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5 PRODUCTION CLUSTER IN THE AGRO-INDUSTRIAL COMPLEX AS A FACTOR IN ENSURING FOOD SECURITY

ABSTRACT

The research focuses on the functioning of grain product cluster enterprises. The study addressed the growth rate and operational characteristics of grain product cluster enterprises.

Sustainable development of Kazakhstan's economic sectors and sectors requires the exploration and implementation of new, more efficient forms of production and business activities. Given the current complex socio-economic conditions in agricultural production, the grain product cluster is becoming one of the most in-demand sectors in the agro-industrial sector. Therefore, a priority area of national policy is to increase production volumes both to fully meet domestic demand and to increase exports. This approach requires the unification of efforts by all agricultural sector entities, coordination of activities, and a focus on achieving high end results.

One of the triggers for solving this problem is the integration of commodity producers, which allows for the unification of all links in the production cycle in the technological chain "raw material production – finished product production" within a single complex. A study of domestic and international experience shows that integrated entities such as grain product clusters achieve high levels of efficiency and competitiveness. The development of grain product cluster models and mechanisms, the modernization of agricultural and processing industries, and the selection of methods and tools that enhance agribusiness's responsiveness to innovative development require appropriate theoretical and methodological support, taking into account the specifics of production in each industry. Practical experience shows that, despite the intensification of integration processes in grain product clusters, inefficiencies and the disintegration of a number of such formations are occurring. This is largely due to the fact that, under the new economic conditions, the traditional mechanism of the grain product cluster in Kazakhstan's agro-industrial complex does not allow for the systematic implementation of large-scale innovation processes, limiting itself to minor (local) changes.

Successful implementation of projects to form and develop grain product clusters requires in-depth study, generalization, and systematization of the experience of using such a mechanism by both national and foreign companies that have achieved high results in this area. Currently, the grain product cluster remains in its early stages of development, largely due to the specific high-risk characteristics of its industries.

KEYWORDS

Assessment methodology, growth rate, integral indicator, optimization model, trends, development, food security, strategy, socio-economic status, influence, efficiency, grain, trend, trigger, function, location, result.

The special role of grain in the agricultural sector's commercial output is determined by its strategic importance as a staple food and a crucial — and for some livestock sectors, a crucial — feed component. Furthermore, the Republic of Kazakhstan, due to its inherent natural and other characteristics, has become a major grain producer. In the context of economic transformation, maintaining grain production and ensuring the rational use of its development potential is largely determined by the functioning of the grain product cluster.

Grain production in the republic has always been one of the most important characteristics of the country's economic independence and prosperity. This highly valuable commodity is strategic in nature, which determines significant state interest in grain production; on the other hand, it is the foundation for the development of the grain product cluster in the agricultural sector.

The key feature of the grain product cluster's functioning is the specific nature and purpose of the goods it processes, namely grain and grain products, and their high share in the national food consumption structure. Bread and grain products, as a vital and irreplaceable commodity, enjoy guaranteed demand from the population. They satisfy approximately a third of the population's daily food needs, up to 50% of the daily protein requirement, 30 to 50% of the required energy, up to 50–60% of B vitamins, and up to 80% of vitamin E. Moreover, grain protein, with its high nutritional value, is significantly cheaper than animal protein, which, to a certain extent, helps to combine the issues of quantity and quality into a single whole. Grain production is a special element of the grain product sub-complex. Grain crops occupy approximately half of the area under agricultural crops and decisively determine the level and pace of development not only of farming but of agricultural production as a whole. As the largest branch of agriculture, grain production forms the basis of the country's food supply and serves as the raw material base for the development of flour and cereal milling, feed milling, starch production, alcohol production, brewing, and other industries. Grain production is largely responsible for the employment of a significant portion of the population, as well as the sectoral, regional, and national economic efficiency of the agricultural sector [1].

Along with the social significance of grain as a valuable, essential, and everyday food product for the population, as well as the basis for livestock production, the financial aspect is also of considerable importance. Grain is one of the most reliable sources of income for commodity producers, giving them relative independence in the reproduction process. The strategic importance of grain in the country's food supply is also determined by significant export reserves, which can become a significant source of foreign exchange revenue for the national budget (**Table 5.1**).

The discrepancy between per capita grain production and consumption across the country, as well as the local nature of production of certain types of grain, necessitate the transportation of grain from one region to another. A key feature of grain, distinguishing it from other agricultural products, is its high transportability and suitability for long-term storage, allowing for the rapid implementation of long-distance interregional grain shipments.

In determining the principles of formation and operation of a grain product cluster, a methodological approach is adopted that views the cluster as a complex system of market relations through which the production structure spontaneously adapts to the volume and structure of social needs, distributing production factors among various industries [2]. Alternatively, a cluster can be conceptualized as a collection of markets of various types, interconnected by a common goal — ensuring the normal functioning of the reproduction process in the region. Thus, a grain product cluster is a geographically distinct, complex economic system comprising a set of commodity relations and connections between its entities, which include rural producers, enterprises and organizations involved in the storage, processing, and drying of grain, and its processing, as well as infrastructure facilities that facilitate the accelerated flow of materials, financial resources, and information.

Table 5.1 Grain requirements for the production of processed products

Name	Potential capacity of enterprises, tons	Domestic demand, tons	Required amount of grain for potential processing, tons	Required amount of grain for domestic consumption, tons	Required area for potential production, thousand hectares
Flour	5,139,550	1,800,000	7,342,214	2,580,000	6,440
Compound feed	2,418,750	2,665,700	2,845,588	3,136,117	2,496
Cereals	503,337	337,400	1,198,421	1,997,368	1,051
Alcohol, thousand dal	30,189	3,719	928,892	114,418	814
Total	–	–	12,315,115	7,827,903	10,801

The study examined the works of the following authors on assessing the effectiveness of grain product clusters: M. R. Hagerty [3], L. Kaufman, P. J. Rousseeuw [4], T. Hastie [5].

An analysis of the methods showed that the most probabilistic assessment model is possible using a non-stationary time series with a mathematical model that allows for the assessment of grain cluster development trends and its key characteristics. For this purpose, an algorithm was developed that applies the theoretical principles of modeling two-parameter monotonic functions. The created program automates the process of finding empirical approximating functions for the trend. The described algorithm uses the least-squares method and a theorem based on the general property of linear dependence of parameters in a class of functions. This program is capable of approximating trends not only for linear functions but also for nonlinear ones (e.g., quadratic, logarithmic, hyperbolic, exponential, and others).

This method for determining an empirical approximating function in the class of monotone two-parameter functions is more efficient than other methods, requiring less execution time.

A time series is a set of observations measured over specified temporal or spatial intervals and arranged chronologically. Examples of such series include annual demand for a commodity, weekly prices for a commodity, food production, etc. Different economists and statisticians define time series using different terms. Some of the definitions are given below:

– W. N. van Wieringen [6] describes a time series as a set of quantitative data arranged in the order of their occurrence;

– H. Morris [7] defines a time series as a set of statistical observations arranged chronologically;

– K. D. Patterson [8] considers a time series to be statistical data collected, recorded, or observed in successive increments;

– C. Y. Chen et al. [9] characterize a time series as a set of quantities relating to different periods of time or to variables such as steel production, per capita income, gross national product, tobacco prices, or the industrial production index;

– C. H. Meyers [10] defines a time series as a sequence of repeated measurements of a variable, made periodically over time;

– W. Z. Hirsch [11] describes a time series as a sequence of values of the same variable corresponding to successive points in time;

– S. Spiegel [12] defines a time series as a set of observations made at a specific time, usually at equal time intervals.

In time series analysis, special attention is paid to identifying patterns in their dynamics over a long period. The goal of statistics is to provide a characterization of changes in statistical indicators over time. How does a country's gross national product and national income change from year to year? What are the trends in increasing or decreasing unemployment and wages? Are there significant fluctuations in grain yields, and can a trend toward their increase be identified? These questions can only be answered using specialized statistical methods designed to analyze development and change over time, or, as is customary in statistics, to study dynamics. Studying patterns of change over time is a complex and labor-intensive research process, as any phenomenon under study is influenced by numerous factors acting in various directions.

In statistical analysis of dynamics, it is necessary to clearly distinguish between two main elements – trend and variability – in order to provide a quantitative characterization of each using specific indicators.

To construct a classical mathematical model of a time series, its components must be analyzed. These components include the trend or tendency, periodic fluctuations, and random fluctuations. In other words, this can be symbolically described as follows

$$y_t = f(T, P, E),$$

where y_t represents the level of the time series, i.e., the value of a specific indicator at time t; T denotes the trend or tendency that determines the underlying dynamics of the series over a significant time interval; P represents periodic fluctuations that exhibit a similar pattern of development over specific periods of time, associated with seasons. In other words, these are deviations from the mean that occur periodically and are characterized by seasonality; E denotes random fluctuations, which represent deviations from the mean of the series at specific points in time and are caused by external factors.

Obviously, not all time series have the same set of components. For example, the stationary series mentioned earlier in the introduction is described as follows

$$y_t = \underline{y} + E.$$

In other words, the time series depends on the mean value of the level, i.e., the mathematical expectation $\underline{y}$, which remains unchanged and is constant over the entire time interval. Furthermore, the series depends on random fluctuations or a random component, which can be expressed as $E = y_t - \underline{y}$.

However, most time series are characterized by non-stationarity and can be described as follows

$$y_t = f(t) + E,$$

where the function $f(t) = T$ represents a time dependence describing the patterns of changes in the levels of the time series over the entire time interval under consideration; in other words, it is a trend. In contrast, E represents random fluctuations [13].

Functions describing a trend can be divided into two groups:

1. The first group includes monotonic functions and functions that do not exhibit limiting growth. In other words, these functions continue to grow over time.

2. The second group, in contrast, exhibits limiting growth, or in other words, reaches a saturation level.

To more accurately identify the type of function describing a trend, the following preparatory steps are carried out:

1. Identifying the type of time series to determine its components. An assessment is made of whether the time series is stationary, consisting only of random fluctuations and a mean, or non-stationary with a trend or periodicity, or both.

2. Given that periodic and random fluctuations are not considered, excess noise is removed using smoothing methods.

To determine the trend of stationarity or non-stationarity in a time series, methods for identifying the type of time series are used.

The following methods are used to achieve this goal.

Before selecting a model for a time series trend, it is important to establish the presence of a trend in the series. If a time series follows a trend, the levels of the series are correlated with each other, meaning that each subsequent level depends on the previous one. This relationship between the values of the series is known as the autocorrelation of the series levels. The following formula is used to measure the degree of autocorrelation

$$r_{y_t - y_{t-\tau}} = \frac{\underline{y_t y_{t-\tau}} - \underline{y_t}\,\underline{y_{t-\tau}}}{\sigma_{y_t}\sigma_{y_{t-\tau}}},$$

where

$$\underline{y_t y_{t-\tau}} = \frac{\sum_{t=\tau+1}^{n} y_t y_{t-\tau}}{n-\tau},$$

$$\underline{y_t} = \frac{\sum_{t=\tau+1}^{n} y_t}{n-\tau},$$

$$\underline{y_{t-\tau}} = \frac{\sum_{t=\tau+1}^{n} y_{t-\tau}}{n-\tau}.$$

τ is the magnitude of the time shift and takes values as natural numbers. For $\tau = 1$, the first-order autocorrelation coefficient is calculated, $\tau = 2$ the second, and so on. This coefficient is between -1 and +1, and the closer it is to them, the more pronounced the correlation is. Thus, if the time series has a trend, the absolute value of the first-order coefficient will be close to one. Whereas for a stationary time series with small fluctuations in levels, this coefficient will be close to zero. For further shifts $\tau = 2, 3, \ldots$, the periodicity of the time series is studied, namely, the period of oscillations, which is equal to the shift at which the coefficient is closest to ±1. For example, a monotonically increasing or decreasing time series will have a positive correlation coefficient close to one; however, the greater the magnitude of the shift, the further it will move away from one [14]. Thus, if the time series has a trend, the absolute value of the first-order autocorrelation coefficient will be close to one.

5.1 DEVELOPMENT TRENDS AND ANALYSIS OF THE GRAIN PRODUCT CLUSTER

The regional grain product cluster is based on its territorial isolation and close ties between enterprises from various industries within the cluster, including those involved in the production of the final product. Participants in the regional grain product cluster include: agricultural enterprises; agricultural machinery enterprises; food processing enterprises; integrated agro-industrial complexes (corporations); consulting organizations; research institutes; educational institutions; government agencies; and financial institutions. The cluster core may include enterprises specializing in grain production, storage, and processing, around which infrastructure organizations are concentrated. The regional cluster was formed in three stages: the preliminary stage, during which the clustering potential is determined and a program for implementing cluster projects is developed; the main stage involves activating clustering processes in the region and determining the composition of participants in cluster schemes; and the final stage involves assessing the cluster's performance based on indicators characterizing economic development [15]. Cluster development as a tool for enhancing regional competitiveness and innovative economic development is a new approach to the country's regional development. The objectives of the Kazakhstan cluster initiative are to create conditions for maximizing Kazakhstan's competitive advantages in developing the non-resource sector of the economy by engaging private businesses in the industry.

The main grain producer in the Republic of Kazakhstan is the northern region: Akmola, Kostanay, and North Kazakhstan regions, which account for approximately 66% of the country's gross harvest.

The total area under grain crops is shown in **Table 5.2**.

Table 5.2 Dynamics of grain crop area in the Republic of Kazakhstan, 2020–2024, thousand hectares

Crop Name	2020	2021	2022	2023	2024	Specific gravity, 2024, %
Wheat	11,354.4	11,296.6	12,057.1	12,719.4	12,810.6	81.4
Barley	2,517.0	2,976.8	2,728.8	2,157.5	2,175.6	13.8
Buckwheat	95.8	67.5	55.1	87.1	119.9	0.8
Grain corn	150.1	156.3	162.8	188.7	188.4	1.2
Rye	21.5	21.2	23.9	43.9	34.3	0.2
Oats	235.2	243.5	228.9	202	197.9	1.3
Millet	43.4	50.9	50.5	38.2	37.4	0.2
Sorghum (dzhugara)	3	8.3	7.8	9	17.4	0.1
Corn mixture	86.4	91.8	85.9	69.6	61.3	0.4
Triticale	1.5	0.8	1.6	5.6	6.3	0.04
Rice	101.5	102.0	102.3	99.6	87.9	0.6
Total grains	14,609.8	15,015.7	15,504.7	15,620.6	15,737	100

Source: Office for National Statistics [16, 17]

Analyzing **Table 5.2**, the dynamics of sown areas of grain crops in the republic of Kazakhstan, wheat in 2018 amounted to 11,354.4 thousand hectares, and in 2022 it increased to 12,810.6 thousand hectares, which is an increase of 81.4% of the share, also showed an increase in grain crops buckwheat from 95.8 thousand hectares to 119.9 thousand hectares, grain corn 150.1 thousand hectares to 188.4 thousand hectares, rye 21.5 thousand hectares to 34.3 thousand hectares, sorghum (dzhugara) 3 thousand hectares to 17.4 thousand hectares, triticale 1.5 thousand hectares to 6.3 thousand hectares.

The area sown to barley decreased from 2,517,000 hectares in 2018 to 2,175,600 hectares in 2018, accounting for 13.8% of the total. Oats, millet, mixed cereals, and rice also saw their area sown to decrease by 0.6% to 1.3%.

In 2024, wheat will account for the largest share of grain sown area across all farm categories in the the Republic of Kazakhstan (81.4%), followed by barley (13.8%), followed by other crops, which range from 0.1% to 1.3%.

Fig. 5.1 shows the share of grain crop area across all farm categories. In 2022, wheat (81.4%) accounted for the largest share of grain sown area across all farm categories in the republic, followed by barley (13.8%), followed by other crops, which ranged from 0.1% to 1.3%. **Table 5.3** shows the dynamics of grain crops by farm category.

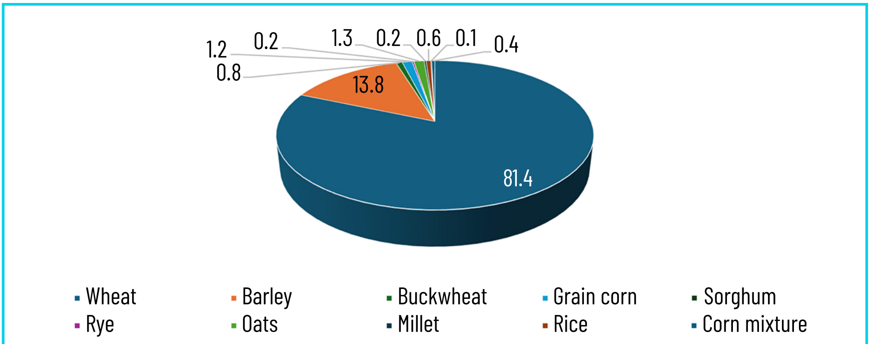

Fig. 5.1 Proportion of grain crop acreage in all farm categories in the republic of Kazakhstan in 2024, %

Table 5.3 Dynamics of grain crop acreage by farm category in the Republic of Kazakhstan, 2020–2024, thousand hectares

Category of farms	2020	2021	2022	2023	2024	2024/2020, %	2024/2023, %
1	2	3	4	5	6	7	8
Wheat							
All categories of farms	11,354.4	11,296.6	12,057.1	12,719.4	12,810.6	112.8	100.7
Agricultural enterprises	7,685.1	7,516.6	7,998.9	8,443.8	8,525.7	110.9	101.0
Individual entrepreneurs and peasant (farm) households	3,669.3	3,780.1	4,058.1	4,275.6	4,284.8	116.8	100.2
Barley							
All categories of farms	2,517.0	2,976.8	2,728.8	2,157.5	2,175.6	86.4	100.8
Agricultural enterprises	1,330.7	1,632.4	1,463.7	1,100.3	1,141.9	85.8	103.8
Individual entrepreneurs and peasant (farm) households	1,186.3	1,344.4	1,265.1	1,057.2	1,033.7	87.1	97.8
Buckwheat							
All categories of farms	95.8	67.5	55.1	87.1	119.9	125.2	137.7
Agricultural enterprises	38.7	24.9	26.9	47.2	61.5	158.9	130.3
Individual entrepreneurs and peasant (farm) households	57.1	42.6	28.2	39.9	58.4	102.3	146.4
Grain corn							
All categories of farms	150.1	156.3	162.8	188.7	188.4	125.5	99.8

Continuation of Table 5.3

1	2	3	4	5	6	7	8
Agricultural enterprises	30.4	36.3	35.7	54.6	60.5	199.0	110.8
Individual entrepreneurs and peasant (farm) households	113.8	114.7	122	128.9	122.9	108.0	95.3
Households of the population	5.9	5.3	5.2	5.2	5	84.7	96.2
Rye							
All categories of farms	21.5	21.2	23.9	43.9	34.3	159.5	78.1
Agricultural enterprises	7.6	7.1	10.1	25.3	22.9	301.3	90.5
Individual entrepreneurs and peasant (farm) households	13.9	14.1	13.8	18.5	11.3	81.3	61.1
Oats							
All categories of farms	235.2	243.5	228.9	202	197.9	84.1	98.0
Agricultural enterprises	152.5	161.7	151.3	134.6	128.8	84.5	95.7
Individual entrepreneurs and peasant (farm) households	82.7	81.7	77.4	67.4	69.1	83.6	102.5
Households of the population	-	0.1	0.2	-	-	-	-
Millet							
All categories of farms	43.4	50.9	50.5	38.2	37.4	86.2	97.9
Agricultural enterprises	20.0	22.4	26.5	18.0	18.3	91.5	101.7
Individual entrepreneurs and peasant (farm) households	22.8	28.1	23.5	19.8	18.5	81.1	93.4
Households of the population	0.6	0.4	0.5	0.4	0.6	100.0	150.0
Sorghum (dzhugara)							
All categories of farms	3	8.3	7.8	9	17.4	580.0	193.3
Agricultural enterprises	1.9	3.1	3.5	4.5	10.8	568.4	240.0
Individual entrepreneurs and peasant (farm) households	1.1	5.1	4.3	4.5	6.6	600.0	146.7
Corn mixture							
All categories of farms	86.4	91.8	85.9	69.6	61.3	70.9	88.1
Agricultural enterprises	53.3	61.5	57	43.1	46.9	88.0	108.8

Continuation of Table 5.3

1	2	3	4	5	6	7	8
Individual entrepreneurs and peasant (farm) households	33.1	30.3	28.9	26.5	14.4	43.5	54.3
Triticale (wheat-rye hybrid)							
All categories of farms	1.5	0.8	1.6	5.6	6.3	420.0	112.5
Agricultural enterprises	1.5	0.6	1.3	4.2	6.3	420.0	150.0
Individual entrepreneurs and peasant (farm) households	–	0.2	0.3	1.4	–	–	0.0
Rice							
All categories of farms	101.5	102.0	102.3	99.6	87.9	86.6	88.3
Agricultural enterprises	55.5	49.6	48.4	46	42.7	76.9	92.8
Individual entrepreneurs and peasant (farm) households	46	52.3	53.9	50.6	45.2	98.3	89.3
Total grains	14,609.8	15,015.7	15,504.7	15,620.6	15,737	–	–

Source: Bureau of National Statistics [16, 17]

As **Table 5.3** shows, the country's sown area is increasing, driven by rising investment and domestic market demand. A total of 128 million tenge in loans have been issued to 15 farms for spring sowing through JSC Agrarian Credit Corporation. An increase in the area under oilseed, forage, vegetable, and melon crops, as well as social crops such as buckwheat and sugar beet, is planned. At the same time, the area under monocultures and moisture-intensive crops such as wheat, rice, and cotton will be reduced. Furthermore, 97 investment projects in agricultural crops are planned. **Table 5.4** shows the sown area by region.

Table 5.4 Grain crop sown area by region in the Republic of Kazakhstan, 2024, thousand hectares

Region	Wheat	Barley	Buckwheat	Grain corn	Rye	Oats	Millet
1	2	3	4	5	6	7	8
Republic of Kazakhstan	12,810.6	2,175.7	119.9	188.4	34.3	197.9	37.4
Abay	257.4	50.3	3.0	4.2	4.4	4.5	–
Akmola	4,024.8	483.0	1.3	0.9	0.6	49.1	2.2
Aktobe	276.6	73.9	–	1.1	2.4	0.9	3.8

Continuation of Table 5.4

1	2	3	4	5	6	7	8
Almaty	38.9	83.2	–	50.2	0.3	1.3	–
Atyrau	–	0.0	–	–	–	0.2	–
West Kazakhstan	133.2	49.1	0.1	–	8.4	1.4	3.7
Zhambyl	153.9	211.7	–	18.5	–	–	0.4
Zhetysu	100.3	160.7	1.8	44.6	–	1.3	1.1
Karaganda	744.3	142.1	–	0.2	0.3	16.9	0.2
Kostanay	3,518.4	281.6	15.6	11.6	8.8	50.8	7.6
Kyzylorda	11.1	0.3	–	0.7	–	0.0	0.6
Pavlodar	693.4	118.7	75.7	3.8	2.8	25.4	14.4
North Kazakhstan	2,421.1	401.9	8.7	5.0	3.1	37.7	0.1
Turkestan	215.2	48.3	–	45.1	0	–	0.9
Ulytau	20.9	10.3	–	–	–	0.1	–
East Kazakhstan	189.1	59.7	13.7	2.6	3.1	8.2	2.4
Astana city	1.6	–	–	–	–	–	–
Almaty city	–	–	–	–	–	–	–
Shymkent city	10.4	0.9	–	0.1	–	–	–

Source: National Statistics Bureau [16, 17]

Next, let's examine grain production in the republic (**Table 5.5**).

Table 5.5 Grain production dynamics in the Republic of Kazakhstan, 2020–2024, thousand tons

Crop Name	2020	2021	2022	2023	2024	2024 /2020, %	2024 /2023, %
1	2	3	4	5	6	7	8
Wheat	13,944.1	11,451.7	14,258.0	11,814.1	16,404.5	138.9	75.5
Barley	3,971.2	3,830.1	3,659.3	2,366.8	3,287.2	138.9	15.1
Buckwheat	82.7	45.0	40.1	78.0	89.8	115.1	0.4
Grain corn	862.1	896	958.1	1,129.5	1,098	97.2	5.1
Rye	22.5	23.2	29.8	39.8	59.8	150.3	0.3
Oats	336.1	267.0	240.2	182.3	229.1	125.7	1.1

Continuation of Table 5.5

1	2	3	4	5	6	7	8
Millet	40.2	42.6	39.9	35.8	37.2	103.9	0.2
Sorghum (dzhugara)	2.3	6.6	4.2	4.5	18.6	413.3	0.1
Corn mixture	117.1	107.6	96.0	57.6	58.5	101.6	0.3
Triticale	2.0	1.6	2.7	3.9	8.2	210.3	0.0
Rice	482.9	560.7	556.8	503.8	431.4	85.6	2.0
Total grains	15,892.0	13,402.0	16,225.8	12,719.8	21,722.3	134.0	100

Table 5.5 shows the dynamics of grain production in the Republic of Kazakhstan by gross harvest. In 2024, the gross grain harvest increased by 34% compared to 2023, reaching 21,722.3 thousand tons, including wheat and barley – by 38.9% (16,404 thousand tons and 3,287.2 thousand tons), buckwheat – by 15.1% (89.8 thousand tons), rye – by 1.5 times (59.8 thousand tons), oats – by 25.7% (229.1 thousand tons), millet – by 3.9% (37.2 thousand tons), sorghum (dzhugara) by 4.1 times (18.6 thousand tons), corn mixture – by 1.6% (58.5 thousand tons), triticale – by 2.1 times (8.2 thousand tons), grain corn decreased – by 2.8% (1,098 thousand tons), rice – by 14.4% (431.4 thousand tons).

Wheat also occupies the largest share in the production of grain crops, 75.5% of the total volume of grain crops, then barley – 15.1%, grain corn – 5.1%, other grain crops vary from 0.1 to 2% (**Fig. 5.2**).

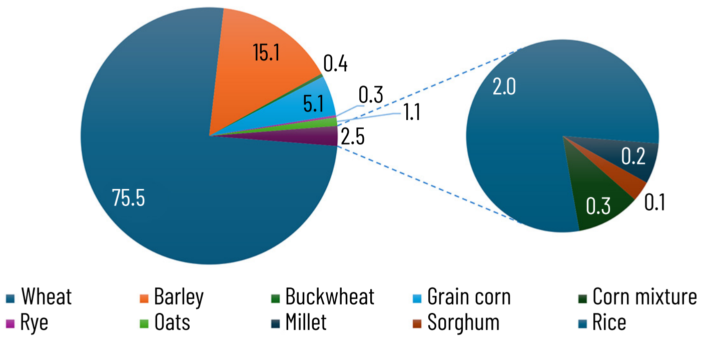

Fig. 5.2 Share of grain production in the republic of Kazakhstan in 2024, %

The gross wheat harvest in the country in 2024 increased by 17.6% compared to 2020 and 2021, and by 38.9% compared to 2023 (**Table 5.6**).

Table 5.6 Gross wheat harvest dynamics in all farm categories by region of the Republic of Kazakhstan for 2020–2024, thousand tons

Region	2020	2021	2022	2023	2024	2024 /2020, %	2024 /2023, %	Specific gravity, 2024, %
Akmola	3,994.8	3,293.6	4,127.6	3,355.0	4,616.3	115.6	137.6	28.1
Kostanay	3,923.6	2,330.6	3,455.0	2,587.3	4,809.2	122.6	185.9	29.3
North Kazakhstan	2,988.3	2,874.3	3,299.8	2,802.6	3,546.6	118.7	126.5	21.6

Note: compiled by the author based on data [16, 17]

Gross grain harvests generally meet the country's domestic needs and provide export potential. At the current stage of development of the country's grain product cluster, it is important to consider various organizational and economic factors to ensure consistent technological processes are not disrupted during grain production, processing, and sales, to avoid significant product losses, and ultimately to meet consumer demand.

At the same time, economic relations between enterprises should be based solely on mutually beneficial terms, excluding any elements of dictatorship by either the state or monopolistic enterprises consuming agricultural products and producing material and technical resources. As in any reproductive process, the full grain production cycle concludes with post-harvest processing, procurement, storage, and processing. Improving grain quality and, consequently, revenue from its sale, requires producers to complete a full range of technological operations within a short timeframe: cleaning, drying, correctly forming commercial batches of grain according to quality characteristics and varietal composition, and storing it for subsequent sale.

5.2 OPTIMIZATION MODEL OF GRAIN PRODUCTION

In today's agricultural economic environment, improving the economic efficiency and competitiveness of grain production is a crucial component of the successful functioning of the grain industry. The development of grain production creates an objective economic environment for improving the allocation of crop acreage, creating sustainable preconditions for increasing grain production volumes.

An analysis of the grain cluster's performance in the agro-industrial complex revealed that, in recent years, the development of grain production has not met the requirements of a rational organization of agricultural production. It is worth noting that, despite some positive trends that emerged in 2020–2024, the achieved level of grain production efficiency does not allow the grain product cluster to conduct expanded reproduction. In the grain production of most of the enterprises under consideration, the structure of grain crop acreage does not meet the requirements for the development of a rational farming system.

It goes without saying that improving the economic efficiency of grain production is impossible without the creation of a real mechanism to ensure the sustainable and balanced development of the grain product cluster [18]. Changes in the size of the grain industry inevitably lead to variations not only in individual crop and livestock sectors, but also in the entire sectoral structure of clusters as a whole. The vast majority of farms in the region do not produce only one type of agricultural product and can rationally combine the production of various crop and livestock products. And, of course, within the framework of the ongoing research in the grain product cluster, while adhering to scientifically sound agricultural practices, it is not possible to limit ourselves to the cultivation of grain and leguminous crops alone.

The most important factor determining the positive development of the grain product cluster is the formation of an optimal sectoral structure [19]. A rational sectoral structure represents a balanced relationship between the crop and livestock sectors that allows for the most complete and efficient use of available resources and the achievement of maximum economic benefits.

Global and domestic experience demonstrates that determining the optimal structure of the crop and livestock sectors is most effectively achieved using modeling methods. Modeling the industry structure helps grain-producing farms with limited production resources achieve increased grain production efficiency with minimal labor and cost expenditure.

Optimizing the parameters of agro-industrial complex sectors contributes to the effectiveness of management decisions aimed at increasing the gross output of grain farming, and also optimizes profit margins and profitability, which, in turn, positively impacts the social conditions of rural development [20].

Optimization of the industry structure of the grain product cluster is driven by the fact that the actual combination of individual parameters of crop production sectors and, accordingly, the production structure of grain, legumes, and forage crops, as well as the nutritional value of feed, directly determines the development of livestock sectors [21].

The following objectives were set during the model calculations:

1. Statistical processing of actual data on the components of the grain product cluster of the agro-industrial complex.

2. Approximation of a functional relationship smoothing the actual data.

The tasks are solved using probabilistic statistical research methods. This includes:

– describing changes in actual data through constructing a time series;

– obtaining an analytical form of two-parameter nonlinear regressions reflecting the main characteristics of the change dynamics;

– constructing statistical estimates of the validity of the dynamic relationship;

– testing hypotheses for the adequacy of the regression model of dynamics.

This approach allows for a more accurate assessment of the trends and development potential of the grain product cluster, which, in turn, can be used to develop effective development strategies for this sector [22]. **Table 5.7** contains a selection of the most significant indicators for assessing the production of material and technical resources.

As can be seen from **Table 5.7**, the maximum changes during the analyzed period occurred with the production of mowers, including mowers mounted on a tractor, not included in other groups. Their number increased 311 times in 2024 compared to 2015. But it is not possible to use this indicator, as well as the number of crawler tractors, in further calculations, since in some periods there is no data on them, and this will not allow building high-quality forecast models. Growth is also observed in all other indicators. For example, the number of agricultural and forestry tractors increased by 467 units, or 1.37 times, and grain harvesters – by 402 units, or 2.56 times.

Table 5.7 Production of material and technical resources for the grain product cluster in the Republic of Kazakhstan in 2015–2024

Indicator	Years, *i*									
	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Tractors for agriculture and forestry, pieces, $x_1(i)$	1,256	1,448	1,362	1,209	1,227	941	292	350	1,047	2,398
Seeders, planters and seedling machines, units, $x_2(i)$	152	170	206	206	6	19	185	236	223	197
Mowers, including mowers mounted on a tractor, not included in other groups, pieces, $x_3(i)$	–	15	–	1	24	93	69	155	238	383
Row harvesters, pieces, $x_4(i)$	278	342	221	286	356	297	401	457	512	1,078
Combine harvesters, pieces, $x_5(i)$	258	565	524	491	489	544	210	303	395	924
Crawler tractors, units, $x_6(i)$	3	4	6	–	1	–	–	–	–	–

Source: Bureau of National Statistics [16, 17]

Let's present the characteristics of changes in the indicators of the production of material and technical resources for the grain product sub-complex, expressed by the formula

$$\hat{x}_k(i) = \frac{100 x_k(i+1)}{x_k(i) + x_k(i+1)}, \tag{5.1}$$

where $x_k(i)$ and $x_k(i+1)$ – indicators of i and $i+1$ consecutive years when:
$x_1(i)$ – production quantity of agricultural and forestry tractors;
$x_2(i)$ – production quantity of seeders, planters and seedling machines;

$x_3(i)$ – production quantity of mowers, including mowers mounted on a tractor, not included in other groups;
$x_4(i)$ – production quantity of row headers;
$x_5(i)$ – quantity of production of grain harvesters.

According to (5.1), the dynamics of changes in the indicators of the production of material and technical resources for the grain product sub-complex can be presented in the form of **Tables 5.8** and **5.9**.

Table 5.8 Dynamics of changes in the production of material and technical resources for the grain product sub-complex in the Republic of Kazakhstan in 2016–2024

Years, *i*	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
$x_1(i)$	53.55	48.47	47.02	50.37	43.40	23.68	54.52	74.95	69.61
$x_2(i)$	52.80	54.79	50.00	2.83	76.00	90.69	56.06	48.58	46.90
$x_3(i)$	No data	No data	No data	96.00	79.49	42.59	69.20	60.56	61.67
$x_4(i)$	55.16	39.25	56.41	55.45	45.48	57.45	53.26	52.84	67.80
$x_5(i)$	68.65	48.12	48.37	49.90	52.66	27.85	59.06	56.59	70.05

Source: Bureau of National Statistics [16, 17]

Table 5.9 Grain production and grain processing products in the Republic of Kazakhstan in 2014–2024, thousands of tons

Years, *i*	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
Grain production, $y(i)$	12,864.8	18,231.1	17,162.2	18,673.7	20,634.4	20,585.1	20,273.7	17,428.6	20,065.3	16,375.9
Production of ego processing products	4,163.1	4,073.9	4,093.7	3,955.9	4,205.5	4,129.2	4,032.1	3,533.9	3,642.0	3,588.0

Source: Bureau of National Statistics [16, 17]

The materials of **Table 5.9** show that grain production in the Republic of Kazakhstan fluctuated greatly. Thus, in 2018, growth was noted – by 5366.3 thousand tons, or 1.42 times. In 2017 – a decrease, in 2018 – growth, which lasted for the next two years, then again a decrease, etc. If to compare grain production in 2024, then its volume was 16,375.9 thousand tons, which is 10,584.6 less than in 2015, or 1.65 times. The 2024 indicator ranks second from the bottom after 2015 in terms of the lowest volumes of grain production in the Republic of Kazakhstan for 2015–2024. The indicator of grain processing production also fluctuates in the analyzed period, but not so significantly. Its minimum volumes were recorded in 2022 – 3,533.9 thousand tons, and the maximum in 2019 – 4,205.5, which is 671.6 thousand tons less, or 1.19 times.

Let's present the characteristics of changes in grain production indicators, expressed by the formula

$$\hat{y}(i) = \frac{100y(i+1)}{y(i)+y(i+1)}, \tag{5.2}$$

where $y(i)$ and $y(i+1)$ — indicators of i and $i+1$ consecutive years.

According to (5.2), the dynamics of changes in grain production indicators can be presented in the form of **Table 5.10**.

Table 5.10 Dynamics of changes in the production of material and technical resources for the grain product subcomplex in the Republic of Kazakhstan in 2016–2024

Years, *i*	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
$\hat{y}(i)$	58.63	48.49	52.11	52.49	49.94	49.62	46.23	53.52	44.94

Thus, **Table 5.10** received processed statistical data describing the dynamics of changes in the production of material and technical resources for the grain product cluster in the Republic of Kazakhstan in 2016–2024.

The purpose of this stage is the analysis of paired regression dependencies of changes in grain production indicators $\hat{y}(i+1)$ of the $(i+1)$-th year, that is, changes in the indicators $\hat{x}_k(i)$ of material and technical resources for the grain product cluster of the i-th year, constructed according to the algorithm.

5.3 REGRESSION ANALYSIS OF THE DEPENDENCE OF GRAIN PRODUCTION INDICATORS ON TRACTOR PRODUCTION INDICATORS

Thus, the regression dependence of the change $f_1(i+1)$ in grain production on the change $\hat{x}_1(i)$ in the production of tractors for agriculture and forestry has the following form

$$f_1(i+1) = \frac{\hat{x}_1^2(i)}{0.02\hat{x}_1^2(i)+0.06}. \tag{5.3}$$

Differentiating the empirical function $f_1(i+1)$ on $\hat{x}_1(i)$, it is possible to obtain the elasticity coefficient

$$K_e = \frac{\partial f_1(i+1)}{f_1(i+1)\partial \hat{x}_1(i)}\hat{x}_1(i) = \frac{0.12}{0.02\hat{x}_1^2(i)+0.06}.$$

Based on the statistical data $\hat{x}_1(i)$ of **Table 5.2**, the elasticity coefficient K_e takes values less than 1. Therefore, if $\hat{x}_1(i)$ changes by 1%, $f_1(i+1)$ will change by less than 1%.

It is possible to present the data of **Table 5.2** in the form of a variation series. The graphical representation of the regression dependence can be presented in the form of **Fig. 5.3**.

From **Fig. 5.3** it follows that a 15-percent increase in the production of agricultural and forestry tractors contributes to the growth of grain production.

The coefficient of correlation and analytical values of paired regression is –0.0018, which indicates the fact of non-correlation. Non-correlation is explained by the absence of linear dependence. At the same time, the error relative to the method of averages is 0.238, that is, there are insignificant differences between the actual data and the values determined by formula (5.3).

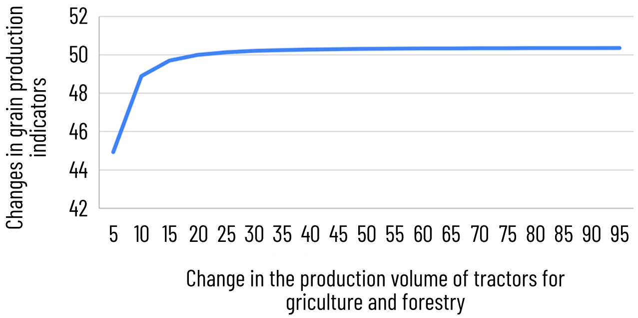

Fig. 5.3 Regression dependence of change in $f_1(i+1)$ of grain production on change $\hat{x}_1(i)$ in agricultural tractor production

Let's consider the differences $d_1(i)$ between the empirical values of $f_1(i+1)$, calculated according to formula (5.3), and actual grain production data $\hat{y}(i)$

$$d_1(i) = f_1(i) - \hat{y}(i),$$

presented in **Table 5.11**.

Table 5.11 Comparison of empirical values of $f_1(i)$ and actual grain production data

Years, *i*	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
$f_1(i)$	50.32	50.31	50.31	50.32	50.29	50.11	50.32	50.35	50.34
$\hat{y}(i)$	58.63	48.49	52.11	52.49	49.94	49.62	46.23	53.52	44.94
$d_1(i)$	-8.31	1.82	-1.80	-2.18	0.35	0.49	4.10	-3.17	5.41

To test the hypothesis for the adequacy of the proposed model, it is possible to assume that the difference $d_1(i)$ is a random variable obeying a Gaussian distribution with a mean of $\mu = -0.37$ and a standard deviation of $\sigma = 4.12$.

In other words, the probability that, for any indicator $\hat{x}_1(i)$, the probability of deviation of the empirical values of $f_1(i)$, calculated according to formula (5.3), from the actual grain production data $\hat{y}(i)$, is determined by the formula

$$P(d_1) = 1 - erf\left(\frac{-0.37 + d_1}{4.12}\right) + erf\left(\frac{-0.37 - d_1}{4.12}\right).$$

In a study based on Pearson's χ^2, due to the fact that the critical region for this statistic is right-sided: $[K_{kp}; +\infty)$, where the boundary value

$$K_{kp} = \chi^2(k - r - 1; \alpha).$$

According to the χ^2 distribution tables and the values of σ, $k = 5$, $r = 2$ (parameters μ and σ are estimated from the sample), this corresponds to $K_{kp}(0.05;\ 2) = 5.95$ for a significance level of $\alpha = 0.05$. Due to the fact that

$$K_{obs} = 0.123 < K_{kp}(0.05; 2),$$

this confirms the adequacy of the hypothesis for applying the proposed model.

5.4 REGRESSION ANALYSIS OF THE RELATIONSHIP BETWEEN GRAIN PRODUCTION INDICATORS AND THE PRODUCTION OF TRANSPLANTING EQUIPMENT

The regression relationship between the change in $f_2(i + 1)$ of grain production and the change $\hat{x}_2(i)$ in the production of seeders, planters, and transplanting machines is as follows

$$f_2(i+1) = \sqrt{\frac{\hat{x}_2(i)}{0.003\hat{x}_2(i) - 0.0008}}. \qquad (5.4)$$

Differentiating with respect to the empirical function $f_2(i + 1)$, it is possible to obtain the elasticity coefficient

$$K_e = \frac{\partial f_2(i+1)}{f_2(i+1)\partial \hat{x}_2(i)}\hat{x}_2(i) = \frac{44.44(0.003\hat{x}_2(i) - 0.0008)}{\left(\hat{x}_1(i) - 0.27\right)^2}.$$

Based on statistical data $\hat{x}_2(i)$, the elasticity coefficient K_e takes values less than 1. Therefore, for a 1% change in $\hat{x}_2(i)$, $f_2(i+1)$ will change by less than 1%.

By representing the data $\hat{x}_2(i)$ as a variation series, a graphical representation of the regression relationship can be shown in **Fig. 5.4**.

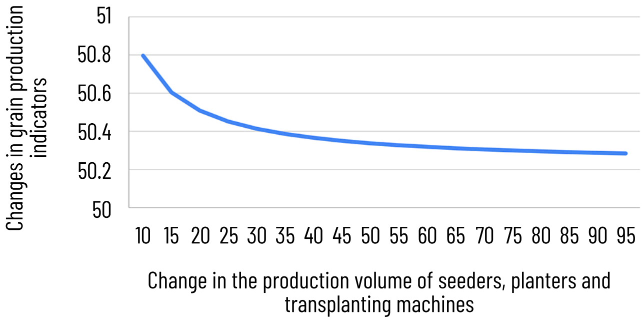

Fig. 5.4 Regression dependence of change in $f_2(i+1)$ in grain production on change $\hat{x}_2(i)$ in production of seeders, planters, and transplanters

From **Fig. 5.4**, it follows that changes in the production of seeders, planters, and transplanters do not contribute to growth in grain production.

The correlation coefficient and analytical values of the paired regression are -0.503, indicating a lack of correlation. This lack of correlation is explained by the lack of a linear relationship. Moreover, the error relative to the mean method is 0.373, indicating minor discrepancies between the actual data and the values determined by formula (5.4).

Let's consider the differences $d_2(i)$ between the empirical values of $f_2(i)$, calculated according to formula (5.3), and the actual grain production data $\hat{y}(i)$

$$d_2(i) = f_2(i) - \hat{y}(i),$$

presented in **Table 5.12**.

Table 5.12 Comparison of empirical values of $f_2(i)$ and actual grain production data

Years, *i*	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
$f_2(i)$	50.33	50.33	50.34	52.34	50.30	50.29	50.33	50.34	50.35
$\hat{y}(i)$	58.63	48.49	52.11	52.49	49.94	49.62	46.23	53.52	44.94
$d_2(i)$	-8.30	1.84	-1.77	-0.16	0.36	0.67	4.10	-3.18	5.41

To test the hypothesis for the adequacy of the proposed model, it is possible to assume that the difference $d_2(i)$ is a random variable obeying a Gaussian distribution with a mean of $\mu = -0.11$ and a standard deviation of $\sigma = 4.06$.

In other words, the probability that, for any indicator $\hat{x}_2(i)$, the probability of deviation of the empirical values of $f_2(i)$, calculated according to formula (5.4), from the actual grain production data $\hat{y}(i)$ is determined by the formula

$$P(d_2) = 1 - erf\left(\frac{-0.11 + d_2}{4.06}\right) + erf\left(\frac{-0.11 - d_2}{4.06}\right).$$

In a study based on Pearson's χ^2, due to the fact that the critical region for this statistic is right-sided: $[K_{kp}; +\infty)$, where the boundary value

$$K_{kp} = \chi^2(k - r - 1; \alpha).$$

According to the χ^2 distribution tables and the values of σ, $k = 5$, $r = 2$ (parameters μ and σ are estimated from the sample), this corresponds to $K_{kp}(0.05;2) = 5.95$ for a significance level of $\alpha = 0.05$. Due to the fact that

$$K_{obs} = 0.117 < K_{kp}(0.05;2),$$

this confirms the adequacy of the hypothesis for applying the proposed model.

5.5 REGRESSION ANALYSIS OF THE DEPENDENCE OF GRAIN PRODUCTION INDICATORS ON CHANGES IN MOWER PRODUCTION

The regression dependence of the change in $f_3(i+1)$ in grain production on the change in mower production, including tractor-mounted mowers not included in other groupings, is as follows

$$f_3(i+1) = \sqrt{\frac{1}{0.002\hat{x}_3(i) + 0.004}}. \qquad (5.5)$$

Differentiating the empirical function $f_3(i+1)$ with respect to $\hat{x}_3(i)$, it is possible to obtain the elasticity coefficient

$$K_e = \frac{\partial f_3(i+1)}{f_3(i+1)\partial \hat{x}_2(i)} \hat{x}_3(i).$$

Based on statistical data $\hat{x}_3(i)$, the elasticity coefficient K_e takes values less than 1. Therefore, with a 1% change in $\hat{x}_3(i)$, $f_3(i+1)$ will change by less than 1%.

By representing the data $\hat{x}_3(i)$ as a variation series, a graphical representation of the regression dependence can be shown in **Fig. 5.5**.

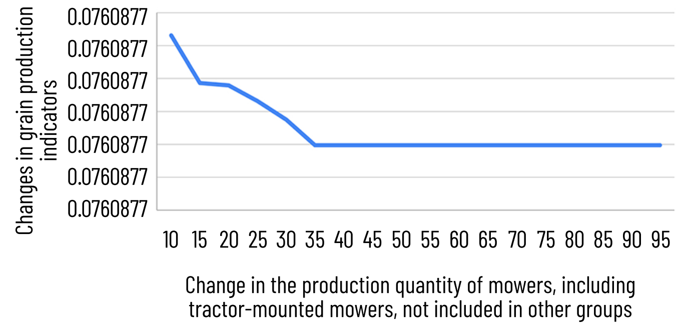

Fig. 5.5 Regression dependence of change in $f_3(i+1)$ of grain production on change $\hat{x}_3(i)$ in mower production, including tractor-mounted mowers not included in other groupings

Fig. 5.5 shows that the change in mower production, including tractor-mounted mowers not included in other groupings, is 0.603.

The correlation coefficient and analytical values of the paired regression are 0.603, indicating a lack of correlation. This lack of correlation is explained by the lack of a linear relationship. Moreover, the margin of error relative to the mean method is 1.88, indicating significant discrepancies between the actual data and the values determined by formula (5.5), which are explained by the small sample size of the observed indicator.

Let's consider the differences $d_3(i)$ between the empirical values of $f_3(i)$, calculated according to formula (5.3), and the actual grain production data $\hat{y}(i)$

$$d_3(i) = f_3(i) - \hat{y}(i),$$

presented in **Table 5.13**.

Table 5.13 Comparison of empirical values of $f_3(i)$ and actual grain production data

Years, *i*	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
$f_3(i)$	47.65	47.65	47.65	47.65	47.65	47.65
$\hat{y}(i)$	52.49	49.94	49.62	46.23	53.52	44.94
$d_3(i)$	-4.85	-2.29	-1.97	1.42	-5.87	2.71

To test the hypothesis for the adequacy of the proposed model, it is possible to assume that the difference $d_3(i)$ is a random variable obeying a Gaussian distribution with a mean of $\mu = -1.81$ and a standard deviation of $\sigma = 3.37$.

In other words, the probability that, for any indicator $\hat{x}_3(i)$, the probability of deviation of the empirical values of $f_3(i)$, calculated according to formula (5.5), from the actual grain production data $\hat{y}(i)$ is determined by the formula

$$P(d_3) = 1 - erf\left(\frac{-0.81 + d_3}{3.37}\right) + erf\left(\frac{-0.81 - d_3}{3.37}\right).$$

In a study based on Pearson's χ^2, due to the fact that the critical region for this statistic is right-sided: $[K_{kp}; +\infty)$, where the boundary value

$$K_{kp} = \chi^2(k - r - 1; \alpha).$$

According to the χ^2 distribution tables and the values of σ, $k = 5$, $r = 2$ (parameters μ and σ are estimated from the sample), this corresponds to $K_{kp}(0.05;\ 2) = 5.95$ for a significance level of $\alpha = 0.05$. Due to the fact that

$$K_{obs} = 0.551 < K_{kp}(0.05; 2),$$

this confirms the adequacy of the hypothesis for applying the proposed model.

5.6 REGRESSION ANALYSIS OF THE DEPENDENCE OF CHANGES IN GRAIN PRODUCTION INDICATORS ON CHANGES IN ROW HEADER PRODUCTION INDICATORS

The regression dependence of changes in $f_4(i+1)$ in grain production on changes in $\hat{x}_4(i)$ of row header production is as follows

$$f_4(i+1) = \sqrt{\frac{1}{0.002\hat{x}_4(i) + 0.004}}. \tag{5.6}$$

Differentiating the empirical function $f_4(i+1)$ with respect to $\hat{x}_4(i)$, it is possible to obtain the elasticity coefficient

$$K_e = \frac{\partial f_4(i+1)}{f_4(i+1)\partial \hat{x}_4(i)} \hat{x}_4(i).$$

Based on statistical data $\hat{x}_4(i)$, the elasticity coefficient K_e takes values less than 1. Therefore, with a change in $\hat{x}_4(i)$ by 1%, $f_4(i+1)$ will change by less than 1%.

By representing the data $\hat{x}_4(i)$ as a variation series, a graphical representation of the regression dependence can be shown in **Fig. 5.6**.

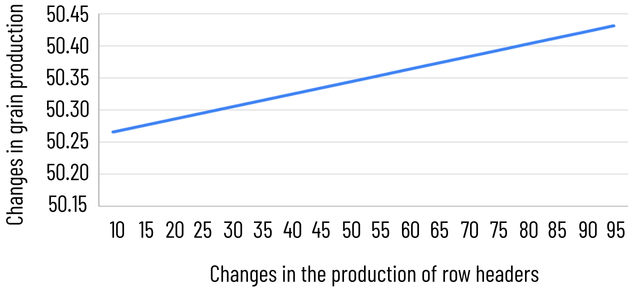

Fig. 5.6 Regression dependence of change in $f_4(i+1)$ of grain production on change $\hat{x}_4(i)$ in row header production

The correlation coefficient and analytical values of the paired regression are 0.11, indicating a lack of correlation. This lack of correlation is explained by the lack of a linear relationship. Moreover, the error relative to the average method is 1.29, indicating minor discrepancies between the actual data and the values determined by formula (5.6).

Let's consider the differences $d_4(i)$ between the empirical values of $f_4(i)$, calculated according to formula (5.6), and the actual grain production data $\hat{y}(i)$

$$d_4(i) = f_4(i) - \hat{y}(i),$$

presented in **Table 5.14**.

Table 5.14 Comparison of empirical values of $f_4(i)$ and actual grain production data

Years, *i*	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
$f_4(i)$	50.14	50.17	50.14	50.14	50.16	50.14	50.14	50.14	50.12
$\hat{y}(i)$	58.63	48.49	52.11	52.49	49.94	49.62	46.23	53.52	44.94
$d_4(i)$	-8.49	1.68	-1.97	-2.35	0.22	0.52	3.92	-3.37	5.18

To test the hypothesis for the adequacy of the proposed model, it is possible to assume that the difference $d_4(i)$ is a random variable obeying a Gaussian distribution with a mean of $\mu = -0.52$ and a standard deviation of $\sigma = 4.12$.

In other words, the probability that, for any indicator $\hat{x}_4(i)$, the probability of deviation of the empirical values of $f_4(i)$, calculated according to formula (5.6), from the actual grain production data $\hat{y}(i)$ is determined by the formula

$$P\left(\left|d\right|>d_0\right)=1-erf\left(\frac{-0.52+d_0}{4.12}\right)+erf\left(\frac{-0.52-d_0}{4.12}\right).$$

When studying using the Pearson criterion, due to the fact that the critical region for this statistic is right-sided: $[K_{kp};+\infty)$, where the boundary value

$$K_{kp}=\chi^2(k-r-1;\alpha).$$

According to the χ^2 distribution tables and the values of σ, $k=5$, $r=2$ (parameters μ and σ are estimated from the sample), this corresponds to $K_{kp}(0.05;2)=5.95$ for a significance level of $\alpha=0.05$. Due to the fact that

$$K_{obs}=0.134<K_{kp}(0.05;2),$$

this confirms the adequacy of the hypothesis for applying the proposed model.

5.7 REGRESSION ANALYSIS OF THE DEPENDENCE OF CHANGES IN GRAIN PRODUCTION INDICATORS ON CHANGES IN COMBINE HARVESTER PRODUCTION INDICATORS

The regression dependence of changes in $f_5(i+1)$ in grain production on changes in $\hat{x}_5(i)$ of combine harvester production is as follows

$$\hat{y}(i+1)=\sqrt{\frac{1}{0.002\hat{x}_4(i)+0.004}}. \tag{5.7}$$

Differentiating with respect to the empirical function $f_5(i+1)$, it is possible to obtain the elasticity coefficient

$$K_e=\frac{\partial f_5(i+1)}{f_5(i+1)\partial\hat{x}_5(i)}\hat{x}_5(i).$$

Based on statistical data $\hat{x}_5(i)$, the elasticity coefficient K_e takes values less than 1. Therefore, with a 1% change in $\hat{x}_5(i)$, $f_5(i+1)$ will change by less than 1%.

By representing the data $\hat{x}_5(i)$ as a variation series, a graphical representation of the regression dependence can be shown in **Fig. 5.7**.

The correlation coefficient and analytical values of the paired regression are 0.11, indicating a lack of correlation. This lack of correlation is explained by the lack of a linear relationship. Moreover, the error relative to the average method is 0.308, indicating minor discrepancies between the actual data and the values determined by formula (5.6).

Let's consider the differences $d_5(i)$ between the empirical values of $f_5(i)$, calculated according to formula (5.7), and the actual grain production data $\hat{y}(i)$

$$d_5(i) = f_5(i) - \hat{y}(i),$$

presented in **Table 5.15**.

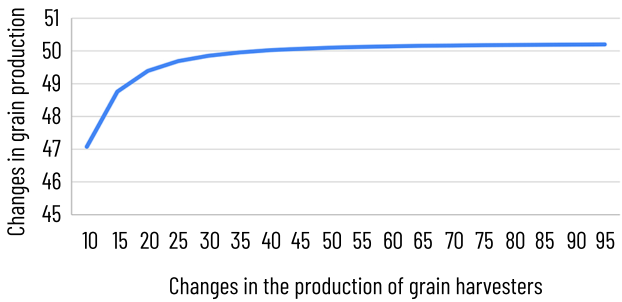

Fig. 5.7 Regression dependence of change in $f_5(i+1)$ of grain production on change in $\hat{x}_5(i)$ of combine harvester production

Table 5.15 Comparison of empirical values of $f_5(i)$ and actual grain production data

Years, *i*	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
$f_5(i)$	50.17	50.09	50.09	50.10	50.11	49.80	50.14	50.13	50.17
$\hat{y}(i)$	58.63	48.49	52.11	52.49	49.94	49.62	46.23	53.52	44.94
$d_5(i)$	-8.46	1.60	-2.02	-2.39	0.17	0.18	3.91	-3.39	5.23

To test the hypothesis for the adequacy of the proposed model, it is possible to assume that the difference $d_5(i)$ is a random variable obeying a Gaussian distribution with a mean of $\mu = -0.57$ and a standard deviation of $\sigma = 4.11$.

In other words, the probability that, for any indicator $\hat{x}_5(i)$, the probability of deviation of the empirical values of $f_5(i)$, calculated according to formula (5.7), from the actual grain production data $\hat{y}(i)$ is determined by the formula

$$P(d_5) = 1 - erf\left(\frac{-0.57 + d_5}{4.11}\right) + erf\left(\frac{-0.57 - d_5}{4.11}\right).$$

In a study based on the Pearson criterion, due to the fact that the critical region for this statistic is right-sided: $[K_{kp}; +\infty)$, where the boundary value

$$K_{kp} = \chi^2(k - r - 1; \alpha).$$

According to the χ^2 distribution tables and the values of σ, $k = 5$, $r = 2$ (parameters μ and σ are estimated from the sample), this corresponds to $K_{kp}(0.05;\ 2) = 5.95$ for a significance level of $\alpha = 0.05$. Due to the fact that

$$K_{obs} = 0.138 < K_{kp}(0.05; 2),$$

this confirms the adequacy of the hypothesis for applying the proposed model.

The obtained research results are based on analytical functions (5.3)–(5.7), representing paired nonlinear regressions of the dependencies of changes in grain production indicators on changes in indicators of material and technical resources for the grain products subcomplex in the Republic of Kazakhstan. Consequently, functions (5.3)–(5.7) determine trends and thereby determine a set of forecasts for changes in grain production. The presented methodological approach, which allows for the selection of the best approximating function from a class of monotonic two-parameter functions. The value of each of these functions at a point corresponding to the generalized average over argument x, according to economic and mathematical modeling for processing observation results, are united by a common property characterizing the logic of their combination to solve the problem.

Due to the combined influence of five indicators of material and technical resources:

– production of tractors for agriculture and forestry;
– production of seeders, planters, and transplanters;
– the production volume of mowers, including tractor-mounted mowers, not included in other groupings;
– the production volume of row reapers;
– the production volume of combine harvesters.

As a result, it is possible to obtain the $d_1(i)$, $d_2(i)$, $d_3(i)$, $d_4(i)$, $d_5(i)$ between the empirical values of $f_1(i)$, $f_2(i)$, $f_3(i)$, $f_4(i)$, $f_5(i)$, calculated according to formulas (5.3)–(5.7), and the actual grain production data $\hat{y}(i)$, presented in **Table 5.16**.

Table 5.16 Differences between the empirical values calculated according to formulas (5.3)–(5.7) and the actual grain production data

Years, *i*	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
$d_1(i)$	–8.31	1.82	–1.80	–2.18	0.35	0.49	4.10	–3.17	5.41
$d_2(i)$	–8.30	1.84	–1.77	–0.16	0.36	0.67	4.10	–3.18	5.41
$d_3(i)$	–	–	–	–4.85	–2.29	–1.97	1.42	–5.87	2.71
$d_4(i)$	–8.49	1.68	–1.97	–2.35	0.22	0.52	3.92	–3.37	5.18
$d_5(i)$	–8.46	1.60	–2.02	–2.39	0.17	0.18	3.91	–3.39	5.23

In the next step, to further refine the problem under study, it is proposed using forecasting tools. For this purpose, sixty-three graphs were created using Excel (for twenty-one indicators in three forecast scenarios: optimistic, probabilistic, and pessimistic). **Table 5.17** derives the equations for five indicators characterizing the performance of the grain product subcomplex, demonstrating the highest quality of forecast values (i.e., having the highest R^2 approximation coefficient).

Table 5.17 Forecast of changes in selected indicators of the performance of the grain product subcomplex in the Republic of Kazakhstan until 2026

Forecast variant	**Equation**	**Year**				**2026 to 2023, %**
		2023	**2024**	**2025**	**2026**	
1	**2**	**3**	**4**	**5**	**6**	**7**
		Row reapers, pieces				
Optimistic	$y = 4.2663x^2 + 2.3132x + 236.12$	795	890.3	952.1	1,013.5	127.5
Probability	$y = 3.3108x^2 + 12.056x + 218.76$		826.9	888.7	950.4	119.5
Pessimistic	$y = 2.3562x^2 + 21.963x + 200.78$		770.8	832.6	882.3	111.0
		Production of grain processing products, thousand tons				
Optimistic	$y = -1.6957x^2 - 29.492x + 4231.3$	3,588	3,665.2	3,610.2	3,555.7	99.1
Probability	$y = -2.7316x^2 - 18.788x + 4212$		3,604.1	3,544.3	3,484.6	97.1
Pessimistic	$y = -3.4089x^2 - 12.034x + 4200.2$		3,550.7	3,496.8	3,442.5	95.9
		Other industrial uses of grain, thousand tons				
Optimistic	$y = 4.711x^2 + 85.951x + 621.64$	2,053.8	2,380.2	2,526.3	2,672.1	130.1
Probability	$y = 2.4842x^2 + 108.66x + 581.15$		2,232.9	2,378.8	2,524.8	122.9
Pessimistic	$y = 0.2462x^2 + 131.51x + 540.4$		2,085.8	2,230.7	2,376.5	115.7

Continuation of Table 5.17

1	2	3	4	5	6	7
Granaries, units						
Optimistic	$y = 1.1241x^2 + 32.823x + 3726.1$	4,219	4,300.2	4,346.3	4,392.4	104.1
Probability	$y = 0.3716x^2 + 40.499x + 3712.4$		4,250.4	4,296.5	4,342.6	102.9
Pessimistic	$y = -0.2592x^2 + 46.82x + 3701.4$		4,202.5	4,252.7	4,302.9	102.0
Transportation by road, thousands of tons						
Optimistic	$y = 5.789x^2 – 158.54x + 1804.9$	1,081.6	747.2	671.6	596.0	55.1
Probability	$y = 4.5809x^2 – 146.17x + 1782.7$		670.0	592.6	515.1	47.6
Pessimistic	$y = 1813.1e\text{-}0.09x$		594.5	513.2	431.9	39.9
Potential personal consumption of grain by the population, thousands of tons						
Optimistic	$y = 0.0511x^2 + 3.9524x + 308.72$	353.2	366.2	370.3	374.4	106.0
Probability	$y = -0.0362x^2 + 4.8375x + 307.15$		360.1	364.4	368.7	104.4
Pessimistic	$y = -0.0877x^2 + 5.3532x + 306.25$		355.7	361.7	365.1	103.4

Based on the three forecast scenarios, the maximum growth is expected for other industrial grain use, at 130.1%. Even under the pessimistic forecast, this growth will be 115.7% in 2026 compared to 2023.

Overall, four indicators in **Table 5.16** show growth. The second-largest change is in the number of row headers, at 127.5% under the optimistic forecast. The largest decrease in the forecast value is for grain transportation by road, at 39.9% under the pessimistic forecast.

Fig. 5.8 and **5.9** show forecast graphs for the number of grain storage facilities and other industrial grain use. These indicators have the highest R^2 approximation coefficient. Thus, for the number of grain storage facilities in the Republic of Kazakhstan through 2026, R^2 has a maximum value under the optimistic forecast – 0.9838. Therefore, there is a high probability, approximately 98%, that this forecast will be realized. For other industrial uses of grain, R^2 also has a maximum value with an optimistic forecast – 0.9344, that is, with a 93% probability it will be realized.

For the remaining indicators in **Table 5.16**, the following forecasts will be fulfilled. For row harvesters and potential personal grain consumption, the optimistic forecast is expected, with an 84% and 85% probability of occurrence, respectively. For grain processing and road transportation, the pessimistic forecast is expected, with an 82% probability for both indicators. It is not possible to derive all sixty-three graphs used in this research paper due to space limitations.

However, it should be noted that for eleven of them, the approximation coefficient R^2 ranged from 0.9003 (the pessimistic forecast for other industrial grain use) to 0.9838 (the optimistic forecast for the number of grain storage facilities). R^2 is an indicator of forecast quality: the closer its value is to one, the higher the probability of fulfillment. For ten graphs, the approximation coefficient ranges from

0.8025 to 0.8702, and for nine, from 0.705 to 0.7932. This means that the reliability of the calculations for twenty-nine forecast scenarios ranges from 70 to 98%.

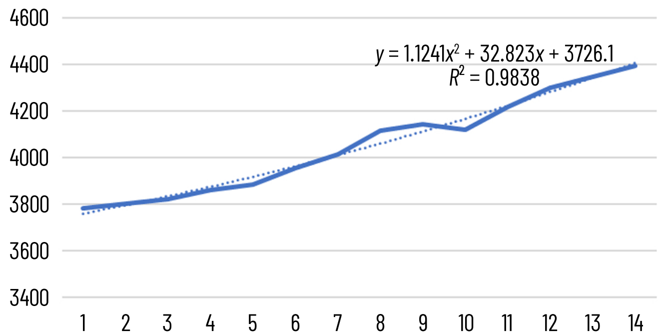

Fig. 5.8 Optimistic forecast for the number of grain storage facilities in the republic of Kazakhstan until 2026, units

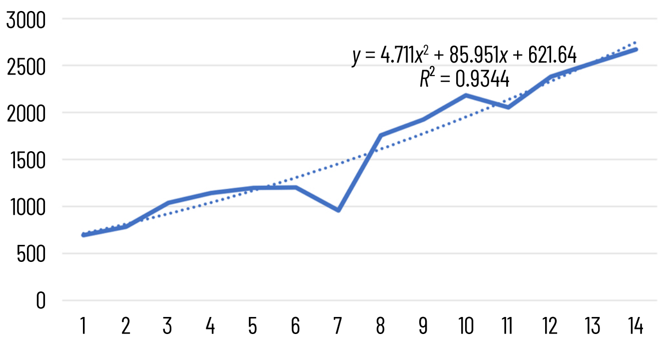

Fig. 5.9 Optimistic forecast for other industrial grain use in the republic of Kazakhstan until 2026, thousands of tons

The developed grain production optimization model, based on modern mathematical modeling technologies, represents an important and effective analytical method. Its advantage lies in its ability to provide a detailed and in-depth assessment of the grain product sector's performance, taking into account numerous key aspects.

This tool considers multiple components of the grain product cluster, such as:

1. Production of material and technical resources: assessing the availability of the necessary resources for the efficient operation of the entire system.

2. Grain cultivation and processing: analyzing the efficiency of grain production and processing processes, taking into account various needs, including food and technical ones.

3. Grain processing for various purposes: considering the diverse needs of grain processing, including its use in the food industry, technical processes, and feed production.

4. Storage systems: assessing the effectiveness of grain storage methods and systems that affect grain quality and availability.

5. Transportation: analyzing transport logistics and the efficiency of grain transportation from production sites to processing and sales points.

6. Sales processes: assessing strategies and methods for marketing grain and its processed products, including wholesale and retail sales.

The model not only provides a means of accurately assessing the current state of the grain product cluster but also has a powerful forecasting tool. This methodology not only provides a powerful means of accurately analyzing the current state of the grain product cluster but also has broad potential for forecasting future trends over various periods. Its versatility allows for its successful application across various industries and fields of activity, opening up new opportunities for additional research and analysis.

The efficient functioning of a grain product cluster is determined by the system of economic relations between its partners, through which the economic interests of enterprises are expressed.

The primary form of economic relations between producers, purchasers, and processors of agricultural products, as well as market participants involved in their sale and storage, is a business contract, which defines the mutual obligations of the parties during the performance of certain actions. Through this contract, agricultural enterprises regulate the volume of services provided and the mutual supply of materials, tariffs and prices for products and services, and determine penalties for violations of terms regarding volume, assortment, quality, and delivery times. Such relationships make it possible not only to avoid significant raw material losses and significantly reduce production and distribution costs, but also to improve the quality of the final product.

The complex problems of grain production in the Republic of Kazakhstan encompass the entire value chain. Addressing these interconnected issues requires the implementation of a range of measures and significant investment, which must be sustained over a long period. The effects of individual measures interact and should reinforce each other, ensuring increased efficiency in grain production. It is advisable to "switch on" self-organization mechanisms and actively utilize them. Therefore, to effectively implement a set of measures for grain production development, it is necessary to develop a Strategy in which the effects of previous measures are enhanced by the implementation of subsequent ones. In other words, a synergistic approach must be applied when developing such a Strategy.

The need to develop a Strategy is also driven by the following factors:

— the grain product cluster strives to produce only high-margin products, particularly wheat. Due to the spontaneous search for high-margin crops and imperfect industry regulation, overproduction of certain products occurs;

– the grain product cluster lacks the necessary methods and information to accurately determine the range and volume of agricultural crop production;

– state agricultural management bodies use ineffective forecasting and strategic marketing methods.

An important objective of state agricultural policy is to improve the quality and competitiveness of agricultural products and improve the well-being of rural residents.

The effective functioning of the grain product cluster is impossible without active government intervention. In the conditions of the functioning of a socially-oriented market economy, the possibility of state regulation is objectively determined by the nature of a mixed economy, which is characterized by a combination of competition, freedom of choice of buyer and seller with the need for the state to ensure equal "rules of the game" for all economic entities in the grain product cluster and social protection for the low-income part of the population.

Under these conditions, the development of economic relations in the grain product cluster is associated with the emergence of a number of contradictions:

– the desire of economic entities in the grain sector to achieve leadership positions, which leads to the replacement of perfect competition with monopoly, which is unacceptable in a market economy;

– the differentiation of economic actors, the ruin of some of them resulting from fierce competition, and the need for social protection for low-income groups;

– the limited regulatory impact of the market mechanism on the reproduction process, which fails to ensure environmental safety, the development of fundamental science, education, healthcare, etc.;

– the consolidation of capital for the development of scientific and technological progress, the implementation of its most significant achievements in the form of various innovations. The elimination of these contradictions cannot be achieved through market self-regulation. They require appropriate action from society, represented by the state.

Creating favorable conditions for the production and promotion of agricultural products on the market and providing after-sales service to customers contribute to increasing their competitiveness. It's clear that, given the same prices, the highest-quality product will be in greatest demand. Therefore, agro-industrial enterprises should pay significant attention to analyzing and assessing their competitiveness.

State support for the development of economic entities within the grain product cluster at the regional level serves two main functions: compensatory (reimbursement of a portion of acquisition and construction costs) and incentive (reimbursement of a portion of production costs).

Clusters are recognized as an important tool for promoting innovation, industrial development, competitiveness, and economic efficiency. The main goal of cluster support is to increase the competitiveness of cluster participants and the regional economies as a whole. The development of cluster initiatives in Kazakhstan can be divided into three stages. In the first stage, from 2006 to 2012, clusters were formed in priority economic sectors. In the second stage, from 2014 to 2020, territorial clusters were formed in the regions. As a cluster development operator, QazIndustry facilitated the consolidation of regional enterprise groups into territorial clusters to enhance the competitiveness of enterprises and their products.

Together with cluster participants, project pools were developed for further financing with the participation of both the state and the clusters. The third stage began in 2020 and is currently ongoing. This stage is characterized by the formation of a methodological and legal platform for the operation of territorial clusters and the provision of state incentives. In June of this year, the Rules for the Competitive Selection of Territorial Clusters, as well as the Rules for the Formation and Maintenance of a Register of Territorial Clusters, were approved within the framework of the Law "On Industrial Policy". The rules provide for co-financing of the costs of joint projects by territorial cluster participants, with up to 50% of costs (up to 30,000 MCI) reimbursed by the state. Cluster policy participants are entitled to co-financing of up to 50% of costs (up to 3,000 MCI) to support the functioning of the cluster organization. Funding is also planned for the implementation of a project to modernize shared laboratories for testing and evaluating products from regional cluster participants (up to 40,000 MCI). QazIndustry regularly provides analytical, informational, consulting, and technical support to the pilot regional clusters.

CONCLUSIONS

A study of the grain product cluster in the Republic of Kazakhstan using mathematical modeling aims to provide a high-quality forecast to substantiate effective development scenarios. To determine a methodology for assessing the state of the grain product cluster, statistical processing of actual data on the components of the grain product cluster in the agro-industrial complex and approximation of a functional relationship smoothing the actual data were conducted. The tasks are solved using probabilistic statistical research methods. Of all existing methods, two-parameter regression modeling in economic research was selected. In general, two-parameter regression is a simple and effective tool for analyzing and evaluating economic data, which can be particularly useful in situations of limited resources.

The obtained research results are based on analytical functions representing paired nonlinear regressions of the relationships between changes in grain production indicators and changes in material and technical resource indicators for the grain product cluster in the Republic of Kazakhstan.

Consequently, the functions determine trends and, thereby, provide a set of forecasts for changes in grain production. The value of each of these at the point corresponding to the generalized average for argument x is determined using economic and mathematical modeling for processing observation results.

The developed grain production optimization model, based on modern mathematical modeling technologies, represents an important and effective analytical method. Its advantage lies in its ability to provide a detailed and in-depth assessment of the grain product sector's performance, taking into account numerous key aspects. The model not only accurately assesses the current state of the grain product cluster but also provides a powerful forecasting tool. Its versatility allows for the successful application of the method across various industries and fields of activity, opening up new opportunities for additional research and analysis.

In conclusion, it should be noted that in Address to the Nation "A Fair Kazakhstan: Law and Order, Economic Growth, and Social Optimism", the President of the Republic of Kazakhstan emphasized the need for systemic efforts to unlock the country's industrial potential. K.-J. Tokayev highlighted a list of 17 major projects compiled by the government, with a particular emphasis on the development of high-value added value. An important point is the maximum use of domestic raw materials and components, as well as the development of related industries around large enterprises.

The construction of a deep wheat processing plant in Kostanay is a large-scale undertaking, designed to process 415,000 tons of wheat per year. The project operator is Kostanay Grain Industry LLP. Completion is scheduled for 2027, and the total investment is 70 billion tenge. The plant will produce several types of products: lysine (40,000 tons per year), gluten (35,300 tons per year), bioethanol (60,000 tons per year), carbon dioxide (56,000 tons per year), feed vinasse (99,000 tons per year), and bran (28,000 tons per year). Upon completion of construction and reaching design capacity, 650 permanent jobs are planned to be created. Gluten, a high concentration of which is found in Kazakh grain, has a wide range of global applications in its pure form. The products are sold in Europe and the Americas. In addition to gluten, deep grain processing will yield glucose-fructose syrup, wheat starch, modified starch, and bran. This is a virtually waste-free process. The project concept has already been developed, technology and equipment suppliers have been identified, and negotiations are underway. The design and integration of the basic designs will be carried out with the participation of the Austrian company Vogelbusch. Process engineering is also actively underway with local and international equipment suppliers. A memorandum of cooperation has been signed between the KazFoodProducts group of companies, the Chinese company Myande Group, and the Akimat of the Kostanay region. This partnership strengthens the project's international ties and opens up opportunities for the application of advanced technologies at all stages of the plant's construction and operation.

USE OF ARTIFICIAL INTELLIGENCE

The author confirms that AI ChatGPT (GPT-3.5, GPT-4, GPT-5.x) was used exclusively for searching open sources or sources of the last 5 years for literature review.

The author conducted a full check of all materials obtained with the AI participation, by checking each fragment with primary sources and current scientific literature. All citations and references were checked by the author, edited and academically supplemented.

The use of AI tools did not affect the scientific results, empirical conclusions, statistical models and the author's research position.

CONFLICT OF INTEREST

The author declares that there is no conflict of interest in this study, including financial, personal or any other that may affect the results described in this work.

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