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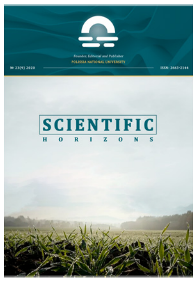

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Forecasting husbandry development using time series

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Abstract. Building time series models based on historical data is a pressing challenge in the agricultural sector. This is essential, as analysing and predicting processes related to the food security of the state, region, and business entities are of paramount importance in management. With the help of forecasts, enterprises can adjust their production activities in such a way as to satisfy demand and deliver products to consumers on time. The research aims to predict the trends in the growth of cattle and cow populations and identify the most suitable forecasting timeframe. Statistical methods related to autoregression are used for this type of analysis: autoregressive

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models, moving average models or a combination of both, integrated variable structure models, and models that include seasonal effects and exogenous factors with an autoregressive and moving average component in the model. Monthly statistical data on the number of cattle and cows are used, among them mean, standard deviation, minimum and maximum values, asymmetry, and kurtosis. The dynamics of the decrease in the number of cattle and cows are shown. The studied series were checked for stationarity. The time series data for the cattle population underwent a Box-Cox transformation. The optimal parameters of the models used are given. Predictive values for periods (months) were obtained and the change in the number of cattle over the last 15 years was analysed. Constructed time series are compared with the actual values, which are illustrated in the graphs. Estimates of root-mean-square deviation, and mean absolute percentage error for different forecasting terms are given. By comparing these estimates for different time intervals, the optimal period for the forecast (24 months) was determined. This study allows farms and enterprises in the industry to predict a possible number of products (milk, meat) that could be collected or obtained in the future. It helps to take the necessary management steps: plan resource needs, improve efficiency, increase profits, reduce costs, and adapt to changes in the market

Keywords: husbandry; predict; management; Box-Cox transformation

INTRODUCTION

Animal husbandry is one of the key branches of agriculture. It performs the functions of the main source of raw materials, materials of various spheres of the economy. At the same time, animal farming is the main supplier of vital products, means of forming the country's food independence, consumer of the machine-building industry, and transport industry. The relationship between animal agriculture and other sectors of the economy and economy determines the nature of the current problems of the industry, as well as management methods for overcoming them. As such, A. Chub (2021) research demonstrated that animal husbandry constitutes an integral and crucial component of Ukraine's agro-industrial complex. The importance of this branch of the economy is determined by the need to provide food products of animal origin in the population's diet.

Since 2013, the state of the industry has shown both a decline in the potential of livestock farming in the domestic environment and a decrease in its share in the global development of the industry. During the last decade, there has been a tendency to decrease the number of cattle and cows in Ukraine (State Statistics Service of Ukraine (n.d.). The development of domestic animal agriculture in the near and distant perspectives should be based on the achieved results and management experience of its rational management and following the provision of economic-technological, normative-legal, state regulation and organizational-management components at the national level, addressing the peculiarities of the management of industries in economically developed countries the world, which, in turn, requires further scientific and practical research and development (Zamula *et al.*, 2020).

A. Lavruk & N. Lavruk (2020) considered the current state of animal husbandry. To facilitate a successful revitalization and intensive growth of the animal husbandry industry, it is necessary to promote transparency in the actions of government and executive authorities. This means implementing transparent and open processes in decision-making, attracting investment, and developing policies in the industry. N. Parajua (2022) analysed changes in agriculture, livestock, woodland management, and fishing in the Spanish agricultural and food system. Said study also revealed trends, opportunities and problems related to these industries. P. Zharuk and L. Zharuk (2020) analysed the results of modern world development of sheep breeding, its state in Ukraine and development trends. Changes are taking place in sheep breeding in different countries – in some, a significant decrease in the number of livestock, in others – an increase. In the conditions of the modern world market, the production of meat and dairy products from mutton, and mutton with preservation of quality characteristics of wool, fur and fur raw materials is a promising direction of the industry development.

N. Shyian and I. Kotelnikova (2019) emphasised negative trends in the field of animal husbandry that can lead to serious problems. A decline in the cattle population, especially cows, can lead to a decrease in the industry's product output and result in unprofitability in meat and milk production. V. Zamlynskyi (2019) assessed the current status of the animal husbandry industry in Ukraine and internationally to formulate a strategic development plan. This plan aims to enhance the involvement of small and medium-sized enterprises in animal husbandry, implement programs for conserving resources, and mitigate environmental pollution. O. Shubravska and K. Prokopenko (2018) demonstrated strategies for encouraging the adoption of innovative management solutions in Ukraine's agricultural sector. It is shown that the production of organic products, along with purely health and ecological effects, is favourable to significantly increase the income of Ukrainian farmers, their ability for further innovative development, and also to improve the state's balance of payments.

The analysis covers the level and dynamics of the indicators that determine it. S. Koliadenko *et al.* (2020) examined potential avenues for Ukrainian agricultural product exports. Employing mathematical modelling, complex economic processes were analysed, and optimal solutions were found based on available data and information. The method of a continuous system of non-periodic functions was used to address the instability of market conditions and the variability of demand, which are characteristic of the agricultural sector. This makes it possible to determine forecasts and adapt them to real conditions more accurately. M. Ribeiro & L. Coelho (2020) assessed the predictive attributes of regression ensemble models in agribusiness-related case studies and compared their effectiveness.

The research aims to forecast trends in the development of the number of cattle and cows using a model that specializes in analysing dynamics in time series and determining the appropriate forecasting period.

MATERIALS AND METHODS

Data Overview. Research data on the number of cattle (including cows) in the period from January 1, 2008, to January 1, 2023, were obtained from the website of the Main Department of Statistics in the Khmelnytskyi region of Ukraine (n.d.).

SARIMAX Models. The basis of this study is the Box-Jenkins model (Zhang, 2003; Ediger & Akar, 2007) (Autoregressive Integrated Moving Average, ARIMA), which enables forecasts based on time series, that is, historical observations. The ARIMA model integrates elements from both the autoregressive (AR) model and the moving average (MA) model.

AR (p) $$y_t = c + \sum_{n=1}^{p} \alpha_n y_{t-n} + \varepsilon_t\,, \tag{1}$$

MA (q) $$\varepsilon_t = \sum_{n=1}^{q} \theta_n \varepsilon_{t-n}\,. \tag{2}$$

Three integers are used to parameterize the model: (p, d, q). p – number of members of the autoregression; d – number of non-seasonal differences; q – number of moving average conditions.

SARIMAX (Seasonal Auto-Regressive Integrated Moving Average with eXogenous factors) is a modification of the ARIMA model. While ARIMA is based on an autoregressive integrated moving average, SARIMAX extends this model by adding seasonal changes and external factors that help account for changes in a given time series. Thus, SARIMAX is the seasonal equivalent of SARIMA and Auto ARIMA models.

Two types of parameters must be specified in the SARIMAX model parameter. The first is similar to the ARIMAX (p, d, q) model, and the second is to determine the effect of seasonality. You need to know 4 parameters: P – Seasonal AR specification; D – Seasonal Integration order; Q – Seasonal MA; s – Seasonal periodicity.

Mathematically, the model can be stated as follows:

$$\phi_p(L)\underline{\phi}_P(L^s)\Delta^d\Delta_s^D y_t = A(t) + \theta_q(L)\underline{\theta}_Q(L^s)\epsilon_t \tag{3}$$

where $\phi_p(L)$ – is the non-seasonal autoregressive lag polynomial; $\underline{\phi}_P(L^s)$ – is the seasonal autoregressive lag polynomial; $\Delta^d\Delta_s^D y_t$ – is the time series, difference d times, and seasonally differenced D times; $A(t)$ – is the trend polynomial (including the intercept); $\theta_q(L)$ – is the non-seasonal moving average lag polynomial; $\underline{\theta}_Q(L^s)$ – is the seasonal moving average lag polynomial.

The evaluation measure used for time series forecasting in this study is root mean square deviation (RMSE) and mean absolute percentage error (MAPE) (Hyndman & Koehler, 2006, Zhang X *et al*, 2015):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(E_t - F_t)^2}, \tag{4}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|E_t - F_t|}{E_t}, \tag{5}$$

where E_t and F_t are actual and predicted values, n – number of values.

To apply the technique of time series forecasting, it is necessary to test the series for stationarity using the Dickey-Fuller (ADF) test (Dickey & Fuller, 1981). This test detects the presence of stochastic trend behaviour in time series using a hypothesis test.

H_0: process is non-stationary;

H_1: process is stationary.

If the series is non-stationary, then the Box-Cox transform can be used to obtain a series that will satisfy the conditions of stationarity (Atkinson & Corbellini, 2021; He *et al.,* 2019). The basis of the Box-Cox Transformation is the exponent and the coefficient λ, which varies from -5 to 5. All values of λ are considered and the value that gives the best approximation of the normal distribution curve is selected. The transformation of Y has the form:

$$y(\lambda) = \begin{cases} \frac{y^\lambda - 1}{\lambda}, if\ \lambda \neq 0; \\ y,\ if\ \lambda = 0. \end{cases} \tag{6}$$

Software used for calculations and visualizations: *Jupyter Notebook*.

RESULTS AND DISCUSSION

Predicting the future of the agricultural sector, a pivotal component of the economy holds significant importance for both developed and developing nations. Moreover, it enables the formulation of future agricultural policies, facilitates investment planning, and allows for the implementation of necessary measures. In the immediate future, estimating the number of farm animals has many advantages for management decisions. The most successful forecast using monthly data can be obtained by improving seasonal forecasting methods. In this research, the SARIMAX forecasting method was used for predicting monthly cattle and cow populations. The proposed method is focused on finding the most relevant values of past observations through identical estimates. In addition, conducts tests for all relevant seasonal factors, enhancing the effective modelling of seasonality within the dataset.

Time series models of the dynamics of changes in the number of farm animals in this study were built considering the RMSE and MAPE values. Using the proposed method, monthly changes in the number of cattle and cows for Ukraine until 2025 were predicted. The dynamics of changes in the number of cattle (including cows) in the period from January 1, 2008, to January 1, 2023, in the Khmelnytskyi region were considered (Fig. 1).

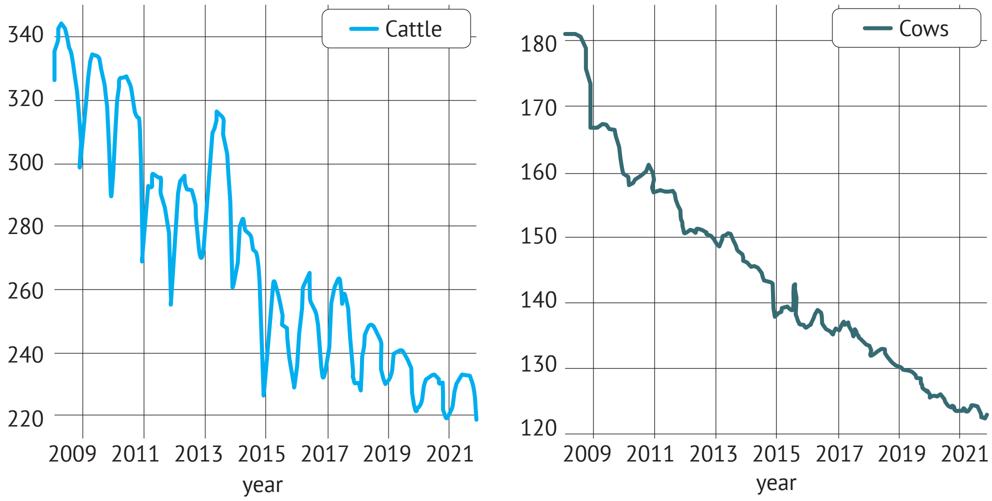

Figure 1*. Dynamics of changes in the number of cattle and cows (thousands of heads) from January 1, 2008, to January 1, 2023*

Source: *authors' elaboration from (Main Department of Statistics in the Khmelnytskyi region of Ukraine, n.d.)*

Figure 1 shows that over the last 15 years, the population of cattle and cows has a general tendency to decrease. The trend and seasonality are visible on the graph of the cattle population. Table 1 shows the summary monthly statistical data for the above-mentioned period of the number of agricultural animals.

Table 1. *Statistical data on the number of cattle and cows*

Metrics	N	Mean	Std.	Min.	Max.	Skew.	Kurt.
Cattle	180	267.15	36.69	217.5	344	0.52	-1.04
Cows	180	143.12	16.33	121.7	182.6	0.62	-0.46

Source: *author's elaboration*

The table shows the minimum, maximum, mean, skewness, and kurtosis for the monthly data set used in this study to characterize the number of cattle and cows. Thus, the maximum number of cattle was 344,000 heads in May 2008. And already in November 2012, it reached its minimum value of 217.5 thousand heads. A positive sign in the skewness coefficient indicates that most of the data is greater than mathematical expectation, and a negative kurtosis coefficient indicates that the curve of the theoretical distribution has a lower peak than the curve of the normal distribution. Also, the correlation coefficient between cattle and cows is 0.941, which indicates a high dependence between the values. Let's check for the stationarity of the series using ADF (augmented Dickey-Fuller test) (Table 2).

Table 2. *The results of the test for stationarity using the Dickey-Fuller test*

	p-value	conclusion
Cattle	0.6104	non-stationary
Cows	0.0139	stationary

Source: *author's elaboration*

The authors apply the Box-Cox Transformation to the time series of the number of cattle. The optimal parameter λ=-1.9767. Table 3 presents the best SARIMAX models for predicting cattle and cow populations using the AIC criterion (Akaike information criterion). In Figure 2 shows the actual value of the time series and the value of the constructed models for the time series. It can be seen visually that the models fit the actual values well, which indicates the optimality of the found model parameters.

Table 3. *SARIMAX model parameters and AIC-criterion values for time series characterizing cattle and cows*

	Model	AIC
Cattle	SARIMAX(0, 1, 0) × (0,1, 1, 12)	-4071.359
Cows	SARIMAX(1, 1, 9) × (1,1, 1, 12)	465.673

Source: *author's elaboration*

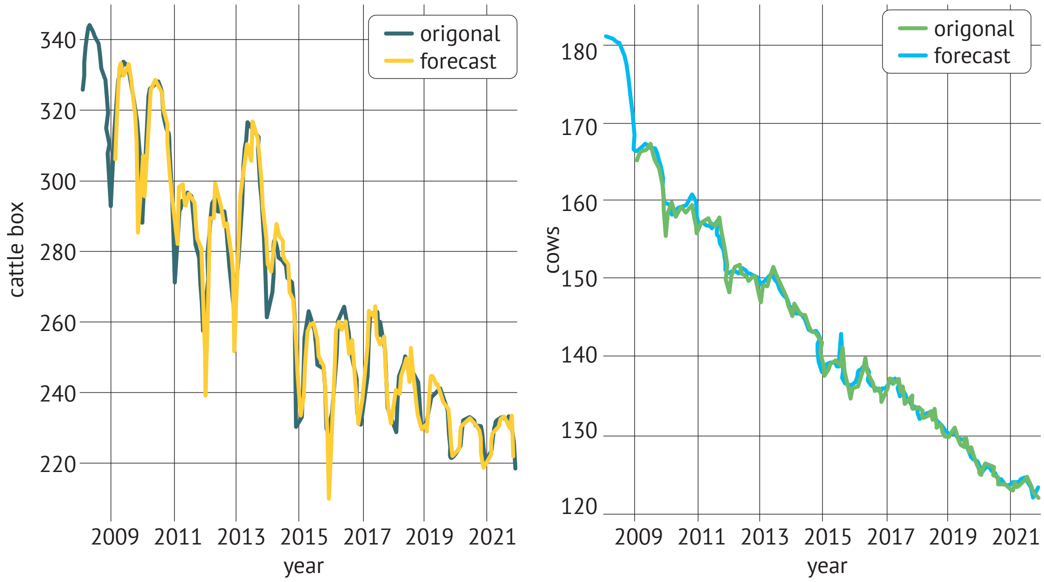

Figure 2*. Original and forecast values of time series*

Source: *author's elaboration*

The forecasting time horizon (comparing the size of the receiver window size (RWS) sliding window) was set to 24 months (Table 4) since this value of RWS has the lowest root mean squared error (RMSE) and mean absolute percentage error (MAPE) estimates and the best average absolute percentage accuracy (MAPA) for both time series.

Table 4. *Rolling window size comparison*

	Cattle			Cows		
RWS	**RMSE**	**MAPE**	**MAPA (%)**	**RMSE**	**MAPE**	**MAPA (%)**
12	2.928	0.008	99.2	0.605	0.005	99.5
24	2.178	0.005	99.5	0.529	0.004	99.6
36	2.201	0.006	99.4	0.570	0.005	99.5
48	3.052	0.008	99.2	0.630	0.005	99.5

Source: *author's elaboration*

In this context, accuracies have been calculated using MAPA and MAPE.

$$\text{MAPA \%} = (1 - \text{MAPE}) * 100$$

since it is a percentage-based metric, it offers easier interpretation compared to RMSE.

Tables 5 (5.1 and 5.2) show the forecasted monthly values of cattle and cow numbers, respectively.

Table 5. *Forecast monthly values of the number of cattle and cows*

Table 5.1 Forecast monthly values of the number of cattle, thousand units												
Year	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
2023	211	217	234	248	240	227	220	221	236	245	236	218
2024	212	217	235	249	241	227	220	222	237	246	236	218
Table 5.2 Forecast monthly values of the number of cows, thousand units												
2023	121	122	122	122	122	122	122	121	121	120	120	120
2024	120	120	120	120	121	120	120	119	119	119	118	119

Source: *author's elaboration*

For more accurate forecasting of the number of farm animals, it is possible to use an ensemble of methods that consider not only seasonality but also the specifics of this business. To accurately forecast information, it is necessary to consider the regional affiliation of enterprises and the number of cattle in the given region. When there are significant fluctuations in the number of farm animals, it is possible to predict the average number of animals more accurately. This will help in making informed management decisions about land for livestock grazing, marketing, trading, and storage of livestock products.

Agribusiness requires effective management decisions, the preparation and adoption of which can provide forecasting based on hindsight and considering the multifactorial impact. Management, knowing the forecast for a certain period, can use information about forecasted prices to protect their positions, keeping the number of farm animals within acceptable limits. It is crucial to acknowledge that time series forecasting has its limitations. Forecast results may be inaccurate if unforeseen events or changes occur that are not accounted for in the model. Therefore, to make management decisions regarding development, it is worth combining time series analysis with other methods and considering expert experience to obtain more accurate forecasts. In the context of livestock production, time series can be based on various factors, such as the production of milk, meat, and eggs, the number of animals, the costs of feeding and treating animals, and so on. To forecast the dynamics of the development of animal husbandry, historical information on relevant indicators over a certain period will be needed.

According to S. Lv *et al.* (2022), the vital step in time series forecasting is comprehending the data model and identifying the specific business questions that need to be addressed using that data. By delving into the problem area, developers can differentiate between random fluctuations and stable, consistent trends in historical data more effectively. This understanding is invaluable when fine-tuning a forecasting model to generate optimal predictions. It is also crucial when deciding which forecasting method to employ. Y. Abdullayev and M. Baxtiyor (2020) and A. Durmanov *et al.* (2019) conceptualized and employed a systematic approach to forecasting, relying on a mathematical model depicting the potential evolution of animal husbandry in farms. Mathematical models of prognostic-analytical problems are proposed, which allow, based on endogenous parameters of models at the level of the economy, to investigate and forecast the production of livestock products at the regional level in an integrated manner.

Forecasting the dynamics of livestock development using time series can be a useful management tool for analysing and predicting trends in the livestock sector (Chen *et al.*, 2020). To precisely capture the seasonal fluctuations in the observed sequence and achieve superior prediction outcomes, the production values for animal husbandry and fishery in various quarters spanning from 2018 to 2021 were forecasted and examined using the grey seasonal model (GSM). The findings highlighted the relatively high prediction accuracy of GSM. R. Mutwiri (2019) introduced a Seasonal Autoregressive Integrated Moving Average (SARIMA) model, specifically tailored for forecasting tomato prices. The model was constructed using monthly data spanning from 1981 to 2013 in Kenya. Tomato price forecasting from January 2003 to December 2016. The SARIMA $(2,1,1) \times (1,0,1)$ 12 model was identified as the best model. The following accuracy estimates were obtained: RMSE=32.063, MAPE=125.251, and MAE=22.3. P. Manigandan *et al.* (2021) conducted a study to forecast the seasonality and growth trend of natural gas production in the USA up to the year 2025. SARIMA and SARIMAX models were analysed. The SARIMA model showed the best RMSE and MAPE accuracy estimates: RMSE=131.73, MAPE=15.93.

Y. Chi (2021) using soybean data from January 1990 to January 2021 and an ensemble of SARIMA (Seasonal AutoRegressive Integrated Moving Average) and NARNN (Nonlinear Autoregression Neural Network) time series models forecast monthly soybean prices. The comparative analysis demonstrated that the Hybrid-LM model, comprising 8 neurons in the hidden layer and 3-time delays, exhibited superior accuracy compared to the NARNN-LM model with similar specifications and the SARIMA model (ARIMA $(0,1,3) \times (0,0,2)$). This conclusion was drawn based on the Hybrid-LM model's lowest MSE in the study. In U. Sirisha *et al.* (2022), ARIMA, and SARIMA models, as well as a Long Short-Term Memory (LSTM) deep learning model were chosen to forecast the time series of financial data of online companies. It was shown that the best RMSE and MAPA estimates were achieved with the LSTM algorithm. Received an accuracy of 97.01%.

S. Raju *et al.* (2022) compared the predictive accuracy of various models, including stacking (STACK), gradient boosting regression (GBR), extreme gradient boosting regression (XGBR), and random forest regression (RFR) ensembles. Additionally, it evaluates the performance of multilayer perceptron neural networks (MLP), extreme learning machines (ELM), and support vector regression (SVR) as reference models for forecasting demand. The comparison encompasses several stages, including data preprocessing, data transformation, standardization, feature selection, cross-validation, and the implementation of a regression ensemble framework. Analysing historical data allows us to make informed management decisions, guiding business strategies and providing insights into future trends. (Abraham *et al.*, 2020; Atalan, 2023). This research compares traditional time series forecasting techniques with artificial neural networks.

From the aforementioned studies, it is evident that selecting an appropriate model depends on the characteristics of the subject under investigation, the volume of historical data, and the presence of seasonality. Seasonality in agriculture (and in animal husbandry) plays a key role. Managing seasonality in livestock production can be an important aspect for agricultural enterprises to optimize production and maximize the benefit of peak periods of productivity and market demand.

CONCLUSIONS

The results obtained as a result of this study show that the number of cattle (including cows) has a clear tendency to decrease. SARIMAX (0; 1; 1) × (0; 1; 0; 12) and SARIMAX (1; 1; 9) × (1; 1; 0; 12) models were built, which were chosen to determine the number of farm animals for the next 2 years, show that by the end of 2024 there will be a gradual decrease in the number of cattle (including cows). The conducted research included the study of trends in the development of cattle and cows and, the determination of the stationarity of the studied time series. The Box-Cox method was used to transform data on the number of cattle. The optimal parameters of the models used for forecasting were determined. Forecast values for different periods (in months) were obtained, and an analysis of the dynamics of the number of cattle during the last 15 years was carried out. Constructed time series were compared with the actual data displayed on the graphs. Estimates of root mean square deviation and mean absolute error in percentages for different forecast periods were also provided.

Monthly statistical data on the number of cattle and cows are mean, standard deviation, minimum and maximum values, asymmetry, and excess. The dynamics of the decrease in the number of cattle and cows are shown. The optimal period for the forecast was determined (24 months). This research contributes to the formulation of strategies and actions that are critical to effective management: resource planning, productivity improvement, profitability maximization, cost optimization, and adaptation to changes in market conditions. These research results allow businesses to make informed decisions aimed at increasing their competitiveness and sustainability in a changing economic environment.

The presented research results of this article show such properties of time series as trends, seasonality, and variability. Therefore, the SARIMAX model was used. A promising avenue for future research involves exploring ensembles of time series, leveraging larger historical datasets, and conducting comparative analyses of various time series construction models. This will make the analysis and forecasts more accurate and reliable, as well as reveal more regularities in the dynamics of the number of cattle and cows.

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CONFLICT OF INTEREST

None.

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Прогнозування розвитку тваринництва на основі часових рядів

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Анотація. Побудова часових рядів з використання історичних даних є однією з актуальних проблем управління в аграрному секторі, оскільки аналіз і прогнозування процесів, пов'язаних з продовольчою безпекою держави, регіону, суб'єктів господарювання має вирішальне значення. За допомогою прогнозів підприємства можуть налаштовувати свою виробничу діяльність таким чином, щоб задовольнити попит і вчасно постачати продукцію споживачам. Метою цього дослідження є прогноз динаміки розвитку поголів'я великої рогатої худоби та корів та визначення оптимального періоду прогнозування. Для такого типу аналізу використовуються статистичні методи, пов'язані з авторегресією: авторегресійні моделі, моделі ковзного середнього або комбінації обох, інтегровані моделі зі змінною структурою та моделі, які включають сезонні ефекти та екзогенні фактори з авторегресійним і ковзним середнім компонентом у моделі. Наведені помісячні статистичні дані кількості великої рогатої худоби і корів: середнє, середнє квадратичне відхилення, мінімальне і максимальне значення, асиметрія і ексцес. Показана динаміка зниження поголів'я великої рогатої худоби і корів. Досліджені ряди перевірені на стаціонарність. До часового ряду кількості великої рогатої худоби застосовувалось перетворення Бокса-Кокса. Наведені оптимальні параметри моделей, що використовуються. Отримані прогнозні значення для часових проміжків (місяці) та проаналізована зміна кількості поголів'я великої рогатої худоби за останні 15 років. Побудовані часові ряд зіставляються з фактичними значеннями, що проілюстровано на графіках. Наведені оцінки середньоквадратичного відхилення, середньої абсолютної похибки у відсотках для різних термінів прогнозування. Порівнюючи ці оцінки для різних часових інтервалів, був визначений оптимальний часовий період для прогнозу (24 місяці). Дане дослідження дозволяє господарствам і підприємствам у галузі розуміти, яка кількість продукції (молока, м'яса) може бути зібрана або отримана в майбутньому. Це допомагає зробити необхідні управлінські кроки: планувати потреби в ресурсах, покращити ефективність, збільшити прибуток, знизити витрати і адаптуватися до змін на ринку

Ключові слова: тваринництво; моделювання; управління; перетворення Бокса-Кокса