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MACHINE LEARNING APPROACHES TO PREDICTIVE MODELING OF LIVESTOCK DEVELOPMENT

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Abstract. The subject of this research is the forecasting of the population dynamics of sheep and goats in Ukraine under wartime, economic, and climatic challenges that directly affect livestock farming and national food security. The present study is of particular pertinence, given the pivotal role that small ruminants play in ensuring the supply of meat, dairy products and wool. A decline in animal numbers may result in shortages of livestock products, deterioration of the socio-economic situation in rural areas, and a reduction in Ukraine's export capacity. The purpose of the paper is twofold: firstly, to develop short- and medium-term forecasting models for sheep and goat populations by combining classical statistical techniques with modern machine learning approaches; and secondly, to identify the strengths and weaknesses of these models across different forecasting horizons. The methodological framework utilised is founded upon statistical data of an official nature, as recorded by the Main Department of Statistics in the Odesa region for the period 2007–2025. Four approaches were employed: the SARIMAX statistical model; the additive Prophet model; and LSTM neural networks, which were implemented using PyTorch and Keras. Forecast performance was evaluated using the RMSE, MAE, MAPE and MASE metrics, enabling a comprehensive comparison of the models. The results confirm that the sheep and goat population in Ukraine has been in persistent decline, with sharper falls observed since the start of the full-scale war. The Keras-based LSTM model proved to be the most accurate for short-term forecasts (12 months), while the PyTorch-based LSTM model demonstrated the greatest stability for medium-term predictions (24 months). The SARIMAX and Prophet models achieved moderate accuracy but struggled to reproduce peaks and troughs in the time series. The study's scientific novelty lies in its integration of statistical and neural network forecasting approaches, while explicitly accounting for wartime disruptions and crisis-related factors. This makes the research one of the first attempts to adapt hybrid forecasting models to the Ukrainian livestock sector in wartime. The practical value lies in the ability to use the developed models at both the micro and macro levels. Individual farms can use them to optimise production and resource planning, while policymakers can use the forecasts to design effective state support programmes, strengthen food security strategies and ensure the sustainable recovery of the agricultural sector.

Keywords: food security, time series, machine learning, forecasting, SARIMAX, PyTorch, Keras, Prophet.

JEL Classification: C23, Q10, Q18

1. Introduction

Since February 2022, the full-scale aggression of the Russian Federation has significantly transformed the conditions for livestock farming in Ukraine, resulting in the loss of access to pastures, damage to production infrastructure, disruption to logistics, and the forced outflow of labour. In practice, this has resulted in a steady reduction in the number of cattle. According to official data from the Main Department of Statistics in the Odesa region, the number of sheep and goats in the region decreased from over 450,000 at the beginning of 2007 to fewer than 250,000 at the beginning of 2025 (The State Statistics Service of Ukraine. Main Department of Statistics in Odesa Region).

These dynamics confirm the practical importance of creating short- and medium-term forecasts of livestock numbers to inform management decisions, such as planning state support, adapting production

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programmes and assessing food security risks. Consequently, the present study focuses on the quantitative forecasting of time series for sheep and goat numbers, utilising statistical and neural network approaches. This enables the consideration of both seasonality and changes in trends influenced by military, economic and climatic factors.

Generalising papers describe the initial assessments of the impact of the invasion on Ukraine's agricultural sector (e.g., logistics, investment, financing and security), setting the context for changing trends in livestock production. Papers highlighting the challenges and policy responses associated with the war, as well as the consequences for the competitiveness of livestock products, are particularly notable.

Nehrey and Finger (2024) and Shebanina et al. (2023) analysed the impact of the war on the agricultural sector. This included loss of access to key pastures, damage or destruction of infrastructure, disruption to logistics chains, migration of farmers, and a reduction in production. These factors have affected livestock, particularly sheep and goats, which traditionally play an important role in providing products such as milk, meat and wool (Liudvenko et al., 2024; Ishchuk & Lyakhovska, 2024).

Tomchuk and Kapula (2023) investigated the problematic aspects of export activities in the agricultural sector. The study highlights the impact of military action on the processes of European integration in the agribusiness sector and emphasises the devastating consequences for agriculture following a large-scale war.

Abdullaieva et al. (2022) examined the challenges and dangers posed by the Russian Federation's full-scale invasion of Ukraine, which has impacted food security in the European Union.

Pavelko et al. (2024) conducted an analysis of the losses incurred by the agricultural sector of the Ukrainian economy during the war years. A linear regression model was constructed for the purpose of forecasting the dynamics of bank lending to agriculture. A number of critical tasks have been identified as being of pressing importance in the context of the present situation in Ukraine, which has been exacerbated by the introduction of martial law and active hostilities.

In the study conducted by Shcherbak (2024), the structure of capital investments in the agricultural sector of Ukraine was analysed, and the planned indicators for the livestock sector were examined in the context of the state programme for the development of the agricultural sector. The present study examined the degree to which key parameters of the Strategy for Sustainable Development of Ukraine for the period until 2030 had been implemented. It was determined that the priority for the investment strategy in the agro-industrial complex today is to create conditions that give a wide range of agricultural producers real access to credit resources. This would enable them to update fixed assets and replenish current assets in a timely and effective manner.

In this context, it is crucial to assess the current dynamics of the number of these animals and identify potential future scenarios. This enables one to understand the scale of the problem and formulate effective solutions. Using four modern time series forecasting models – PyTorch, Keras, SARIMAX and Prophet – enables one to take into account complex nonlinear trends, seasonality and possible changes caused by extreme events.

Forecasts for 12 and 24 months ahead enable the short- and medium-term prospects for the industry's development to be assessed. The analysis involves studying the impact of the war on agricultural production and the long-term ability of farms to restore capacity.

The aim of this study was to forecast the development of the sheep and goat population over 24 and 12 months using four models (PyTorch, Keras, SARIMAX and Prophet), which are employed in the study of time series forecasting.

2. Literature Review

Recent advances in forecasting models and spatial-temporal analysis are facilitating the development of new livestock-related forecasts using various methods. The autoregressive integrated moving average (ARIMA) model has proven useful for monitoring disease in sheep and goats (Warnasekara et al., 2021; Anwar et al., 2022).

Anuththara and Weerathilake (2021) investigated the prediction of the populations of goats and sheep, as well as their meat production, in Sri Lanka using exponential smoothing models. Trend analysis of the goat population data revealed a downward trend after 1978. Similarly, mutton production data showed a downward trend from the outset of the observation period.

Aljohani et al. (2024), Jaiswal and Bhattacharjee (2022) and Akram et al. (2022) examined the potential of the livestock market in South Asian and Middle Eastern countries using time series analysis. In particular, they found that meat consumption in Pakistan is expected to increase by 15% by the end of the decade.

The study by Wei et al. (2023) focuses on the relationship between the economic development of agriculture and animal husbandry, and the factors that affect carbon emissions. The results show that, in rural areas, per capita consumption expenditure has a negative impact on carbon emissions, whereas carbon emission intensity and total agricultural machinery power have the opposite effect.

The study by Gokulakrishnan et al. (2024) aimed to model and forecast the prices of small ruminant feeds. Based on the accuracy and error rates of the sample forecasts, the best models for forecasting prices were found to be ARIMA (1,1,0) for sheep feed and SARIMA (1,1,0)(1,0,0) for goat feed.

The paper by Klaharn et al. (2024) presents a study of the dynamics and seasonal patterns involved in forecasting poultry production and export indicators. The authors assessed and compared the predictive capabilities of a set of time series models (SARIMA, NNAR, ETS, TBATS, STL and THETA) to make this assessment. The findings indicate consistent trends of increasing poultry production and exports. Al Khatib et al. (2021) conducted a comparative analysis of different forecasting models (ARIMA, BATS, TBATS and Holt linear trend) to evaluate the dynamics of egg production in India. The Holt linear trend method produced the best results, predicting positive dynamics in the country's egg production. Omar et al. (2024) developed a model to forecast dairy production in Egypt and identified ARIMA (1,1,3) as the optimal model for this purpose. Delaney et al. (2022) investigated milk forecasting on over 1,000 farms. Year-ahead forecasts were generated for each farm individually. A study comparing methods (Seasonal Naïve, LSTM and Prophet) showed that the method using CBR data augmentation outperformed the other evaluated methods.

In the study undertaken by Sharma et al (2022), an analysis was conducted of the Prophet forecasting technique, with a subsequent comparison being made with the traditional ARIMA model. The findings of the study demonstrated that the Prophet model exhibited superior forecasting accuracy. In their study, Hasnain et al. (2022) utilised the Prophet model to analyse and predict air quality in Jiangsu province. In their study, Jha et al. (2021) developed a time series forecasting model for supermarket sales using the Prophet library. As stated by Wibawa et al. (2022), the time series was analysed using a Convolutional Neural Network.

Xu (2022) implemented a CNN-LSTM model in the PyTorch environment for the purpose of predicting stock prices in the stock market. In their seminal study, Kolluru et al. (2024) sought to explore the potential of machine learning algorithms, specifically long-short term memory (LSTM) networks and PyTorch-Ray, to predict household electricity consumption within the context of Smart IoT systems.

Ferraz et al. (2023) constructed univariate and multivariate time series forecasting models with the aim of resolving issues pertaining to seafood.

Studies (Etxegarai et al., 2022; Venkatesan & Cho, 2024) focus on forecasting the efficient use of solar energy in agriculture using deep learning models. Tools based on artificial neural networks are considered. The results demonstrate that a convolutional neural network is more accurate.

3. Materials and Methods

Data on the number of sheep and goats from January 31, 2007 to January 1, 2025 was obtained from the website of the Main Department of Statistics in the Odesa region of Ukraine (The State Statistics Service of Ukraine. Main Department of Statistics in Odesa Region).

The study used four models for time series forecasting: Prophet, LSTM (PyTorch), LSTM (Keras) and SARIMAX.

Prophet is an additive time series forecasting model developed by Meta (formerly Facebook) that focuses on ease of use, high accuracy, and adaptability to seasonality and changes in data. This model is employed extensively in the analysis of data characterised by a pronounced seasonal component, trends, and events with the potential to influence the dynamics of the series. It consists of the following components:

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

Here $g(t)$ is the linear trend of the time series:

$$g(t) = (k + a(t)\delta)t + b , \quad (2)$$

where k is the base growth rate, $a(t)$ is the trend change indicator, δ is the trend speed change.

$s(t)$ is the seasonal component. To describe seasonality, Fourier series are used:

$$s(t) = \sum_{n=1}^{N} \left[a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right) \right], \quad (3)$$

where P is the seasonality period; $h(t)$ accounts for given anomalous days (external events or holidays) that have a significant impact on the time series; ϵ_t – error that contains information not taken into account by the model.

Prophet uses stochastic gradient descent to estimate model parameters.

The Prophet is implemented using the Prophet library (Python). The input data for the model is a time series in DataFrame format, comprising columns ds (date) and y (value). The result is a forecast with the ability to visualize components (trend, seasonality, events).

For time series prediction, the Long Short-Term Memory (LSTM) architecture implemented using the PyTorch library was utilised. LSTM represents an extension of recurrent neural networks (RNNs) that facilitates the efficient storage of information regarding long-term dependencies in time series, rendering it particularly advantageous for the modelling of complex patterns in data.

The input layer accepts vector representations of the time series in the form of multidimensional tensors.

The LSTM hidden layer (or multiple layers) is responsible for storing the internal state and memory required for detecting temporal dependencies. The fully connected linear layer transforms the output of the hidden layers into the space of predicted values.

The linear function was utilised to generate the final prediction. The model hyperparameters, including the number of neurons in the hidden layers, the number of LSTM layers, and the regularization level (dropout), were tuned to achieve optimal performance.

A recurrent neural network (RNN) employing the Long Short-Term Memory (LSTM) architecture was utilised, a technique that facilitates the efficient capture of long-term dependencies in the data. The model was implemented using the Keras library, which is based on the TensorFlow framework.

The input data is represented as a three-dimensional tensor of size (samples, timesteps, features), where samples is the number of examples in the training set; timesteps is the number of time steps in each example; and features is the number of features at each time step. Hidden layers: LSTM layer with 50 neurons, with a hyperbolic tangent (tanh) activation function. The layer returns a sequence (return_sequences=True) to enable multi-level learning. The output layer is a dense layer (Dense) with one neuron and linear activation (linear), which provides a prediction of the value of the target variable at the next time step.

The Lion optimisation algorithm was used to train the model, providing fast and stable minimisation of the loss function. The model was trained for 250 epochs, with the mini-batch size set to eight. To prevent overfitting, an early stopping mechanism was employed that stops training if the loss function on the validation set does not improve for ten consecutive epochs.

The SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous regressors) model is an extension of the SARIMA model, which is used to model time series that exhibit seasonality and trends, as well as the influence of external factors. It is one of the most popular models, combining the advantages of statistical analysis with the ability to consider external regressors. The SARIMAX model combines several key components: autoregression, integration, a moving average, seasonality and exogenous variables.

SARIMAX can be written as follows:

$$\Phi_p(B^s)\phi_p(B)(1-B)^d(1-B^s)^D y_t = \\ = \Theta_q(B^s)\theta_p(B)\varepsilon_t + \mathrm{X_t}\beta, \quad (4)$$

where B is the shift operator; y_t is the value of the time series at time t; ε_t is the residuals (noise); $\mathrm{X_t}\beta$ is the contribution of exogenous variables.

In order to build a model, the series must first be tested for stationarity using the Dickey-Fuller (ADF) test. The model parameters are then selected using an automatic selection algorithm (AIC/BIC). The parameters are then estimated using the maximum likelihood method.

In this study, the following indicators are used to determine the accuracy of time series forecasting:

root mean square error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(E_i - F_i)^2}, \quad (5)$$

mean absolute estimate (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|E_i - F_i\right|, \quad (6)$$

mean absolute percentage estimate (MAPE)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|E_t - F_t\right|}{E_t}\cdot 100\%, \quad (7)$$

and mean absolute scaler error (MASE)

$$MASE = \frac{MAE}{\frac{1}{n-1}\sum_{i=2}^{n}\left|E_i - E_{i-1}\right|}, \quad (8)$$

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

Two scenarios were employed in a time series forecasting exercise, designed to reveal the impact of training data composition on forecasting performance. In the first scenario, 192 months of training data and 24 months of testing data were used. The second scenario used 204 months of training data and the remaining 12 months for testing. Figure 1 illustrates the data distribution scheme for training and testing.

The calculations and model building were performed in the Jupyter Notebook environment using the following Python libraries: pandas, numpy, scikit-learn, statsmodels, prophet, keras, pytorch and matplotlib.

4. Results

Changes in the number of sheep and goats in the Odesa region between January 31, 2007 and January 1, 2025 are studied (Fig. 2).

Figure 2 illustrates the changes in the number of sheep and goats in the Odesa region between January 1, 2007 and January 1, 2025. The graph shows that the number of sheep and goats steadily decreased throughout the entire period. While the number was more than 450 thousand in 2007, by 2025 this figure had decreased to less than 250 thousand. There are noticeable regular seasonal fluctuations, which are associated with cyclical factors such as animal slaughter, changes in livestock reproduction and seasonal demand for livestock products. Since 2014–2015, however, the rate of population decline has become more abrupt. This may be due to economic, climatic, or social factors, such as changes in agricultural

Figure 1. Training testing data composition

Source: authors' elaboration

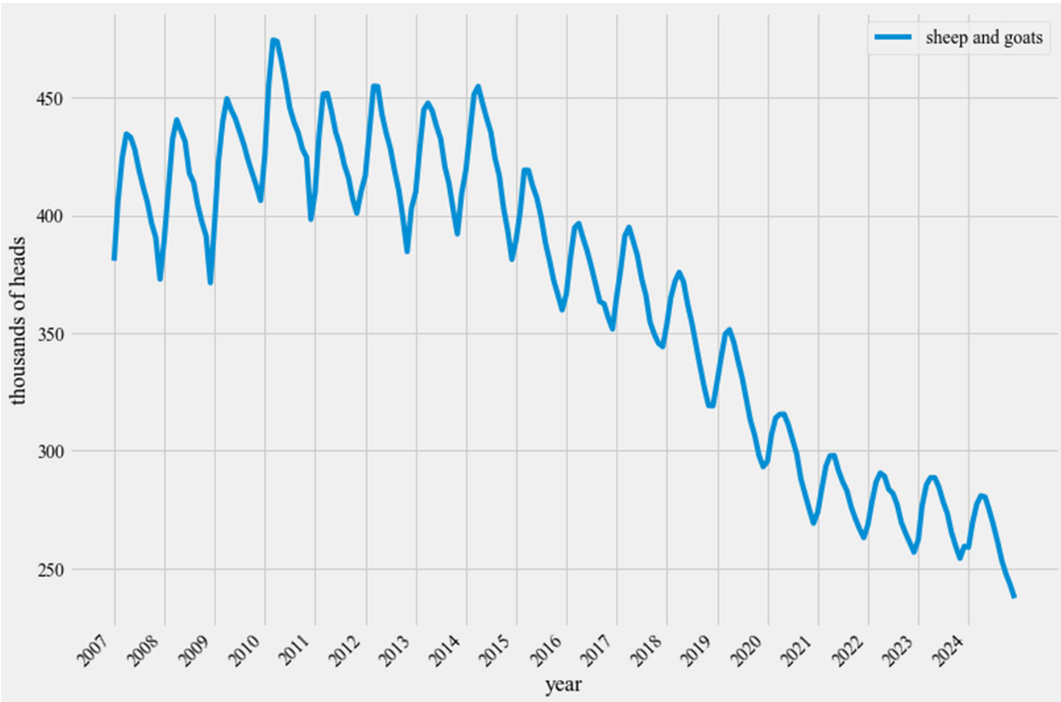

Figure 2. Dynamics of changes in the number of sheep and goats in the period from January 31, 2007 to January 1, 2025 in the Odesa region

Source: authors' elaboration from (The State Statistics Service of Ukraine. Main Department of Statistics in Odesa Region, n.d.)

policy, the deterioration of conditions for animal husbandry, or reduced demand for the industry's products (Novykova, 2024). By the end of the period, the number of sheep and goats had reached its lowest level of the entire analysed period, possibly due to the constant shelling of the Odesa region by the aggressor country (Novikova et al., 2023).

Table 1 presents statistical characteristics of the number of sheep and goats in the Odesa region for the period from 2007 to 2024.

The average number of sheep and goats over this period is 366,370. This reflects the long-term downward trend, despite the average level. The relatively high standard deviation of 64,560 indicates significant variability in the number of livestock. This suggests significant seasonal and long-term fluctuations. The negative value of asymmetry (-0.36) indicates that the data distribution is slightly skewed towards smaller values, confirming the general downward trend. The negative value of kurtosis (-1.24) suggests that the distribution of numbers is flatter than normal. This suggests that the maximum and minimum values are less pronounced.

Figure 3 shows the observed and predicted values for the different models (SARIMAX, Prophet, PyTorch and Keras). SARIMAX (red line) appears to describe

Table 1
Statistical characteristics of the number of sheep and goats, thousand heads

Metrics	N	Mean	Std.	Min.	Max.	Skew.	Kurt.
Sheep and goats	216	366.37	64.56	237.40	474.50	-0.36	-1.24

Source: *authors' elaboration*

the seasonality well, although the forecast seems somewhat smoother than the actual values, particularly at peak points. Prophet (blue line) provides the best initial fit, but exaggerates the peak in mid-2023. PyTorch (green line) matches the actual values well, although there is a slight instability in mid-2024. Keras (orange line) is quite close to the real data and shows smaller fluctuations than the other models.

Table 2 shows the results of assessing the forecasting quality of different models over a period of 24 months. The PyTorch model shows the lowest values for all metrics, indicating the best forecasting quality of all the models. Figure 3 shows that the PyTorch forecast is the most stable, being particularly close to the actual values at midpoints. This model effectively considers seasonality and trends without excessive fluctuations. Second place in terms of forecasting accuracy goes to SARIMAX. Although the estimates are slightly larger than those in PyTorch (particularly for MAPE and MASE), the model generally demonstrates a good fit to the data. As can be seen in the graph, SARIMAX predicts seasonality but smooths out peak values (e.g., in mid-2023). This is confirmed by the slightly larger absolute estimates. The Keras estimates are noticeably larger than those of PyTorch and SARIMAX, but smaller than those of Prophet. The high MASE value (0.640) suggests poorer performance than simple baseline models. Figure 3 shows that, while the Keras models do capture seasonality, the predictions deviate slightly from the real data at peak and trough points. This corresponds to the high MAE and MAPE values.

The Prophet model demonstrates the poorest performance of all the models examined, with the most elevated estimates (notably MAPE = 1.721, signifying substantial inaccuracy in predicting relative changes). As demonstrated in Figure 3, this model has a tendency to overestimate peaks and underestimate downward trends. In comparison to alternative models, it demonstrates a comparatively diminished capacity to adapt to local data features.

As shown in Fig. 4, Keras (orange line) closely follows the actual data, with only minor deviations. It takes seasonality and trends into account, providing smooth forecasts. Prophet (the blue dashed line) is generally consistent with the actual values, but shows slightly larger deviations at peak points and during periods of decline. The utilisation of PyTorch (green dashed

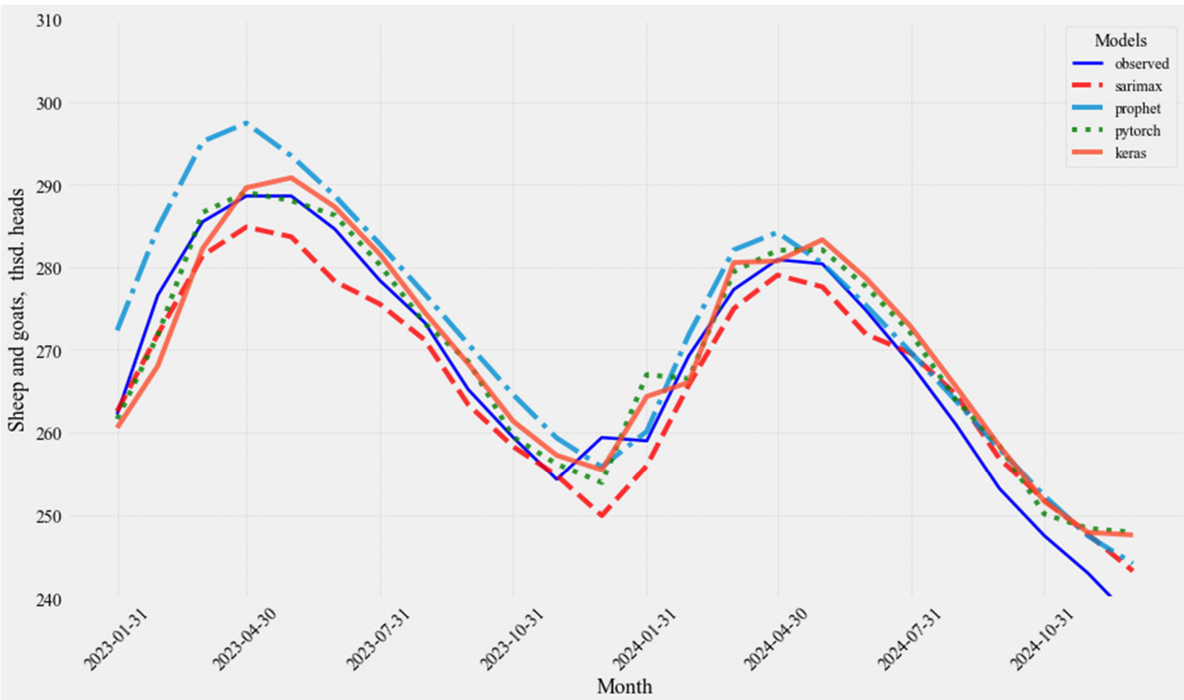

Figure 3. Forecast of sheep and goat numbers by models for 24 months

Source: authors' elaboration

Table 2
Evaluating the forecasting quality of different models for 24 months

len(train)=192, len(test)=24				
	rmse	mae	mape	mase
pytorch	3.548	2.619	0.996	0.458
sarimax	3.945	3.410	1.280	0.596
keras	4.255	3.662	1.395	0.640
prophet	5.289	4.599	1.721	0.804

Source: authors' elaboration

line) reveals significant fluctuations in the forecasts, particularly at decline points. The graph illustrates that this model accentuates both the peaks and declines. The SARIMAX model (red dashed line) visually demonstrates significant deviations from the actual data. The forecast demonstrates a marked overestimation at peak points and does not reflect seasonality.

As demonstrated in Table 3, the Keras model demonstrates the lowest values for all metrics. The model demonstrates optimal prediction quality with minimal estimates. Prophet is the second-best model in terms of prediction quality. The estimates (particularly MAPE) are marginally elevated in comparison to those of Keras, yet remain within acceptable limits. A comparative analysis reveals that PyTorch exhibits significantly inferior performance across all metrics when benchmarked against Keras and Prophet. A substantial excess of MAPE (2.012) signifies pronounced deviations from the actual data. It is evident that the SARIMAX model is the least effective of the models under consideration in this prediction. The elevated values of the estimates, notably MAPE (4.913) and MASE (2.136), signify the model's inability to adapt to the data.

As demonstrated in Figure 4 and Table 3, the Keras model has been identified as the optimal solution in terms of quality. The model provides superior forecasts in terms of metrics and graphical representation. This model has been developed to optimise the consideration of seasonality and trends. The term "Prophet" is an acceptable option, but it is clear that further refinement is required in order to improve the accuracy at extreme points. It is evident that both PyTorch and SARIMAX exhibit substantial discrepancies, both graphically and in terms of metrics. SARIMAX demonstrated an inability to adequately adapt to the data, while PyTorch exhibited instability in forecasts.

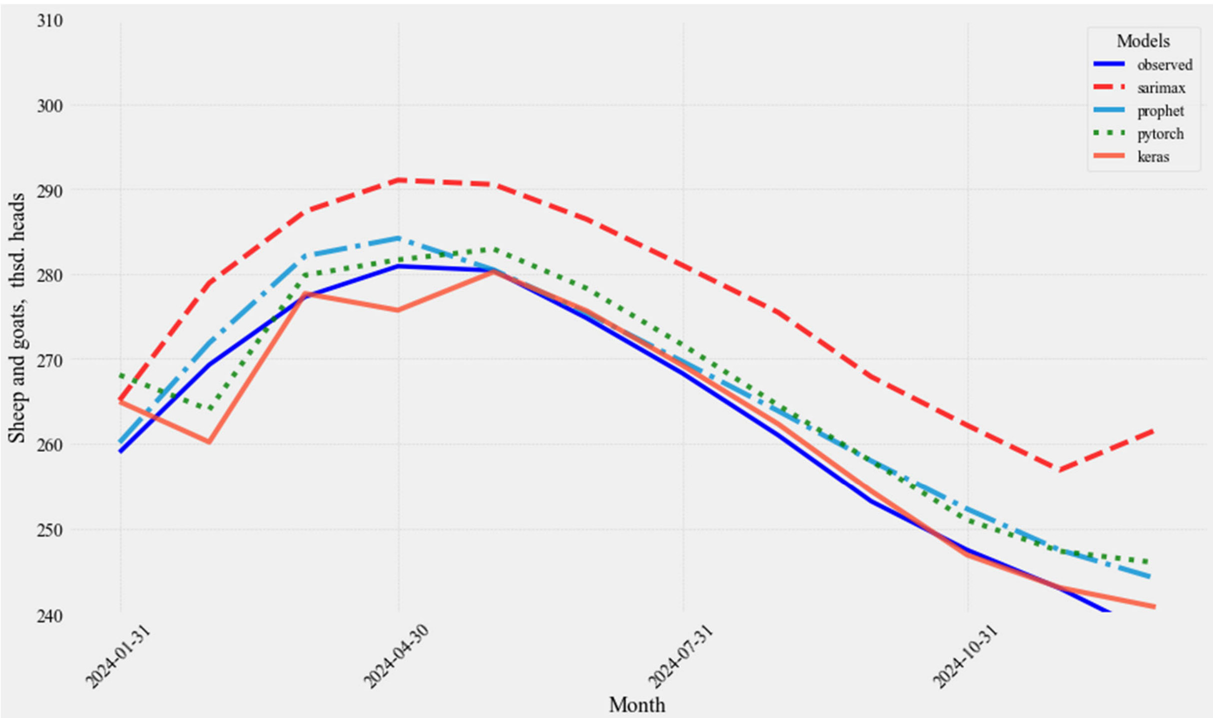

Figure 4. Forecast of sheep and goat numbers by models for 12 months

Source: authors' elaboration

Table 3
Evaluating the forecasting quality of different models for 12 months

len(train)=204, len(test)=12				
	rmse	mae	mape	mase
keras	3.676	2.432	0.923	0.409
prophet	3.698	3.129	1.223	0.526
pytorch	5.826	5.158	2.012	0.868
sarimax	13.399	12.698	4.913	2.136

Source: authors' elaboration

As demonstrated in Table 4, the findings of the model analysis indicate that the quality of the model may be contingent upon the duration of the forecast period. PyTorch has been shown to perform better on long-term forecasts, while Keras has been demonstrated to show high accuracy on shorter horizons.

The findings of the present study demonstrate that the best forecasting quality for the 24-month horizon is demonstrated by the PyTorch and SARIMAX models, with PyTorch being the leader. At the 12-month mark, the Keras model demonstrates the highest level of accuracy, while PyTorch and SARIMAX exhibit a substantial decline in performance. The MAE and RMSE metrics are consistent with graphical observations: smaller values indicate smaller absolute and root mean square errors. As demonstrated in Figure 1, the presence of elevated MAPE values for both the Prophet and SARIMAX models is indicative of significant relative deviations, particularly during periods of peak or decline.

5. Discussion

The findings substantiate the assertion that the precision of forecasting the number of sheep and goats in Ukraine is contingent on the selection of model and forecasting horizon. In particular, the Keras model demonstrated optimal performance in the short-term forecasting context (12 months), while the PyTorch model exhibited superior long-term stability (24 months). The SARIMAX and Prophet models exhibited average efficiency; however, they were deficient in reproducing peak and decline values.

Forecasting the number of sheep and goats is a complex task, as this process depends on a wide range of factors that can significantly affect the results of forecasts. These factors include the duration of military aggression, climatic conditions and natural factors, economic parameters, biological and genetic characteristics, and technological support. It is imperative that all these factors are given full consideration when creating forecast models. Although classical statistical approaches, such as SARIMAX, are capable of modelling historical trends with a high degree of accuracy, the integration of additional variables, including climatic, economic and biological factors, is more effectively achieved through the use of deep neural networks (PyTorch, Keras) and specialised algorithms (Prophet), resulting in more accurate forecasting.

Thus, the SARIMAX(1,0,0)×(2,0,0) model was used to forecast milk production in the study (Perez-Guerra et al., 2023), where the obtained estimates were RMSE = 8.0, MAPE = 9.0 and MAE = 46.0. This demonstrates the capabilities of statistical methods in modelling agricultural processes, but also indicates their limitations when integrating a large number of factors. Similarly, Omar et al. (2024) used ARIMA to forecast milk production in Egypt, achieving acceptable results based on historical data. This confirms that classical models are useful for short time series but less effective in the face of significant external shocks.

A comparison with other studies shows that the results obtained are partially consistent with previous

Table 4
General analysis of models

	24 months	12 months	Conclusions
keras	Results are worse, but still remain stable	Best model for short-term forecasting	For tasks where a forecast for the year is needed
PyTorch	Leader in accuracy in long-term forecasting	Works worse for shorter periods	Suitable for analyzing data with pronounced long-term trends and seasonality
SARIMAX	Second place	Worst results	Strong deviations in short-term forecasting indicate insufficient adaptability to local changes in data
Prophet	Average results	Average results	The forecast has a tendency to exaggerate peaks and not adapt to declines, as can be seen from the high values of MAPE and MAE

Source: authors' elaboration

work. For instance, Sharma et al. (2022) discovered that the Prophet model exhibited superiority over the conventional ARIMA model in the context of forecasting agricultural data. This finding is corroborated by the present study, which also validates the model's efficacy in the realm of short-term forecasting. In contrast, Xu (2022) observed the high stability of LSTM architectures. However, the results of this study demonstrate a decrease in the accuracy of PyTorch-LSTM for short-term forecasting and an advantage for long-term forecasting. This indicates the sensitivity of neural network models to the specifics of the data and the chosen forecasting horizon. In the studies by Anuththara and Weerathilake (2021) and Aljohani et al. (2024), classical methods such as exponential smoothing and SARIMA produced acceptable results for livestock forecasting in Asian countries. However, these studies showed that, in Ukrainian conditions, the accuracy of these methods is lower than that of neural network models. Therefore, combining statistical and modern methods enables a more thorough consideration of seasonality and the impact of external shocks, including military ones.

It is also important to take war factors into account. As noted by Abdullaieva et al. (2022), Nehrey & Finger (2024) and Liudvenko et al. (2024), the war in Ukraine has led to a significant decrease in livestock numbers and logistical disruptions, reducing the predictive stability of models based solely on historical data. Therefore, combining statistical and modern methods enables a more comprehensive consideration of both seasonality and the impact of external shocks.

This study is novel in its combination of several approaches (SARIMAX, Prophet, Keras and PyTorch) to forecast the number of small cattle in Ukraine, taking military factors into account. Previously, such models were mostly used for other purposes, such as milk or meat production and market indicators, but not to analyse the impact of war on the sheep breeding industry.

The practical significance of the results lies in the possibility of using the proposed models for both farms and government agencies. Short-term forecasts (12 months) facilitate the expeditious planning of the restoration of production capacities, while long-term (24 months) forecasts can underpin industry support strategies and the formulation of food security policy in wartime conditions.

6. Conclusions

The study demonstrated the effectiveness of utilising contemporary machine learning methodologies and traditional statistical approaches to forecast the number of sheep and goats in Ukraine under military, economic and climatic challenges. A comparison of four models (PyTorch, Keras, SARIMAX and Prophet) was undertaken in order to identify the strengths and weaknesses of each depending on the forecasting horizon.

In the context of short-term forecasting (12 months), the Keras model emerged as the most effective model, demonstrating the lowest error values across all metrics. This enables agricultural enterprises to meticulously plan the current agricultural year, encompassing activities such as grazing management, feed procurement, cost optimisation, and livestock population regulation. Prophet can be used as an alternative, but this must take into account errors during periods of peak fluctuations.

In the context of long-term forecasting (24 months), the PyTorch model emerged as the most stable, a finding that incorporates both trends and seasonal fluctuations. This horizon is instrumental in the strategic planning of infrastructure development, the assessment of the economic profitability of the industry, and the determination of the needs for state support. SARIMAX can be utilised as a backup method, but necessitates additional parameter tuning and is less sensitive to local peak values.

It is important to note that the selected time horizons (12 and 24 months) facilitate a comprehensive evaluation of both seasonal dynamics and long-term trends in livestock decline. This creates the basis for effective management of the livestock industry, which is of critical importance in the context of war and the transformation of the agricultural sector.

The potential for future research lies in the expansion of the set of variables for prediction, incorporating a range of factors including, but not limited to, climatic, economic, biological and technological elements. It is further posited that future endeavours may encompass the integration of hybrid models, which combine statistical and neural network approaches. Additionally, the impact of political and socio-economic decisions on the recovery and development of the sheep and goat industry is to be assessed.

7. Gements

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