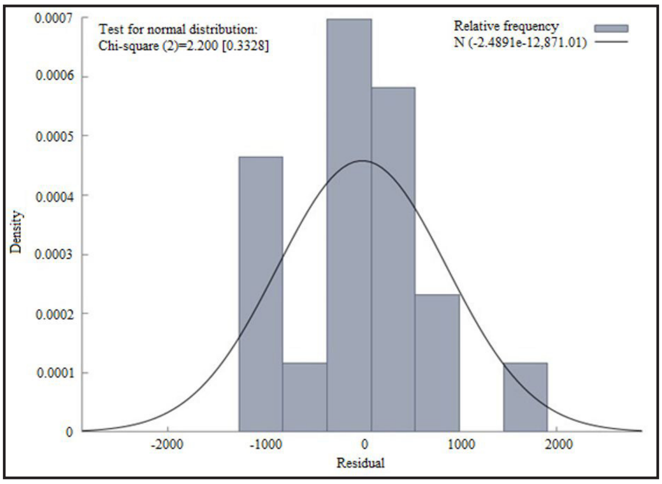
The test results show that the coefficients of all variables (initial and their squares) are not statistically significant (p>0.05). This indicates that there is no systematic change in the variance of the residuals depending on the values of these variables. The test statistic TR2 is 13.191, with a p-value of 0.511526 using a Chi-square distribution with 14 degrees of freedom. This p-value indicates that there is no reason to reject the null hypothesis of homoscedasticity (absence of heteroscedasticity). According to the results of the White test, it is possible to conclude that there is no significant evidence of heteroscedasticity in the model residuals. This is a good sign since heteroscedasticity can cause inefficient estimates of standard errors and, as a result, to incorrect conclusions about the statistical significance of the coefficients. Thus, it is possible to assume that the model adequately describes the data in terms of the stability of the variance of the residuals. The results of the assessment of the normality of the residual distribution are shown in Figure 4.

According to the data obtained, the average balance is close to 0 (-2.48914e-12), which is a positive characteristic of the model. The standard deviation is 871.01, which indicates the dispersion of the residuals relative to their mean. Most of the residuals are in the range of -360.14 to 546.16, with the main concentration around -133.57 to 319.59. This demonstrates that most residuals do not deviate significantly from the mean. The test of the normality of the residuals (using the Chi-square test) shows that the p-value is 0.33279, which is higher than the standard threshold

	Coefficient	Statistical error	t-statistics	p-value
const	-2.22167e+09	3.43572e+09	-0.6466	0.5531
Productivityofgr~	-2.37046e+06	3.40050e+06	-0.6971	0.5241
InternalR_Dcosts~	1028.27	1548.44	0.6641	0.543
Averageannualpre~	89965.5	65251.2	1.379	0.2401
Volumeofconsumpt~	-301346	1.00917e+06	-0.2986	0.7801
Consumptionoforg~	-64806.9	678707	-0.09549	0.9285
Consumptionofpes~	4.54158e+06	1.53192e+07	0.2965	0.7816
Combinedwaterand~	2.29489e+07	3.54306e+07	0.6477	0.5525
sq_Productivityo~	93488	136562	0.6846	0.5312
sq_InternalR_Dco~	-0.0490078	0.0712331	-0.6880	0.5293
sq_Averageannual~	-120.26	92.445	-1.301	0.2632
sq_Volumeofconsu~	38470.2	95190.2	0.4041	0.7068
sq_Consumptionof~	-559.956	23250.5	-0.02408	0.9819
sq_Consumptionof~	-2.74128e+06	1.34873e+07	-0.2032	0.8489
sq_Combinedwater~	-59316.7	90874.5	-0.6527	0.5495
Uncorrected R-squared = 0.694274				
Test statistics: TR^2 = 13.191209				
p-value = P (Chi-square (14) > 13.191209) = 0.511526				

Source: compiled by the authors using the Gretltoolkit

Table 5. Results of White's test for heteroscedasticity for the LSR model (dependent variable: u^2).



Source: compiled by the authors using the Gretltoolkit

Figure 4: Estimation of normality of residuals distribution in the LSR model.

	Coefficient	Statistical error	t-statistics	p-value
const	17743.2	8997.68	1.972	0.0769
Productivityofgr~	12.9488	72.5999	0.1784	0.862
InternalR_Dcosts~	-0.00368316	0.0657731	-0.056	0.9564
Averageannualpre~	6.48583	4.1302	1.57	0.1474
Volumeofconsumpt~	81.9098	187.659	0.4365	0.6718
Consumptionoforg~	-13.5675	62.1881	-0.2182	0.8317
Consumptionofpes~	2024.36	1859.95	1.088	0.302
Combinedwaterand~	-105.411	49.2402	-2.141	0.058
uhat_1	1.01001	0.280529	3.6	0.0048
Uncorrected R-squared = 0.564511				
Test statistics: LMF = 12.962714				
p-value = P (F(1.1) > 12.9627) = 0.00484				
Alternative statistics: TR^2 = 10.725717				
p-value = P (Chi-squared (1) > 10.7257) = 0.00106				
Ljung-Box Q’ = 6.92461				
p-value = P (Chi-square (1) > 6.92461) = 0.0085				

Source: compiled by the authors using the Gretltoolkit

Table 6: Results of the Breusch-Godfrey test for first-order autocorrelation for the LSR model, using observations from 2004-2022 (T=19).

of 0.05. This means that there is no reason to reject the null hypothesis that the residuals are normally distributed. Consequently, it can be assumed that the residuals are normally distributed, which is an important prerequisite for statistical tests and confidence in the intervals in linear regression. To further analyse the quality of the model, the presence of autocorrelation was assessed since its presence can lead to a bias in the estimates of the standard errors of the coefficients, making statistical conclusions about them unreliable (Table 6 above). To detect the presence of autocorrelation in the model residuals, the Broich-Godfrey test was applied.

The analysis of the autocorrelation of the residuals using the Broich-Godfrey test was used to conclude that there is autocorrelation in the model residuals. This can be the result of dynamic dependencies not accounted for by the model or the presence of trends, seasonality or other time dependencies in the data. The presence of autocorrelation requires model adjustment, possibly by adding lags to the dependent variable or by using models specifically designed for time series. Moreover, the tests for heteroscedasticity and normality of the residuals showed that these problems were not present, which simplifies the process of modifying the model to account for autocorrelation only. Thus, the LSR model for analysing grain harvest shows that the main factors affecting the resulting indicator (Gross_harvest) are grain yields and research and development costs. To correct the shortcomings in the previous model (LSR with HAC errors) associated with the autocorrelation of the residuals, an ARMAX model was built in Gretlfor which observations from 2004-2022 were used. (T=19), the dependent variable is Gross_harvest, and the standard errors are calculated via Hessian (Tables 7-9).

The interpretation of the results suggests that the constant is not statistically significant (Tables 7 and 8). The autoregressive parameter (phi_1) shows that previous values of the variable have a positive impact on the current ones, albeit on the verge of statistical significance; the moving average parameter (theta_1) is a significant coefficient, indicating a strong influence of errors of the previous period on the current one. The Productivity_of_grains metric has a significant and positive coefficient, indicating that grain yields have a strong influence on Gross_harvest. Consumption_of_pesticides has a statistically significant coefficient, indicating a positive effect of pesticide consumption on Gross_harvest. Model characteristics: the R-squared value indicates that the model explains almost 99% of the variability in the dependent variable, which is a good result. The corrected R-squared (0.980826) is also high, given the number of parameters in the model. The log plausibility ratio, and information content criteria (Akaike, Schwartz, Hannan-Quinn) help assess the quality of the model concerning the number of parameters;

	Coefficient	Statistical error	z	p-value
const	2191.68	7517.58	0.2915	0.7706
phi_1	0.410903	0.221361	1.856	0.0634
theta_1	1	0.162993	6.135	<0.0001
Productivity_of_grains	1700.14	35.4587	47.95	<0.0001
Internal_R_D_costs_by_industry	0.0322136	0.0700613	0.4598	0.6457
Average_annual_precipitation	2.41336	2.0585	1.172	0.241
Volume_of_consumption_of mineral_fertilizers	-19.409	76.2072	-0.2547	0.799
Consumption_of_organic_fertilizers	-38.6374	55.3344	-0.6983	0.485
Consumption_of_pesticides	2306.04	928.42	2.484	0.013
Combined_water_and_wind_erosion	-28.4238	38.4502	-0.7392	0.4598

Source: compiled by the authors using the Gretltoolkit based on Environmental Indicators of environmental monitoring and assessment (2024) and Statistics of agriculture, forestry, hunting and fishing (2024)

Table 7: ARMAX model results for analysing grain harvest in the Republic of Kazakhstan.

Indicator	Value
Average dependant Variable	18035.98
Square sum Remainder	8345247
R-square	0.967149
F (7.11)	438.2468
Log Plausibility	-150.3911
Crit. of Schwartz	324.3377
Parameter rho	0.55927
Statistical Deviation of Dependent Variable	3756.712
Statistical Model Error	871.0102
Correction R-square	0.946244
P-value (F)	1.46e-12
Crit. Akaike	316.7822
Crit. Hannan-Quinn	318.0609
Statistical Durbin-Watson	0.866984

Source: compiled by the authors using the Gretltoolkit based on Environmental Indicators of environmental monitoring and assessment (2024) and Statistics of agriculture, forestry, hunting and fishing (2024)

Table 8: Statistical indicators and quality assessments of the ARMAX model.

the lower the value, the better the model in terms of the balance between complexity and quality. Thus, the ARMAX model proved to be effective in explaining the change in Gross_harvest, with high R-squared values and significant coefficients for the key predictors. The analysis of the normality of the ARMAX model's error distribution shows that the P-value (0.852673) is significantly higher than 0.05, indicating that there are no grounds to reject the null hypothesis that the errors are normally distributed (Figure 5). This is an indication that the model residuals do not deviate from the normality assumption, which is important for the credibility of the results of statistical tests conducted on the model coefficients.

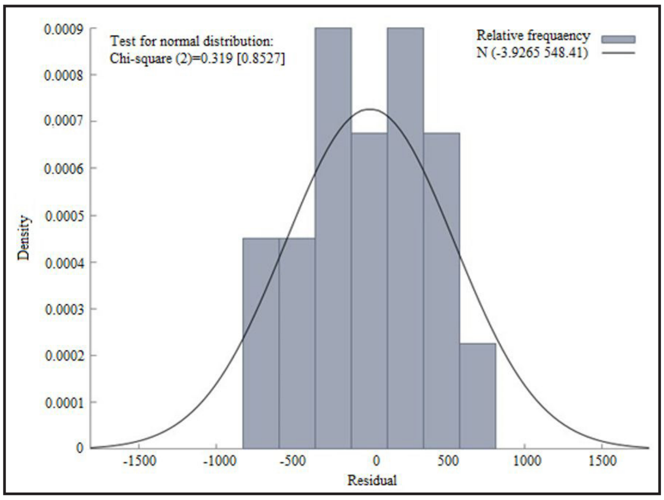
The distribution of the residuals shows a fairly symmetrical distribution around the mean value (-3.92649), with a relatively even distribution of frequencies across the intervals from the central part to the extreme values. Thus, the mean of the residuals is close to zero, which is typical for well-specified models. The standard deviation of the residuals (548.414) is moderate, indicating that the residuals are not significantly scattered around the mean. The shape of the distribution based on frequency analysis further confirms the conclusions of the normality test. An ARMAX model that is adequately specified in terms of the distribution of balances. The normal distribution of the residuals confirms that the model assumptions about the normality of the errors are met, which is relevant for estimating confidence intervals and performing other statistical tests. This suggests that the model can be used for reliable statistical inference and forecasting. The next step was to test for autocorrelation up to the order of 3 (Table 9).

Indicator	**Value**
Test statistics (Ljung-Box Q')	0.923505
Degrees of freedom	1
p-value	0.3366

Source: compiled by the authors using the Gretltoolkit

Table 9: Results of the Leung-Box test for the presence of autocorrelation of residuals.

The analysis of the results of the Leung-Box test indicates that there is no statistically significant autocorrelation of the residuals up to order 3, as the p-value (0.3366) is significantly higher than the threshold level (0.05). This indicates that the model residuals are time-independent at the lags considered, which is a desirable property in a regression model, especially if the goal is to make predictions. The autocorrelation test of the residuals shows that there is no significant autocorrelation in the ARMAX model residuals up to the third order, which in turn indicates that the model adequately accounts for the time dependence between observations and the assumptions of independence of the residuals are met. This increases confidence in the accuracy and reliability of statistical conclusions drawn from this model. As a result of the study, it is possible to conclude that the model of LSR with HAC errors is characterised by simplicity in application and interpretation and allows taking into account heteroscedasticity through the use of standard errors. At the same time, the identified problems with the autocorrelation of the residuals can lead to a bias in the estimates



Source: compiled by the authors using the Gretltoolkit

Figure 5: Estimation of normality of residuals distribution in ARMAX model.

and standard errors. Moreover, the LSR model does not address potential temporal dependencies between consecutive observations.

The ARMAX model addresses both autocorrelation and exogenous inputs, rendering it more flexible and adaptive to the data. The high R-squared and corrected R-squared values indicate that the model explains the variability of the data well. The ARMAX model demonstrated the absence of significant autocorrelation of the residuals, which indicates the correct specification of time dependencies. The residuals are normally distributed, which confirms the adequacy of the model assumptions and the possibility of applying traditional statistical methods. Each of the models used for the analysis has strengths and weaknesses. The choice between these models should be based on the specific goals of the analysis and the specifics of the data. However, for a more in-depth analysis that addresses time dependencies and ensures high accuracy and reliability of the results, the ARMAX model is preferable. This model is better suited for time series, where time dependencies play a key role. The two models together provide a comprehensive analytical toolkit that allows not only the estimation of past Analyses of the results of the Lewng-Box test indicate that there is no statistically significant autocorrelation of residuals up to order 3, as the p-value (0.3366) is significantly higher than the threshold level (0.05). This indicates that the model residuals are time-independent at the lags considered, which is a desirable property in a regression model, especially if the goal is to make predictions.

The autocorrelation test of the residuals shows that there is no significant autocorrelation in the ARMAX model residuals up to the third order, which in turn indicates that the model adequately accounts for the time dependence between observations and the assumptions of independence of the residuals are met. This increases confidence in the accuracy and reliability of statistical conclusions drawn from this model. As a result of the study, it is possible to conclude that the model of LSR with HAC errors is characterised by simplicity in application and interpretation and allows taking into account heteroscedasticity through the use of standard errors. At the same time, the identified problems with the autocorrelation of the residuals can lead to a bias in the estimates and standard errors. Moreover, the LSR model does not address potential temporal dependencies between consecutive observations. The ARMAX model addresses both autocorrelation and exogenous inputs, making it more flexible and adaptive to the data conditions. The high R-squared and corrected R-squared values indicate that the model explains the variability of the data well. The ARMAX model demonstrated the absence of significant autocorrelation of the residuals, which indicates the correct specification of time dependencies. The residuals are normally distributed, which confirms the adequacy of the model assumptions and the possibility of applying traditional statistical methods.

The analysis of the econometric models revealed important insights into the factors influencing grain production in Kazakhstan. In the LSR model, the coefficient for grain yields demonstrated a statistically significant positive effect on the gross grain harvest, indicating that an increase in productivity directly contributes to higher overall production. Specifically, the results suggested that for each unit increase in grain yield, there was an associated increase of approximately 1,683.42 units in the gross grain harvest. This underscores the critical importance of enhancing agricultural practices and investing in research and development to boost yield, thereby improving the country's grain output. In contrast, the ARMAX model provided a more nuanced understanding of the dynamics at play. The autoregressive parameter showed that past values of grain production positively influence current outputs, highlighting the relevance of historical performance in shaping present-day agricultural success. Additionally, the moving average component of the model indicated that previous errors significantly impact current results, emphasizing the need for continuous monitoring and adjustment of agricultural strategies. The ARMAX model's superior ability to incorporate both autoregressive elements and external influences makes it a preferred choice for analyzing grain production in this context. It effectively captures the complexities of time series data and allows for a more robust interpretation of how various factors interact over time.

Relevant examples from Kazakhstan provide deeper insights into the practical implications of the identified factors. For instance, in recent years, the adoption of modern agricultural technologies, such as precision farming and improved seed varieties, has led to notable increases in wheat yields. Regions like North Kazakhstan have successfully implemented these innovations, resulting in higher grain outputs and contributing significantly to the overall national harvest. Additionally, adverse climatic events, such as droughts, have been documented to impact grain production adversely, particularly in years when rainfall was significantly below average. These case studies highlight the importance of integrating technological advancements and adaptive strategies in agricultural practices to mitigate the effects of external challenges and enhance grain production sustainability in Kazakhstan.

The results of this study provide valuable insights into the dynamics of grain production in Kazakhstan, contributing to both the understanding of agricultural productivity and the development of strategies to enhance the sector's sustainability. As the analysis shows, factors such as grain yields and research and development investments significantly impact the overall production, while climatic conditions and agricultural practices also play key roles. The autoregressive and ARMAX models used in the study revealed that past yields have a considerable influence on present grain production. This finding aligns with previous research, such as Z. Zhanaltay's (2023) analysis of agricultural transformation in Kazakhstan, which highlighted the importance of long-term planning and policy adjustments to improve agricultural productivity. The observed challenges—low levels of investment and technological development —persist as major barriers to enhancing the efficiency of grain production. Our study confirms that without significant investment in modern technologies and R&D, the grain sector may struggle to fully capitalize on its export potential and adapt to changing climatic conditions.

Additionally, the analysis confirms that Kazakhstan's grain production faces external challenges such as fluctuating climatic conditions, poor infrastructure, and inefficient policies, consistent with the findings of Tokenova et al. (2019) and Razakova (2013). For example, Tokenova et al. pointed out that logistical issues in storage, transportation, and export are key limiting factors. In our study, the inclusion of variables such as average precipitation and soil erosion indicators further underscores the vulnerability of grain yields to environmental conditions. The ARMAX model, which accounts for these external variables, proved particularly useful in predicting grain harvest trends, confirming that climate factors like precipitation play a critical role. One of the key findings is the significant positive impact of R&D investments on grain production. This result supports the assertions by Mistry et al. (2017) and Wang et al. (2021b) that innovation and technological adoption are essential to maintaining competitive agricultural output. However, despite some government initiatives to support innovation, Kazakhstan still lags behind other countries in the adoption of advanced agricultural technologies. The findings suggest that a more focused approach to promoting technological innovation could yield substantial improvements in both grain yields and overall agricultural sustainability. Moreover, studies by Gaba et al. (2020) and Peltoniemi et al. (2021) suggest that biodiversity and sustainable land management practices are critical to long-term agricultural productivity. The fluctuations in yields observed in this study indicate that greater attention needs to be paid to sustainable farming methods, such as the use of organic fertilizers and biodiversity conservation strategies. Incorporating these practices could mitigate some of the risks associated with climate change and improve the resilience of the agricultural sector.

A comparative analysis of grain production in Kazakhstan and other major grain-producing countries, including Canada, the United States, Ukraine, Australia, and Argentina, reveals significant differences in agricultural strategies, climate conditions, and policy frameworks. Canada and the United States benefit from advanced technological innovations, including precision farming, genetically modified crops, and large-scale mechanization. These factors contribute to high yields despite challenging climatic conditions. In both countries, extensive government subsidies and insurance programs mitigate risks related to weather variability and global market fluctuations. Additionally, well-developed transportation infrastructure ensures efficient grain distribution domestically and internationally. Ukraine, with its fertile black soil and relatively favorable climate, maintains a strong position as a major grain exporter. However, logistical inefficiencies and political instability pose challenges to stable production and export capacities. Despite these limitations, Ukraine's agricultural sector has increasingly focused on technological modernization, including the adoption of high-yield seed varieties and digital farming practices. Australia presents a unique case due to its dry climate and dependence on water-efficient farming techniques. The country's grain industry has adapted through extensive research into drought-resistant crops and conservation agriculture, which maximizes productivity while minimizing water use. Government policies promoting sustainability and climate resilience have played a key role in supporting agricultural stability. Argentina, another leading grain producer, benefits from a combination of fertile land and a strong tradition of commercial farming. However, fluctuating economic policies, export restrictions, and inflation pose challenges to long-term agricultural growth. The country has invested heavily in biotechnology, particularly in soybean and wheat production, to maintain competitive yields and profitability. Kazakhstan, in comparison, faces unique constraints related to extreme climate variability, water shortages, and less-developed agricultural infrastructure. While the country has made strides in adopting sustainable farming practices and increasing investment in research and development, challenges remain in mechanization, irrigation efficiency, and supply chain logistics. Strengthening trade partnerships, improving transportation networks, and fostering innovation in climate adaptation strategies will be critical for enhancing Kazakhstan's competitiveness in the global grain market.

The findings also highlight the strategic importance of cereal exports, as pointed out by Wang et al. (2021a), particularly in the context of global food security. Kazakhstan's position as one of the largest grain exporters, coupled with the challenges posed by climate change and shifting international markets, requires a comprehensive export strategy that aligns with global demand while ensuring domestic food security (Jia & Zhen, 2021; Jumabayev et al., 2023; Zhenskhan et al., 2022). In conclusion, the results of this study underscore the need for a multi-faceted approach to improving grain production in Kazakhstan. Addressing both internal factors, such as investment in R&D and agricultural innovation, and external factors, such as climate resilience and infrastructure improvements, is essential for boosting productivity and ensuring the sector's sustainability. These findings provide a foundation for future policy recommendations aimed at increasing the competitiveness of Kazakhstan's grain sector while addressing the broader challenges posed by climate change and market fluctuations (Orazov et al., 2021; Zhupankhan et al., 2022; Karatayev et al., 2022; Barrett et al., 2017).

This research is relevant for determining how risk factors and the international economy affect the agricultural sector in Kazakhstan and should be addressed when developing strategies to improve agricultural productivity and sustainability, which is directly related to the modelling and data analysis conducted in the study. Thus, the studies emphasise the complexity and multidimensionality of the problems associated with grain production in the Republic of Kazakhstan, including the impact of climate change, water shortages, changes in the global food balance, and the introduction of innovations. The results obtained in this paper contribute to a deeper understanding of the processes that shape the current dynamics in agricultural production and emphasise the importance of integrating scientific approaches into the practice of agricultural management.

The findings have significant practical applications for policymakers and stakeholders in the agricultural sector. Recommendations include optimizing land use, integrating modern agricultural technologies, and improving sustainability practices to enhance productivity and mitigate negative externalities. These insights can inform agricultural policies aimed at ensuring long-term food security and economic resilience.

Conclusion

An economic analysis of the Kazakhstani agricultural sector has revealed significant changes in the volume and structure of arable land and the dynamics of grain yields in 2004-2022. The observed decline in the share of arable land under grain crops and changes in wheat harvest volumes point to the importance of a detailed analysis of internal and external factors affecting the country's agricultural sector.

The results of the study show that despite the overall decline in the share of arable land under grain, there are still significant fluctuations in the share of wheat in the total crop harvest. The paper proves that these fluctuations are related to various factors, a grouping of which and the presentation of measurable indicators for each group was used to study the mechanisms of their influence on grain production and provide a database for building econometric models. The study presents a logical model that illustrates the relationship between groups of factors (environmental and climatic; technical and economic; technological and innovation dynamics; social factors and development; political and regulatory environment; impact of globalisation) and their impact on grain production.

The study of grain products in Kazakhstan demonstrated how modelling serves as a tool for analysing the impact of various factors on the agro-industrial complex. Two key models, the LSR-error HAC and ARMAX, were used to estimate the impact of environmental, economic and technological factors on grain harvest.

The LSR model with HAC errors addressed the heteroscedasticity and autocorrelation of the data, which helped to improve the accuracy of the estimates. Yields and R&D expenditures were the main factors with a significant impact on gross grain harvest, highlighting the importance of innovation and improved agricultural technologies to increase efficiency. The ARMAX model, including autoregressive components and external variables, is more suitable for time series analysis, considering time dependencies and external influences on grain production. This determined the dynamics and main trends in grain production in detail. Thus, the use of the LSR and ARMAX models was used not only to analyse the current state of the grain industry but also to formulate sound strategic recommendations for improving the sustainability and development of grain production in Kazakhstan.

Corresponding author:
Gulnar Lukhmanova
Zhetysu University named after I. Zhansugurov
040009, 187A Zhansugurov Str., Taldykorgan, Republic of Kazakhstan
E-mail: gulnar.lukhmanova@gmail.com

References

[1] Baidybekova, S. K., Sauranbay, S. B. and Yermekbayeva, D. D. (2022) "Agricultural sector of the economy as the basis of the country's food security", *Bulletin of "Turan" University*, Vol. 4, No. 96, pp. 11-25. E-ISSN 2959-1236, ISSN 1562-2959. DOI 10.46914/1562-2959-2022-1-4-11-25.

[2] Barrett, T., Feola, G., Khusnitdinova, M. and Krylova, V. (2017) "Adapting agricultural water use to climate change in a post-Soviet context: Challenges and opportunities in Southeast Kazakhstan", *Human Ecology*, Vol. 45, No. 6, pp. 747-762. E-ISSN 1572-9915, ISSN 0300-7839. DOI 10.1007/s10745-017-9947-9.

[3] Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (2024a) "*Statistics of agriculture, forestry, hunting and fishery sectors*". [Online]. Available: https://stat.gov.kz/ru/industries/business-statistics/stat-forrest-village-hunt-fish/ [Accessed: Aug. 15, 2024]. (In Ruusian).

[4] Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (2024b) "Environmental indicators for environmental monitoring and assessment". [Online]. Available: https://stat.gov.kz/ru/ecologic-indicators/ [Accessed: Aug. 15, 2024]. (In Ruusian).

[5] Gaba, S., Cheviron, N., Perrot, T., Piutti, S., Gautier, J. L. and Bretagnolle, V. (2020) "Weeds enhance multifunctionality in arable lands in south-west of France", *Frontiers in Sustainable Food Systems*, Vol. 4, No. 71. ISSN 2571-581X. DOI 10.3389/fsufs.2020.00071.

[6] Jia, M. and Zhen, L. (2021) "Analysis of food production and consumption based on the Emergy method in Kazakhstan", *Foods*, Vol. 10, No. 7, p.1520. ISSN 2304-8158. DOI 10.3390/foods10071520.

[7] Jumabayev, S., Dulambayeva, R., Kussainova, L. and Yesmagambetov, D. (2023) "Approaches to assessing the food security of the regions of Kazakhstan in modern conditions", *Public Policy and Administration*, Vol. 22, No. 4, pp. 503-518. ISSN 2640-2688. DOI 10.13165/VPA-23-22-4-09.

[8] Kalenska, S. (2022) "Food security and innovative solutions in crop production", *Plant and Soil Science*, Vol. 13, No. 2, pp. 14-26. E-ISSN 2706-7696, ISSN 2706-7688. DOI 10.31548/agr.13(2).2022.14-26.

[9] Karatayev, M., Clarke, M., Salnikov, V., Bekseitova, R. and Nizamova, M. (2022) "Monitoring climate change, drought conditions and wheat production in Eurasia: The case study of Kazakhstan", *Heliyon*, Vol. 8, No. 1, p. e08660. E-ISSN 2405-8440. DOI 10.1016/j.heliyon.2021.e08660.

[10] Lukhmanova, G., Baisholanova, K., Shiganbayeva, N., Abenov, B., Sambetbayeva, A. and Gussenov, B. S. (2019a) "Innovative development of the agricultural sector of the Republic of Kazakhstan", *Espacios*, Vol. 40, No. 32, pp. 178-181. ISSN 0798-1015. [Online]. Available: https://www.revistaespacios.com/a19v40n32/a19v40n32p06.pdf [Accessed: July 20, 2024].

[11] Lukhmanova, G., Sartanova, N., Mezhov, S., Mishchenko, I., Mishchenko, I. and Bedelbayeva, A. (2019b) "Integration interaction of the EAEU countries as a factor to improve competitiveness in the agribusiness", *Journal of Advanced Research in Law and Economics*, Vol. 10, No. 6, pp. 1801-1806. ISSN. 2068-696X. [Online]. Available: https://journals.aserspublishing.eu/jarle/article/view/4954 [Accessed: July 20, 2024].

[12] Marmul, L., Levaieva, L. and Runcheva, N. (2020) "Investment in environmentalization and comprehensive programs for development of the grain industry", *University Economic Bulletin*, Vol. 15, No. 3, pp. 31-37. E-ISSN 2414-3774, ISSN 2306-546X. DOI 10.31470/2306-546X-2020-46-31-37.

[13] Mistry, M. N. and Wing, I. S. (2017) "Simulated vs. empirical weather responsiveness of crop yields: US evidence and implications for the agricultural impacts of climate change", *Environmental Research Letters*, Vol. 12, No. 7, p. 075007. ISSN 1748-9326. DOI 10.1088/1748-9326/aa788c.

[14] Namazova, A. S. and Wei, F. (2020) "Grain production overview of research in Kazakhstan", *Capital of Science*, Vol. 6, No. 23, pp. 119-128. E-ISSN 2658-6177. (In Russian).

[15] Orazov, A., Nadtochii, L., Bozymov, K., Muradova, M. and Zhumayeva, A. (2021) "Role of camel husbandry in food security of the Republic of Kazakhstan", *Agriculture*, Vol. 11, No. 7, p. 614. ISSN 2077-0472. DOI 10.3390/agriculture11070614.

[16] Peltoniemi, K., Velmala, S., Fritze, H., Lemola, R. and Pennanen, T. (2021) "Long-term impacts of organic and conventional farming on the soil microbiome in boreal arable soil", *European Journal of Soil Biology*, Vol. 104, p. 103314. ISSN 1164-5563. DOI 10.1016/j.ejsobi.2021.103314.

[17] Razakova, D. (2013) "Current trends and outlooks of the development of the Kazakhstan grain market", *World Applied Sciences Journal*, Vol. 25, No. 6, pp. 875-881. E-ISSN 1991-6426, ISSN 1818-4952. DOI 10.5829/idosi.wasj.2013.25.06.13357.

[18] Serhiienko, O., Tatar, M., Guryanova, L., Shapran, O. and Bril, M. (2023) "Improvement of Financial Instruments of the Agricultural Sector and Food Security Efficiency Increasing", *Economic Studies (Ikonomicheski Izsledvania)*, Vol. 32, No. 5, pp. 115-142. ISSN 0205-3292.

[19] Tokenova, S., Kadrinov, M. and Alpyssova, V. (2019) "Progress of grain production developmentin Kazakhstan and Mongolia", *IOP Conference Series: Earth and Environmental Science*, Vol. 341, No. 1, p. 012207. ISSN 2577-0640. DOI 10.1088/1755-1315/341/1/012207.

[20] Wang, Y., Huang, P., Khan, Z.A. and Wei, F. (2021a). "Potential of Kazakhstan's grain export trade", *Ciência Rural*, Vol. 52, No. 1, p. e20210199. ISSN 1678-4596. DOI 10.1590/0103-8478cr20210199.

[21] Wang, Z., Zhang, T., Tan, C., Xue, L., Bukovsky, M. and Qi, Z. (2021b) "Modeling impacts of climate change on crop yield and phosphorus loss in a subsurface drained field of Lake Erie region, Canada", *Agricultural Systems*, Vol. 190, p. 103110. ISSN 0308-521X. DOI 10.1016/j.agsy.2021.103110.

[22] Yuksel, K., Nursoy, M. and Zhumaxanova, K.M. (2023) "Assessment of the agro-industrial complex efficiency in the country's economy", *Bulletin of "Turan" University*, Vol. 97, No. 1, pp. 196-211. ISSN 1562-2959. DOI 10.46914/1562-2959-2023-1-1-196-211.

[23] Zhanaltay, Z. (2023) "Agricultural development of Kazakhstan", *Eurasian Research Journal*, Vol. 5, No. 4, pp. 45-58. ISSN 2519-2442. DOI 10.53277/2519-2442-2023.4-03.

[24] Zhenskhan, D., Pyagay, A., Bespayeva, R., Kadrinov, M., Omarkhanova, Z. and Tatikova, A. (2022) "The current state of food security in Kazakhstan, in the context of Eurasian economic union. Environmentally overview in the case of climate change's scenarios", *Journal of Environmental Management & Tourism*, Vol. 13, No. 5, pp. 1300-1310. E-ISSN 2068-7729. DOI 10.14505/jemt.v13.5(61).08.

[25] Zhupankhan, A., Tussupova, K. and Berndtsson, R. (2018) "Water in Kazakhstan, a key in Central Asian water management", *Hydrological Sciences Journal*, Vol. 63, No. 5, pp. 752-762. ISSN 2150-3435. DOI 10.1080/02626667.2018.1447111.