CJES Caspian Journal of Environmental Sciences
Online ISSN: 1735-3866
Print ISSN: 1735-3033

# Forecasting is a key instrument of state regulation in the development of agricultural sector of the Republic of Kazakhstan

**Bakyt Kalykova[1], Kulmaganbet Akhmetov[2], Galizhan Madiyev[1], Ukilyay Kerimova[1], Zhanar Karymsakova[1]***

*1. Higher School of Business and Law, Department of Management and Organization of Agribusiness named after Kh.D. Churin, Kazakh National Agrarian Research University, 8 Abay Ave., Almaty, Kazakhstan*
*2. Department of IT Technologies and Automation, Faculty of Water Resources and IT Technologies, Kazakh National Agrarian Research University 8 Abay Ave., Almaty, Kazakhstan*

* *Corresponding author's E-mail: zhanar.koyshybekovna@gmail.com*

## ABSTRACT

The purpose of the study is to develop a mathematical model for astrological forecasting of agricultural development, which can serve as a basis for the balanced development of related sectors within the country's agro-industrial complex and contribute to achieving the highest efficiency of its functioning. Forecasting enables the transformation of the agricultural sector from a source of risks into a driver of stable economic growth and a guarantor of national security. The forecasting methodology proposed in this research is based on the combined application of statistical evaluation methods aimed at obtaining an adequate trend-based astrological simulation model. Implementation of the proposed algorithm using the method of astrological forecasting produced reliable and effective results, particularly in modeling the economic development of agricultural production within Kazakhstan's agro-industrial complex.

**Keywords:** Forecasting, Astrological modeling, Horoscope, Solar system, Astrological matrix, Melon crops.
**Article type:** Research Article.

## INTRODUCTION

The high effectiveness of an economic management system oriented toward the full and rational use of resource potential, the implementation of advanced machinery and technologies with minimal costs and within optimal timeframes, largely depends on the quality of forecasting and planning. However, traditional management methods in the agricultural sector – based mainly on statistical approaches – have several limitations: they often fail to account for uncertainty, nonlinearity, and variability in the source data, which significantly reduces the accuracy of forecasts. The most common extrapolative approach in forecasting practice involves projecting previously identified trends into the future, effectively reproducing past dynamics without considering changing external conditions. Such a scheme, to some extent, resembles the so-called astrological method, which, while using a different computational framework, captures not only long-term tendencies but also situational fluctuations. For predicting the dynamics of agricultural sector development, it appears relevant to employ models that consider the regularities of multi-year cycles associated with the so-called "horoscopic years" (Rat, Ox, Tiger, Rabbit, Dragon, Snake, Horse, Goat, Monkey, Rooster, Dog, and Pig). This approach makes it possible to identify deviations of actual crop yields from the general trend and to statistically measure cyclical fluctuations influenced by climatic and soil factors (Ganesh 2002; Sivakumar 2006; Lobell & Burke 2010; Wulff 2017). Crop yield serves

Caspian Journal of Environmental Sciences, Vol. 24 No. 2 pp.385-404 Received: Sep. 10, 2025 Revised: Nov. 13, 2025 Accepted: Jan. 26, 2026
DOI: 10.22124/cjes.2026.9574

Publisher: University of Guilan,

as an integral result of the interaction between natural-climatic and agro-technical-economic conditions. It reflects the productivity of a specific crop under given circumstances and represents the primary focus of this research (Feng *et al.* 2019; Lobell *et al.* 2020; Jägermeyr *et al.* 2021; Mehrabi *et al.* 2021). Long-term climatic fluctuations objectively manifest in the multi-year variation of crop yields across different regions, allowing these patterns to be considered as a foundation for developing forecasting models. Thus, the use of astrologically oriented modeling can be interpreted as the application of the systematic component of the natural factor – namely, the statistically measurable variability of yields over multi-year cycles. This makes the proposed approach a potentially significant tool for forecasting agricultural production.

**Literature review**

In developed countries, the management of the agricultural sector is based on recognizing the priority role of state regulation, which focuses on institutional and financial support for agricultural entrepreneurs – the most vulnerable participants in the food supply infrastructure (Birner & Resnick 2010; Change & Feindt 2018; Smith 2018; Pe'Er *et al.* 2019; Swinnen 2021). The key objective of government policy is to create conditions for the innovative development of agricultural organizations operating in a market environment and to ensure their sustainable competitive advantages in international trade (Co-operation & Development 2018; Commission 2020; Filassi & de Oliveira 2021). This concept rests on the premise that the long-term and balanced development of the agro-industrial complex (AIC) as a strategically important segment of the economy is possible only through systematic forecasting and development programs (Zhylkybek *et al.* 2014). The use of long-term forecasting forms the prerequisites for rational resource allocation, efficient investment, and the strategic growth of the core areas of AIC. In the European Union, forecasting serves as the foundation for state regulation of both the national and agricultural economies. A deliberately maintained high level of agricultural prices stimulates exports and strengthens the position of the agricultural sector in foreign markets. In the United States, forecasting is regarded as one of the fundamental instruments of economic regulation. Two levels of state regulation are distinguished – federal and regional (state-level). Regional forecasting performs the function of detailing and adjusting national forecasts and programs in the agricultural domain. Particular attention in forecasting calculations is devoted to demand dynamics, production volumes, and pricing processes (Lyson 2016; Salamon *et al.* 2017; Sasaki 2025). The French planning system has undergone several evolutionary stages. Initially, during the post-war period, a directive model was employed, borrowed from the Soviet Union. Beginning in the late 1960s, there was a transition to indicative planning, which made it possible to coordinate the interests of the state and private business. Since the 1990s, strategic planning has become dominant, driven by the integration of the national market into the broader European economic space (Tikhonov *et al.* 2014; Tikhonov & Neverov 2014; Tikhonov & Neverov 2016). The Japanese model of planning is characterized by a highly centralized process, implemented according to a “top-down” principle. All major corporations maintain specialized planning departments. The process generally includes four sequential stages: formulation of initial assumptions, identification of key problems, development of long-term strategies, and preparation of medium- and short-term plans. As in France, Japan maintains a nationwide forecasting system, which is often referred to in the academic literature as indicative planning. In recent decades, France, Japan, and the Republic of Korea have entered a new stage of planning, oriented toward achieving comprehensive scientific, economic, and social breakthroughs suited to the challenges of the 21st century. At the current stage, the methodological foundation of forecasting is formed by various economic-mathematical models – ranging from narrowly focused calculations to system-level modeling of interrelated economic processes. In long-term forecasts, particular importance is placed on assessing the production potential of the sector and the degree of its likely realization. In this context, the choice of an adequate forecasting method for crop yields becomes a key factor for both the organization and planning of agricultural production and for improving the validity of managerial decisions. Scientifically verified selection of an optimal forecasting method can significantly increase the effectiveness of strategic management and enhance the outcomes of agricultural policy (Tikhonov *et al.* 2014; Baldwin *et al.* 2024).

## MATERIALS AND METHODS

In the mid-1990s, a fundamentally new class of algorithms emerged in scientific practice, enabling a qualitative breakthrough in time series forecasting. This family of methods includes several variants, among which the ARIMA (AutoRegressive Integrated Moving Average) algorithm has become the most widely used and serves as the core tool in nearly all specialized forecasting software packages. The effectiveness of such models is directly linked to the stationarity condition of the system under study: the key parameters governing market functioning must remain relatively stable over time. However, fluctuations in individual factors and the transformation of market participants' strategies are permitted. These dynamics are reflected within the model, thereby enhancing the accuracy of predictive estimates. The methodological framework of this study is determined by broader economic objectives, including the sustainable development of the agricultural sector, based on the rational use of resource potential and the improvement of overall economic management efficiency. To achieve these practical objectives, a software tool was developed to automate the entire cycle of forecasting calculations. The software was designed in the MS Excel environment using the VBA (Visual Basic for Applications) programming language. This ensures seamless integration of the tool into the standard MS Office, allowing users to generate additional analytical solutions directly within a familiar working interface.

## RESULTS AND DISCUSSION

The significant dependence of agricultural production on natural and climatic conditions has long been an established fact requiring no further argument or empirical proof (Falvey 1996; Abdusamatov 2006; Bakkuev *et al.* 2022; Baldwin *et al.* 2024). This dependence is interpreted as a universal regularity, confirmed by long-term variations in crop yields across different regions. It is emphasized that this variability forms a systematic component that must be accounted for when forecasting agricultural production indicators.

**Table 1.** Procedure for calculating the horoscope rank based on the dynamics of melon crop yields in the Republic of Kazakhstan.

| **Years** | **Sequential number ($P_t$)** | **Yield of melon crops (c ha$^{-1}$)** | **$Y_{p(t)}$ = f(t)** | **Horoscope rank (calculated yield level; $P_y$)** | **d= $P_t$ - $P_y$** | **$d^2$** |
|---|---|---|---|---|---|---|
| Goat - 2003 | 1 | 79 | 95.89 | 8 | -7 | 49 |
| Monkey - 2004 | 2 | 72 | 83.02 | 6 | -4 | 16 |
| Rooster - 2005 | 3 | 69 | 76.81 | 5 | -2 | 4 |
| Dog - 2006 | 4 | 59 | 59.11 | 2 | 2 | 4 |
| Pig - 2007 | 5 | 59 | 64.86 | 3 | 2 | 4 |
| Rat - 2008 | 6 | 58 | 53.51 | 1 | 5 | 25 |
| Ox - 2009 | 7 | 67 | 70.76 | 4 | 3 | 9 |
| Tiger - 2010 | 8 | 78 | 89.38 | 7 | 1 | 1 |
| Rabbit - 2011 | 9 | 97 | 102.56 | 9 | 0 | 0 |
| Dragon - 2012 | 10 | 119 | 109.38 | 10 | 0 | 0 |
| Snake - 2013 | 11 | 127 | 116.35 | 11 | 0 | 0 |
| Horse - 2014 | 12 | 135 | 123.47 | 12 | 0 | 0 |
| Goat - 2015 | 13 | 144.5 | 130.74 | 13 | 0 | 0 |
| Monkey - 2016 | 14 | 153.2 | 138.17 | 14 | 0 | 0 |
| Rooster - 2017 | 15 | 159.3 | 153.49 | 16 | -1 | 1 |
| Dog - 2018 | 16 | 167.1 | 169.41 | 18 | -2 | 4 |
| Pig - 2019 | 17 | 171.7 | 177.60 | 19 | -2 | 4 |
| Rat - 2020 | 18 | 158.9 | 145.75 | 15 | 3 | 9 |
| Ox -2021 | 19 | 161.1 | 161.37 | 17 | 2 | 4 |
| Tiger -2022 | 20 | 177 | 185.95 | 20 | 0 | 0 |
| Rabbit - 2023 | 21 | 186.1 | 194.44 | 21 | 0 | 0 |
| Dragon - 2024 | 22 | 206.8 | 203,09 | 22 | 0 | 0 |
| Average | | 126.83 | 126.83 | | | |
| SD | | 50.99 | 48.92 | | | |
| Variance | | 2600.31 | 2393.41 | | | |
| Minimum | | 58.00 | 53.51 | | | |
| Maximum | | 212.40 | 211.89 | | | |

The novelty of the proposed approach lies in the use of a calendar-astrological dimension (based on the years of the Eastern zodiac) as a distinctive indicator of climatic fluctuations. Although this methodological technique may appear unconventional, it effectively serves as a means of structuring natural and climatic variability and formalizing its influence on agricultural development. The study aims to construct a long-term forecast for key sectors of Kazakhstan's agro-industrial complex, taking into account the specific climatic manifestations within the framework of the proposed model. Using the example of forecasting the yield of melon crops, the step-by-step implementation of this approach is demonstrated. Initially, a trend in yield dynamics is identified based on time series data. Next, using MS Excel tools (specifically, the "Function wizard" and the formula = RANK.EQ), the rank of each corresponding year relative to the overall trend is determined. The subsequent stage involves testing the sample for outliers and computing robust estimates of means and variances in accordance with the methodology proposed by Tsymbalenko T.T. *et al.* (Tsymbalenko & Tsymbalenko 2018). Ordinary estimates of the studied variational series were computed in MS Excel and are presented in Table 1, where, the sample arithmetic mean $\bar{y}$ = 126.83(c ha$^{-1}$); the sample variance $S^2_y$ = 2600.31; and the sample standard deviation $S_y$ = 50.99

– for minimum values:

$$T_{\min_i} = \frac{\bar{y} - y_{\min_i}}{S_y}$$

– for maximum values:

$$T_{\max_i} = \frac{y_{\max_i} - \bar{y}}{S_y}$$

$T_{min1} = \frac{126.83-58}{50.99} = 1.35$ $T_{min2} = \frac{126.83-59}{50.99} = 1.33$ $T_{max21} = \frac{206.8-126.83}{50.99} = 1.57$

In the examined variational series the following values stand out (Table 1): 58; 59; 206.8. We test these values for possible classification as gross errors (outliers) using the Smirnov-Grubbs test referenced in Larchenko (2023). We compare the obtained test statistics with the corresponding critical values $T_{cr}(\alpha;n)$ at the chosen significance level ($\alpha$ = 0.05) and the rank positions in the ordered series (ordered descending for minima and ascending for maxima) for the observations 58, 59, 206.8 and 212.4: $T_{cr}(0.05;23)$ = 2.823 (Larchenko 2023). The full fragment of the forecasting technology for melon crop yield with elements of astrological modeling implemented in MS Excel is illustrated in Fig. 1. All calculated Smirnov-Grubbs statistics are: 1.68; 1.52; 1.17, which are less than the critical value 2.823, therefore the values 58; 59; 206.8 cannot be regarded as gross errors. These calculations were performed in MS Excel and the results were output automatically in cells N41 and N42. Next, the trend in the dynamics of variability is analyzed and evaluated. Deviations of the level of a dynamic series from its trend are referred to as fluctuations. Fluctuations occur over time and at specific moments; in our case they are expressed in the horoscopic years. We test the hypothesis of the existence of a trend in the time series of melon crop yields. Using the horoscope-year ordering, we determine the rank order $P_{yi}$ of melon yields in the ranked series, which does not always coincide with the chronological sequence ranks $P_{ti}$ (Table 1).

For the period 1991-2023, the equation of *the trend* for melon crop yield has the following form:

$Y_{pt} = 48.067 + 5.3676 \times t + 0.0763 \times t^2$ and its coefficient of determination is $R^2 = 0.92$.

To account for the annual variability of melon crop yields associated with the horoscopic years and the planet Earth, in the trend equation we replace the calendar ordinal year with the difference between the ranks of the observed-level series and the ranks of the years in the sequence, without altering the original chronology or the horoscope-year labels. In doing so we estimate the magnitude of the variability and model the characteristics of the $i$-$^{th}$ horoscopic year. The result is *a situational model* that adequately describes the year-to-year fluctuations of yield by horoscopic years, i.e.:

$$y_{p_t} = 48.067 + 5.3676 \cdot (t_i - d_i) + 0,0763 \cdot (t_i - d_t)^2 \quad (1)$$

Fragments of the calculation results obtained with this model are shown in Fig. 1 (data for 1953-2020 are omitted there).

Regardless of the form and construction method of an economic-mathematical model, the question of its practical applicability for analysis and forecasting can only be settled after establishing *adequacy* – i.e., the degree to which the model corresponds to the process or object under study. Therefore, the main purpose of studying the fluctuations is to test the adequacy of the examined economic-mathematical production function. The statistical study of melon-yield variability pursues the following tasks:

- measurement of the magnitude (strength) of fluctuations;
- study of the type of fluctuations and decomposition of complex variability into heterogeneous components;
- research of changes in variability over time;
- study of the spatial (or other cross-sectional) variation of variability across units of analysis;
- study of factors driving variability and their statistical-mathematical modeling.

The main absolute indicators that characterize the magnitude of fluctuations include the following:

1) amplitude (or range) of fluctuations – defined as the difference between the largest algebraic deviation from the trend during the period and the smallest algebraic deviation.

$$A_R = e_{\max} - e_{\min}; \quad (2)$$

2) mean absolute deviation, calculated by the formula:

$$|\bar{e}| = \frac{\sum_{t=1}^{n} |e_i|}{n} \quad (3)$$

where $e_i$ is deviations of actual levels from the trend;

$n$ is the number of levels.

3) the standard deviation of residuals is considered the principal absolute indicator of variability. If the examined period represents a sample used to estimate the general variability of the process for forecasting (extrapolation), the estimate of the population standard deviation of residuals is calculated by:

$$S_{y(t)} = \sqrt{\frac{\sum_{t=1}^{n} (y_i - y_{pi})^2}{n - P}} \quad (4)$$

where $P$ is the number of trend parameters, including the intercept;

$y_i$ is $i$-$^{th}$ level of the studied indicator;

$y_{pi}$ is the calculated value of the $i$-$^{th}$ level corresponding calculated (trend) value.

Along with absolute measures, the system of variability indicators should also include relative measures, which express the comparable intensity of the fluctuation process across different time series. Relative indicators are obtained by relating absolute measures to the mean level of the series for the same period. Based on the standard deviation, the coefficient of variability (or fluctuation coefficient) is defined as:

$$V_{y(t)} = \frac{S_{y(t)}}{\bar{y}} \quad (5)$$

In relation to crop yields, and based on empirical data across different crops and regions, the degree of fluctuation can be classified as follows: $V_{y(t)} < 0.1$ (weak); $0.1 < V_{y(t)} \leq 0.2$ (moderate); $0.2 < V_{y(t)} \leq 0.4$ (strong); $V_{y(t)} > 0.4$ (very strong).

Finally, the system of fluctuation indicators must be complemented with stability indicators, reflecting the opposite property of variability.

The stability coefficient is defined as:

$$\delta = 1 - V_{y(t)} \qquad \textbf{(6)}$$

or equivalently, as the complement of the coefficient of variability to unity.

An essential characteristic of variability is the type of fluctuation observed in the dynamic series. In time-series analysis, three primary or "pure" types of fluctuations can be distinguished: sawtooth (or pendulum-type) fluctuations, where the signs of deviations from the trend alternate strictly in succession; long-period or cyclical fluctuations, where several consecutive levels deviate from the trend in the same direction, followed by a series of deviations in the opposite direction, and so on; random fluctuations, where both the sign and magnitude of deviations occur in a random sequence, with equal probability for any combination of deviations from the trend.
In practice, none of these types occur in a completely pure form; typically, one type predominates within a given process. Identifying the dominant type of variability is of significant practical importance for forecasting and for developing measures aimed at reducing fluctuations or mitigating their negative effects. For example, when sawtooth-type variability prevails, a considerably smaller insurance reserve is required than under long-period variability of equal intensity. This is because production shortages in one year are immediately offset by above-average yields the following year in the case of sawtooth fluctuations, whereas under long-period fluctuations, several consecutive years may exhibit below-average yields.

| | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q | R | S |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Forecasting the production of melon crops in the Republic of Kazakhstan using astrological modeling in the MS Excel environment | | | | | | | | | | | | | | | | | | |
| 2 | Forecasting the produ | Serial number of the year | Melon cro | Calculate d data for the model | Point forecastT очечный прогноз | The upper limit of the forecast | The lower limit of the forecast | Py | $d_t=P_t-P_y$ | $d_t^2$ | $e_t=Y_t-Y_{pt}$ | $e_t^2$ | $\|(e_t)\|$ | $e_t*e_{t-1}$ | $e_t - e_{t-1}$ | $(e_t - e_{t-1})^2$ | $(\|e_t\|/y_t)$ | Criterion of peaks (turning points) | |
| 3 | Snake -1989 | | | | | | | 0 | 0 | | | | | | | | | | |
| 4 | Horse - 1990 | | | | | | | 0 | 0 | | | | | | | | | | |
| 5 | Sheep - 1991 | 1 | 95,84 | | | | | 8 | -7 | 49 | -16,893 | 285,39 | 16,89 | 186,19 | 5,87 | 34,46 | 0,213841 | | |
| 6 | Hare 2011 | 21 | 194,44 | | | | | 21 | 0 | 0 | -8,341 | 69,58 | -8,34 | -30,95 | 12,05 | 145,23 | 0,044821 | ЛОЖЬ | |
| 7 | Dragon - 2012 | 22 | 203,09 | 203,09 | | | | 22 | 0 | 0 | 3,710 | 13,76 | 3,71 | | | 0,00 | 0,01794 | | |
| 8 | Hare - 2023 | 23 | | | 211,89 | 258,40 | 170,38 | 253 | -7 | 49 | -0,41 | 1861,31 | 175,91 | 926,38 | 20,60 | 570,70 | 1,643864 | 0 | |
| 9 | Horse -2024 | 24 | | | 220,85 | 264,78 | 176,91 | nter the number of pairs.trend | | | 3 | | Total number of turning pointsк | | | | | 0 | |
| 10 | Hare - 2025 | 25 | | | 263,06 | 316,45 | 209,61 | The COE of the S(t) residues | | | 9,90 | | Mathematical expectation of the number of turning points | | | | | 13,33 | |
| 11 | Horse - 2026 | 26 | | | 258,19 | 318,20 | 204,18 | Coeff-t of oscillation Vy(t | | | 0,08 | | Variance | | | | | 3,59 | |
| 12 | Sheep-2027 | 27 | | | 263,03 | 320,61 | 205,44 | Coef of random fluctuat d | | | 2511,68 | | Estimated number of turning points | | | | | 10 | <13 |
| 13 | Monkeys - 2028 | 28 | | | 258,19 | 319,43 | 196,94 | Factorial variance | | | 8,00 | | Checking the mean of the residuals using the t-test | | | | | -0,018 | <2,003 |
| 14 | Chicken -2029 | 29 | | | 267,90 | 344,27 | 191,54 | Cf. linear deviation | | | 0,075 | | Normality test using the R/S criterion | | | | | 3,23 | 1,95-6,55 |
| 15 | | | | | | | | Determination coefficient R2 | | | 0,97 | | d - the Darbin-Watson criterion | | | | | 1,70 | 1,15-1,54 |
| 16 | | | | | | | | Correlation index h | | | 0,980 | | Average growth rate in the past | | | | | 1,036 | 103,60% |
| 17 | | | | | | | | Approximation error | | | 7,47% | | Average growth rate in the future | | | | | 1,037 | 10374,80% |
| 18 | | | | | | | | | | | | | Spearman Rank Correlation Coefficient | | | | | 0,924 | >0,3597 |
| 19 | Average | | 126,81 | 122,96 | | | | | | | -0,360 | | 1st-order autocorrelation coefficient | | | | | 6,216 | |
| 20 | Standard Deviation | | 50,95 | 46,94 | | | | | | | 9,41 | | | | | | | | |
| 21 | Variance | | 2600,31 | 2147,15 | | | | | | | 88,63 | | | | | | | | |
| 22 | Minimum | | 58,00 | 53,51 | | | | | | | -16,89 | $T_{min}$= | 1,349795 | <2,823 | | | | | |
| 23 | Maximum | | 212,40 | 203,09 | | | | | | | 15,03 | $T_{max}$= | 1,678057 | <2,823 | | | | | |
| 24 | Swing range | | 154,40 | 149,58 | | | | | | | 31,92 | | | | | | | | |
| 25 | The amount | | 2917,10 | 2705,11 | | | | | | | 0,41 | | | | | | | | |

**Fig. 1.** Fragment of the forecasting technology for melon crop yields in the Republic of Kazakhstan using elements of astrological modeling in MS Excel.

Different fluctuation types are generally driven by different causal mechanisms: sawtooth variability often arises from self-oscillating mechanisms within the system itself. Long-period variability is typically associated with external cyclical factors, such as solar activity, seasonal changes, or hypothetical meteorological cycles. Random variability is usually interpreted as the superposition ("interference") of multiple oscillatory processes differing in nature and cycle length. To study the type of variability, several analytical methods have been proposed. For instance, M. J. Kondel (Ibragimov & Has' Minskii 2013) introduced the criterion of "turning points", or local extrema, in a series of deviations from the trend. They demonstrated that, under conditions of random fluctuation distribution over time, the expected number of local extrema (turning points) can be expressed as:

$$K_m = \frac{2}{3}(n-2) \tag{7}$$

at a standard deviation

$$\sigma = \sqrt{\frac{16n-29}{90}} \tag{8}$$

The criterion of randomness at a 5% significant level (i.e., with a 95% confidence probability) is defined by the inequality:

$$k > \left\lfloor k_m - 1.96\sqrt{\sigma_k^2} \right\rfloor, \tag{9}$$

where the square brackets denote the integer part of a number, and *k* represents the total number of turning points, determined as follows: a level of the sequence $e_i$ is considered a maximum if it exceeds both adjacent levels, i.e. $e_{i-1} < e_i > e_{i+1}$, and a minimum if it is lower than both neighbors, i.e. $e_{i-1} > e_i < e_{i+1}$. In both cases, $e_i$ is regarded as a turning point, and the total number of turning points for the residual sequence $e_i$ is denoted by *k*. If inequality (9) is not satisfied, the trend model is considered inadequate. In our case, as shown in cell R28 (see Fig. 1), the total number of turning points determined according to the above principle equals k = 13, which exceeds the calculated expected value (10) obtained via formulas (7) and (8) in cell R31. Since inequality (9) holds true, the horoscopic trend model can be considered *adequate.* For a "sawtooth" type fluctuation, the number of turning points is exactly $n - 2$; for long-period fluctuations, it equals twice the number of cycles within the period *n*, since each cycle contains *α* extremum. By measuring the actual number of turning points and comparing it with the expected value under different fluctuation types, the predominant type of variability can be determined. Another approach to identifying the type of variability – which takes into account not only the sequence of deviations from the trend but also their magnitudes – is autocorrelation analysis. This method involves computing autocorrelation coefficients in the series of deviations from the trend with shifts of 1, 2, 3, etc. The resulting set of autocorrelation coefficients forms the autocorrelation function. Even the first-order autocorrelation coefficient (with a one-year lag) can provide a reliable indication of the dominant fluctuation type.
The first-order autocorrelation coefficient is calculated as follows:

$$A_e = \frac{\sum_{i=1}^{n-1} e_i e_{i+1}}{\frac{e_1^2}{2} + \sum_{i=2}^{n-1} e_i + \frac{e_n^2}{2}} \tag{10}$$

In the case of "sawtooth" fluctuations, all products in the numerator will be negative, and a significant coefficient value will be obtained. For long-period fluctuations, most products in the numerator will be positive, yielding a significant positive coefficient. When fluctuations are randomly distributed over time, positive and negative products occur with equal probability, so the coefficient will be approximately zero. The statistical significance of the autocorrelation coefficient's deviation from zero is verified using special statistical tables. In our case, as shown in cell R38 (Fig. 1), the value of the first-order autocorrelation coefficient, calculated using formula (10), equals $A_e = 6.21$, which indicates the *long-periodic nature* and *statistical significance* of the observed variability. To verify the absence of significant autocorrelation in the residual sequence $e_i$, several criteria may be used, the most common of which is the Durbin-Watson *d*-statistic. The calculated value of this criterion is determined by the following formula:

$$d = \frac{\sum_{i=2}^{n}(e_i - e_{i-1})^2}{\sum_{i=1}^{n} e_i^2} \qquad \textbf{(11)}$$

It should be noted that if the Durbin-Watson statistic lies within the interval from 2 to 4, it indicates the presence of a negative correlation; in this case, the statistic must be transformed using the formula $d' = 4 - d$, and the transformed value $d'$ is used for further analysis. The calculated value of $d$ (or $d'$) is compared with the upper ($d_2$) and lower ($d_1$) critical values of the Durbin-Watson statistic, obtained from reference tables (Fig. 1). If the computed value $d$ (or $d'$) is greater than the upper critical value $d_2$, the null hypothesis of independence between the residuals – that is, the absence of autocorrelation – is accepted. If the computed value $d$ (or $d'$) is less than the lower critical value $d_1$, the null hypothesis is rejected, and the model is considered inadequate. If $d$ (or $d'$) lies between $d_1$ and $d_2$ (including these limits), there is insufficient evidence to make a conclusive judgment, and further analysis (e.g., with a larger dataset) is recommended. In our case, the Durbin-Watson statistic, calculated using formula (11), equals $d = 1.70$ (cell R34), which is greater than its upper critical value (1.54, cell S34). This indicates that the analyzed statistical data *do not exhibit autocorrelation*, confirming the adequacy of the proposed model. If the residual sequence $e_i$ follows a normal distribution, its mathematical expectation should equal zero. This condition can be tested using the student's t-test, calculated as:

$$t = \frac{\bar{e} - 0}{S_e}\sqrt{n} \qquad \textbf{(12)}$$

where $\bar{e}$ - the arithmetic mean of the residual sequence $e_i$; $S_e$ = the standard deviation of that sequence. If the calculated value $t$ is less than the critical (tabulated) value $t_\alpha$ of Student's distribution at a given significance level α and with degrees of freedom $n$-1, the null hypothesis – that the mathematical expectation of the random sequence equals zero – is accepted. Otherwise, the hypothesis is rejected, and the model is considered inadequate. In our case (Fig. 1), the calculated value of the $t$-statistic obtained using formula 12 – which tests the hypothesis that the mathematical expectation of the residual sequence levels $e_i$ equals zero – is $t$ = - 0.018, as shown in cell R32. This value is much smaller than the critical value (2.003), given in cell S32, which is determined from the Student's distribution table at a significance level of α = 0.05 and degrees of freedom $n$-1 or 23-1 = 22. Therefore, the null hypothesis that the expected value of the residuals equals zero is accepted, indicating that systematic deviations are absent and the *model is adequate* to the observed data. To further verify the normality of the residual distribution, various methods may be applied – such as the analysis of skewness and kurtosis coefficients, the Westergaard method, or the RS criterion. In this study, we use the RS criterion, which is one of the simplest and most effective tools for checking the normality of distribution. The RS criterion is calculated according to the following formula:

$$RS = \frac{R_{range}}{s_{\dot{y}}} = \frac{e_{\max} - e_{\min}}{\sqrt{\sum_{i=1}^{n} e_i \,/(n-1)}} \qquad \textbf{(13)}$$

The calculated RS value is then compared with the tabulated critical limits (lower and upper boundaries). If the calculated RS value falls outside the interval between these boundaries, the hypothesis of normal distribution is rejected at the chosen significance level; otherwise, it is accepted. In our case, the computed RS value, obtained using formula (13), equals RS = 3.23 (cell R33, Fig. 1). This value falls within the critical interval of 1.95 – 6.55 (cell S33, determined from the table "Critical limits of RS ratio"). Therefore, the null hypothesis of normal distribution of residuals is accepted, confirming once again that the constructed *model is adequate*. To perform further economic analysis and to forecast the yield of melon crops in the Republic of Kazakhstan, it is necessary to establish the presence of a growth trend in the time series of crop yields.

The average annual growth rate is determined using the following formula: $T = \text{n-1}\sqrt{\frac{\tilde{y}_{tn}}{\tilde{y}_{t0}}}$, where $\tilde{y}_{tn}$ and $\tilde{y}_t0$ = final and initial theoretical levels (calculated from the trend); $n$ – number of levels.

For the Republic of Kazakhstan, the average annual growth rate equals

$T = (23\text{-}1)\sqrt{\frac{211.89}{95.89}} \approx 1.036$ or $103.64\%$ , in cell R35 (Fig. 1).

Over the period 1991-2023, the yield of melon crops in the Republic of Kazakhstan increased on average by 3.64% per year, or by 1.03 c ha$^{-1}$.

Below we present the calculated indicators of yield variability.

1) Range of fluctuations relative to the trend. This is calculated using formula (2)
$A_k$ = 15.03 – (-16.89) = 31.92
c ha$^{-1}$, reported in cell K43 (Fig. 1).

2) Range of fluctuations of the actual series:
$R = y_{max} - y_{min}$ or $R$ = 212.4 - 58 = 154.4 c ha$^{-1}$, n cell C43 (Fig. 1),
where $y_{max}$ and $y_{min}$ are the maximum and minimum levels of the dynamic series (Table 1).

For the Republic of Kazakhstan, the difference between the yield levels of a good and a bad year amounted to 154.4 c ha$^{-1}$; the difference between the maximal and minimal deviations of actual levels from the trend was 31.92 c ha$^{-1}$.

3) Mean absolute deviation. Computed using formula (3). The numerator equals 175.91, calculated in cell M27 in MS Excel (Fig. 1). Thus, the mean absolute deviation is:

$$\left|\overline{E}\right| = \frac{\sum_{t=1}^{n}\left|E_t\right|}{n} = \frac{175{,}91}{23} = 7{,}648 \text{ c ha}^{-1}. \quad \textbf{(14)}$$

Over the period 1991-2023, melon crop yields in Kazakhstan deviated from the trend level by 7.648 c ha$^{-1}$ on average.

4) Standard deviation of residuals, calculated according to formula (4):

$S_{(t)} = \sqrt{\frac{1861.31}{23-3}} \approx 9.65$ c ha$^{-1}$, cell K29 (Fig. 1).

For the period 1991-2023, the yield of melon crops deviated from the trend level by an average of 9.65 c ha$^{-1}$.
It should be noted that this standard deviation of residuals differs from the conventional standard deviation calculated automatically in cell K39 using the built-in STDEV.P function in MS Excel. The value computed in our model accounts for the trend parameters. Therefore, after selecting the most appropriate trend function, the number of trend parameters, including the intercept term, must be entered manually in cell K28 (Fig. 1).

5) Coefficient of variability, calculated using formula (5):

$V_{y(t)} = \frac{9.65}{126.83} \approx 0.08 \approx 8.0\%$ cell K30, (Fig. 1).

Thus, the variability of yield can be characterized 0.02 < 0.1 as low, amounting to 8.0% of the long-term average level. This means that, on average, the yield of melon crops in Kazakhstan deviated from the long-term mean level by approximately 8.0% per year.

The stability coefficient was then determined according to formula (6):

$K_{stab} = 1 - 0.08 = 0.92$ or 92.0%.

This indicates that, on average, 92.0% of the trend level is maintained annually, despite natural yield fluctuations.

Next, the type of fluctuations was identified based on the number of turning points. The expected mean number of turning points in a series of randomly distributed deviations of actual yield levels from the trend was determined using formula (7):

$$K_m = \frac{2}{3}(23-2) = 14$$

The standard deviation of this indicator was calculated according to formula (8):

$$\sigma = \sqrt{\frac{16 \times 23 - 29}{90}} \approx 1.94$$

Based on the series of deviations between actual and theoretical yield levels, the empirical number of turning points was determined. The number of deviations exceeding 1.3 is $K_a = 8$ or 1.4 – $K_{ab} = 6$, was also calculated to further characterize the amplitude and periodicity of yield fluctuations. Since the number of these deviations falls within the acceptable limits: $K_m \pm 2\times \sigma = 14 \pm 2\times 1.94 = 14 \pm 3.88$, the hypothesis of a random distribution of yield fluctuations of melon crops over time is confirmed. Thus, as a result of the analysis conducted above, an astrological model of the main trend of yield dynamics over the horoscopic years was constructed. In addition, the indicators, degree, and type of yield variability for melon crops in the Republic of Kazakhstan were determined and summarized in Table 2. Since the previously calculated stability index does not reflect the evolutionary changes of levels and only characterizes the stability of the series under minimal fluctuations, the Spearman rank correlation coefficient was calculated to assess the stability of yield dynamics. This coefficient is determined according to the formula:

$$K_p = 1 - \frac{6\sum d^2}{n^3 - n}, \qquad (15)$$

where d is the difference between the ranks of the levels of the studied series and the ranks of the corresponding years (see Table 1 and Fig. 1; the computed value $\sum d^2 = 134$ is shown in cell J27), and $n$ is the number of paired observations.

The rank correlation coefficient between the years and the levels of the dynamic series may vary from –1 to ± 1. If the level of each subsequent year exceeds that of the previous one, the ranks of the yield levels and years coincide, indicating a continuous upward trend. When $K_p = 0$, growth is unstable. The closer $K_p$ is to ± 1, the more stable the increase (or decrease) of the studied indicator.

The Spearman rank correlation coefficient for the yield of melon crops was calculated using the formula:

$K_p = 1 - \frac{6 \times 134}{23^3 - 23} = 1 - 0.16 = 0.934$ cell R37, (Fig. 1).

The obtained value of this stability coefficient confirms the presence of a steady upward trend in the studied indicator. Therefore, the forecasting model must ensure that the established growth rate of the predicted indicator is maintained. If this condition is not satisfied, it becomes necessary to introduce a correction factor into the model to account for the observed rate of growth by raising the variable to a power equal to the growth rate coefficient, i.e. $y_{(n-1)} = f(y_i)^T$

**Table 2.** Results of the analysis of yield variability for melon crops in the Republic of Kazakhstan.

| Average yield (c ha$^{-1}$) | Variability indicators: absolute | | | | Degree of variability | Stability coefficient | Actual number of “turning points” | $K_m \pm 2\cdot b$ | Type of variability |
|---|---|---|---|---|---|---|---|---|---|
| | Actual | Theoretical | Residuals | Coefficient of variability (%) | | | | | |
| 126.83 | 154.4 | 31.92 | 9.65 | 8.0 | weak | 0.93 | 6-8 | 14 ± 3.88 | random |

A conclusion about the adequacy of the trend model is drawn when all of the above tests of the residual sequence properties yield positive results. Therefore, the *situational (astrological) trend model* constructed in this study is considered *adequate.*

In the course of economic analysis, it is important to determine the relative contribution of systematic and random variability in the yield of melon crops. To this end, the following indicators were calculated:

**Total variance**

$$G_{tot}^2 = \frac{\sum(y_i - \bar{y})^2}{n-1} \qquad \textbf{(16)}$$

Where $y_i$ is actual levels of the sries; $\bar{y}$ is average level of the series over the period; *n* is the number of levels.

For the Republic of Kazakhstan, the total variance equals

$G^2_{tot} = \frac{2600.31}{23-1} = 118.195$, in cell C40 (Fig. 1).

This indicator characterizes the overall variability of melon crop yields, determined by both natural meteorological factors and manageable (anthropogenic) influences.

**Residual (random) variance**. It is calculated using the formula:

$$G_{res}^2 = \frac{\sum(y_i - \tilde{y}_{(t)})^2}{n-1}$$ or $G^2_{res} = \frac{1949.86}{23-1} = 88.63$ in cell K40 (Fig. 1).

This indicator summarizes the deviations of actual yield values from theoretical ones, which are mainly caused by factors beyond human control, primarily meteorological conditions.

**Coefficient of random variability**. This coefficient characterizes the influence of random factors on the overall variability of crop yield. The lower its value, the less dependent the yield is on meteorological fluctuations. It is determined by the formula:

$\delta = G^2_{res} / G^2_{res}$ hence $\delta = \frac{88.63}{2359.61} = 0.04$ or 4% in cell K31 (Fig. 1).

For the period 1991-2023, the share of random factors in the annual variability of melon crop yield in the Republic of Kazakhstan was 4%.

**Factor (explained) variance**:

$G^2_{act} = G^2_{tot} - G^2_{res}$, hence $G^2_{act} = 2359.61-88.63 =2270.98$, in cell K32 (Fig. 1).

This indicator reflects the systematic (explained) component of yield variability, determined primarily by manageable factors, such as agrotechnical practices, irrigation, fertilization, and land-use policies.

**Coefficient of determination**. This coefficient expresses the proportion of total variance explained by systematic (factorial) influences. The higher its value, the stronger the dependence of yield on controlled agricultural and organizational factors. For the theoretical time series interpolated according to the astrological trend model, it is computed as:

$R^2 = 1- G^2_{res} / G^2_{res}$, hence $R^2 =1-0.04 = 0.96$ or 96% in cell K34 (Fig. 1).

Thus, over the period 1991-2023, 96% of the annual variability in melon crop yield in the Republic of Kazakhstan was determined by controlled factors. It should be noted that the modified trend model developed in this study provides a robust description of the dynamics of yield variability for melon crops. This is confirmed by the coefficient of determination, which increased from 0.92 (in the original trend model) to 0.96 after modification, indicating a stronger explanatory capacity of the refined model.

**Correlation index**, calculated using the well-known formula:

$\eta = \sqrt{1 - \frac{G_{res}^2}{G_{tot}^2}}$ or $\eta = \sqrt{0.96} \approx 0.981$ in cell K35 (Fig. 1).

This indicator characterizes the degree of dependence of yield on the level of agrotechnical practices, organizational efficiency, and production management. In the case of the Republic of Kazakhstan, the correlation between yield and controllable factors is strong. The correlation coefficient is considered statistically significant according to Fisher's criterion at a confidence level of 0.95 and $n = 23$, where correlation coefficients exceeding 0.05 are deemed significant.

Following the above statistical validations, a point and interval forecast of melon crop yield was developed for the next 7-10 years. As discussed earlier, it is fully justified to apply the systematic component of the natural (environmental) factor in agricultural forecasting – expressed through the astrological cycle and reflected in the dynamic variability of yield. This concept refers to the statistically measurable long-term oscillations in agricultural crop productivity, particularly in melons. Accordingly, for the length of the forecast horizon, the established dynamic pattern of yield variability by the horoscopic years is replicated, i.e., modeled to extend the observed cyclical behavior into the predictive period. The chronological sequence of the years continues throughout the forecast horizon, beginning with 2023 – the year of the Rabbit, in which astrological modeling is implemented. This approach reflects the energetic potential of the events characteristic of the current year. In the adopted astrological matrix, 2023 occupies cell (¹07), located at the intersection of the fourth row and the seventh column, which corresponds to the planet Mars. Hence, the development of yield dynamics during this period occurs under the influence and synchronization of Mars. Based on this alignment, a decline in yield growth is expected, corresponding to the average value of its long-term variability. To account for this, the average deviations (variability) observed in the preceding horoscopic cycles are subtracted from the current order value of the forecast year – specifically, the deviations (fluctuations) corresponding to the previous (adjacent) year, the Year of the Dragon (denoted as *K*), and the Year of the Snake. The calculations then proceed sequentially through the subsequent horoscopic years across the entire forecast horizon ($k = const$),
Following this adjustment, the astrological model for forecasting the yield of melon crops by horoscopic cycles takes the following generalized form:

$y_{(n+i)} = 48.067 + 5.3679 \times (n + i - k - d) - 0.0763 \times (n + i - k - d)^2$, i = 1, 2…..*L*,

where *k* – average variability value of the previous (*adjacent to the forecast start)* year according to the horoscopic cycles ($k = const$),

$d_i$: average variability value of the *i*-th forecasted year;

*L:* length of the forecast period (lead time).

The results of the point forecast, computed in the MS Excel environment, are presented in Fig. 1.

The interval forecast is calculated with consideration of the annual yield variability using the following formula:

$U_i = y_{(n+i)} \pm S_{n+1} \times K_i$ **(17)**

where

$$K_i = t_\alpha \cdot \sqrt{1 + \frac{1}{n} + \frac{(n+L)^2}{\sum_{i=1}^{n+L} t_i^2} + \frac{\sum_{i=1}^{n+L} t_i^4 - 2(n+L)^2 \cdot \sum_{i=1}^{n+L} t_i^2 + n(n+L)^4}{n \cdot \sum_{i=1}^{n+L} t_i^4 - (\sum_{i=1}^{n+L} t_i^2)^2}}, \quad i = L, L-1, \cdots, 1, \tag{18}$$

$t_a$ = tabulated Student's t-value at the significance level $\alpha = 0.05$ (for degrees of freedom $f = 23-3 = 20$, $t_\alpha = 2.093$);

$t_i$ = ordinal number of the point forecast;

$S_{n+i}$ = standard deviation of the $i$-th forecast year, which, taking yield variability into account, is recommended to be calculated as:

$$S_{n+i} = y_{n+i.} . V_{y(t)} \quad \textbf{(19)}$$

For example, given the previously determined coefficient of variability (0.08), the standard deviation for 2023 is calculated as: $S_{(2023)} = 17{,}99 \times 0.08 = 1.26$ c ha$^{-1}$. We constructed an interval forecast of the mean annual yield of melon crops for 2023-2030. To do this, first computed the average yield for the year located at the midpoint of the lead time, since the point forecast of the mean annual level equals the trend-based point forecast for the year at the midpoint of the forecasting base. The trend equation for RK is given by equation (20).

$$U_i = y_{(n+i)} \pm V_{y(i)} \cdot y_{n+i} \cdot K_i \quad \textbf{(20)}$$

The procedure for calculating the coefficient (Madiyev *et al.*) in the MS Excel environment is illustrated in Fig. 2.

| | A | B | C | D | E | F | G | H | I | J | K |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Calculation of the coefficient (K) for interval forecasting | | | | | | | | | | |
| 2 | The preemption index | $(n+L)^2$= | $2(n+L)^2$= | $n(n+L)^4$= | $t_i$ | $t_i^2$ | $t_i^4$ | $\Sigma t_i^2$ | $\Sigma t_i^4$ | $(\Sigma t_i^2)^2$ | K |
| 3 | | | | | | | | 0 | 0 | | |
| 4 | 7 | 576 | 1152 | 7299072 | 29 | 841 | 707281 | 4760 | 3312596 | 2,3E+07 | 2,49 |
| 5 | 6 | 529 | 1058 | 6156502 | 28 | 784 | 614656 | 3919 | 2605315 | 1,5E+07 | 2,51 |
| 6 | 5 | 484 | 968 | 5153632 | 27 | 729 | 531441 | 3135 | 1990659 | 9828225 | 2,54 |
| 7 | 4 | 441 | 882 | 4278582 | 26 | 676 | 456976 | 2406 | 1459218 | 5788836 | 2,59 |
| 8 | 3 | 400 | 800 | 3520000 | 25 | 625 | 390625 | 1730 | 1002242 | 2992900 | 2,66 |
| 9 | 2 | 361 | 722 | 2867062 | 24 | 576 | 331776 | 1105 | 611617 | 1221025 | 2,80 |
| 10 | 1 | 324 | 648 | 2309472 | 23 | 529 | 279841 | 529 | 279841 | 279841 | 3,18 |
| 11 | n= | 17 | | | | | | | | | |
| 12 | (n+1)/n= | 1,05882 | | | | | | | | | |
| 13 | $t_\alpha$= | 2,1604 | | | | | | | | | |

**Fig. 2.** Calculation of the coefficient $K_i$ using MS Excel.

The probable forecast errors at a confidence level of 0.95 (Student's $t$-criterion with degrees of freedom $n - 3$ (23 – 3 = 20) and significant level of 0.05, yielding 2.093 for the forecasted years are presented in Table 3. All remaining computations are also summarized in this table. The plot of the point and interval forecasts for melon crop yields in Kazakhstan is shown in Fig. 2. As evident from the graph, both the point and the interval forecasts preserve the pattern of annual yield variability by horoscopic years, while showing a pronounced tendency toward an increasing overall growth rate. Thus, with a probability of 0.96, the average annual yield of melon crops in the Republic of Kazakhstan for the period 2023-2030 is expected to remain within the range presented in Table 3.

**Table 3.** Forecast Results for melon crop yields in the Republic of Kazakhstan (c ha$^{-1}$).

| Years | Point forecast value | $\pm V_{y(i)} \cdot y_{n+i} \cdot K_i$ | Interval forecast value: Upper bound | Lower bound |
|---|---|---|---|---|
| 2023 | 211.89 | ± 0.08 · 211.89 · 2.51 | 253.40 | 170.38 |
| 2024 | 220.85 | ± 0.08 · 220.85 · 2.55 | 264.78 | 176.93 |
| 2025 | 263.03 | ± 0.08 · 263.03 · 2.60 | 316.45 | 209.61 |
| 2026 | 258.19 | ± 0.08 · 258.19 · 2.68 | 312.20 | 204.18 |
| 2027 | 263.03 | ± 0.08 · 263.03 · 2.81 | 320.61 | 205.44 |
| 2028 | 258.19 | ± 0.08 · 258.19 · 3.04 | 319.43 | 196.94 |
| 2029 | 267.90 | ± 0.08 · 267.90 · 3.65 | 344.27 | 191.54 |
| 2030 | 239.21 | ± 0.08 · 239.21 · 3.80 | 311.93 | 166.49 |

Based on the above methodology, further studies and forecasting of agricultural production in AIC RK were carried out by constructing production functions incorporating elements of astrological modeling implemented in modern IT environments. Specifically, forecasts were developed for crop yields and gross harvests, as well as for the livestock and poultry population and the main types of gross livestock production. The calculation procedures for these indicators are analogous to those described above; therefore, only the results of the point and interval forecasts are presented in the following tables. The final forecasting results are summarized in Tables 4-7 below

**Table 4.** Forecast results for crop yields in the Republic of Kazakhstan (c ha$^{-1}$).

| **Years** | **Point forecast value** | $\pm V_{y(i)} \cdot y_{n+i} \cdot K_i$ | **Interval forecast value** | |
|---|---|---|---|---|
| | | | **Upper bound** | **Lower bound** |
| 1 | 2 | 3 | 4 | 5 |
| | | **Wheat** | | |
| 2019 | 10.80 | ± 0.015 · 10.8 · 3.293 | 11.33 | 10.27 |
| 2020 | 10.21 | ± 0.015 · 10.21 · 3.373 | 10.72 | 9.70 |
| 2021 | 13.49 | ± 0.015 · 13.49 · 3.469 | 14.19 | 12.79 |
| 2022 | 8.84 | ± 0.015 · 8.84 · 3.585 | 9.31 | 8.37 |
| 2023 | 8.69 | ± 0.015 · 8.69 · 3.725 | 9.17 | 8.21 |
| 2024 | 8.40 | ± 0.015 · 8.40 · 3.900 | 8.89 | 7.91 |
| 2025 | 9.98 | ± 0.015 · 9.98 · 4.123 | 10.59 | 9.37 |
| 2026 | 8.52 | ± 0.015 · 8.52 · 4.421 | 9.08 | 7.96 |
| 2027 | 10.07 | ± 0.015 · 10.07 · 4.841 | 10.80 | 9.34 |
| 2028 | 10.43 | ± 0.015 · 10.43 · 5.490 | 11.28 | 9.58 |
| 2029 | 11.80 | ± 0.015 · 11.80 · 6.674 | 12.98 | 10.62 |
| 2030 | 10.92 | ± 0.015 · 10.92 · 9.942 | 12.54 | 9.30 |
| | | **Grain crops** | | |
| 2019 | 11.50 | ± 0.05 · 11.50 · 3.293 | 13.33 | 9.67 |
| 2020 | 10.93 | ± 0.05 · 10.93 · 3.373 | 12.71 | 9.15 |
| 2021 | 10.40 | ± 0.05 · 10.40 · 3.469 | 12.14 | 8.66 |
| 2022 | 10.09 | ± 0.05 · 10.09 · 3.585 | 11.84 | 8.34 |
| 2023 | 8.96 | ± 0.05 · 8.96 · 3.725 | 10.57 | 7.35 |
| 2024 | 10.31 | ± 0.05 · 10.31 · 3.900 | 12.25 | 8.37 |
| 2025 | 13.55 | ± 0.05 13.55 · 4.123 | 16.25 | 10.85 |
| 2026 | 9.60 | ± 0.05 · 9.60 · 4.421 | 11.65 | 7.55 |
| 2027 | 11.75 | ± 0.05 · 11.75 · 4.841 | 14.50 | 9.00 |
| 2028 | 8.40 | ± 0.05 · 8.40 · 5.490 | 10.63 | 6.17 |
| 2029 | 12.74 | ± 0.05 · 12.74 · 6.674 | 16.85 | 8.63 |
| 2030 | 8.37 | ± 0.05 · 8.37 · 9.942 | 12.39 | 4.35 |
| | | **Oilseed crops** | | |
| 2023 | 7.15 | ± 0.09 · 7.16 · 2.51 | 8.63 | 5.68 |
| 2024 | 7.32 | ± 0.09 · 7.32 · 2.55 | 8.85 | 5.80 |
| 2025 | 7.50 | ± 0.09 · 7.50 · 2.60 | 9.08 | 5.92 |
| 2026 | 7.68 | ± 0.09 · 7.68 · 2.68 | 9.31 | 6.04 |
| 2027 | 7.85 | ± 0.09 · 7.86 · 2.81 | 9.55 | 6.15 |
| 2028 | 8.03 | ± 0.09 · 8.03 · 3.04 | 9.80 | 6.27 |
| 2029 | 8.22 | ± 0.09 · 8.22 · 3.65 | 10.04 | 6.39 |
| | | **Melon crops** | | |
| 2023 | 211.89 | ± 0.08 · 211.89 · 2.51 | 253.40 | 170.38 |
| 2024 | 220.85 | ± 0.08 · 220.85 · 2.55 | 264.78 | 176.91 |
| 2025 | 263.03 | ± 0.08 · 263.03 · 2.60 | 316.45 | 209.61 |
| 2026 | 258.19 | ± 0.08 · 258.19 · 2.68 | 312.20 | 204.18 |
| 2027 | 263.03 | ± 0.08 · 263.03 · 2.81 | 320.61 | 205.44 |
| 2028 | 258.19 | ± 0.08 · 258.19 · 3.04 | 319.43 | 196.94 |
| 2029 | 267.90 | ± 0.08 · 267.90 · 3.65 | 344.27 | 191.54 |
| 1 | 2 | 3 | 4 | 5 |
| | | **Cotton** | | |
| 2023 | 28.95 | ± 0.12 · 28.95 · 2.51 | 36.95 | 20.94 |
| 2024 | 26.62 | ± 0.12 · 26.62 · 2.55 | 34.06 | 19.18 |
| 2025 | 40.39 | ± 0.12 · 40.39 · 2.60 | 51.82 | 28.96 |
| 2026 | 38.62 | ± 0.12 · 38.62 · 2.68 | 49.68 | 27.55 |
| 2027 | 33.75 | ± 0.12 · 33.75 · 2.81 | 43.55 | 23.96 |
| 2028 | 33.01 | ± 0.12 · 33.01 · 3.04 | 42.72 | 23.30 |
| 2029 | 35.30 | ± 0.12 · 35.30 · 3.65 | 45.83 | 24.77 |
| | | **Potato** | | |
| 2023 | 231.82 | ± 0.09 · 231.82 · 2.51 | 285.44 | 178.20 |
| 2024 | 242.13 | ± 0.09 · 242.13 · 2.55 | 299.00 | 185.26 |
| 2025 | 269.63 | ± 0.09 · 269.63 · 2.60 | 334.29 | 204.98 |

| | | | | |
|---|---|---|---|---|
| 2026 | 266.20 | ± 0.09 · 266.20 · 2.68 | 331.94 | 200.45 |
| 2027 | 273.07 | ± 0.09 · 273.07 · 2.81 | 343.65 | 202.49 |
| 2028 | 279.95 | ± 0.09 · 279.95 · 3.04 | 358.35 | 201.54 |
| 2029 | 269.63 | ± 0.09 · 269.63 · 3.65 | 360.37 | 178.90 |
| | | **Sugar beet** | | |
| 2023 | 188.82 | ± 0.09 · 188.82 · 2.51 | 231.58 | 149.98 |
| 2024 | 195.19 | ± 0.09 · 195.19 · 2.55 | 240.08 | 154.59 |
| 2025 | 201.78 | ± 0.09 · 201.78 · 2.60 | 249.16 | 159.31 |
| 2026 | 208.60 | ± 0.09 · 208.60 · 2.68 | 259.04 | 164.14 |
| 2027 | 215.64 | ± 0.09 · 215.64 · 2.81 | 270.21 | 169.08 |
| 2028 | 222.92 | ± 0.09 · 222.92· 3.04 | 284.04 | 174.13 |
| 2029 | 230.44 | ± 0.09 · 230.44 · 3.65 | 306.37 | 179.29 |
| | | **Tobacco** | | |
| 2023 | 23.93 | ± 0.08 · 23.93 · 2.51 | 28.88 | 18.98 |
| 2024 | 26.05 | ± 0.08 · 26.05 · 2.55 | 31.52 | 20.58 |
| 2025 | 27.38 | ± 0.08 · 27.38 · 2.60 | 33.25 | 21.51 |
| 2026 | 26.58 | ± 0.08 · 26.68 · 2.68 | 32.45 | 20.71 |
| 2027 | 26.32 | ± 0.08 · 26.32 · 2.81 | 32.40 | 20.23 |
| 2028 | 25.52 | ± 0.08 · 25.52 · 3.04 | 31.91 | 19.13 |
| 2029 | 27.11 | ± 0.08 · 27.11 · 3.65 | 35.27 | 18.96 |
| | | **Vegetables** | | |
| 2023 | 238.70 | ± 0.05 · 238.70 · 2.51 | 271.34 | 206.05 |
| 2024 | 245.57 | ± 0.05 · 245.57 · 2.55 | 279.68 | 211.46 |
| 2025 | 276.51 | ± 0.05 · 276.51 · 2.60 | 315.71 | 237.30 |
| 2026 | 273.07 | ± 0.05 · 273.07 · 2.68 | 312.95 | 233.19 |
| 2027 | 273.07 | ± 0.05 · 273.07 · 2.81 | 314.81 | 231.33 |
| 2028 | 273.07 | ± 0.05 · 273.07 · 3.04 | 318.29 | 227.85 |
| 2029 | 273.07 | ± 0.05 · 273.07 · 3.65 | 327.41 | 218.73 |

**Table 5.** Forecast results for the gross harvest of agricultural crops (in post-processing weight) across all farm categories in the Republic of Kazakhstan (thousand tons).

| Years | Point forecast value | | Interval forecast value | |
|---|---|---|---|---|
| | | $\pm V_{y(i)} \cdot y_{n+i} \cdot K_i$ | **Upper bound** | **Lower bound** |
| **1** | **2** | **3** | **4** | **5** |
| | | **Grain crops** | | |
| 2026 | 17696.02 | ± 0.18 · 17696.02 · 2.66 | 26058.86 | 9333.18 |
| 2027 | 18097.10 | ± 0.18 · 18097.10 · 2.73 | 26889.30 | 9304.90 |
| 2028 | 16815.31 | ± 0.18 · 16815.31 · 2.85 | 25342.62 | 8288.00 |
| 2029 | 14574.28 | ± 0.18 · 14574.28 · 3.07 | 22547.79 | 6600.78 |
| 2030 | 15796.83 | ± 0.18 · 15796.83 · 3.67 | 26100.41 | 5493.26 |
| | | **Wheat** | | |
| 2026 | 14057.33 | ± 0.20 · 14057.33 · 2.66 | 21483.05 | 6631.61 |
| 2027 | 13698.95 | ± 0.20 · 13698.95 · 2.73 | 21138.27 | 6259.62 |
| 2028 | 12906.87 | ± 0.20 · 12906.87 · 2.85 | 20223.08 | 5590.67 |
| 2029 | 11443.45 | ± 0.20 · 11443.45 · 3.07 | 18441.50 | 4445.41 |
| 2030 | 11979.18 | ± 0.20 · 11979.18 · 3.67 | 20712.96 | 3245.39 |
| | | **Oilseed crops** | | |
| 2023 | 1919.24 | ± 0.20 · 1919.24 · 2.51 | 2869.45 | 969.04 |
| 2024 | 2133.95 | ± 0.20 · 2133.95 · 2.55 | 3206.83 | 1061.08 |
| 2025 | 2362.14 | ± 0.20 · 2362.14 · 2.60 | 3574.62 | 1149.66 |
| 2026 | 2603.80 | ± 0.20 · 2603.80 · 2.68 | 3980.38 | 1227.22 |
| 2027 | 2858.93 | ± 0.20 · 2858.93 · 2.81 | 4440.85 | 1277.01 |
| 2028 | 3127.54 | ± 0.20 · 3127.54 · 3.04 | 5002.52 | 1252.55 |
| 2029 | 3409.62 | ± 0.20 · 3409.62 · 3.65 | 5865.81 | 953.43 |
| | | **Melon crops** | | |
| 2023 | 1713.00 | ± 0.20 · 1713.00 · 2.51 | 2577.14 | 928.09 |
| 2024 | 1874.67 | ± 0.20 · 1874.07 · 2.55 | 2835.01 | 1005.99 |
| 2025 | 2044.63 | ± 0.20 · 2044.63 · 2.60 | 3113.99 | 1085.88 |
| 2026 | 2222.89 | ± 0.20 · 2222.89 · 2.68 | 3420.33 | 1167.47 |
| 2027 | 2409.46 | ± 0.20 · 2409.46 · 2.81 | 3767.89 | 1250.45 |
| 2028 | 2604.32 | ± 0.20 · 2604.32 · 3.04 | 4195.17 | 1334.50 |
| 2029 | 2807.49 | ± 0.20 · 2807.49 · 3.65 | 4868.17 | 1419.32 |

| | | | | |
|---|---|---|---|---|
| **Cotton** | | | | |
| 2023 | 396.13 | ± 0.17 · 396.13 · 2.51 | 547.58 | 244.69 |
| 2024 | 400.58 | ± 0.17 · 400.58 · 2.55 | 555.45 | 245.71 |
| 2025 | 346.23 | ± 0.17 · 346.23 · 2.60 | 481.69 | 210.77 |
| 2026 | 334.05 | ± 0.17 · 334.05 · 2.68 | 466.38 | 201.71 |
| 2027 | 367.28 | ± 0.17 · 367.28 · 2.81 | 514.69 | 219.88 |
| 2028 | 371.86 | ± 0.17 · 371.86 · 3.04 | 523.13 | 220.58 |
| 2029 | 362.43 | ± 0.17 · 362.43 · 3.65 | 511.96 | 212.91 |
| **Vegetables** | | | | |
| 2023 | 3196.86 | ± 0.08 · 3196.86 · 2.51 | 3745.28 | 2648.43 |
| 2024 | 3369.19 | ± 0.08 · 3369.19 · 2.55 | 3953.70 | 2784.68 |
| 2025 | 4013.23 | ± 0.08 · 4013.23 · 2.60 | 4717.78 | 3308.67 |
| 2026 | 4308.71 | ± 0.08 · 4308.71 · 2.68 | 5074.63 | 3542.78 |
| 2027 | 4110.42 | ± 0.08 · 4110.42 · 2.81 | 4850.69 | 3370.16 |
| 2028 | 3822.73 | ± 0.08 · 3822.73 · 3.04 | 4520.57 | 3124.89 |
| 2029 | 4013.23 | ± 0.08 · 4013.23 · 3.65 | 4756.16 | 3270.29 |
| **Potato** | | | | |
| 2023 | 2674.30 | ± 0.20 · 2674.30 · 2.51 | 3723.00 | 1625.60 |
| 2024 | 2917.67 | ± 0.20 · 2917.67 · 2.55 | 4079.53 | 1755.81 |
| 2025 | 3956.82 | ± 0.20 · 3956.82 · 2.60 | 5565.49 | 2348.14 |
| 2026 | 5040.59 | ± 0.20 · 5040.59 · 2.68 | 7151.30 | 2929.88 |
| 2027 | 5040.59 | ± 0.20 · 25040.59 · 2.81 | 7249.69 | 2831.49 |
| 2028 | 4080.02 | ± 0.20 · 4080.02 · 3.04 | 6017.38 | 2142.66 |
| 2029 | 4080.02 | ± 0.20 · 4080.02 · 3.65 | 6407.96 | 1752.08 |

**Table 6.** Forecast results for livestock and poultry numbers across all farm categories in the Republic of Kazakhstan (thousand head).

| **Years** | **Point forecast value** | $\pm V_{y(i)} \cdot y_{n+i} \cdot K_i$ | **Interval forecast value** | |
|---|---|---|---|---|
| | | | **Upper bound** | **Lower bound** |
| **1** | **2** | **3** | **4** | **5** |
| **Cattle** | | | | |
| 2024 | 5909.712 | ± 0.01 · 5909.712 · 3.293 | 6041.598 | 5777.826 |
| 2025 | 6093.027 | ± 0.01 · 6093.027 · 3.373 | 6232.281 | 5953.773 |
| 2026 | 6245.739 | ± 0.01 · 6245.739 · 3.469 | 6392.463 | 6099.015 |
| 2027 | 6477.332 | ± 0.01 · 6477.332 · 3.585 | 6634.431 | 6320.233 |
| 2028 | 6831.842 | ± 0.01 · 6831.842 · 3.725 | 7003.850 | 6659.834 |
| 2029 | 7222.409 | ± 0.0.1 · 7222.409 · 3.900 | 7412.492 | 7032.326 |
| 2030 | 7510.764 | ± 0.01 · 7510.764 · 4.123 | 7719.299 | 7302.229 |
| 2031 | 7928.500 | ± 0.01 · 7928.500 · 4.421 | 8163.694 | 7693.306 |
| **Cows** | | | | |
| 2024 | 2740.37 | ± 0.01 · 2740.37 · 3.293 | 3013.744 | **2577.537** |
| 2025 | 2840.87 | ± 0.01 · 2840.87 · 3.373 | 3193.276 | 2667.997 |
| 2026 | 3005.30 | ± 0.01 · 3005.30 · 3.469 | 3424.021 | 2817.321 |
| 2027 | 3216.32 | ± 0.01 · 3216.32 · 3.585 | 3594.980 | 3143.270 |
| 2028 | 3369.12 | ± 0.01 · 3369.12 · 3.725 | 3834.777 | 3332.529 |
| 2029 | 3583.65 | ± 0.0.1 · 3583.65 · 3.900 | 4056.582 | 3498.097 |
| 2030 | 3777.34 | ± 0.01 · 3777.34 · 4.123 | 4333.539 | 3699.094 |
| 2031 | 4016.32 | ± 0.01 · 4016.32 · 4.421 | 4608.970 | 3879.172 |
| **Sheep and goats** | | | | |
| 2023 | 17914.60 | ± 0.09 · 17914.60 · 2.51 | 18802.17 | 17027.03 |
| 2024 | 17997.48 | ± 0.09 · 17997.40 · 2.55 | 18910.66 | 17084.31 |
| 2025 | 18166.02 | ± 0.09 · 18166.02 · 2.60 | 19113.43 | 17218.60 |
| 2026 | 18310.67 | ± 0.09 · 18310.67 · 2.68 | 19296.61 | 17324.74 |
| 2027 | 18680.40 | ± 0.09 · 18680.40 · 2.81 | 19724.55 | 17636.25 |
| 2028 | 19136.54 | ± 0.09 · 19136.54 · 3.04 | 20254.67 | 18018.42 |
| 2029 | 20037.54 | ± 0.09 · 20037.54 · 3.65 | 21272.65 | 18802.44 |
| 2030 | 20855.92 | ± 0.09 · 20855.92 · 3.74 | 22229.43 | 19482.42 |
| 2031 | 18824.16 | ± 0.09 · 18824.16 · 3.85 | 20173.65 | 17474.67 |
| 2032 | 18648.73 | ± 0.09 · 18648.73 · 3.87 | 20148.55 | 17148.91 |
| **Pigs** | | | | |
| 2023 | 922.30 | ± 0.08 · 922.30 · 2.51 | 1044.96 | 799.64 |
| 2024 | 877.62 | ± 0.08 · 877.62 · 2.55 | 992.86 | 762.38 |

| | | | | |
|---|---|---|---|---|
| 2025 | 880.50 | ± 0.08 · 880.50 · 2.60 | 995.84 | 765.16 |
| 2026 | 827.53 | ± 0.08 · 827.53 · 2.68 | 936.19 | 718.86 |
| 2027 | 808.58 | ± 0.08 · 808.58 · 2.81 | 915.39 | 701.77 |
| 2028 | 792.31 | ± 0.08 · 792.31 · 3.04 | 897.93 | 686.69 |
| 2029 | 806.79 | ± 0.08 · 806.79 · 3.65 | 915.74 | 697.85 |
| 2030 | 769.89 | ± 0.08 · 769.89 · 3.74 | 921.56 | 698.77 |
| 2031 | 505.72 | ± 0.08 · 505.72 · 3.85 | 878.56 | 661.22 |
| 2032 | 479.43 | ± 0.08 · 479.43 · 3.87 | 1044.96 | 431.36 |
| | | **Horses** | | |
| 2025 | 1799.79 | ± 0.12 · 1799.79 · 2.51 | 1853.13 | 1746.45 |
| 2026 | 1909.96 | ± 0.12 · 1909.96 · 2.55 | 1968.17 | 1851.75 |
| 2027 | 2026.91 | ± 0.12 · 2026.91 · 2.60 | 2091.43 | 1962.39 |
| 2028 | 2150.64 | ± 0.12 · 2150.64 · 2.68 | 2224.55 | 2076.73 |
| 2029 | 2281.15 | ± 0.12 · 2281.15 · 2.81 | 2374.76 | 2187.54 |
| 2030 | 1799.79 | ± 0.12 · 1799.79 · 3.04 | 1853.13 | 1746.45 |
| 2031 | 1909.96 | ± 0.12 · 1909.96 · 3.65 | 2374.76 | 1851.75 |
| | | **Camels** | | |
| 2023 | 161.38 | ± 0.09 · 161.38 · 2.51 | 168.52 | 178.20 |
| 2024 | 166.40 | ± 0.09 · 166.40 · 2.55 | 173.93 | 185.26 |
| 2025 | 171.01 | ± 0.09 · 171.01 · 2.60 | 178.97 | 204.98 |
| 2026 | 180.64 | ± 0.09 · 180.64 · 2.68 | 189.32 | 200.45 |
| 2027 | 193.68 | ± 0.09 · 193.68 · 2.51 | 203.34 | 184.02 |
| 2028 | 208.22 | ± 0.09 · 208.22 · 2.51 | 219.08 | 205.11 |
| 2029 | 217.05 | ± 0.09 · 217.05 · 2.51 | 228.99 | 214.96 |
| 2030 | 228.38 | ± 0.09 · 228.38 · 2.55 | 259.74 | 228.52 |
| 2031 | 244.13 | ± 0.09 · 244.13 · 2.60 | 272.72 | 236.20 |
| 2032 | 254.46 | ± 0.09 · 254.46 · 2.68 | 288.32 | 243.07 |

**Poultry**

| 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|
| 2023 | 35035.00 | ± 0.09 · 35035.00 · 2.81 | 39491.73 | 28976.67 |
| 2024 | 35635.60 | ± 0.09 · 35635.60 · 3.04 | 40545.21 | 29524.79 |
| 2025 | 36936.90 | ± 0.09 · 36936.903 · 3.65 | 41396.51 | 29874.69 |
| 2026 | 39939.90 | ± 0.09 · 39939.90 · 2.51 | 43101.84 | 30771.96 |
| 2027 | 39939.90 | ± 0.09 · 39939.90 · 2.55 | 46859.94 | 33019.86 |
| 2028 | 44344.30 | ± 0.09 · 44344.30 · 2.60 | 52375.67 | 36312.93 |
| 2029 | 45045.00 | ± 0.09 · 45045.00 · 2.68 | 53651.59 | 36438.41 |
| 2030 | 43343.30 | ± 0.09 · 43343.30 · 2.81 | 52191.34 | 34495.26 |
| 2031 | 47947.90 | ± 0.09 · 47947.90· 3.04 | 58602.77 | 37293.03 |
| 2032 | 45745.70 | ± 0.09 · 45747.70 · 3.65 | 57149.90 | 34341.50 |

**Table 7.** Forecast results for the gross output of livestock production (in post-processing weight) across all farm categories in the Republic of Kazakhstan (thousand tons).

| **Years** | **Point forecast value** | $\pm V_{y(i)} \cdot y_{n+i} \cdot K_i$ | **Interval forecast value** | |
|---|---|---|---|---|
| | | | **Upper bound** | **Lower bound** |
| **1** | **2** | **3** | **4** | **5** |
| | | **All types of meat (in slaughter weight). thousand tons** | | |
| 2024 | 871.871 | ± 0.18 · 871.871 · 2.66 | 899.356 | 844.386 |
| 2025 | 901.100 | ± 0.18 · 901.100 · 2.73 | 930.191 | 872.009 |
| 2026 | 931.931 | ± 0.18 · 931.931 · 2.85 | 962.856 | 901.006 |
| 2027 | 961.661 | ± 0.18 · 961.661 · 3.07 | 994.608 | 928.714 |
| 2028 | 1018.618 | ± 0.18 · 1018.61 · 3.67 | 1054.845 | 982.390 |
| 2029 | 1060.660 | ± 0.20 · 1060.66 · 2.66 | 1100.092 | 1021.227 |
| 2030 | 1121.721 | ± 0.20 · 1121.72 · 2.73 | 1165.714 | 1077.727 |
| 2031 | 1169.769 | ± 0.20 · 1169.77 · 2.85 | 1218.786 | 1120.751 |
| 2032 | 1232.331 | ± 0.20 · 1232.33 · 3.07 | 1288.543 | 1176.119 |
| | | **All types of milk. thousand tons** | | |
| 2025 | 4959.882 | ± 0.20 · 4959.882 · 2.51 | 5062.216 | 4857.548 |
| 2026 | 5098.307 | ± 0.20 · 5098.307 · 2.55 | 5206.033 | 4990.582 |
| 2027 | 5213.494 | ± 0.20 · 5213.494 · 2.60 | 5326.724 | 5100.264 |
| 2028 | 5373.650 | ± 0.20 · 5373.650 · 2.68 | 5494.143 | 5253.156 |
| 2029 | 5536.420 | ± 0.20 · 5536.420 · 2.81 | 5665.292 | 5407.549 |

| | | | | |
|---|---|---|---|---|
| 2030 | 5720.317 | ± 0.20 · 5720.317 · 3.04 | 5859.504 | 5581.130 |
| 2031 | 5900.089 | ± 0.20 · 5900.089 · 3.65 | 6051.539 | 5748.639 |
| 2032 | 6087.708 | ± 0.20 · 6087.708 · 3.04 | 6254.666 | 5920.751 |
| 2033 | 6284.683 | ± 0.20 · 6284.683 · 3.65 | 6472.300 | 6097.059 |
| | | **Eggs (million pieces)** | | |
| 2023 | 1713.00 | ± 0.20 · 1713.00 · 2.51 | 2577.14 | 928.09 |
| 2024 | 1874.67 | ± 0.20 · 1874.07 · 2.55 | 2835.01 | 1005.99 |
| 2025 | 2044.63 | ± 0.20 · 2044.63 · 2.60 | 3113.99 | 1085.88 |
| 2026 | 2222.89 | ± 0.20 · 2222.89 · 2.68 | 3420.33 | 1167.47 |
| 2027 | 2409.46 | ± 0.20 · 2409.46 · 2.81 | 3767.89 | 1250.45 |
| 2028 | 2604.32 | ± 0.20 · 2604.32 · 3.04 | 4195.17 | 1334.50 |
| 2029 | 2807.49 | ± 0.20 · 2807.49 · 3.65 | 4868.17 | 1419.32 |
| | | **Wool (thousand tons)** | | |
| 2023 | 396.13 | ± 0.17 · 396.13 · 2.51 | 547.58 | 244.69 |
| 2024 | 400.58 | ± 0.17 · 400.58 · 2.55 | 555.45 | 245.71 |
| 2025 | 346.23 | ± 0.17 · 346.23 · 2.60 | 481.69 | 210.77 |
| 2026 | 334.05 | ± 0.17 · 334.05 · 2.68 | 466.38 | 201.71 |
| 2027 | 367.28 | ± 0.17 · 367.28 · 2.81 | 514.69 | 219.88 |
| 2028 | 371.86 | ± 0.17 · 371.86 · 3.04 | 523.13 | 220.58 |
| 2029 | 362.43 | ± 0.17 · 362.43 · 3.65 | 511.96 | 212.91 |

## CONCLUSION

Astrology, regarded as a discipline that studies the patterns and regularities of the real world, possesses its own subject of inquiry and a distinct methodological foundation, the central objective of which is the substantiation of a universal modeling method. It employs a well-developed mathematical apparatus, specific analytical techniques, precise terminology, and a highly informative symbolic language. Similar to other exact sciences, astrological forecasting is based on rigorous principles and methodologies and relies on substantial statistical data. Practical validation of the reliability and utility of conclusions, recommendations, and forecasts derived through astrological methods confirms their scientific consistency and applicability.

The analysis revealed that agricultural crop yields exhibit dependence on so-called low-frequency energy, which can be interpreted through numerical series associated with the positions of planets in the Solar System and cosmic cycles. Consequently, forecasting the development of crop production is advisable when accounting for the combined influence of the Eastern zodiac years and planetary characteristics, i.e., in relation to variations in low-frequency energy parameters. Long-term forecasts of climatic conditions correlated with horoscope cycles can serve as a basis for adapting agricultural technologies, while the availability of retrospective data enables modeling of future developments.

A significant increase in interest toward specialized user software that enhances visualization and automates the construction of situational astrological models of agrarian dynamics has contributed to the development of a forecasting methodology utilizing the capabilities of MS Excel. The proposed combined algorithm for medium- and long-term yield forecasting of grain crops is characterized by implementation simplicity, does not require specialized software, and is universal for applications at various levels of planning and management. The situational trend model incorporating astrological parameters, constructed on the basis of time series, provides a comprehensive description of the dynamics of crop and livestock production indicators in AIC of the Republic of Kazakhstan.

Based on statistical analysis of time series incorporating astrological factors, econometric features of dynamics in the crop and livestock sectors of Kazakhstan's AIC were identified. Systems of situational (horoscopic) trend models for forecasting key indicators were developed, and the methodology of astrological yield modeling was improved. In addition, practical recommendations were proposed to enhance model-based decision support tools at various levels of governmental and corporate management within the agricultural sector.

The presented methodological approaches to constructing situational astrological models and forecasting production indicators can be effectively applied both in long-term and short-term agricultural planning, as well as in the preparation of business plans for agrarian enterprises. The obtained forecast values make it possible to account for changes in resource and product prices, thereby enabling more accurate cost and output planning. The developed forecasting technology in MS Excel ensures flexibility and operational efficiency of calculations, making it suitable for both short-term and long-term forecasting. The implementation of these research results in practice will contribute to improving the economic efficiency of the agricultural sector of the Republic of Kazakhstan.

**ACKNOWLEDGEMENT**
The article was prepared within the framework of the grant project of the State Institution "Science Committee" of the Ministry of Science and Higher Education of the Republic of Kazakhstan, project No. AP19678876, entitled "Effective system of macroeconomic instruments for state regulation of innovative development of the agro-industrial complex of the Republic of Kazakhstan".

**REFERENCES**

Abdusamatov, H 2006, Monitoring the shape and diameter of the sun on the service module of the Russian segment of the ISS. *Journal of Optical Technology,* 73:236-241.

Bakkuev, E, Kokov, N, Kokova, S, Sarbasheva, E & Bezirova, Z 2022, Integration factors of growth in agriculture of the Kabardino-Balkarian Republic. *AIP Conference Proceedings*, 2022.

Baldwin, K, Williams, B, Turner, D, Tsiboe, F, Raszap Skorbiansky, S, Sichko, C, Jones, J & Toossi, S 2024, US agricultural policy review, 2023 (Report No. EIB-285). *US Department of Agriculture, Economic Research Service*.

Birner, R & Resnick, D 2010, The political economy of policies for smallholder agriculture. *World development,* 38**:**1442-1452.

Change, C 2023, Agricultural Policy Monitoring and Evaluation.

C0-operation, OFE 2018, *Agricultural policy monitoring and evaluation*, *OECD Publishing*.

Commission, E 2020, Farm to fork strategy: for a fair, healthy and environmentally-friendly food system. *Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions,* 381**:**1-9.

Falvey, L 1996, *Food environment education: Agricultural education in natural resource management*, lindsay falvey.

Feindt, PH 2018, EU agricultural policy. *Handbook of European policies.* Edward Elgar Publishing.

Feng, S, Hao, Z, Zhang, X & Hao, F 2019, Probabilistic evaluation of the impact of compound dry-hot events on global maize yields .*Science of the total environment,* 689**:**1228-1234.

Filassi, M & De Oliveira, ALR 2021, Competitiveness drivers for soybean exportation and the fundamental role of the supply chain. *Revista de Economia e Sociologia Rural,* 60**,** e235296.

Ganesh, J 2002, Principles of forecasting: a handbook for researchers and practitioners.

Ibragimov, IA & Has'minskii, RZ 2013, *Statistical estimation: asymptotic theory*, Springer Science & Business Media.

Jägermeyr, J, Muller, C, Ruane, AC, Elliott, J, Balkovic, J, Castillo, O, Faye, B, Foster, I, Folberth, C & Franke, JA 2021, Climate impacts on global agriculture emerge earlier in new generation of climate and crop models. *Nature Food,* 2**:**873-885.

Larchenko, O 2023, MATHEMATICAL METHODS OF ECONOMIC ANALYSIS SOLVING PROBLEMS.

Lobell, DB & Burke, MB 2010, On the use of statistical models to predict crop yield responses to climate change. *Agricultural and forest meteorology,* 150**:**1443-1452.

Lobell, DB, Deines, JM & Tommaso, SD 2020, Changes in the drought sensitivity of US maize yields. *Nature Food,* 1**:**729-735.

Lyson, HC 2016, National policy and state dynamics: A state-level analysis of the factors influencing the prevalence of farm to school programs in the United States. *Food Policy,* 63**:** 23-35.

Madiyev, G, Kerimova, U, Yespolov, A, Bekbossynova, A & Rakhimzhanova, G 2018, Macroeconomic aspects of innovation-driven growth of agribusiness in the Republic of Kazakhstan. *Journal of Advanced Research in Law and Economics,* 9**,** 5.61-569

Mehrabi, Z, McDowell, MJ, Ricciardi, V, Levers, C, Martinez, JD, Mehrabi, N, Wittman, H, Ramankutty, N & Jarvis, A 2021, The global divide in data-driven farming. *Nature Sustainability,* 4**:**154-160.

Pe'er, G, Zinngrebe, Y, Moreira, F, Sirami, C, Schindler, S, Muller, R, Bontzorlos, V, Clough, D, BezáK, P & Bonn, A 2019, A greener path for the EU Common Agricultural Policy. *Science,* 365:449-451.

Salamon, P, Banse, M, Barreiro-Hurle, J, Chaloupka, O, Donnellan, T, Erjavec, E, Fellmann, T, Hanrahan, K, Hass, M & Jongeneel, R 2017, Unveiling diversity in agricultural markets projections: from EU to Member States. *A Medium Term Outlook with the AGMEMOD Model; JRC Technical Report; Publications Office of the European Union: Luxembourg*.

Sasaki, H 2025, Sustainable Agriculture and Agricultural Environmental Policy. *Economics of Sustainable Agriculture.* Springer.

Sivakumar, MV 2006, Climate prediction and agriculture: current status and future challenges. *Climate research,* 33:3-17.

Smith, VH 2018, US agricultural policy beyond 2018: *implications for the World Trade Organization*, International Centre for Trade and Sustainable Development.

Swinnen, J 2021, The political economy of agricultural and food policies.

Tikhonov, V, Kondrashova, O & Neverov, A 2014, Using nonlinear description methods for description of the sun and earth links in the prediction of yield in the Steppe Ural region. *Russian Agricultural Sciences,* 40**:**229-232.

Tikhonov, V & Neverov, A 2014, Long-term crop yield forecasting in the Urals steppe zone using modern methods for the estimation of solar-terrestrial relations. *Arid Ecosystems,* 4**,** 294-298.

Tikhonov, V & Neverov, A 2016, Modeling of the expected yield in the steppe district of the Cis-Ural region taking into account the lag variables and changes of the distance from the mass center of the Solar system to the Earth. *Russian Agricultural Sciences,* 42**:**163-166.

Tsymbalenko, T & Tsymbalenko, O, Type and distribution tendency of main economic index numbers in agricultural industry. *Problems of tourism development on rural areas***,** 133.

Wulff, SS 2017, Time series analysis: Forecasting and control. Taylor & Francis.

Zhylykbek, T, Akhmetov, K, Asaev, R & Tokseitov, B 2014, Research on development of production indicators of agriculture of Almaty region with the method of the astrological computer simulation. News of the National Academy of Sciences of the Republic of Kazakhstan. *NEWS of the national Academy of sciences of the Republic of Kazakhstan. Series of agricultural sciences,* 6:78-87.

***Bibliographic information of this paper for citing:***

Kalykova, B, Akhmetov, K, Madiyev, G, Kerimova, U, Karymsakova, Z 2026, Forecasting is a key instrument of state regulation in the development of agricultural sector of the Republic of Kazakhstan. Caspian Journal of Environmental Sciences, 24: 385-404.