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FORECASTING THE DEVELOPMENT OF POULTRY FARMING BASED ON TIME SERIES

Purpose. *The purpose of this work is to forecast the dynamics of the development of the poultry population for a period of 2 years with the help of various models, which are applied to study time series.*

Methodology / approach. *To conduct a comprehensive study on forecasting the number of poultry population, three predictive models were proposed: two based on regression methods, including SARIMAX and FbProphet, and one with a probabilistic approach using GluonTS. These models were selected to explore different methodological perspectives, ensuring a robust analysis of forecasting accuracy and applicability across varying data patterns and time horizons. To assess the quality of the forecast, the indicators of the mean absolute error, the standard deviation, the mean absolute error in percentage and the mean absolute scaled error for 24 months of forecasting are determined and analysed. The study was conducted based on regional data (using the example of the Khmelnytskyi region of Ukraine).*

Results. *The study successfully applied advanced data science methods to predict changes in poultry population using a number of efficient models. Analysis of historical data allowed us to determine the optimal parameters of the models and obtain forecast values for time periods (months). The studied series of dynamics of monthly changes in the poultry population was tested for stationarity using the Box-Cox transformation. The constructed time series are compared with the actual values, which is illustrated in the graphs. The results demonstrate that the SARIMAX(3,1,2)(1,1,1,12) model provides the best forecast accuracy compared to the other two models, confirming its effectiveness for forecasting tasks. These results highlight the potential of modern forecasting methods in the agricultural sector, offering a data-driven foundation for more effective decision-making in poultry management.*

Originality / scientific novelty. *This study fills a gap in applying advanced forecasting methods to poultry population prediction by systematically comparing SARIMAX, FbProphet, and GluonTS models. Unlike previous research, which often relied on simpler statistical approaches, this study integrates machine learning techniques to enhance forecasting accuracy. The findings confirm an increasing trend in the time series and demonstrate that the SARIMAX model outperforms the alternatives, providing the most precise forecasts for the next two years.*

Practical value / implications. *This study allows poultry farms and enterprises to predict the dynamics of poultry population, which is a critical case for optimising production processes. The use of more accurate forecasting models helps to more effectively plan resources (feed, housing area, personnel), regulate production volumes (eggs, meat), and also ensures supply stability. In addition,* *the ability to pre-estimate future changes allows enterprises to adapt to market fluctuations, reduce losses, minimise excess costs and make informed management decisions.*

***Key words:** poultry farming, time series, forecasting trends, poultry population prediction.*

1. INTRODUCTION

The agricultural sector is a key part of the country's economy and plays an important role in ensuring food security, creating jobs, developing rural communities and influencing the environment and human health. The poultry industry significantly contributes to food security, drives economic growth, and fosters technological advancements, maintaining its relevance in today's world. It is important from various points of view, contributing to food security, economy, science and conservation of natural resources. 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.

Poultry farming is an important branch of agricultural production, making a significant contribution to meeting the basic needs of people. The relevance of the poultry industry in the country is determined by such key factors as food security, economic contribution, export opportunities, low cost of production, etc. This industry provides people with food products with high energy value, is very attractive for investments, has a huge potential for economic development and is mobile in terms of organisational and technical capabilities and return on capital investments, is characterised by early maturing, high rates of reproduction and use of feed protein, relatively low energy consumption, high the level of mechanisation and automation of production processes. The current state of poultry farming in Ukraine is characterised by a large production of eggs, which is supplied to both the domestic and export markets, as well as the production of poultry meat, in particular broiler chickens and other types of poultry. This important component of animal husbandry provides the population with high-quality protein. Farms raise chickens to obtain eggs and meat in various systems of maintenance.

In Ukraine, the poultry industry is generally developing, with a tendency to increase the poultry population, the volume of poultry meat production, and egg production (State Statistics Service …, 2024). This is primarily due to the growing demand from the consumers and food industry. In addition, poultry meat has become a substitute for the majority of meat consumers of other types of meat given the fact that in recent years there has been a significant reduction in the supply of cattle and pig meat, and accordingly their prices are also increasing (Polehenka, 2019).

Despite significant progress in the application of time series analysis in poultry production, there are still several unresolved issues that require further research and exploration. The selection of the most appropriate time series models for specific poultry production tasks remains challenging due to the different seasonal and cyclical patterns. Also, the development of user-friendly decision support systems for farmers based on time series forecasts remains limited. Addressing these issues through interdisciplinary research and collaboration between data scientists, agricultural economists, and industry stakeholders can enhance the effectiveness of time series applications in poultry production.

The purpose of this work is to forecast the dynamics of poultry population development for a period of 2 years using various models used for time series analysis.

2. LITERATURE REVIEW

In modern poultry research, meeting the demand for products and the export potential of the industry is of great importance. In particular, Yatsiv (2021) notes that poultry enterprises in Ukraine almost completely cover the domestic demand for eggs and poultry meat, demonstrating high export potential. However, the development of the industry depends on the capacity of the domestic market and export opportunities, as well as on the level of concentration of production, which is typical for most enterprises in this industry.

An important component of the efficiency of poultry farming is capital investment. Sakhatskyi et al. (2022) emphasise that a close relationship between investment levels and the income of enterprises in the industry is critical to ensuring sustainable development. Investment in technology and infrastructure has a direct impact on the efficiency of poultry farming and meat production. Hryvkivska & Krasnorutskyy (2023) analysed the production of poultry meat during 2000–2023, and chicken eggs and the state and prospects for the development of export-import operations in regional poultry markets and Ukraine's participation in these processes were revealed. A detailed review of the supply of poultry products on the markets and the reasons for its change during 2021–2023 was conducted. It is substantiated that future success is determined by planning all business processes for the long term.

One of the problems is the influence of external factors on the competitiveness of poultry enterprises. Diachenko (2020) analyses the main factors that determine competitiveness in domestic and foreign markets, in particular, the lower maneuverability of small poultry farms. Problems associated with adapting to market changes, as well as limitations in technological capabilities, leave these enterprises in difficult conditions. In regional markets for poultry products, the balance of supply and demand is important, which directly affects the development of local enterprises. Savchenko (2023) focuses on the influence of these factors on the state of regional markets. Analysis of regional markets and trends in product supply changes helps to predict possible changes in the industry for the future.

In addition, forecasting production indicators and changes in the egg market is no less important. It has been found that various forecasting methods, in particular time series models, are effective in calculating future production volumes. Bumanis et al. (2023) investigate machine learning methods that have shown better accuracy compared to traditional models such as ARIMA. In particular, these methods allow for more accurate prediction of egg production and forecasting market trends. Al Khatib et al. (2021) investigated egg production in India using various time series models: ARIMA, BATS, TBATS, and Holt's linear trend. Holt's linear trend was shown to be the best model for forecasting. According to this model, egg production in India is increasing. Alnafissa et al. (2021) predicted self-sufficiency and food security in poultry meat. This study was based on secondary data and economic and statistical equations. Indicators related to applied food security and financing and water requirements for poultry meat were calculated.

Deep learning and Internet of Things (IoT) technologies are also being used in the poultry industry. Orakwue et al. (2022) present a smart system for monitoring environmental conditions, which allows for more effective management of production processes. The use of such technologies can significantly increase the efficiency of management and forecasting in poultry farming. Bumanis et al. (2022) proposed a cyber-physical model as the basis for developing an intelligent poultry farm management system. The processed data is used by a decision support system to determine optimal feeding and housing. In Görgülü & Akilli (2018), model egg production curves were constructed using nonlinear regression analysis and least squares support vector machines. The present study shows that least squares support vector machine methods can be used successfully in the modelling of egg production curves in laying hens.

Forecasting productivity, consumption and prices are important elements in the management of the industry. ARIMA models and other statistical approaches presented in works such as Cohen & Horovitz (2023) and Mo et al. (2023) help to analyse market changes based on time series, which is key for making strategic decisions in the industry. Tikiwala et al. (2023) demonstrated the applicability of machine learning models in automatically predicting egg production in poultry systems. In developing this machine learning model for forecasting, the authors used the ARIMA model during time series analysis. Omomule et al. (2020) investigated various factors that enhance the high performance of fuzzy models for predicting egg production on farms. A limited sample of total egg production and factors affecting production were used to develop the fuzzy model.

Titus et al. (2021) investigated guinea fowl production in Kenya using univariate autoregressive integrated moving average (ARIMA) and autoregressive fractional integrated moving average (ARFIMA) models. Okorie et al. (2023) conducted a time series analysis of annual crop yield data in six East African countries using an autoregressive integrated moving average (ARIMA) model. Biswas (2021) constructed an ARIMA model to forecast rice area and production in West Bengal. Time series modelling using the ARIMA (p,d,q) model was developed for individual univariate series of both rice area and production since 1962. Palabicak & Binici (2023) investigated the dynamics of sheep population changes in Turkey as a developing country under the influence of global and national dynamics and crises. Future projections were made using the Box Jenkins method. As a result of projections made by the ARIMA (4,2,1) model, it is assumed that sheep population will increase. However, the failure of governments to pay adequate attention to the agricultural sector for 42 years has meant that the country has failed to capitalise on its current geopolitical advantage, and by 2021, the number of sheep remained at the level of 1980.

Fang et al. (2020) developed a broiler tracking algorithm utilising a deep regression network, which is based on the AlexNet deep learning model and uses the

ReLU activation function. This approach enables the tracking of individual broiler chickens within a group using deep learning techniques. Experimental results indicate that the TBroiler algorithm achieves superior tracking accuracy while maintaining an efficient processing speed. In paper by Mgaya (2019) an ARIMA model is built to forecast the consumption of livestock products. This paper identifies the prospects of increasing the use of animal feed as a market opportunity for farmers by forecasting the consumption of livestock products such as eggs, milk, chicken and beef. The result shows that the consumption of all livestock products will increase, hence the expected demand for animal feed. In paper by Chen et al. (2021) an automated price forecasting system for agricultural commodities using machine learning methods was investigated. An automated system for forecasting agricultural commodity prices is proposed. In two series of experiments, five popular machine learning algorithms, ARIMA, SVR, Prophet, XGBoost and LSTM, were compared with large historical datasets in Malaysia and the best performing algorithm, LSTM model with mean square error of 0.304, was selected as the forecasting engine of the proposed system. Sharma et al. (2022) analysed the Prophet forecasting technique and compared it with the traditional ARIMA model. It was shown that the Prophet model provides better forecasting accuracy. The study by Akram et al. (2022) used time series data for 1996–2019 to forecast red meat production in Pakistan for the next six years. Different time series models are fitted to select the most suitable one. The results showed that the random walk with drift model is the most suitable model due to the minimum AIC and SBIC values. Red meat production in Pakistan is expected to increase by 15.8% in 2025 compared to 2019. Zamani et al. (2021) investigated seasonal variations in vertical price transmission, focusing on asymmetric price adjustments to analyse changes in market interactions between stages of the value chain. The results of the panel threshold model suggest that wholesale and agricultural price adjustments to deviations from market equilibrium are more symmetric at higher temperatures.

Other important studies are works on the impact of temperature on production, such as the work of Goyal et al. (2022), which shows the significant impact of temperature conditions on production performance in poultry farming and the possibilities of their prediction using machine learning.

Despite a sufficient number of works devoted to the application of time series in poultry farming, the problem of high-quality forecasting of poultry products remains relevant, since more accurate forecasting allows optimising production processes, reducing costs, and ensuring the stability of supply to the market.

Taking into account the previous empirical analysis, the following research hypothesis and research question were formulated:

- Hypothesis: The use of time series forecasting models, such as SARIMAX (Seasonal Auto-Regressive Integrated Moving Average with eXogenous factors), FbProphet and GluonTS, allows for more accurate forecasting of poultry population dynamics, which, in turn, will contribute to more effective management of resources and production processes in the poultry industry.
- Research question: Which forecasting model provides the highest accuracy in

predicting changes in poultry population?

This study fills the existing gap in the analysis of forecasting models, in particular in assessing their effectiveness in the agricultural sector. The scientific novelty lies in the comparative analysis of modern forecasting methods and the development of recommendations for their use to improve the accuracy of forecasts in poultry farming.

3. METHODOLOGY

Data overview. Research data on the poultry population in the period from January 1, 2008 to January 1, 2024 were obtained from the website of the Main Department of Statistics in the Khmelnytskyi region of Ukraine (Main Department of Statistics …, n.d.).

The study selected the SARIMAX, FbProphet, and GluonTS models because they are powerful tools for time series forecasting and allow for taking into account various aspects of the data. The GluonTS library is based on deep learning for time series forecasting, in particular it is able to model complex patterns and relationships in data. The FbProphet model is designed for forecasting time series with seasonality, and is able to automatically detect trend changes and changes in seasonal structure. The SARIMAX model can be effective for time series with seasonality. It is well suited for forecasting poultry populations, as it can take into account seasonal fluctuations.

The selection of these models provides a comprehensive approach to forecasting and allows for comparison of the effectiveness of different approaches.

GluonTS. GluonTS provides a deep learning-based framework for probabilistic forecasting of collections of time series.

Let $Z = \left\{ z_{i,1:T_i} \right\}_{i=1}^{N}$ be a set of N univariate time series, where $z_{i,1:T_i} = (z_{i,1}, z_{i,2}, \ldots, z_{i,T_i})$ and $z_{i,t} \in \mathbf{R}$ denotes the value of the *i-th* time series at time *t*. Let $X = \left\{ x_{i,1:T_i} \right\}_{i=1}^{N}$ be a set of associated, time-varying covariate vectors with $x_{i,t} \in \mathbf{R}^D$. Given a probabilistic model, the goal of forecasting is to predict the probability distribution $p(z_{i,T_i+1:T_i+\tau} \mid z_{i,1:T_i}, X_{i,1:T_i+\tau}; \Phi)$ of future values $z_{i,T_i+1:T_i+\tau}$, with $\tau > 0$, given the past values $z_{i,1:T_i}$, the covariates $X_{i,1:T_i+\tau}$, and the model parameters Φ (Alexandrov et al., 2020; Benidis et al., 2022).

FbProphet. Facebook's Prophet technique belongs to the family of time-series forecasting models (Chadalavada et al., 2020). It consists of the following components:

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t. \quad (1)$$

Here $g(t)$ is a time series trend, a piecewise linear function, $s(t)$ is a seasonal component, $h(t)$ is responsible for given anomalous days, ϵ_t is an error that contains information not taken into account by the model.

SARIMAX model. SARIMAX is a time-series forecasting model that extends ARIMA by incorporating both seasonal variations and external variables. Unlike regression models, SARIMAX belongs to the family of time-series models, improving predictive performance by capturing complex temporal patterns. This makes it a more advanced alternative to ARIMA, particularly for datasets exhibiting seasonality and external influences (Zhang, 2003; Ediger & Akar, 2007).

In SARIMAX models, two sets of parameters must be specified. The first set mirrors the parameters of the ARIMAX model (p, d, q), while the second set accounts for seasonality effects. This requires knowledge of four seasonal parameters:

P – Seasonal autoregressive (AR) order;

D – Seasonal differencing (integration) order;

Q – Seasonal moving average (MA) order;

s – Seasonal frequency or periodicity.

The SARIMAX model can be mathematically represented as follows:

$$\phi_p(L)\underline{\phi}_P(L^s)\Delta^d\Delta_s^D y_t = A(t) + \theta_q(L)\underline{\theta}_Q(L^s)\epsilon_t, \tag{2}$$

where $\phi_p(L)$ – non-seasonal autoregressive (AR) lag polynomial;

$\underline{\phi}_P(L^s)$ – seasonal autoregressive (AR) lag polynomial;

$\underline{\Delta}^d\Delta_s^D y_t$ – the time series data, difference *d* times, and seasonally differenced *D* times;

A(t) – the trend component, including any intercept;

$\theta_q(L)$ – non-seasonal moving average (MA) lag polynomial;

$\underline{\theta}_Q(L^s)$ – seasonal moving average (MA) lag polynomial.

The measure of evaluation used for forecasting time series in this study is root mean square deviation (RMSE), mean absolute error in percentage (MAE) (Rady et al., 2021; Alsuwaylimi, 2023), mean absolute scaler error (MASE) (Hyndman & Koehler, 2006) and mean absolute percentage error (MAPE) (De Myttenaere et al., 2015):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(E_i - F_i)^2}\ , \tag{3}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|E_i - F_i\right|, \tag{4}$$

$$MASE = \frac{MAE}{\frac{1}{n-1}\sum_{i=2}^{n}\left|E_i - E_{i-1}\right|}\ , \tag{5}$$

$$MAPE\% = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|E_t - F_t\right|}{E_t}\ , \tag{6}$$

where E_i and F_i are actual and predicted values, *n* is the number of values.

To apply the time series forecasting technique, we need to check the series for stationarity. For this, we used Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests (Kwiatkowski et al., 1992; van Greunen & Heymans, 2023). This test detects the presence of stochastic trend behaviour in time series using a hypothesis test:

$$H_0: process\ is\ stationary;$$

$$H_1: process\ is\ non-stationary.$$

For a non-stationary series, applying the Box-Cox transformation can help produce a series that meets the requirements for stationarity (Box & Cox, 1964; Phumchusri & Suwatanapongched, 2023). The Box-Cox Transformation relies on an exponent and the parameter λ, which ranges from -5 to 5. Different values of λ are tested, and the one that most closely approximates a normal distribution is chosen. The transformation of Y has the form:

$$y(\lambda) = \begin{cases} \frac{y^{\lambda}-1}{\lambda}, & if\ \lambda \neq 0; \\ y, & if\ \lambda = 0. \end{cases} \tag{7}$$

For time series prediction, 168 (months) of training data and 24 (months) of testing data were used.

Jupyter Notebook Software was used for visualisations and calculations.

4. RESULTS

At the first stage, the dynamics of changes in the poultry population in the analysed period in Khmelnytsky region was considered (Figure 1).

Figure 1. Dynamics of changes in the poultry population (thousands of heads) from January 1, 2008 to January 1, 2024

Source: authors' elaboration from (Main Department of Statistics …, n.d.).

Figure 1 shows the changes in the poultry population (in thousands of heads) for the period from 2008 to 2023. Starting from 2008, the number of birds increased steadily until 2015, reaching a peak of about 14,000 thousand heads. This may indicate an improvement in production conditions or an increase in demand for poultry products. After 2015, there has been a sharp decline in the number of birds, which may be due to various factors, such as economic difficulties, changes in demand for products, the introduction of quarantine measures due to poultry diseases or other factors that negatively affected the industry. Since 2017, a more stable trend has been observed, with some fluctuations, but the overall level remains at around 8,000–9,000 thousand heads.

Table 1 shows the summary monthly statistical data for the above-mentioned period of the number of poultry and egg production.

Table 1

Statistical data (from January 1, 2008 to January 1, 2024) on poultry population and eggs production

Metrics	N	Mean	Std	Min	Max	Skew	Kurt
Poultry population, thousands of heads	192	7591	2498	3067	14991	0.426	0.152
Egg production, millions of pieces	192	86.5	45.4	16.5	228.4	0.581	-0.135

Source: authors' elaboration.

Table 1 shows the minimum, maximum, mean, skewness and kurtosis for the monthly data set used in this study to characterise the poultry population. Thus, the minimum poultry population was observed at the beginning of the study in April 2008 – 3067 thousand heads. And in July 2014, it reached its maximum value of 14991 thousand heads. A positive sign in the skewness coefficient indicates that most of the data is greater than the mathematical expectation, and a positive (negative) kurtosis coefficient indicates that the curve of the theoretical distribution has a higher (lower) peak than the curve of the normal distribution. Poultry population has a moderately positive skewness, indicating a tendency for numbers to increase over time. In the case of eggs, the skewness is also positive, but the kurtosis indicates that fluctuations in egg production tend to be more moderate, with fewer extreme values. The standard deviation for both metrics is quite large, indicating high variability in the data across years, which may be the result of changes in demand, technology, or other economic factors. Also, the correlation coefficient between poultry and eggs is 0.883, which indicates a high dependence between the values.

Let's check the stationarity of poultry population using the KPSS test. Since p-value = 0.02, the time series is not stationary. Therefore, we applied the Box-Cox Transformation. The optimal parameter $\lambda = 0.531$.

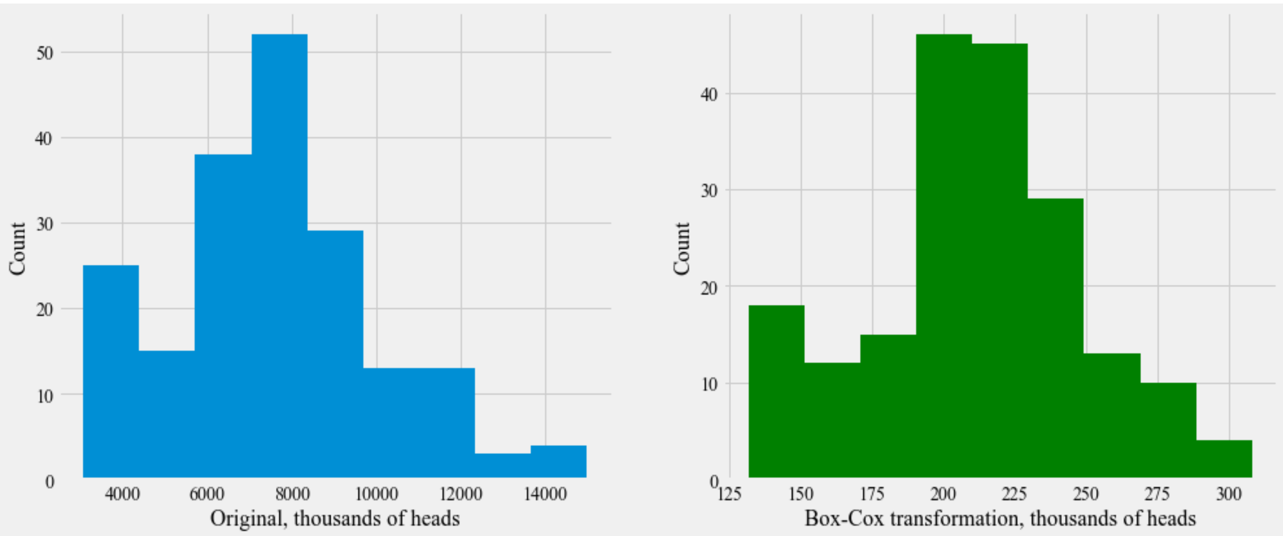

Figure 2. Histograms of the poultry population (original & Box-Cox Transformation)

Source: authors' elaboration.

Figure 2 shows two histograms illustrating the distribution of poultry population (in thousands of heads). The left-hand side shows the original data distribution. The histogram shows that the distribution of poultry population is skewed, with a right-sided "long tail". There is a clear peak around 8,000 heads, but there is a large amount of variability on the right-hand side. The right-hand side shows the same data after a Box-Cox transformation. After the transformation, the data became more symmetric and closer to a normal distribution. The maximum of the histogram is now located in the range of 200–225 thousand heads. The Box-Cox transformation was successfully applied to stabilise the variance and correct the skewness of the original data. The transformed data approximates a normal distribution.

Table 2 shows a summary of the results of the SARIMAX model run in the Jupyter Notebook environment.

Table 2

Summary of the results of the SARIMAX model according to the data on the poultry population (thousands of heads)

Indicator	Coef.	Std. err.	z	$P > \|z\|$	[0.025; 0.975]
ar.L1	1.5774	0.071	22.084	0.000	[1.437; 1.717]
ar.L2	-0.6430	0.120	-5.338	0.000	[-0.879; -0.407]
ar.L3	-0.1783	0.062	-2.879	0.004	[-0.300; -0.057]
ma.L1	-1.7442	0.087	-20.056	0.000	[-1.915; -1.574]
ma.L2	0.9849	0.105	9.336	0.000	[0.778; 1.192]
ar.S.L12	0.2527	0.093	2.730	0.006	[0.071; 0.434]
ma.S.L12	-0.9963	3.630	-0.274	0.784	[-8.111; 6.118]

Source: authors' elaboration.

In Table 2, the columns coef. (coefficients) are the values of the model parameters that determine the influence of various components (AR, MA, seasonal effects); std. err. (standard error) shows the uncertainty estimate of each coefficient; z: Z-statistic, which determines the significance of each coefficient. P>|z| is the probability (p-value) that shows whether the coefficient is statistically significant. Values < 0.05 indicate significance. [0.025, 0.975] is the confidence interval (95%) for the coefficients.

The coefficient ar.L1 = 1.5774 is significant ($p < 0.05$), indicating a strong autocorrelation with the previous period. The coefficients ar.L2 and ar.L3 are also significant, but their impact is smaller. ma.L1 = -1.7442 is significant and has a strong impact. The coefficient ma.L2 is also significant. The seasonal components ar.S.L12 = 0.2527, ma.S.L12 = -0.9963 are not significant ($p > 0.05$).

From Table 2, it is concluded that the autocorrelation and short-term moving average components are statistically significant, indicating their importance in modeling data dynamics. The seasonal AR component has a noticeable impact, but the seasonal MA is not significant.

Diagnostics of the model showed that the residuals of the model are correctly distributed. In Figure 3, in the upper right graph, KDE is close to the N(0,1) line (N(0,1) is the standard normal distribution). The q-q graph in the lower left corner shows that the ordered distribution of residuals (blue dots) corresponds to a linear trend. The residuals over time (upper left graph) show no clear seasonality and appear to be white noise. This is confirmed by the autocorrelation plot (bottom right), which shows that the residuals of the time series have low correlation.

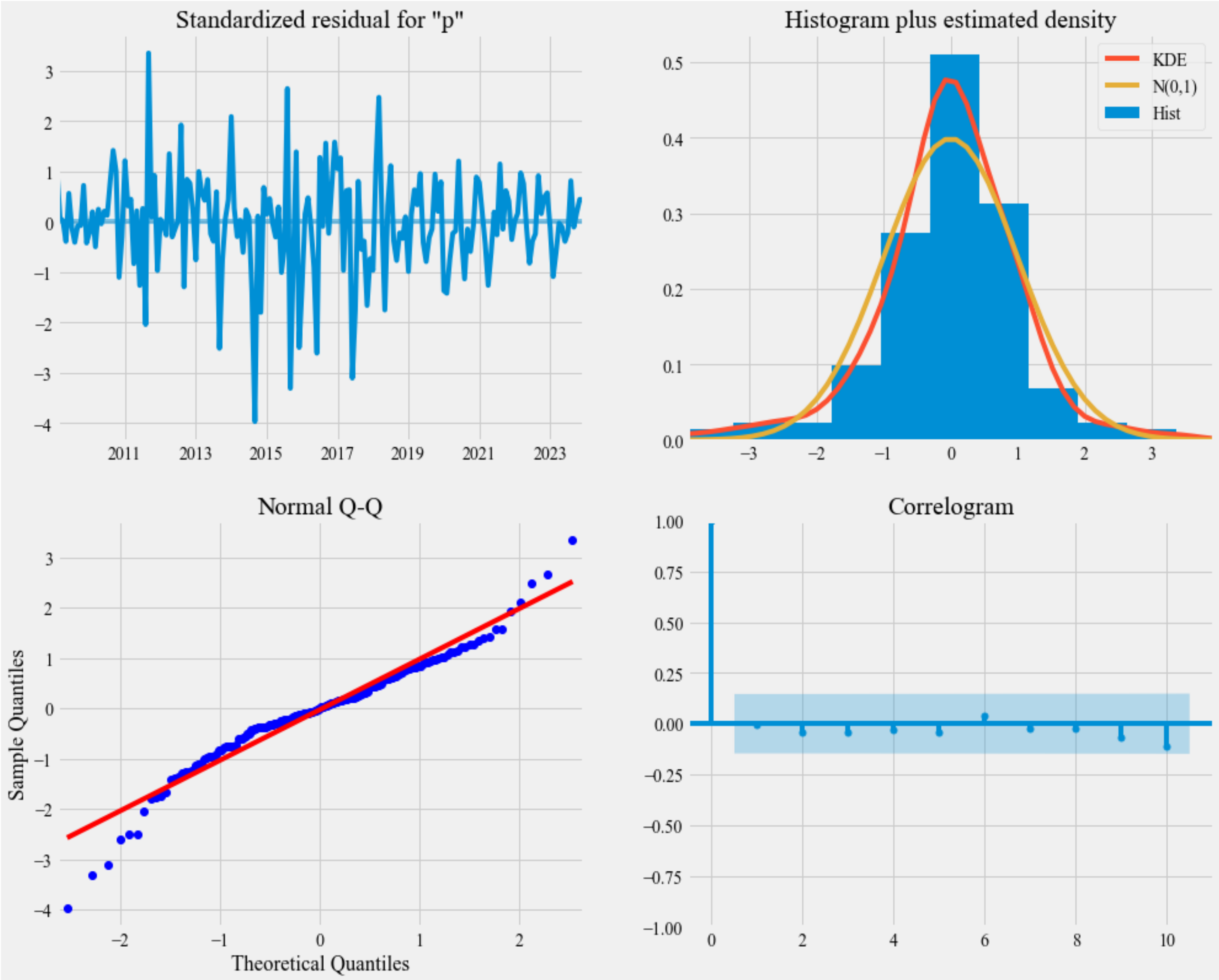

Figure 3. Diagnostics of the SARIMAX model for the time series of the poultry population

Source: authors' elaboration.

Figure 4, constructed using FbProphet, shows the dynamics of the poultry population with historical data (black dots) and predicted values (blue line with confidence intervals). The predicted dynamics for 2024–2025 continue the trend of moderate stability with small fluctuations. The model predicts seasonal changes, but without significant increases or decreases. The confidence interval (blue area) shows possible deviations from the forecast, which increase over time, which is typical for long-term forecasting.

Figure 5 presents the results of the FbProphet library in terms of the general trend and annual seasonality.

The top graph shows the trend: from 2008 to 2015, there was a sharp increase in the livestock, which may be due to improved breeding conditions or other favourable factors. After 2015, a decline is visible, indicating possible crisis phenomena. Since 2021, the trend has stabilised and shows a slight increase in the forecast period (2024–2025), which may indicate a potential recovery of the industry.

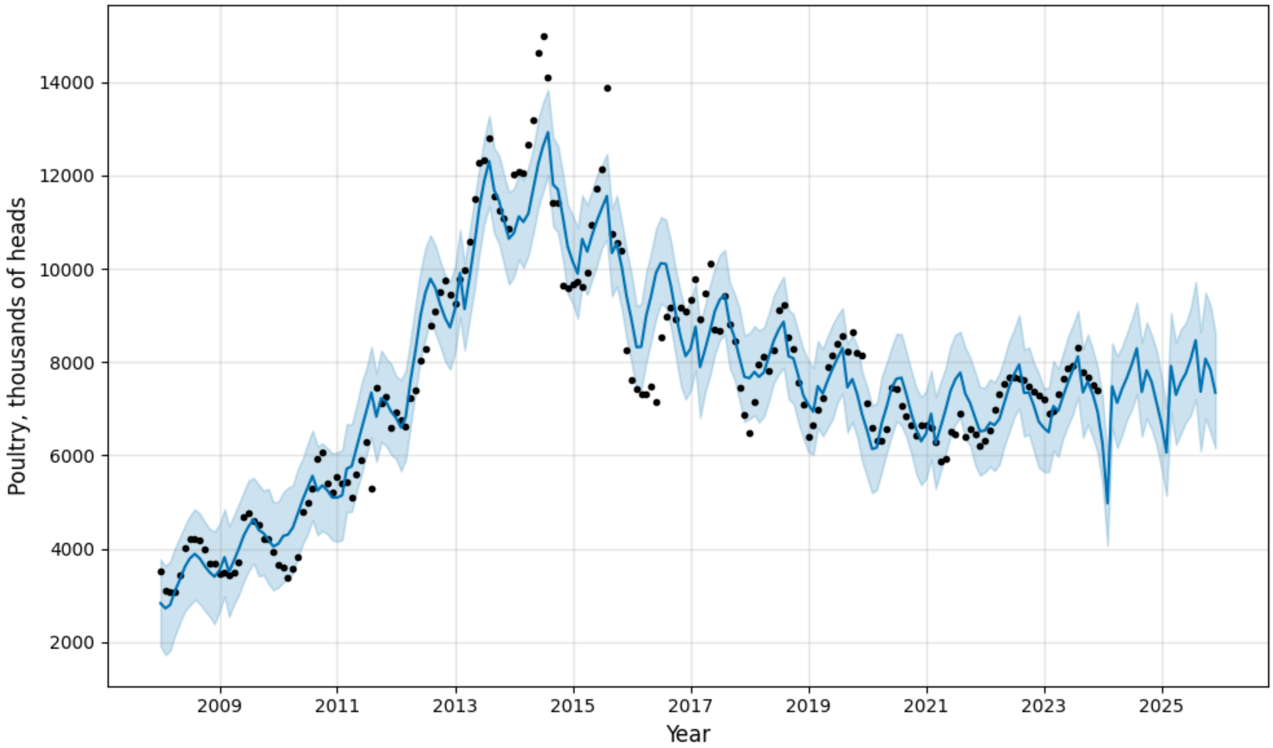

Figure 4. Historical and forecasted data for the poultry population time series, constructed using the FbProphet model

Source: authors' elaboration.

The lower graph (Figure 5) shows a strong seasonal pattern. The largest peaks occur in early spring (March-April), which may be related to biological breeding cycles or preparation for increased demand. The declines occur in January and mid-summer, which may be due to natural population declines or changes in production cycles. There are smaller wave-like fluctuations throughout the year, confirming regular seasonal changes. It should be noted that the bottom graph shows the day of the year on the X-axis, not the size of the poultry population. This is a graph of the seasonal component of the FbProphet model, which shows the average relative changes over the year. These are calculated relative to the average trend determined by the model. The graph shows how the size of the poultry population changes on average over the year (possibly a seasonal peak in spring and a decline in autumn). These are the aggregated average seasonal changes obtained from all years in the sample, which were used to train the model. The trend shows overall long-term changes, while the seasonal component highlights short-term fluctuations that can be critical for demand forecasting and resource management in poultry farming.

Using automatic optimisation (Grid Search), the hyperparameters used in forecasting poultry population using the FbProphet model were determined: changepoint_prior_scale = 0.1 (controls sensitivity to trend changes), n_changepoints = 25 (determines the number of trend change points), seasonality_mode = "multiplicative" (seasonality is modeled multiplicatively), yearly_seasonality = True (annual seasonality is enabled), make_future_dataframe(periods = 24) (generates a new future dataframe that includes

24 future months for forecasting).

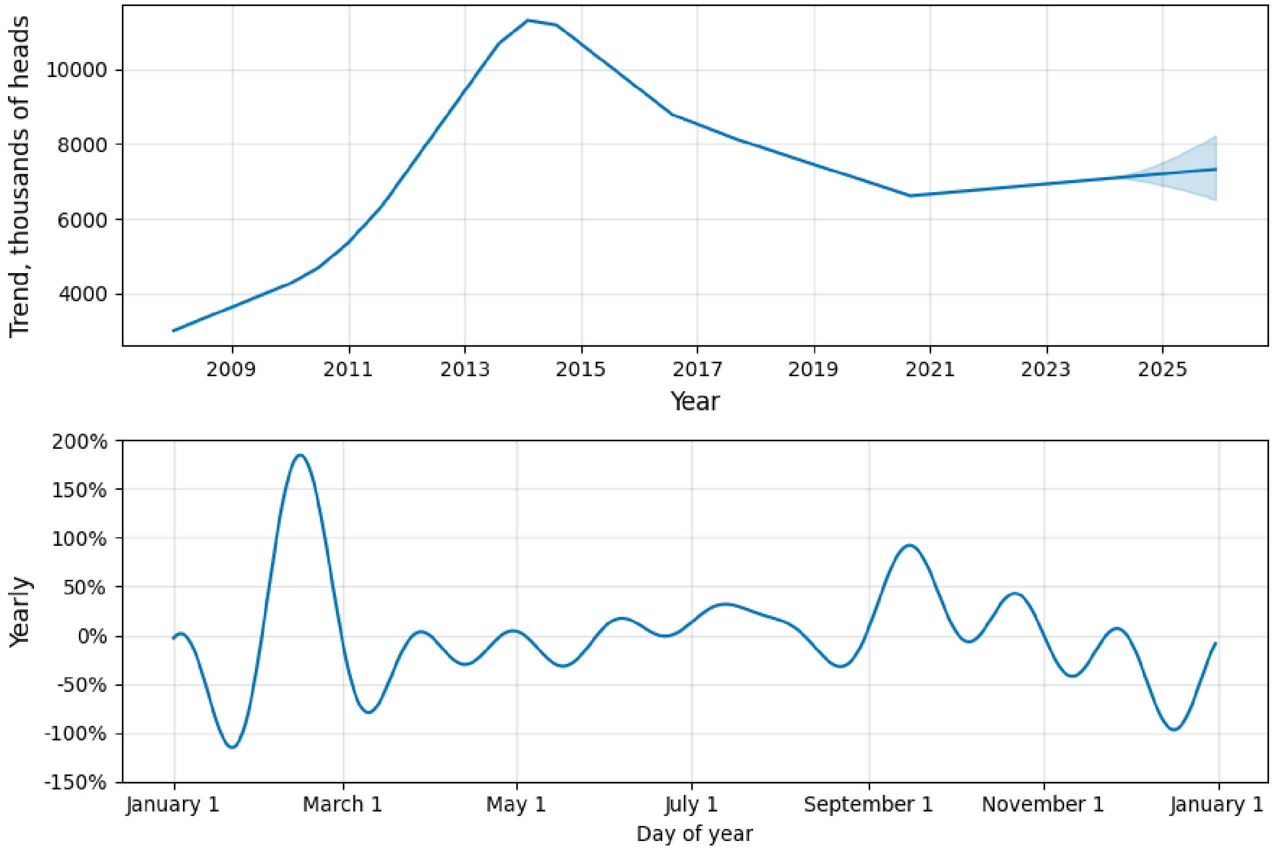

Figure 5. Trend and seasonal components of the poultry population time series

Source: authors' elaboration.

Figure 6 shows the dynamics of the poultry population for the period 2008–2023 and the forecast for 2024–2025 using the GluonTS model. The forecast trend shows that the GluonTS model expects poultry population to fluctuate at the level of 2023 values. The forecast does not show any sharp declines or increases, which may indicate market stabilisation or model smoothing. Dark green range (50% confidence interval) – means that the model expects real values to be in this range with a 50% probability. The light green range (90% confidence interval) is a wider interval that takes into account greater uncertainty: the actual values are 90% likely to be within these limits. The width of the intervals increases over time – this is natural for forecasting, as the uncertainty of the future increases. Although the historical data has pronounced fluctuations, the forecast does not show a clear seasonal trend. The GluonTS forecast shows that the poultry population is likely to remain at the level of previous years, but with possible fluctuations. The confidence intervals indicate potential risks that should be considered when making decisions in the industry.

For forecasting, the DeepAR module from the library was used with the following parameters: freq = "M" (frequency of the time series, monthly data); prediction_length = 24 (number of future periods); context_length = 24 (number of previous periods that the model takes into account when calculating the forecast; trainer = Trainer (epochs = 100) (the model was trained for 100 epochs). The Grid Search method was used to optimise hyperparameters.

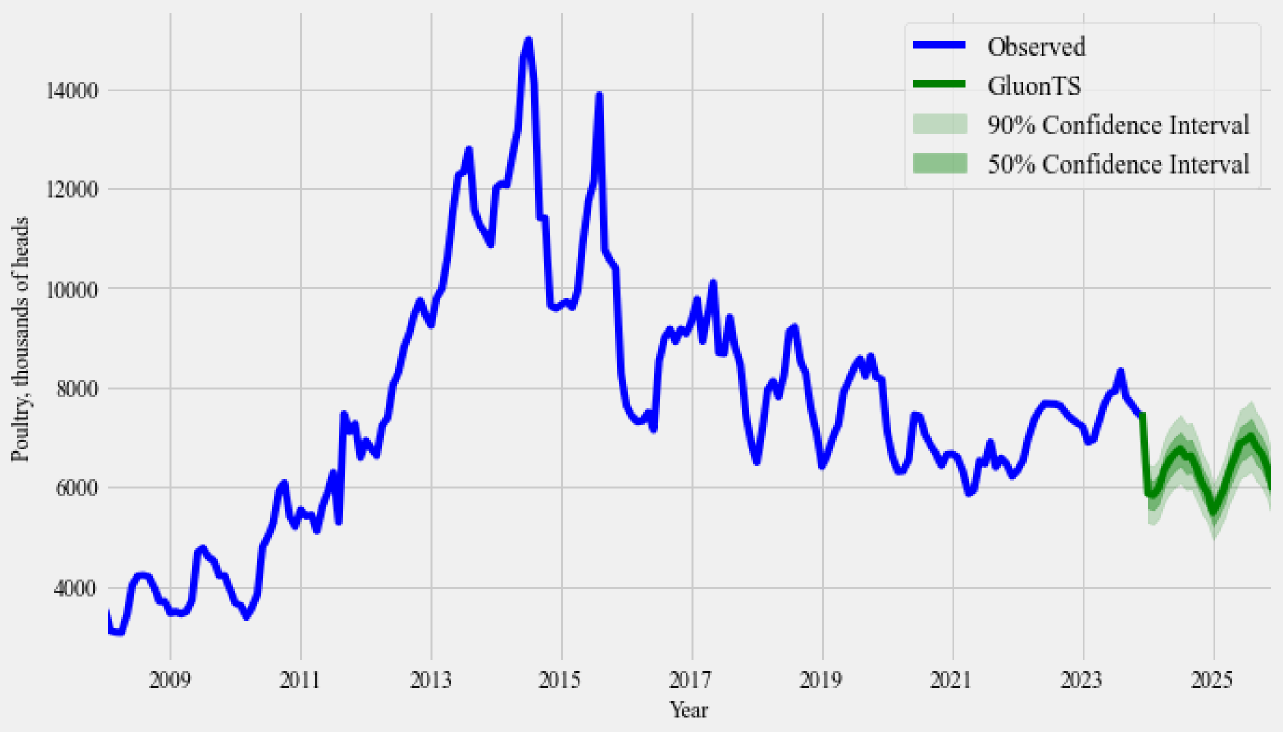

Figure 6. Historical and forecasted data for the poultry population time series constructed using the GluonTS model

Source: authors' elaboration.

Figure 7 shows the actual (observed) and predicted (SARIMAX, FbProphet, GluonTS) values of the poultry population for the period from January 2022 to January 2024.

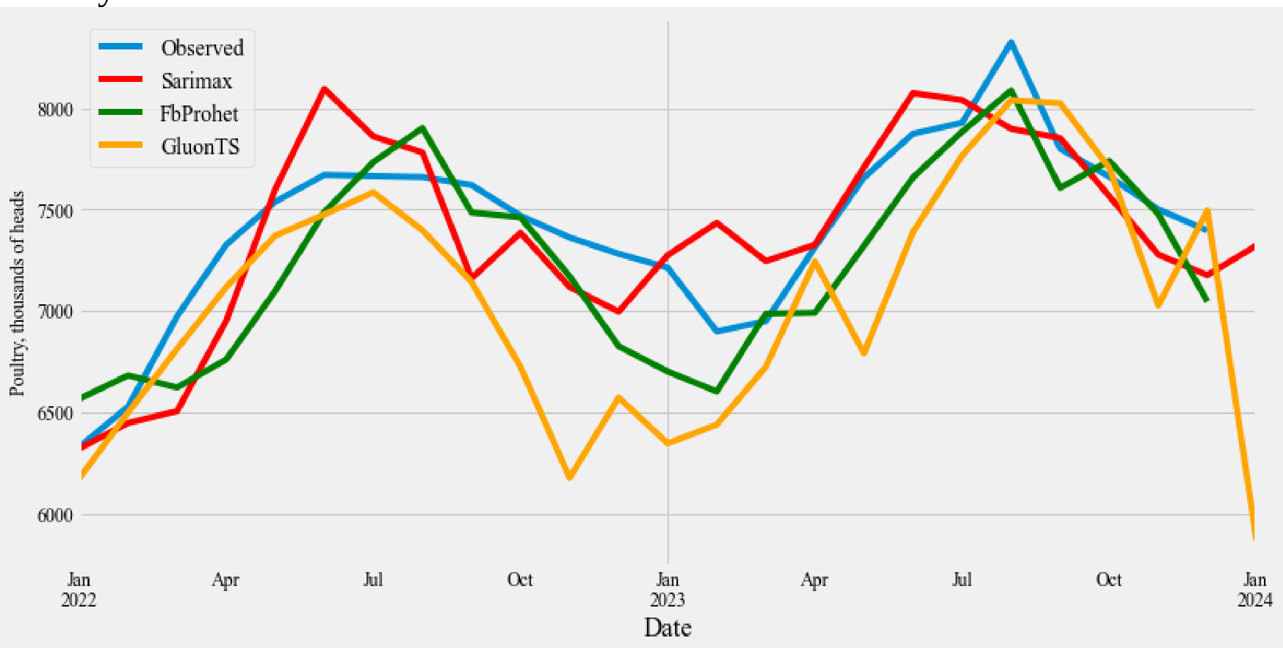

Figure 7. Actual (observed) and projected values between January 2022 and Januar 2024 for various models

Source: authors' elaboration.

The blue line shows the actual values of the poultry population. There is a seasonal dynamic with an increase in the population in the warm period of the year (spring-summer) and a decrease in the winter period. The SARIMAX model (red line) generally follows the actual data well, but there are small deviations at the peak points. For example, in the second half of 2023, SARIMAX predicts slightly higher values than the actual ones. The FbProphet forecast is also quite accurate, but deviations are observed at some critical points, such as the decline in October 2023. A distinctive feature is a smoother forecast compared to SARIMAX. GluonTS shows larger deviations, especially in the summer of 2023, where the predicted values are significantly lower than the actual ones. The model also tends to have more abrupt changes compared to the others. From Figure 7, we draw a general conclusion that SARIMAX and FbProphet show more accurate forecasts, better accounting for seasonal fluctuations. GluonTS tends to have larger deviations, especially in the peak and decline periods.

Table 3 displays the accuracy scores for the three time series models constructed (SARIMAX, FB Prophet, GluonTS). The evaluation was performed using four metrics: RMSE, MAE, MASE, and MAPE. SARIMAX shows the best results in all metrics, indicating its high accuracy in time series modelling.

Table 3

Accuracy estimates for different time series models

Indicator	SARIMAX	FbProphet	GluonTS
RMSE	243.49	292.48	299.19
MAE	213.00	247.95	249.99
MASE	28.75	29.38	32.92
MAPE	2.89	3.37	5.31

Source: authors' elaboration.

Considering Figure 7 and Table 3, it was generally concluded that the SARIMAX model shows the best results in all metrics for forecasting for 24 months, which indicates its high adaptability to data and accuracy of forecasts in the medium term, which is especially important for forecasting poultry populations taking into account seasonality and other influences. Thus, for poultry population forecasting tasks, we use the SARIMAX model.

Table 4 shows the forecasted monthly values of the poultry population found using the SARIMAX(3;1;2)x(1;1;1;12) model.

Table 4

Estimated monthly values of the poultry population, thousand of heads

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2024	7322	7352	7503	7903	8417	8934	9166	9322	8803	8529	8095	7720
2025	7574	7587	7685	8049	8609	9254	9619	9814	9388	9146	8664	8200

Source: authors' elaboration.

Based on the conducted research, a number of practical recommendations have been formulated for poultry enterprises, as well as policymakers dealing with issues of agricultural policy and food security. The use of highly accurate forecasting models allows enterprises to plan production processes more effectively, including the need for feed, energy, labor and veterinary supplies. Time series analysis helps determine the best periods for expanding production or adapting to possible market changes, which allows minimising costs and avoiding overproduction. Understanding the dynamics of the poultry population and predicting its changes helps enterprises respond flexibly to fluctuations in demand, reducing the risks of excess production or product shortages. The use of intelligent forecasting systems will contribute to the development of cyber-physical models for managing poultry farms, which will increase productivity and reduce costs.

5. DISCUSSION

Forecasting the future development of the agricultural sector remains a complex challenge due to the interplay of numerous factors affecting its dynamics. These include climate change, technological advancements, economic policies, shifts in consumer preferences, and global economic trends. The multifactorial nature of these influences complicates the task for analysts and researchers, highlighting the necessity of adaptive forecasting models. The ability to account for uncertainty and potential unforeseen fluctuations is crucial for developing effective strategies in the poultry industry.

More accurate forecasting of agricultural indicators should not only focus on estimating future trends but also incorporate an assessment of potential deviations and associated risks. This enables stakeholders to make informed decisions, optimise resource allocation, and implement risk-mitigation strategies that contribute to sustainable agricultural development.

This study builds upon existing research in agricultural forecasting by providing an in-depth evaluation of three advanced predictive models: SARIMAX, FbProphet, and GluonTS. The comparative analysis examines the models' performance in predicting monthly poultry population dynamics, assessing their accuracy using key statistical metrics, including RMSE, MAE, MASE, and MAPE. This methodological rigor allows for identifying the most effective model in terms of predictive capability, which can be instrumental in strategic agricultural planning, food security policies, and economic forecasting. To build and validate models in the study, libraries of the Jupyter Notebook software environment were used, which ensured the reliability of the results obtained.

A distinguishing advantage of this research lies in its comprehensive approach to modelling, which goes beyond single-method analyses commonly found in previous studies. By incorporating three distinct forecasting techniques and evaluating their effectiveness across multiple accuracy measures, this study provides a robust methodological framework adaptable to regional agricultural indicators.

To contextualise the strengths and weaknesses of the proposed models, the results were compared with findings from other studies. In particular, the study by Tikiwala et al. (2023) used the ARIMA model with an accuracy of 59.21%; Palabicak & Binici (2023) for the model ARIMA(4,2,1) obtained the following estimates: RMSE = 7319316, MAPE = 21.71, MAE = 6395230; and the ARFIMA model used by Titus et al. (2021) had better predictive ability in terms of RMSE (0.4868 versus 0.6268 for ARIMA). The proposed approach demonstrates the possibility of adapting models to the specifics of regional agricultural indicators. This is confirmed by the data of other studies, including Okorie et al. (2023) on crop yields. In the study by Biswas (2021) it is shown that for forecasting rice production, the ARIMA (1,1,1) model has the best accuracy estimates RMSE = 197.82, MAPE = 3.04, MAE = 133.48. In paper by Mgaya (2019) the ARIMA (1,1,0) model for forecasting livestock consumption has the following estimates: RMSE = 1777.1, MAPE = 4.2, MAE = 1194.8. In the study by Sharma et al. (2022) the Prophet model has the forecasting accuracy: RMSE = 8.18, MAPE = 0.005. These comparative insights underscore the adaptability and potential advantages of the selected models in this study, particularly in the context of regional poultry population forecasting.

The developed forecasting models offer practical applications for policymakers, agribusinesses, and economic planners. The predictions for poultry population trends in the Khmelnytskyi region can serve as a basis for optimising production cycles in the poultry industry by predicting demand and supply fluctuations and enhancing food security strategies through more accurate agricultural planning and risk assessment.

6. CONCLUSIONS

The results obtained from this study show that the time series tends to increase gradually. Built SARIMAX, FbProphet, GluonTS models for forecasting the determination of the number of poultry population for the next 2 years show will be a gradual increase in the poultry stock. The best accuracy estimates are achieved when using the SARIMAX (3;1;2)x(1;1;1;12) model: RMSE = 243.49, MAE = 213.00, MASE = 28.75, MAPE = 2.89.

For more accurate forecasting of poultry population, it is recommended to use a set of methods that take into account not only seasonality, but also the specifics of this business. For more accurate forecasting of information, it is necessary to take into account the regional affiliation of enterprises and the poultry population in a particular region. This will allow for the adaptation of forecasts to local conditions, such as climatic features, economic situation and infrastructure. When there are large fluctuations in the prices of eggs and poultry meat, it is very important to more accurately forecast the average number of poultry population, because these factors directly affect the supply and demand in the market. This approach will make it possible to quickly respond to changes and adjust production plans. This will help in making informed decisions regarding the purchase and production of poultry feed, trade and storage of livestock products, marketing and optimisation of logistics processes. In addition, the integration of such data into information systems will allow automating management processes and reduce production costs. Knowing the forecast for a certain period, the business can use information about the forecasted prices for eggs and meat, keeping the poultry population within acceptable limits.

7. LIMITATIONS AND FUTURE RESEARCH

Although our study demonstrates the potential of machine learning methods for predicting poultry population, it is important to note several limitations. Firstly, our analysis was based on historical data on poultry population in Khmelnytskyi region, which is relatively far from war zones. Therefore, the results of the study are relevant for this region, but their generalisation to other regions requires additional analysis taking into account local characteristics. The war significantly affects the poultry sector by disrupting the logistical supply chains of feed, equipment, and access to markets. In addition, the hostilities are causing a loss of production capacity and a decrease in poultry population. Secondly, an important aspect is the integration of external factors, such as macroeconomic conditions, social trends, and policy changes, which can significantly affect the dynamics of the time series. Thirdly, this article focuses only on forecasting the poultry population in the medium term. Forecasting the volume of poultry production requires a separate in-depth study in the future.

A promising direction for further research is the use of ensembles of time series, the use of a larger amount of historical data, and the comparison of different time series construction models. This will allow for greater forecast accuracy, as ensembles of models tend to have higher stability and reduce the risk of overfitting that can occur when using individual methods. The analysis of large amounts of data also opens up opportunities for the application of advanced machine learning methods, such as neural networks and deep learning, to more complex models. Comparing different approaches will allow for the identification of the most effective forecasting strategies in different conditions and for different types of data, which will significantly expand the possibilities of applying these methods in different sectors of the economy.

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