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# Corn price forecasts in the shadow of the Russian–Ukrainian conflict

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**Abstract:** The conflict between Russia and Ukraine has caused serious disruption to agricultural markets, affecting both food prices and food security. In our study, we examine how global economic problems, such as COVID-19 or wartime conditions, affect corn prices and their predictability. We used deep neural network models [Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU)], experimenting with both simple and hybrid versions, as well as univariate and multivariate types. The results show that the GRU model outperformed the other models in predicting corn prices. It was also found that multivariate models tended to yield more accurate results than their univariate counterparts, suggesting that forecast quality can be significantly improved by including additional variables. In the robustness analysis, it was shown that the COVID-19 crisis in 2020 and the Russia–Ukraine war in 2022 led to a deterioration in model performance. The research contributes to the development of forecasting methods for the corn market and provides a basis for decision-making strategies for market players. To ensure methodological rigour, the forecasting results were statistically validated using the Diebold–Mariano test.

**Keywords:** deep learning; forecasting; market shocks; predictive modelling; time series analysis

The war between Russia and Ukraine has caused severe disruption in agricultural markets, affecting food prices and food security (Blikhar et al. 2023; Chen and Jiang 2024; Devadoss and Ridley 2024). By the ninth week after the invasion, the futures price of agricultural commodities had risen by an average of 16%, after which it declined slowly (Goyal and Steinbach 2023). Urak et al. (2024) point out that the combined impact of COVID-19 and the Russian–Ukrainian war had a long-term effect on the volatility of agricultural commodity prices and the related risks.

The effects of geopolitical events did not impact all agricultural products equally. Devadoss and Ridley (2024) specifically emphasise the significant changes in the wheat market. In contrast, Goyal and Steinbach (2023) found that corn futures prices were less affected by the war than wheat. Hudecová and Rajčániová (2023) showed that geopolitical risks stemming from the outbreak of war had a strong influence on the prices of rapeseed, sugar, sunflower, and wheat, but observed no long-term effects on corn and several other agricultural commodities. Hamulczuk et al. (2023) confirm that corn's share in Ukrainian grain exports has been less affected by the war than that of wheat and barley. Nonetheless, with respect to price developments, corn remains among the more sensitive commodities. Goyal et al. (2024), Zhang et al. (2024), and Aliu et al. (2023) report that geopolitical risks significantly influence corn futures prices not only in the short term but also in the medium term.

Based on the limited literature available, it can be concluded that geopolitical risks have affected corn prices in international markets, both in the short and long term. However, no studies have specifically examined how the Russia–Ukraine war has influenced the predictability of corn prices. Our study aims to fill this gap.

Price forecasting is crucial in agricultural markets. Accurate forecasting models enhance the stability and food

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security of global food supply networks (Sun et al. 2023) and are essential for informing policymaking in areas such as global trade, economic growth, and sustainability (Albuquerquemello et al. 2022). Forecasting corn prices is particularly challenging because the market is exposed not only to regular seasonal cycles and weather-related shocks, such as droughts, but also to sudden exogenous crises, including the COVID-19 pandemic and the Russian–Ukrainian conflict. Traditional linear models often struggle to capture such nonlinear dynamics and structural breaks. By contrast, recurrent neural network architectures [Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU)]) are specifically designed to model temporal dependencies and adapt to complex, volatile environments. Their use in this study is therefore not only a methodological choice but a response to the unique forecasting challenges posed by the corn market.

While this research acknowledges the disruptive effects of COVID-19 and the Russia–Ukraine war, these crises do more than simply add noise to the data: they fundamentally reshape market structures by triggering demand shocks, logistical disruptions, and policy interventions. Machine learning models may either adapt to such shifts through flexible pattern recognition or experience a decline in accuracy when structural breaks occur. By comparing model performance across stable and crisis periods, this study also sheds light on the robustness of forecasting models under uncertainty, offering insights into how well different neural network architectures handle exogenous shocks.

Our research aims to investigate the effectiveness and accuracy of various machine learning models for forecasting corn prices, particularly in the context of geopolitical risks stemming from the Russian–Ukrainian war. To achieve this, we formulated the following research questions:

$RQ_1$: Which machine learning models are most effective in predicting corn prices before and after the outbreak of the war?

$RQ_2$: How does the accuracy of forecasting models in periods of external events influencing corn markets compare to years without such external events?

This study makes two significant contributions to the literature. First, it goes beyond traditional forecasting applications by explicitly analysing how geopolitical shocks such as the Russia–Ukraine war and the COVID-19 pandemic influence not only corn price levels but also their predictability. Second, by comparing the performance of RNN, LSTM, and GRU architectures across stable and crisis periods, the research provides new insights into the robustness of deep learning models under conditions of heightened uncertainty. In doing so, the study bridges the gap between methodological advances in machine learning and the pressing economic challenges of agricultural risk management, offering practical insights to traders and analysts to support their choice of forecasting methodology under different market conditions.

**Literature review – price forecasting for agricultural products.** Price forecasting in agricultural commodity markets has undergone a significant methodological shift, moving from linear econometric models to machine learning (ML) and hybrid deep learning (DL) architectures that better capture nonlinearities and dynamic market behaviours. The reviewed literature illustrates that forecasting accuracy is strongly influenced by both the methodological framework and the forecasting horizon.

Early contributions, such as Xiong et al. (2015), demonstrated the advantages of combining linear and nonlinear techniques through a VECM–MSVR (Vector Error Correction Model–Multi-Output Support Vector Regression), applied to interval forecasts of corn and cotton futures. Their approach outperformed single models, including ARIMA–MSVR (Autoregressive Integrated Moving Average–Multi-Output Support Vector Regression) and ARIMA–ANN (Autoregressive Integrated Moving Average–Artificial Neural Network), confirming that integrated structures improve interval prediction accuracy. Ribeiro and dos Santos Coelho (2020) tested ensemble methods (bagging, boosting, stacking) across agribusiness time series, and their results indicate that boosting-based ensembles consistently outperformed individual models. Notably, their hybrid KNN–XGB–SVR (K-Nearest Neighbors–XGBoost–Support Vector Regression) model achieved superior short-term performance for soybean and wheat prices.

A growing body of research has since focused on deep learning-based multivariate models. Ouyang et al. (2019) compared LSTNet (Long- and Short-Term Time Series Network), CNN (Convolutional Neural Network), RNN, ARIMA, and VAR (Vector Autoregression) across various agricultural futures and found that LSTNet – by integrating convolutional and recurrent layers with autoregressive components – delivered the most accurate multivariate forecasts. Liang and Jia (2022) extended this by incorporating exogenous information: they developed a Grey Wolf Optimiser (GWO)–CNN–LSTM model using Baidu and Google search data combined with transfer entropy (TE), which significantly improved price forecasting for corn, soybean, PVC, egg, and rebar futures

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Table 1. Comparative summary of key studies in agricultural price forecasting

| Study | Methodology | Commodity focus | Forecasting horizon | Key finding |
|---|---|---|---|---|
| Xiong et al. (2015) | VECM–MSVR hybrid | corn, cotton | medium | hybrid linear–nonlinear model improved interval forecasts |
| Ribeiro and dos Santos Coelho (2020) | KNN–XGB–SVR ensemble | soybean, wheat | short | hybrid ensemble outperformed individual models |
| Ouyang et al. (2019) | LSTNet (CNN + RNN + AR) | multiple futures | medium | multivariate hybrid DL improved accuracy |
| Liang and Jia (2022) | GWO–CNN–LSTM with online search data & TE | corn, soybean, PVC, egg, rebar | medium | external features improved robustness and precision |
| Guo et al. (2022) | AttLSTM–ARIMA–BP hybrid | corn (input: rice, soybean prices) | medium | composite model had highest accuracy and stability |
| Xu and Zhang (2021) | Bivariate NN (cash + futures) | corn | short | futures input improved next-day cash price forecast |

AR – autoregressive component; ARIMA – autoregressive integrated moving average; Att – attention mechanism algorithm; BP – back propagation; CNN – convolutional neural network; DL – deep learning; GWO – Grey Wolf optimiser; KNN–XGB–SVR – K-Nearest Neighbors–XGBoost–support vector regression; LSTM – Long Short-Term Memory; LSTNet – long- and short-term time series network; NN – neural network; RNN – Recurrent Neural Network; TE – transfer entropy; VECM–MSVR – Vector error correction model–multi-output support vector regression

Source: Authors' own elaboration

in China. Similarly, Guo et al. (2022) proposed an AttLSTM-ARIMA-BP (Att – Attention Mechanism Algorithm, BP – Back Propagation) hybrid model for corn price forecasting in Sichuan province, using rice and soybean prices as external inputs. This composite model outperformed seven benchmark algorithms in terms of accuracy and robustness.

Neural networks also perform well in forecasting short-term spot prices. Xu and Zhang (2021) applied univariate and bivariate feedforward neural networks to forecast daily corn cash prices across more than 500 U.S. locations. Incorporating corn futures prices as an input improved prediction accuracy for next-day prices, emphasising the value of combining cash and futures data.

Across the literature, the forecasting horizon is a crucial factor. Short-term predictions (e.g. one day to one week) benefit from ensemble and shallow neural architectures (Ribeiro and dos Santos Coelho 2020; Xu and Zhang 2021), while medium-term applications (weekly or monthly scales) often favour hybrid deep learning models capable of capturing complex temporal dependencies (Ouyang et al. 2019; Liang and Jia 2022). Hybrid structures that combine deep learning and classical time-series models offer the greatest robustness in volatile conditions (Guo et al. 2022).

In sum, recent studies consistently show that non-linear and hybrid models outperform traditional econometric approaches, especially in multivariate and high-frequency settings. However, most contributions evaluate performance in stable economic periods. The present study addresses this gap by systematically comparing RNN, LSTM, and GRU architectures across different forecasting horizons, both before and during major shocks (COVID-19, Russia–Ukraine war), revealing substantial drops in model performance during volatile periods and highlighting the relative strength of GRU networks under instability.

Table 1 provides a comparative summary of the key methodologies, target commodities, forecasting horizons, and main findings from the reviewed studies.

## MATERIAL AND METHODS

### Applied methods

***Simple recurrent neural network (RNN).*** A RNN is a form of artificial neural network that consists of three fundamental components: the input layer,

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hidden layer, and output layer. In contrast to standard feedforward networks, RNNs differ in two significant ways. Firstly, the nodes within the same hidden layer are interconnected. Secondly, the input to the hidden layer at a given time step comprises not only the current input-layer output but also the hidden-layer output from the previous time step. This architecture enables more effective capture and modelling of temporal dependencies in sequential data. As a result, RNNs can leverage past information to interpret current inputs, making them particularly useful for tasks involving sequential patterns (Bai et al. 2021). A simple RNN model can be described by the following equations:

$$S_t = \left(UX_t + WS_{t-1} + b_h\right) \tag{1}$$

$$y_t = f\left(VS_t + b_0\right) \tag{2}$$

where: $X_t$ – the input at time $t$; $S_t$ – the hidden-layer output; $y_t$ – the output-layer value; $f()$ – an activation function; $b_h$ and $b_0$ – the bias vectors for the hidden and output layers, respectively; $U$, $W$ and $V$ – the input, hidden, and output layer weights.

***Gated recurrent unit (GRU)***. GRU is a specialised type of RNN known for its high accuracy in forecasting time series data. While GRUs share similarities with other architectures, such as LSTM, they require fewer computational resources, which contributes to improved training performance.

The GRU architecture maintains the same input-output structure as a conventional RNN but introduces two gates: the update gate $z_t$ and the reset gate $r_t$. The update gate determines how much of the past information should be retained, while the reset gate controls how the new input is integrated with the stored memory. Unlike LSTM, GRU allows the update gate to manage memory content directly by retaining, updating, or forgetting information as needed. This flexibility enhances computational efficiency and reduces training time. GRU behaviour is governed by the following equations:

$$z_t = \sigma\left(W_z h_{t-1} + U_z X_t\right) \tag{3}$$

$$r_t = \sigma\left(W_r h_{t-1} + U_r X_t\right) \tag{4}$$

$$\tilde{h}_t = \tanh\left(W_0\left(h_{t-1} \odot r\right) + U_0 X_t\right) \tag{5}$$

$$h_t = z_t \odot \tilde{h}_t + \left(1 - z_t\right) \odot h_{t-1} \tag{6}$$

where: $h_{t-1}$ – the hidden state from the previous time step; σ() – the sigmoid activation function, defined as $\sigma(x) = 1/1 + e^{-x}$; $W_z$ and $U_z$ – the weight matrices for the update gate; $W_r$ and $U_r$ – the weight matrices for the reset gate; the intermediate output relies on $W_0$ and $U_0$; $\tilde{h}_t$ and $h_t$ – vectors representing the candidate hidden state and the updated hidden state, respectively (Xiao et al. 2022).

***Long-short term memory (LSTM).*** LSTM networks are a class of RNNs designed to analyse sequential data and are particularly effective at learning long-range temporal dependencies. In LSTM networks, the internal cell states handle short-term memory, while the weight matrices govern long-term learning. LSTM was introduced to address the vanishing-gradient problem in traditional RNNs. The key innovation is to replace the simple hidden layer with an LSTM block, enabling the network to capture and learn long-term dependencies. To predict future values and adjust network weights, it is essential to preserve information from early time steps. Standard RNNs are typically limited to modelling short-term dependencies, while LSTMs overcome this limitation. LSTM units are composed of memory blocks containing three gates: input, output, and forget that manage how data is written, read, and retained in the memory cells. Additionally, these blocks include one or more autoregressive memory cells that allow for continuous learning (Ortu et al. 2022). The LSTM equations are as follows:

$$I_t = \sigma(X_t W_{xi} + W_{hi} h_{t-1} + b_i) \tag{7}$$

$$F_t = \sigma\left(X_t W_{xf} + W_{hf} h_{t-1} + b_f\right) \tag{8}$$

$$\tilde{C}_t = \tanh(X_t W_{xc} + W_{hc} h_{t-1} + b_c) \tag{9}$$

$$C_t = F_t \odot C_{t-1} + I_t \odot \tilde{C}_t \tag{10}$$

$$O_t = \sigma\left(X_t W_{xo} + W_{ho} h_{t-1} + b_o\right) \tag{11}$$

where: $W_{xi}$, $W_{hi}$, $b_i$ – the weights and the bias of the input gate; $W_{xf}$, $W_{hf}$, $b_f$ – weights and bias of the forget gate; $\tilde{C}_t$ – the candidate memory cells; $W_{xc}$, $W_{hc}$, $b_c$ – the weights and the bias of $\tilde{C}_t$; $C_t$ – the current memory cell, $C_{t-1}$ – the prior state; $W_{xo}$, $W_{ho}$, $b_o$ – weights and bias of the output gate (Dai et al. 2022).

The models were implemented in Python 3.9, using machine learning libraries such as Scikit-learn and TensorFlow.

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**Performance evaluation**

In this study, we utilised the mean absolute percentage error (*MAPE*) to evaluate the performance of the predictive models. This metric calculates the average absolute difference between predicted and actual values, expressing error as a percentage of the actual values (Nti et al. 2020).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{12}$$

A lower *MAPE* value indicates higher forecasting accuracy and reliability. Since *MAPE* is independent of the scale of the actual values, it serves as a useful tool for comparing different forecasting models or financial instruments.

**Hyperparameters**

During the model calibration, we employed the GridSearch method for hyperparameter optimisation, which systematically evaluated the possible parameter combinations along a predefined grid. This procedure enabled the identification of the configurations that yielded the best performance. The applied hyperparameters and their respective value ranges are presented in Table 2. Since the hyperparameter ranges were identical across all three models (RNN, LSTM, GRU), only one consolidated table is presented.

For forecasting, the price values were scaled to the [0, 1] range using MinMaxScaler as inputs to the neural network. The dataset was split into training (80%) and testing (20%) subsets. The models were trained using a supervised learning approach, with the input sequence length (or 'rolling window') set to the preceding 50 observations, as detailed in the data section. The model architecture consisted of a three-layer sequential neural network followed by a dense output layer. To ensure robust performance, a grid search (ParameterGrid) was conducted across combinations of neurons, batch_size, activation, and learning_rate, with sequence_length held constant. Each configuration was trained for 50 to 100 epochs using the Adam optimiser and mean_squared_error loss function under a consistent training protocol. The best model was selected based on the lowest *Mean Absolute Error* (*MAE)* on the test set, and additional metrics (*Mean Squared Error – MSE, Root Mean Squared Error – RMSE, Mean Absolute Percentage Error – MAPE*) were computed to facilitate reproducible comparison. To mitigate overfitting, Dropout layers and an Early Stopping strategy were incorporated into the models.

Table 2. Hyperparameters

| Parameters | Value |
|---|---|
| Hidden layers | 3 |
| Hidden layer neuron count | 50, 100, 150 |
| Batch size | 16, 32 |
| Epochs | 50, 100 |
| Activation | Relu, tanh, sigmoid |
| Learning rate | 0.1; 0.01; 0.001 |
| Optimiser | Adam |

Source: Authors' own elaboration

**Tests**

Theil's U is a metric used to assess forecast accuracy by comparing a model's predictions with a naïve forecast (e.g. the value from the previous period). Its value ranges from 0 to 1, where 0 indicates perfect forecasting accuracy and 1 indicates performance equivalent to the naïve forecast. A value exceeding 1 suggests that the naïve forecast outperforms the model. Theil's U is sensitive to large errors and helps assess the extent to which our model outperforms simple forecasting methods.

The Diebold–Mariano test is a statistical procedure utilised for comparing the forecasting accuracy of two competing predictive models. This test examines whether there is a significant difference in the magnitude of the errors produced by the two models. It considers not only the magnitude of the error but also its pattern. The test determines whether one model provides a significantly better forecast than the other, or whether the observed difference is attributable to random variation. The Diebold–Mariano test is particularly valuable when dealing with errors that are not normally distributed or exhibit temporal correlation.

**Data**

This study utilised corn price data spanning from January 1, 2016, to June 30, 2022. The timeframe was selected to capture a variety of market conditions, including a stable period (2018), the COVID-19 pandemic (2020), and the onset of the war-related crisis (2022). Data were retrieved using the yfinance API from www.finance.yahoo.com. Following data cleaning and preprocessing, the dataset was segmented into four analytical subsets. The first subset encompasses a period of economic stability, spanning from January 1, 2016, to June 30, 2018. The second period, from January 1, 2018, to June 30, 2020, was selected to analyse the effects of the COVID-19 pandemic. The third segment, from January 1, 2020, to June 30, 2022, corresponds to the economic disturbances related to the Russia–Ukraine war. These two crisis

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intervals were particularly important for evaluating the models' resilience under volatile conditions. Forecasting was conducted for the six-month (January–June) horizons in 2018, 2020, and 2022. The past 50 closing prices (in the univariate case) served as input features for each rolling training segment, while the models' outputs represented multi-step forecasts covering the subsequent half-year period. For multivariate modelling, the input set was extended to include the opening, highest, and lowest daily prices over the same 50-day window. The downloaded Chicago Board of Trade (CBOT) continuous futures series automatically adjusts for contract rollovers, ensuring continuity in the price data.

***Limitations related to data sources.*** This study relies on U.S. corn futures prices from the CBOT, which are widely regarded as the global benchmark and are freely accessible without restrictions. Given their central role in international trade and their strong correlation with global market expectations, CBOT futures quickly transmitted the war-related shocks to international prices. However, as a global benchmark, these futures data primarily reflect the global spillover effects of region-specific mechanisms (like logistical blockages or policy interventions) rather than capturing the direct, localised price dynamics within the affected region. Therefore, while CBOT futures offer a robust and internationally comparable basis for forecasting, the geopolitical shocks of the war are primarily reflected in their global spillover effects rather than in direct regional dynamics.

## RESULTS AND DISCUSSION

The descriptive statistics (Table 3) summarise the dynamics of corn prices based on 1 631 observations. The average opening price was USD 426.92 cents per bushel, while the mean closing price was very similar at USD 427.09 cents per bushel, indicating relatively balanced market movements. The average of the highest prices (431.65) slightly exceeded both the opening and closing values, whereas the average of the lowest prices (422.50) remained below them. The wide range between the minimum (300.25) and maximum (827.00) values reflects the considerable price fluctuations characterising the corn market during the observed period.

Figure 1 shows the trend in corn futures closing prices from January 1, 2016, to June 30, 2022. The price fluctuated within the range of USD 300 to 450 cents per bushel until 2021, after which it experienced significant volatility.

Table 4 presents the forecasting performance of different recurrent neural network architectures (RNN, GRU, LSTM) for the year 2018, evaluated under both univariate and multivariate modelling frameworks. The results indicate that the Univ_GRU and Univ_LSTM models achieved the lowest error metrics, with *RMSE* values of 3.996 8 and 3.925 6, and *MAE* values of 2.843 5 and 2.883 4, respectively. This suggests that the univariate approach, particularly with GRU and LSTM architectures, yielded more accurate forecasts than multivariate models. The *MAPE* indicator reinforces this finding, as the Univ_GRU model recorded the lowest relative forecasting error (0.754 8%), reflecting the highest accuracy. Among the multivariate models, the Multiv_RNN performed best, although its *RMSE* (4.160 3) and *MAE* (2.934 1) were still higher than those of its univariate counterpart. By contrast, the Multiv_LSTM model produced the weakest results, particularly in terms of *RMSE* (4.367 4) and *MAPE* (0.818 6%), indicating that the inclusion of additional explanatory variables did not improve, and in some cases even worsened, predictive performance. The Theil's U statistic remained low across all models (ranging from 0.005 2 to 0.005 8), highlighting the stability of the forecasts and their superiority relative to a naïve random walk benchmark. Overall, for the year 2018, the univariate models – particularly GRU and LSTM – outperformed the multivariate approaches in terms of predictive accuracy. This implies that during this period, the univariate dynamics sufficiently captured the underlying structure of the time series, whereas including additional variables did not necessarily improve forecasting performance.

Table 3. Descriptive statistics for corn prices for the period 1 January 2016 to 30 June 2022

| Variable | Observations | Mean | SD | Minimum | Maximum |
|---|---|---|---|---|---|
| Open | 1 631 | 426.92 | 121.61 | 302.00 | 817.50 |
| High | 1 631 | 431.65 | 124.37 | 307.25 | 827.00 |
| Low | 1 631 | 422.50 | 119.23 | 300.25 | 814.00 |
| Close | 1 631 | 427.09 | 121.91 | 301.50 | 818.25 |

Source: Authors' own elaboration

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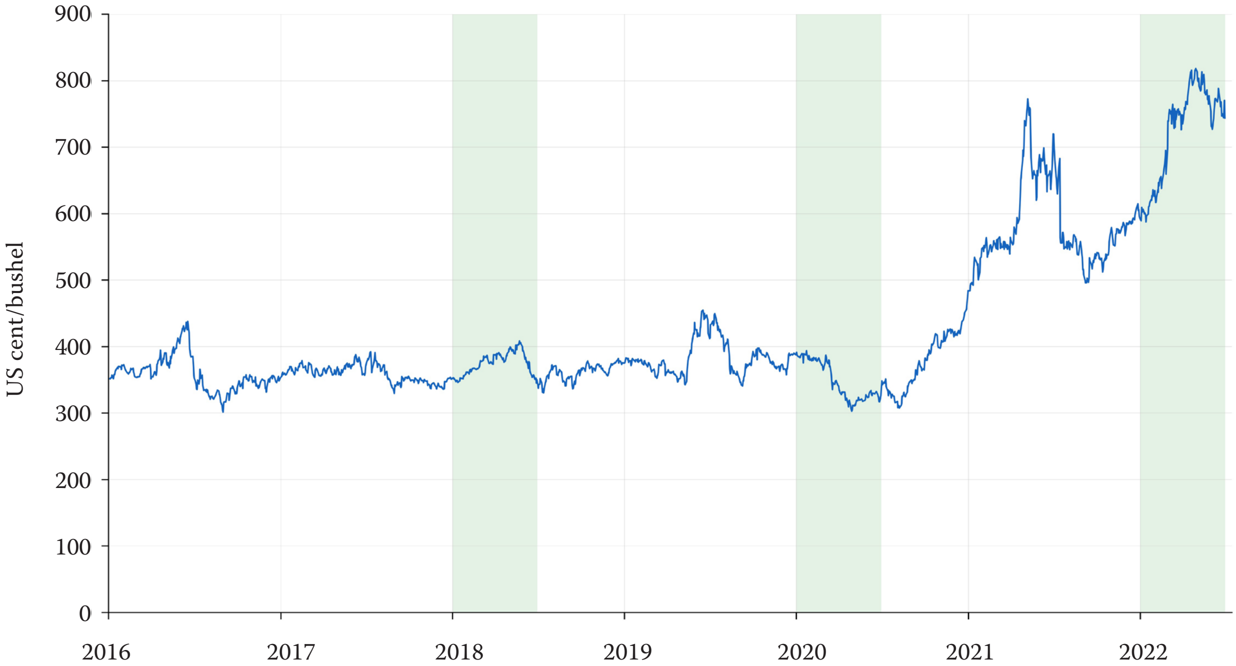


Figure 1. Evolution of corn closing prices between January 1, 2016 and June 30, 2022. The green vertical bands indicate the three forecast periods analysed in the study (2018, 2020, and 2022)

Source: Authors' own elaboration

Table 5 reports the results of the Diebold–Mariano (DM) tests, which assess differences in predictive accuracy across models for 2018. In most model comparisons, *P*-values exceed the 5% significance threshold, indicating no statistically significant differences in forecast accuracy. However, several notable exceptions are evident. The comparison between Univ_RNN and Univ_LSTM yields a *P*-value of 0.040 1, suggesting a statistically significant difference in predictive performance, with the LSTM exhibiting distinct forecasting behaviour compared to the RNN. Similarly, significant differences are observed between Univ_LSTM and Multiv_GRU ($P$ = 0.023 2) and between Univ_LSTM and Multiv_LSTM ($P$ = 0.027 9), implying that multivariate models captured corn price dynamics differently from the univariate LSTM. Other comparisons, such as Univ_GRU vs Multiv_GRU ($P$ = 0.071 3) and Univ_GRU vs Multiv_LSTM ($P$ = 0.082 6), approach significance at the 10% level, suggesting marginal evidence of differences in predictive accuracy. In contrast, model pairs such as Multiv_RNN vs Multiv_GRU, and Multiv_RNN vs Multiv_LSTM exhibit high *P*-values, indicating similar forecasting performance. Overall, the DM test results indicate that, although most models

Table 4. Evaluation of univariate and multivariate neural network models for corn price forecasting (2018)

| Model | RMSE | MAE | *MAPE* (%) | Theil's U |
|---|---|---|---|---|
| Univ_RNN | 4.186 9 | 3.044 2 | 0.808 7 | 0.005 6 |
| Univ_GRU | 3.996 8 | 2.843 5 | 0.754 8 | 0.005 3 |
| Univ_LSTM | 3.925 6 | 2.883 4 | 0.765 1 | 0.005 2 |
| Multiv_RNN | 4.160 3 | 2.934 1 | 0.779 6 | 0.005 5 |
| Multiv_GRU | 4.238 3 | 2.997 3 | 0.796 1 | 0.005 6 |
| Multiv_LSTM | 4.367 4 | 3.088 5 | 0.818 6 | 0.005 8 |

GRU – gated recurrent unit; LSTM – long short-term memory; MAE – mean absolute error; *MAPE* – mean absolute percentage error; RMSE – root mean squared error; RNN – recurrent neural network

Source: Author's own elaboration

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Table 5. Results of Diebold–Mariano tests for comparing corn price forecasting models (2018)

| Model 1 | Model 2 | Stat | *P*-value |
|---|---|---|---|
| Univ_RNN | Univ_GRU | 1.306 0 | 0.194 0 |
| Univ_RNN | Univ_LSTM | 2.074 3 | 0.040 1 |
| Univ_RNN | Multiv_RNN | 0.128 4 | 0.898 0 |
| Univ_RNN | Multiv_GRU | –0.429 2 | 0.668 5 |
| Univ_RNN | Multiv_LSTM | –0.965 8 | 0.336 0 |
| Univ_GRU | Univ_LSTM | 1.099 5 | 0.273 7 |
| Univ_GRU | Multiv_RNN | –0.870 8 | 0.385 5 |
| Univ_GRU | Multiv_GRU | –1.819 2 | 0.071 3 |
| Univ_GRU | Multiv_LSTM | –1.749 9 | 0.082 6 |
| Univ_LSTM | Multiv_RNN | –1.209 8 | 0.228 7 |
| Univ_LSTM | Multiv_GRU | –2.299 4 | 0.023 2 |
| Univ_LSTM | Multiv_LSTM | –2.224 7 | 0.027 9 |
| Multiv_RNN | Multiv_GRU | –0.397 8 | 0.691 4 |
| Multiv_RNN | Multiv_LSTM | –0.716 5 | 0.475 0 |
| Multiv_GRU | Multiv_LSTM | –0.899 2 | 0.370 3 |

GRU – gated recurrent unit; LSTM – long short-term memory; RNN – recurrent neural network
Source: Authors' own elaboration

performed comparably in 2018, LSTM-based architectures often diverged significantly from other recurrent networks. This suggests that LSTM networks may have captured different structural patterns in the corn price series compared to GRU or RNN models, highlighting their distinct modelling characteristics.

Table 6 reports the forecasting performance of different recurrent neural network architectures (RNN, GRU, LSTM) for the year 2020, evaluated under both univariate and multivariate modelling frameworks. The results clearly indicate that the Univ_GRU model achieved the best performance, with the lowest *RMSE* (4.798 8) and *MAE* (3.629 8), as well as the most favourable *MAPE* value (1.042 5%). This suggests that the GRU architecture was particularly effective in capturing the dynamics of corn prices during this period. Among the multivariate models, the Multiv_GRU achieved the strongest performance, although its error metrics (*RMSE* = 5.209 6; *MAE* = 3.868 6) were still higher than those of its univariate counterpart, indicating that including additional explanatory variables did not further improve predictive accuracy. The LSTM-based models produced moderate results: the Univ_LSTM (*RMSE* = 6.032 4; *MAPE* = 1.363 0%) and the Multiv_LSTM (*RMSE* = 5.624 2; *MAPE* = 1.234 1%) performed worse than the GRU, although the multivariate LSTM achieved slightly higher relative accuracy. In contrast, the RNN models (Univ_RNN and

Table 6. Evaluation of univariate and multivariate neural network models for corn price forecasting (2020)

| Model | RMSE | MAE | *MAPE* (%) | Theil's U |
|---|---|---|---|---|
| Univ_RNN | 6.524 1 | 5.094 7 | 1.505 5 | 0.009 3 |
| Univ_GRU | 4.798 8 | 3.629 8 | 1.042 5 | 0.006 9 |
| Univ_LSTM | 6.032 4 | 4.632 2 | 1.363 0 | 0.008 6 |
| Multiv_RNN | 6.332 5 | 5.082 4 | 1.468 5 | 0.009 1 |
| Multiv_GRU | 5.209 6 | 3.868 6 | 1.114 7 | 0.007 4 |
| Multiv_LSTM | 5.624 2 | 4.229 6 | 1.234 1 | 0.008 0 |

GRU – gated recurrent unit; LSTM – long short-term memory; MAE – mean absolute error; *MAPE* – mean absolute percentage error; RMSE – root mean squared error; RNN – recurrent neural network
Source: Authors' own elaboration

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Table 7. Results of Diebold–Mariano tests for comparing corn price forecasting models (2020)

| Model 1 | Model 2 | Stat | $P$-value |
|---|---|---|---|
| Univ_RNN | Univ_GRU | 4.773 2 | 0.000 0 |
| Univ_RNN | Univ_LSTM | 3.439 4 | 0.000 8 |
| Univ_RNN | Multiv_RNN | 0.462 9 | 0.644 2 |
| Univ_RNN | Multiv_GRU | 4.175 8 | 0.000 1 |
| Univ_RNN | Multiv_LSTM | 4.269 0 | 0.000 0 |
| Univ_GRU | Univ_LSTM | –3.638 1 | 0.000 4 |
| Univ_GRU | Multiv_RNN | –4.257 1 | 0.000 0 |
| Univ_GRU | Multiv_GRU | –1.980 8 | 0.049 8 |
| Univ_GRU | Multiv_LSTM | –3.006 7 | 0.003 2 |
| Univ_LSTM | Multiv_RNN | –0.746 7 | 0.456 7 |
| Univ_LSTM | Multiv_GRU | 2.604 0 | 0.010 3 |
| Univ_LSTM | Multiv_LSTM | 2.675 8 | 0.008 5 |
| Multiv_RNN | Multiv_GRU | 3.301 6 | 0.001 3 |
| Multiv_RNN | Multiv_LSTM | 2.015 0 | 0.046 1 |
| Multiv_GRU | Multiv_LSTM | –1.624 6 | 0.106 8 |

GRU – gated recurrent unit; LSTM – long short-term memory; RNN – recurrent neural network
Source: Authors' own elaboration

Multiv_RNN) performed the worst, as reflected in their higher error rates, with Univ_RNN recording the largest *MAPE* (1.505 5%). The Theil's U statistic remained consistently low across all models (0.006 9–0.009 3), indicating that the forecasts outperformed the naïve random walk benchmark. These findings reinforce the pattern observed in 2018, with GRU models maintaining their predictive advantage in both univariate and multivariate settings, although the overall accuracy declined across all architectures.

The Diebold–Mariano test results (Table 7) for the year 2020 reveal several statistically significant differences in predictive performance across the evaluated models. A notable finding is that the Univ_RNN model exhibited significant discrepancies compared to almost all other architectures, including Univ_GRU ($P$ < 0.000 1), Univ_LSTM ($P$ = 0.000 8), Multiv_GRU ($P$ = 0.000 1), and Multiv_LSTM ($P$ < 0.000 1). This indicates that the univariate RNN forecasts followed fundamentally different patterns from those of more advanced structures. The Univ_GRU model also showed substantial differences relative to other approaches. Statistically significant variations were found against Univ_LSTM ($P$ = 0.000 4), Multiv_RNN ($P$ < 0.000 1), and Multiv_LSTM ($P$ = 0.003 2). Interestingly, the comparison between Univ_GRU and Multiv_GRU yielded a $P$-value of 0.049 8, just below the conventional significance threshold, indicating a weak yet notable difference. The LSTM-based comparisons yielded mixed outcomes. While no significant difference was detected between Univ_LSTM and Multiv_RNN ($P$ = 0.456 7), the contrasts between Univ_LSTM and Multiv_GRU ($P$ = 0.010 3) and between Univ_LSTM and Multiv_LSTM ($P$ = 0.008 5) were both statistically significant. For the multivariate models, several noteworthy differences also emerged. The Multiv_RNN vs Multiv_GRU ($P$ = 0.001 3) and Multiv_RNN vs Multiv_LSTM ($P$ = 0.046 1) comparisons showed significant differences, whereas the Multiv_GRU vs Multiv_LSTM pair ($P$ = 0.106 8) did not indicate any significant variation. Overall, the 2020 findings suggest that predictive performance divergences across models were more pronounced than in 2018. In particular, RNN-based models tended to perform more weakly and more inconsistently, while GRU- and LSTM-based architectures provided more stable and accurate predictive patterns for modelling corn price dynamics.

Table 8 presents the forecasting performance of recurrent neural network architectures (RNN, GRU, LSTM) for corn price prediction in 2022, under both univariate and multivariate frameworks. Among the models, the Univ_GRU achieved the best results, with the lowest *RMSE* (12.851 7) and *MAE* (9.965 5), as well as the most favourable MAPE value (1.386 6%). This indicates that the GRU architecture

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Table 8. Evaluation of univariate and multivariate neural network models for corn price forecasting (2022)

| Model | RMSE | MAE | *MAPE (%)* | Theil's U |
|---|---|---|---|---|
| Univ_RNN | 14.607 6 | 11.323 9 | 1.556 5 | 0.010 1 |
| Univ_GRU | 12.851 7 | 9.965 5 | 1.386 6 | 0.008 8 |
| Univ_LSTM | 14.676 0 | 11.621 3 | 1.599 1 | 0.010 1 |
| Multiv_RNN | 15.325 7 | 11.355 3 | 1.568 2 | 0.010 5 |
| Multiv_GRU | 13.724 8 | 10.782 4 | 1.476 3 | 0.009 5 |
| Multiv_LSTM | 14.696 8 | 11.763 1 | 1.642 3 | 0.010 1 |

GRU – gated recurrent unit; LSTM – long short-term memory; MAE – mean absolute error; *MAPE* – mean absolute percentage error; RMSE – root mean squared error; RNN – recurrent neural network
Source: Authors' own elaboration

once again demonstrated superior forecasting ability. Across the multivariate models, the Multiv_GRU yielded the strongest results, although its error metrics (*RMSE* = 13.724 8; *MAE* = 10.782 4; *MAPE* = 1.476 3%) were higher than those of the Univ_GRU, suggesting that including additional explanatory variables did not improve predictive accuracy. The LSTM-based models (Univ_LSTM and Multiv_LSTM) performed more poorly, with higher errors, particularly in *MAPE* (1.599 1% and 1.642 3%). Similarly, the RNN models exhibited the lowest performance, with the Multiv_RNN producing the highest *RMSE* (15.325 7), indicating considerable limitations in predictive precision. Theil's U values remained low (0.008 8–0.010 5), consistent with prior periods. However, the generally higher error rates relative to previous years suggest that corn price dynamics in 2022 were more volatile and harder to model. The 2022 results are consistent with those of the preceding periods, confirming the relative strength of GRU architectures, albeit with notably higher error levels reflecting the increased market volatility. The narrowing performance gap across models suggests that under extreme volatility, even the most flexible architectures face diminishing returns in accuracy.

The Diebold–Mariano test results for 2022 (Table 9) indicate several cases in which significant differences

Table 9. Results of Diebold–Mariano tests for comparing corn price forecasting models (2022)

| Model 1 | Model 2 | Stat | *P*-value |
|---|---|---|---|
| Univ_RNN | Univ_GRU | 2.591 9 | 0.010 7 |
| Univ_RNN | Univ_LSTM | –0.083 8 | 0.933 4 |
| Univ_RNN | Multiv_RNN | –0.590 1 | 0.556 2 |
| Univ_RNN | Multiv_GRU | 1.500 5 | 0.136 0 |
| Univ_RNN | Multiv_LSTM | –0.082 2 | 0.934 6 |
| Univ_GRU | Univ_LSTM | –2.562 1 | 0.011 6 |
| Univ_GRU | Multiv_RNN | –2.197 5 | 0.029 8 |
| Univ_GRU | Multiv_GRU | –1.711 7 | 0.089 5 |
| Univ_GRU | Multiv_LSTM | –2.632 4 | 0.009 6 |
| Univ_LSTM | Multiv_RNN | –0.490 4 | 0.624 7 |
| Univ_LSTM | Multiv_GRU | 1.824 6 | 0.070 5 |
| Univ_LSTM | Multiv_LSTM | –0.027 0 | 0.978 5 |
| Multiv_RNN | Multiv_GRU | 1.265 8 | 0.208 0 |
| Multiv_RNN | Multiv_LSTM | 0.466 0 | 0.642 1 |
| Multiv_GRU | Multiv_LSTM | –1.110 6 | 0.268 9 |

GRU – gated recurrent unit; LSTM – long short-term memory; RNN – recurrent neural network
Source: Authors' own elaboration

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in forecasting performance are observed among the models. In the comparison between Univ_RNN and Univ_GRU, the test statistic was 2.591 9 ($P$ = 0.010 7), indicating a statistically significant difference and suggesting that the two models produced notably different forecasts. In contrast, the comparisons of Univ_RNN with Univ_LSTM ($P$ = 0.933 4) and Univ_RNN with Multiv_RNN ($P$ = 0.556 2) did not reveal significant differences, implying similar forecasting patterns. For the GRU-based models, stronger differences emerged. The comparisons of Univ_GRU with Univ_LSTM ($P$ = 0.011 6), Univ_GRU with Multiv_RNN ($P$ = 0.029 8), and Univ_GRU with Multiv_LSTM ($P$ = 0.009 6) were all statistically significant, indicating that the performance of the GRU model differed substantially from that of other architectures. However, in the case of Univ_GRU versus Multiv_GRU ($P$ = 0.089 5), the result approached significance but did not meet the threshold. The LSTM models showed a more mixed pattern. The Univ_LSTM versus Multiv_GRU comparison produced a nearly significant result ($P$ = 0.070 5), while Univ_LSTM versus Multiv_LSTM ($P$ = 0.978 5) and Univ_LSTM versus Multiv_RNN ($P$ = 0.624 7) showed no meaningful differences. Among the multivariate models, no significant differences were observed. The comparisons between Multiv_RNN and Multiv_GRU ($P$ = 0.208 0), Multiv_RNN and Multiv_LSTM ($P$ = 0.642 1), and Multiv_GRU and Multiv_LSTM ($P$ = 0.268 9) all indicated comparable performance. Overall, the 2022 results suggest that the most pronounced differences occurred between GRU models and other neural architectures, whereas LSTM- and RNN-based models tended to exhibit similar forecasting behaviour. This indicates that GRU models captured somewhat different dynamics in forecasting corn prices during this period than other network architectures.

## CONCLUSION

Our study investigated the performance of various machine learning models in predicting corn prices, particularly in the context of geopolitical risks arising from the Russia–Ukraine war. Accurately forecasting corn prices can significantly benefit agricultural trade and related supply chains, as corn is one of the most important global commodities.

It is acknowledged that higher accuracy during stable market phases is expected, consistent with the finding that model stability is associated with reduced market volatility. The results indicate that the GRU-based model enables market participants to make more accurate forecasts, especially during stable market conditions. By utilising the GRU model, forecasting errors can be reduced through enhanced pattern recognition, suggesting that this approach may support more effective identification of changes in market conditions compared to other models. This capability is particularly valuable for making production, storage, and transportation decisions, as accurate forecasts help optimise costs and improve the efficiency of sales strategies.

At the same time, it is important to acknowledge that CBOT futures prices mainly reflect the international spread of war-related shocks. While these futures markets responded quickly to the conflict and effectively represent global price trends, future research could incorporate additional regional factors – such as Ukrainian export flows, fertiliser and energy prices, or transportation disruptions – to better differentiate local effects from global spillover impacts.

The results of our study not only demonstrate the technical performance of different deep learning models but also offer several important economic interpretations. More accurate price forecasts have direct implications for decision-making across the agricultural value chain. Farmers can optimise planting strategies and input purchases, processors and traders may design more effective hedging strategies, and logistics partners can schedule transportation more efficiently. In times of geopolitical turbulence, such as the Russia–Ukraine war, understanding which model performs best under various conditions can inform the selection of forecasting tools. Beyond the methodological contribution, this research advances the field by shifting the focus from mere price prediction to the predictability of prices under crisis conditions. While previous studies primarily evaluated models under relatively stable environments, our results highlight how geopolitical shocks reduce the accuracy of machine learning forecasts. This dual focus broadens the literature by linking artificial intelligence-based forecasting methods with economic risk assessment and policy-making, underscoring the importance of forecast robustness in volatile markets. From a practical perspective, the findings are highly relevant not as a direct price forecast but as a methodological recommendation for traders and analysts, who can use these insights to select the most robust models for their own risk management. While the current study demonstrated the varying robustness of price-based models, a promising direction for future research is to investigate whether integrating exogenous variables – such as geopolitical risk indicators, transport disruptions, or energy price shocks – could further improve predictive performance under crisis conditions.

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