INNOVATIVE APPROACH TO PREDICTING THE PRICES OF MAIZE: THE PURPOSE OF NEURAL NETWORKS

[a]MICHAELA JANNOVA, [a,b]PAVEL DYTRYCH

[a]*Institute of Technology and Business in České Budějovice, School of Expertness and Valuation, Okružní 517/10, 37001 České Budějovice, Czech Republic*
[b]*Pan-European University (PEU), Tomášikova 20, 820 09 Bratislava, Slovakia*
email: [a]jannova@znalcivste.cz,[b]dytrych@znalcivste.cz

Abstract: Maize prices can be significantly influenced by factors such as weather, demand, supply, pricing policies, and others. This article will provide a specific method for predicting maize yields using neural networks, which can be beneficial for farmers, commodity traders, and other market participants. The contribution aims to create and analyse a model based on neural networks for predicting maize yields and also to identify its position in the commodity market. The price development of maize is measured from 1959 to 2023, and neural networks are used for calculating the results, which are evaluated using Statistica software. It was found that only MLP networks (multilayer perceptron networks) were retained, and it was also found that the correlation coefficient value of all neural structures was higher than 0.959 in all cases. Furthermore, minimal differences were found between individual neural networks. Maize prices were also predicted 30 trading days in advance, and it was found that in practice, the 8th neural network performed best, as it exhibited the best results after validation, with its values closest to zero. In the future, this network should be further trained to achieve increasingly accurate results.

Keywords: Maize, commodity, artificial neural networks, prediction, validation

1 Introduction

Food is a fundamental component necessary for human sustenance. In addition to being consumed, it can also be a valuable commodity for economic purposes due to the productivity of food crops. Maize is globally the most cultivated and consumed crop and is also a significant commodity product that has a significant impact on the economies of many countries. Accurate price prediction can help farmers, traders, and other market participants plan their actions and minimize risks associated with price fluctuations (Macarena Arrien, Aldaya, and Iris Rodriguez, 2021). This is also agreed upon by Medina, Tian, and Abebe (2021), who state that accurate maize yield forecasts are crucial for decision-making in food and energy management strategies. Precisely predicting agricultural commodity prices is a challenging task due to the complexity of the trading market and the variability of influencing factors. Many studies have shown that combining forecasts is an effective strategy for improving forecasting performance compared to individual forecasts. In the field of forecast combination, determining appropriate weights for combination remains an open question (Zeng, 2022). Cheng et al. also agree, stating that accurate and timely crop yield forecasts on a large scale are important for food security and agricultural policy development. However, an adaptive and reliable method for estimating maize yield is currently not available. There is also an inherent trade-off between early yield estimation and forecast accuracy. Yield estimates are crucial for supporting government policy interventions and increasing global food security (Schwalbert et al., 2020). The achievement of state market policies partly depends on the extent to which commodity price changes are transmitted in supply chains (Armah, Kissi, & Fiankor, 2019).

Fluctuations in agricultural commodity prices attract considerable attention. However, the complexity of the futures market for agricultural commodities and the variability of influencing factors makes predicting agricultural commodity prices difficult (Wang et al., 2021). Price transmission between futures and spot prices is a relevant issue, addressing derivatives exchanges for price management practices and efficient price discovery. Given the increased market orientation of the common agricultural policy, the development of new market strategies for European farmers is crucial (Penone, Giampietri, and Trestini, 2022). Maize, which has the highest domestic production, acreage, and consumption, ranks first in China among grains in terms of demand and supply. However, China's comparative advantage in maize has been deteriorating in recent years, and based on recent supply and demand situations and possible trends, it is generally acknowledged that achieving a 95% self-sufficiency rate in maize is difficult. Under current import restriction policies, maize may stand at the crossroads of reforms aimed at addressing its anticipated insufficient supply (Liu et al., 2022). Conversely, Brazil, a significant player in international commodity trade, is currently the third-largest exporter of maize, which is a key input in several food chains (de Souza et al., 2021). Kenya, on the other hand, has become a driving force for trade integration at regional and continental levels, although this process is still ongoing. Kenya, along with Ghana, was the first country to ratify the African Continental Free Trade Agreement (AfCFTA) in May 2018, as it was already engaged in negotiations with its major trading partners. Trade policy can have mixed effects across the economy and within the agricultural sector, reflecting differences between markets and commodities (Binfield et al., 2022). Berger, Dalheimer, and Brummer (2021) argue that the variable import levy on maize imports in the European Union aims to support European producers by isolating domestic prices from low international prices. Such price isolation policies have been associated with increased volatility in the global market. The removal of these distortions was one of the key issues in international negotiations on agricultural trade liberalisation, e.g., the commitment of WTO member states to adhere to the principle of tariffication under the Uruguay Round Agreement on Agriculture. However, the Blair House Agreement effectively allowed the EU to maintain a regime of variable import levies on cereal imports, although their level is substantially lower than in the past. Despite being a cornerstone of the EU's common agricultural policy, empirical evidence of the extent of its effects on price volatility is largely lacking. The income instability of smallholder farmers in developing countries caused by volatile agricultural product prices has been a problem for farmers and agricultural policymakers for many years. A permanent price stabilization mechanism is generally lacking. In some countries, support for production prices has been initiated to stabilize incomes and as an incentive for increased farmer investment and production (Abokyi et al., 2020).

Szerb, Csonka, and Ferto (2022) argue that globalization also has a significant impact on international agricultural trade, and despite globalization, distance has a greater negative impact on bilateral maize trade than on the processing sector. Distance seems to remain a significant factor in explaining trade flows in commodity markets, including maize. Technology, transportation, and global appetite have changed trading relationships between neighbouring and distant countries. The impact of distant food demand on local agricultural production and trade attracts considerable attention from scientists, although little is known about how distant trade affects trading relationships and production between neighbouring countries (Herzberger et al., 2019). Khan, Li, and Maimaitijiang (2022) further state that predicting crop yields before harvest is crucial for food security, trade, and policy-making. Several machine learning methods were used in the past to predict crop yields using various types of variables. Based on time series data, machine learning can also be used to predict future export developments in various states (Krulický, Kalinová, & Kučera, 2020). Šuleř, Rowland, and Krulický (2021) agree, finding that MLP networks have proven to be the most effective in predicting future export developments from the Czech Republic to China. They are also capable of predicting potential extremes.

Predicting commodity prices is important as farmers and commodity traders face various risks associated with price fluctuations. Accurate price prediction can help identify and mitigate these risks through appropriate strategies and hedging. Therefore, the contribution aims to create and analyse a model based on neural networks for predicting maize yields and also to identify its position in the commodity market. For this reason, the following two research questions were formulated:

1) How did maize prices evolve from 1959 to 2023 in response to global events in the commodity market?
2) How successful is artificial intelligence in predicting maize prices for the next 30 trading days?

The contribution is divided into the following sections: Section 1 summarises the demand for the topic. Section 2 provides references to the latest research by experts on the topic. Section 3 contains the methodology of the article. Section 4 summarises the results. Section 5 evaluates the research questions, and the final section summarises the findings.

2 Literature research

The summarising function of maize export from the USA and the bilateral function of maize import from the USA to Mexico, Japan, China, South Korea and the EU are estimated by ARDL estimation methods. Fosu a Wahl (2020) say that export price, technology and delayed export have a positive influence on maize export from the USA, whereas real effective exchange rate and ethanol production have a negative impact on maize export from the USA. Dutta et al. (2019) considers using the information content of the maize implied volatility index (CIV) to predict the yield volatility of the futures market in maize in the USA. Addey (2020), in contrast, examined the costs of the GMO regulation index of (GMORI) USA trading partners in terms of maize and soya export from the USA. The multi-layer model with mixed effects shows that a 1% increase in GMORI results in a loss of income from maize and soya exports from the USA in the amount of USD 71.8 million in fact. Increasing GMORI by 1% results in a USD 20 million loss in Japan, whereas it results in a USD 2.4 million loss in China and a USD 74 million loss of income sustained by the American sector of maize and soya export. Addey (2020) admits that GDP, geographical distance, rate of exchange and price situation are important factors, however, restrictions imposed on GMOs by states influence maize and soya export from the USA. Berger et al. (2021) used a multi-dimensional asymmetric volatility model to assess the effects on the maize market in the case of Argentina. Berger et al. (2021) maintained that variable import duty decreased the volatility of maize prices in the EU market, whereas it proportionally increased volatility in Argentina. Cao and Yuan (2022) selected four cereals – rice, wheat, soya, and maize. They analysed international trade of these commodities from 2002 to 2020 in the Chinese market. Cao and Yuan (2022) found out that Chinese grain was in a state of net import. Annual net import amounts to 62.25 million hectares, which equals the size of Chinese arable land for one crop. The contribution of net import of soya virtual soil resources represents 101 multiples of its crop area, whereas maize, rice and wheat represent approximately 10.42%, 11.69% and 74.66% respectively of its crop area.

The prediction of crop yields before harvest is essential for food safety, grain trade and policymaking. Several methods of machine learning have been used to predict crop yields with the help of several types of variables. Khan et al. (2022) suggests using a geographically weighted random forest approach (GWRFR) to improve the prediction of crop yields at the district level in the Corn Belt in the USA. Khan et al. (2022) trained GWRFR and five other popular machine learning algorithms (multiple linear regression (MLR), partial least-square regression (PLSR), support vector regression (SVR), decision tree regression (DTR) and random forest regression (RFR). They compared GWRFR results with the results of the remaining five models. Khan et al. (2022) found out that GWRFR surpasses the other machine learning algorithms. The method suggested in this paper may be potentially used for improving the yield predictions of different crops in other regions. Etienne et al. (2023) examined the prediction of average seasonal maize prices in the USA and developed an alternative procedure based on futures. The new method achieves similar or better results than two widely monitored average seasonal price predictions, i.e., global agricultural supply and demand estimates. Etienne et al. (2023) attribute the robust performance of the suggested prognosis to its ability to use various coefficients for futures and cash prices in dependence on basic market conditions. A better performance of suggested prognoses is especially notable during a marked market volatility. To sum it up, the method invented by Etienne et al. (2023) complements current prognoses and provides valuable information for executive bodies. Cheng et al. (2022) examined and used indicators, such as GPP, ET, surface temperature (Ts), LAI, soil properties and phenological information on maize to obtain estimates of maize yields with the help of random forest regression (RFR) and machine learning approaches, specifically, gradient boosted decision trees, in China. Cheng et al. (2022) found out that RFR estimated a maize yield more accurately than GBTD; Ts was the best independent indicator for yield estimate, whereas the combination of GPP, Ts, ET and LAI proved to be the best in the case of using more indicators and prediction accuracy was lower with time provided in advance, however, it remained relatively high in the period at least 24 days prior ripeness and the algorithm combination of machine learning with more indicators proved the ability to deal with space heterogeneity.

The fluctuations of exchange rates and certain other variables are important for maize trade flows between Mexico and the USA. Therefore, Luis Jaramillo-Villanueva (2021) analysed the cointegration analysis model and vector error correction model (VECM). Luis Jaramillo-Villanueva (2021) found out that the changes in the real rate of exchange have a positive impact on trade flows, whereas the volatility of the rate of exchange has a negative impact on maize trade flows between Mexico and the USA. Luis Jaramillo-Villanueva (2021) further established that both changes in the real rate of exchange and volatility significantly influence maize trade flows between Mexico and the United States. In contrast, Sayed and Auret (2023) researched maize trading at the South African Futures Exchange (SAFEX) and the impact of speculative activity on volatility. The dynamic relation between volatility and commercial activity was examined from April 2000 to May 2022 with the use of vector autoregression. Sayed and Auret (2023) shed light on the effectiveness of regulation concerning speculators in grain market futures and contributed to the credibility of price limits in terms of effective mitigation of volatility. A similar situation was explored by Xu (2020) on a set of daily maize prices in seven states: Iowa, Illinois, Indiana, Ohio, Minnesota, and Kansas. Xu (2020) evaluated thirty individual models of time series and ten combined prognoses based on six pruning strategies in three evaluation periods beyond time, seven horizons, and two systems (two-dimensional and multi-dimensional). Xu (2020) suggests limiting the recalibration period of the model to less than one month. Xu and Zhang (2021) adopted the same approach to predictions based on a data set of daily cash prices of maize from nearly 500 markets in sixteen states: North Dakota, Iowa, Minnesota, Illinois, Indiana, Ohio, Michigan, Missouri, Nebraska, Arkansas, Kentucky, Wisconsin, South Dakota, Kansas, Oklahoma, and Pennsylvania. Xu and Zhang (2021) specialise in one-dimensional modelling by a neural network (NN) and two-dimensional NN modelling including futures prices. Xu and Zhang (2021) found out that the arrival of new technologies for the analysis and synthesis of large data volumes increased the ability to accurately predict crop yields with the help of high-performance computers. Pinto et al. (2022) evaluated the performance of six models of machine learning in the course of predicting maize yield before harvest. Pinto et al. (2022) used these models: artificial neural networks (ANN), k-nearest neighbours (KNN), random forest (RF), and supportive vector machine (SVM). KNN algorithm achieved the best performance in terms of accuracy and correctness indicators for most of the scenarios examined in this study. In contrast, Asriani et al., (2023) modelled the prediction of maize productivity in Indonesia by Production and Operations Management-Quantitative Method software (POM-QM). Asriani et al. (2023) use a prognosis model based on time series, which consists of three methods, i.e., double moving average (DMA) method, weighted moving average (WMA) method, and simple exponential smoothing (SES) method. The selection of the best model was made based on median absolute deviation (MAD), mean square error (MSE), and median absolute percentage error (MAPE). SES with a lower MAPE value appeared to be the most suitable. Prevailing imperfect transfer of prices in agricultural markets is still an important political problem for most African countries. Yami et al. (2020) dealt with the performance of wholesale markets in white maize in Ethiopia. Yami et al. (2020) determined that regional maize markets adapted to drops in prices faster than to price rises in the central wholesale maize market in Addis Adeba, which indicates a lack of positive asymmetric price transmission.

Predicting the prices of agricultural products is one of the most important research points in the field of predicting time series due to its unique properties. Jaiswal et al. (2021) developed a model based on distributed long short-term memory (DLSTM) for an accurate prediction of non-stationary and non-linear series of agricultural prices. Jaiswal et al. (2021) compared the ability to predict the prices of the newly created DLSTM model with conventional TDNN models (time-delay neural network) and ARIMA, in the example of the international monthly price series of maize and palm oil. Jaiswal et al. (2021) prove the superiority of the DLSTM model over other models from the perspective of various criteria for prediction evaluating. DLSTM model also proved superior over other models in predicting a direction change of the price series. Sanusi et al. (2022) point out the specific and accurate methods of predicting the prices of normally consumed food in Nigeria. There were designed various models, which involved autoregressive integrated moving average (ARIMA), artificial neural networks (ANN), seasonal trend decomposition of time series using LOESS (STLM) and the combination of the three models (hybrid model), to predict the data regarding grain prices. Sanusi et al. (2022) found out that ARIMA is the best model for white maize and imported rice as it corresponds well to stationary data, which was proved in the monitored period. STLM is the most suitable for predicting white beans. Nedeljkovic et al. (2019) defined quantitative models for predicting the future development of maize production in the Serbian Republic. The research methods in use are descriptive analysis and analytical statistical methods, or Box-Jenkins, based on the ARIMA model. Nedeljkovic et al. (2019) found that maize production indicators would show an increase in the last year of the five-year prediction period (2018-2022) despite oscillations in comparison with the previously analysed twenty-two-year period (1996-2017). Moreover, Hašková et al. (2022) examined the business and economic predictions that provide valuable information for the parties involved (corporate owners and managers, investors and shareholders). Hašková et al. (2022) found out that the most frequently used predictions are ANN and GARCH in combination with ARIMA. These methods are sufficiently powerful to detect sector specifics for economic and commercial prediction. On the contrary, Rousek and Mareček (2019) researched the consideration of seasonal oscillations during the smoothing of time series with the use of artificial neural networks in the example of export from the United States to the People's Republic of China. Rousek and Mareček (2019) determined that it is possible to predict the effectiveness of export development with the use of artificial neural networks, namely, with a high degree of accuracy, especially in a short-term horizon, with regard to specific seasonal oscillations.

The Russian invasion of Ukraine on 24/2/2022 accelerated the price rise of agricultural commodities and increased global food insecurity. Ukraine and Russia are top global suppliers of wheat, maize, barley and sunflower oil. This was the purpose why Aliu et al. (2023) explored the relationship between the four agricultural commodities and predicted their future performance at the same time. The series includes a period from 1/1/1990 to 1/8/2022 based on monthly frequencies. The function of VAR impulsive response, variance decomposition, Granger causality test and vector model of error correction were used to analyse relations between variables. Aliu et al. (2023) ascertained that maize prices are an integral part of wheat, barley and sunflower oil price changes. To predict price changes ten months ahead was another aim of this study. Vector autoregression diagram (VAR) and vector error correction model (VECM) estimate an average drop in maize, wheat, barley and sunflower oil prices within the range of 10%.

As can be seen, in the literature review, the topic of predicting maize prices using neural networks is an interesting subject for many researchers, and as such, they are also investigating it. It has been found that a number of these researchers have used neural networks for their calculations, but many other methods have also been employed. Predicting maize prices using neural networks can provide insights into market dynamics and aid further research and development in the fields of agriculture, economics, and machine learning. Overall, accurate maize price prediction using neural networks can bring significant benefits to various market participants and help optimize their decision-making processes. As mentioned before, neural networks were among the methods that were used quite frequently, and that is why we have also chosen them for our research, where we will use them for RQ2 to determine how maize prices have evolved after validation.

3 Data and methods

The price of maize will be measured from 1959 to 2023 to determine if there are any price fluctuations during this long period, and for this purpose, data from the Macrotrends website will be used. Here you can find the prices of the given commodity during the whole day when this commodity is traded. The price of maize is indicated in USD currency per 1 bushel. The datasets for maize will consist of 16,165 input data.

The basic statistical characteristics of the maize price time series used are shown in Figure 1 and Table 1.

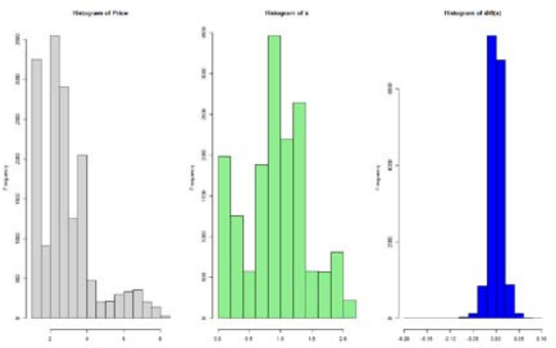

Figure 1 Indicate histogram distribution with raw, log, and log diff series

Figure 1 characterizes the distribution of data in three different histograms, which include the entire monitored period, i.e., from 1/7/1959 to 4/8/2023. A histogram is made up of vertical columns that represent different values of the variable on the horizontal axis (value axis) and their frequency (or relative frequency) on the vertical axis (frequency axis). Columns on the histogram are placed next to each other and their height will depend on the number of observations that fall into the respective interval. A histogram is a useful tool for fast visualization of the characteristics of a data set. The histogram in grey represents the distribution based on planar data, the green one is based on the logarithmic series, and the blue column represents the differential. Predictions are based on two types (level and logarithmic), while only the level prediction is shown in the results section for better clarity. As can be seen from the figure, the distribution of the data gets better when moving from the level prediction to the logarithmic one. The time series data does not show a normal distribution due to the width and length of the time series, but this does not prevent further calculations. The series has the same number of observations, 16,165, but differs in outliers. The following Table 1 presents the descriptive statistics.

Table 1 Descriptive statistics based on the level data

	vars	n	med	trimm	mad	min	max	skew	kurt	se
X1	1	16165	2.56	2.63	1.34	1.01	8.31	1.3	1.6	0.01

Table 1 presents basic statistical methods such as skew, kurtosis, minimum, maximum, and number of observations. Skew expresses the degree of asymmetry of the data distribution around its mean value. Thus, the skew value provides information about the shape and asymmetry of the data distribution. This indicator can be used to get a better idea of the nature of the data set and the distribution of its values. Kurtosis, in turn, provides information about the shape of the data distribution. It measures how significantly the peak (i.e., the highest part) of the data distribution differs from the normal distribution. The result of kurtosis is a numerical value that provides information about the "sharp" or "flat" shape of the data distribution compared to a normal distribution. The interpretation of the kurtosis result depends on the context and specific characteristics of the data set. As can be seen in Table 1, based on the skewness and kurtosis, our data does not have a normal distribution, as skew must equal zero and kurtosis must also equal zero, which is not the case. However, this is quite natural for time series with a daily frequency. Furthermore, Table 1 also shows that the lowest value of maize was 1.01, which occurred on 18/11/1960, and on the contrary, the highest value was 8.31, which was on 21/8/2012.

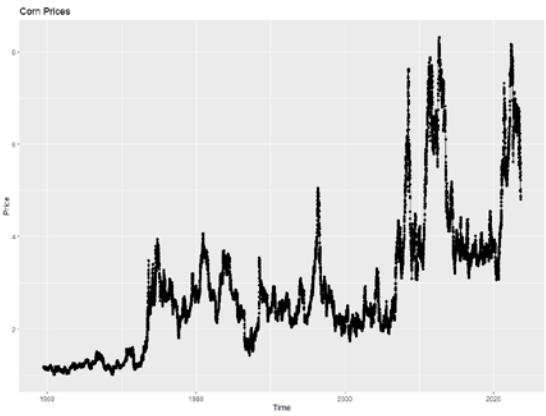

Figure 2 Level series time series

Figure 2 shows the level time series. It is possible to see in which year certain price shocks occurred. For example, in the 1970s one of the first big price shocks came when the price of maize went up. This was mainly caused by the war in Vietnam. Another price shock came between 2008-2009 when there was a global financial crisis. Last but not least price shock came with the war in Ukraine, i.e., in 2022. We will be dealing with this in Figure 5. Furthermore, it is possible to see that the price trend was constantly fluctuating throughout the period, there was no period with a constant price.

The data that will be obtained will then be evaluated through the Statistica 13 software from TIBCO. The first step will be to create a linear regression that will be used for artificial neural networks and then this analysis will be reviewed on a sample for which the following functions will be determined: Linear, polynomial, logarithmic, exponential, weighted distance polynomial, negative exponential smoothing polynomial. In the next step, we will calculate the correlation coefficient which represents the degree of dependence of the price of maize on time, and then we will work with a confidence level of 0.95. Regression will then be performed through neural structures, where multilayer perceptron networks (MLP) and radial basis function networks (RBF) will be constructed. To calculate neural structures, 16,165 data will be used. Time will serve as the independent variable and maize price as the dependent variable. The following Figures 3 and 4 graphically represent the MLP and RBF neural networks.

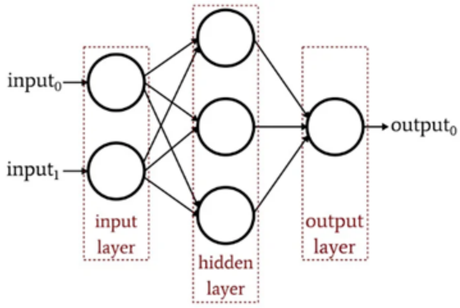

Figure 3 MLP neural networks
Source: Keim, 2019

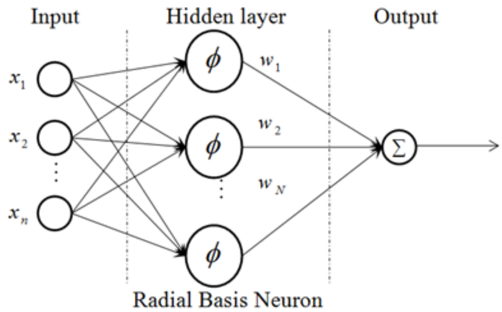

Figure 4 RBF neural networks
Source: He et al., 2019

The MPL neural network has the following mathematical expression (Kudová, 2001):

$$y(\vec{x}) = \sigma(\sum_{i=0}^{n} w_i x_i) \quad \textbf{(1)}$$

The RBF neural network has the following mathematical expression (Kudová, 2001):

$$y(\vec{x}) = e - (\frac{\|\vec{x} - \vec{c}\|}{b})^2 \quad \textbf{(2)}$$

In the next step, the time series will be divided into three groups. These groups will serve for testing, training, and validation. The training group will contain 70% of the data which will then be transformed into neural structures. The other two groups (test and validation) will comprise 15% of the data. The test and validation groups will be used to verify the reliability of the neural network. 1,000 neural networks will be used for the calculations, but only 10 neural networks will be kept, namely those that will show the best characteristics. The hidden layer of Multilayer Perceptron Networks (MLP) will have a minimum of 2 neurons, but a maximum of 20. The RBF hidden layer will use a minimum of 10 neurons, but a maximum of 30 neurons. To activate the hidden layer and the output layer of MLP, the following functions will be used: linear, logistic, Atanh, Exponential, and Sine. The rest of the settings will be left as default (within the ATS tool - automatic network creation). To calculate artificial neural networks, the method of least squares will be used. If there is no improvement, i.e., the value of the square aggregate decreases, the network generation will be terminated. Only the neuron structures that represent the lowest possible set of squared residuals concerning the actual development will be retained. To compute neural networks, we will also use the BFGS algorithm, which is used to adapt machine learning algorithms such as logistic regression and which is a local optimization algorithm. Delays in the time series will not be considered due to demanding calculations and the need for a subsequent additional experiment. A maize price prediction for the next 30 trading days will also be made. This prediction will take place from 4/8/2023 to 14/9/2023. After this prediction, a so-called validation will be created. This means that the difference between the predicted price of maize and the actual price of maize will be examined. This difference is called the residual. The formulas of individual functions are shown in Table 2.

Table 2 Activation function of hidden and output layers of MLP and RBF

Function	Definition	Range
Identity	a	$(-\infty;+\infty)$
Logistic sigmoid	$\frac{1}{1+e^{-a}}$	(0;1)
Hyperbolic tangent	$\frac{e^{a}-e^{-a}}{e^{a}+e^{-a}}$	(-1; +1)
Exponential	e^{-a}	$(0;+\infty)$
Sine	$\sin(a)$	$[0;1]$

Source: Šuleř and Machová, 2020

The least squares method will be used as the error function, which is represented by this formula:

$$E_{SOS} = \frac{1}{2N}\sum_{i=1}^{N}(y_i - t_i)^2 \tag{3}$$

N is the number of trained cases, y_i is the prediction of the target variable t_i, t_i is the target variable of the ith case.

RQ1 will be solved using a time series, looking at how the price of maize has evolved over the past 64 years. For RQ2, validation will be used, thanks to which it will be determined what the difference was between the actual price and the predicted price of the commodity. This difference is called the residual. Using this validation, it will be determined which neural network will be the most suitable for putting into practice. Both the predicted and actual values must be as close as possible to zero for the neural network to be evaluated as the best.

4 Results

Through the chosen procedure, i.e., artificial neural networks, 1,000 neural networks were created, from which only the 10 best networks were selected. These showed the best possible results for predicting the price of maize. Table 3 presents an overview of the mentioned 10 best neural networks.

Table 3: Summary of active networks (Maize – daily data 1959-2023)

Index	Net. name	Train. perf.	Test perf.	Valid. perf.	Train. error	Test error	Valid. error	Train. Alg.	Error fun.	Hidd. Act.	Output act.
1	MLP 1-14-1	0.96	0.97	0.97	0.07	0,07	0.07	BFGS 1196	SOS	Log	Exp
2	MLP 1-17-1	0.96	0.97	0.96	0.09	0,08	0.09	BFGS 539	SOS	Log	Log
3	MLP 1-20-1	0.96	0.97	0.97	0.07	0,07	0.07	BFGS 10000	SOS	Tanh	Iden
4	MLP 1-19-1	0.97	0.97	0.97	0.07	0.07	0.07	BFGS 5953	SOS	Tanh	Exp
5	MLP 1-19-1	0.96	0.97	0.97	0.08	0.09	0.08	BFGS 9999	SOS	Log	Log
6	MLP 1-15-1	0.96	0.97	0.96	0.08	0.08	0.08	BFGS 9999	SOS	Log	Log
7	MLP 1-17-1	0.96	0.97	0.96	0.08	0.08	0.08	BFGS 673	SOS	Tanh	Log
8	MLP 1-14-1	0.96	0.97	0.97	0.08	0.08	0.08	BFGS 600	SOS	Tanh	Log
9	MLP 1-20-1	0.97	0.97	0.97	0.07	0.08	0.08	BFGS 942	SOS	Tanh	Exp
10	MLP 1-20-1	0.96	0.97	0.96	0.08	0.08	0.08	BFGS 691	SOS	Tanh	Log

Source: Authors

Table 3 shows the top 10 neural networks. It is possible to notice that only the MLP networks are retained. It may mean that for this commodity, i.e., maize, perceptron networks (MLP) achieved greater performance than RBF networks, which did not appear in any of the mentioned neural networks. These best structures then ranged from 2 to 20 neurons in the hidden layer. The generation of MLP networks was also compiled using the BFGS variant training algorithm (Broyden-Fletcher-Goldfarb-Shanno). The input layer of all 10 neural networks contains one neuron and is made up of a variable represented by time. The output layer also consists of one neuron and the variable is the development of the maize price. The following two functions, logistic and hyperbolic tangent, were used to activate the hidden neural layer. The functions used to activate the output layer were the following: exponential, logistic, and identity functions. The performance of the neural networks is subsequently presented in Table 4.

Table 4: Correlation coefficients (Maize – daily data 1959-2023)

	Train	Test	Validation
1.MLP 1-14-1	0.964564	0.971125	0.967692
2.MLP 1-17-1	0.960195	0.966868	0.963884
3.MLP 1-20-1	0.964958	0.971554	0.968231
4.MLP 1-19-1	0.966122	0.972624	0.968742
5.MLP 1-19-1	0.960987	0.965754	0.966260
6.MLP 1-15-1	0.960266	0.966363	0.963893
7.MLP 1-17-1	0.961286	0.966881	0.964751
8.MLP 1-14-1	0.962363	0.968860	0.965496
9.MLP 1-20-1	0.965327	0.970116	0.967211
10.MLP 1-20-1	0.959736	0.966298	0.963687

Source: Authors

Table 4 presents the performance of individual retained neural networks. The values of individual datasets for specific neural networks are summarized here. It can be seen that all three sets represent a high degree of performance, as the closer the value approaches 1, the better. All three groups have similar values, which proves the relevance of the training set. This is also proved by the fact that the majority of correlation coefficient values did not fall below the value of 0.959. Specifically, it can be said that the values in the training set ranged from 0.959 to 0.966. In the test set it was from 0.965 to 0.972 and in the validation set the values ranged from 0.963 to 0.968. We can see that slight differences can be found between individual networks, but this has still almost no effect on their overall performance. The following Table 5 presents individual MLP networks.

Table 5: Prediction statistics (Maize – daily data 1959-2023)

Statistics	1.MLP 1-14-1	2.MLP 1-17-1	3.MLP 1-20-1	4.MLP 1-19-1	5.MLP 1-19-1	6.MLP 1-15-1	7.MLP 1-17-1	8.MLP 1-14-1	9.MLP 1-20-1	10.MLP 1-20-1
Minimum prediction (Train)	1.12310	1.00700	1.11072	1.00886	1.00700	1.00700	1.00701	1.23174	1.14251	1.01203
Maximum prediction (Train)	7.50195	7.03628	7.74295	7.38414	7.22926	7.01171	7.06792	7.11324	7.08639	7.05317
Minimum prediction (Test)	1.12321	1.00700	1.11072	1.00886	1.00700	1.00700	1.00702	1.23174	1.14251	1.01203
Maximum prediction (Test)	7.50193	7.03618	7.74298	7.38385	7.22928	7.01171	7.06790	7.11323	7.08635	7.05305
Minimum prediction (Validation)	1.12309	1.00700	1.11072	1.00886	1.00700	1.00700	1.00701	1.23174	1.14251	1.01203
Maximum prediction (Validation)	7.50137	7.03627	7.74202	7.38100	7.22929	7.01168	7.06792	7.11300	7.08623	7.05318
Minimum residual (Train)	-1.68259	-1.72880	-1.80906	-1.65738	-1.64751	-1.82025	-1.61925	-1.64039	-1.37162	-1.71129
Maximum residual (Train)	2.47116	2.51816	2.36742	2.35024	2.86952	1.83692	1.93401	2.49228	1.98456	2.33720
Minimum residual (Test)	-1.48291	-1.53038	-1.60460	-1.45362	-1.60751	-1.78023	-1.40180	-1.45568	-1.37574	-1.50421
Maximum residual (Test)	2.44050	2.48806	2.33796	2.31911	2.83980	1.76879	1.90342	2.32218	2.10926	2.30695
Minimum residual (Validation)	-1.43885	-1.48473	-1.56647	-1.41467	-1.34346	-1.38942	-1.43399	-1.51736	-1.29621	-1.46937
Maximum residual (Validation)	2.17105	2.21576	2.06255	2.05208	2.56552	1.71492	1.63410	2.36896	1.98091	2.05657
Minimum standard residual (Train)	-6.20184	-5.91518	-6.70649	-6.24206	-5.68977	-6.34342	-5.71579	-5.87128	-5.11128	-5.91914
Maximum standard residual (Train)	9.10843	8.61602	8.77643	8.85153	9.91005	6.40150	6.82686	8.92035	7.39539	8.08408
Minimum standard residual (Test)	-5.51511	-5.26249	-6.00922	-5.54845	-5.42641	-6.13991	-4.86938	-5.20713	-5.01630	-5.18004
Maximum standard residual (Test)	9.07647	8.55564	8.75568	8.85202	9.58619	6.10048	6.61186	8.30666	7.69090	7.94445
Minimum standard residual (Validation)	-5.26820	-5.06496	-5.78658	-5.26246	-4.72164	-4.82378	-5.03687	-5.38599	-4.71790	-5.08499
Maximum standard residual (Validation)	7.94909	7.55878	7.61908	7.63358	9.01665	5.95385	5.73977	8.40880	7.21002	7.11709

Table 5 characterizes individual MLP networks and includes an analysis of prediction statistics. It is possible to see the residual values here. The residuals should ideally be close to 0, which would mean that the input data value corresponds to the predicted value. It is possible to read from this table that the neural networks show some residuals, but it cannot be said that they are completely accurate. The following Figure 5 shows these residuals graphically, where all retained neural networks and the actual course of the value of the given commodity (in our case maize) are presented.

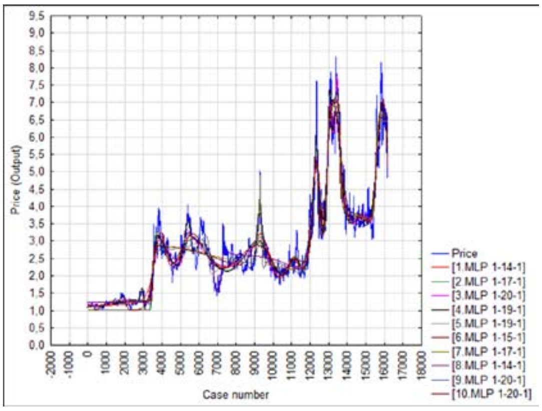

Figure 5: Maize price movement
Source: Authors

In Figure 5, we can see that all the retained neural networks were able to copy the real movement of the maize price almost identically. This article comprised a long-time horizon, using maize price data as far back as 1959, so it is possible to see how the price of maize has fluctuated over the past 64 years. It is possible to see that at the beginning of the observed period, the price of maize had almost constant values. We can only notice small price fluctuations that were not captured by the neural networks. A bigger jump in price came only at the value of about 3300, which was the 1970s. There was a war going on in Vietnam at that time. During this period, the oil crisis also occurred, which mainly affected the West, because life at that time was completely dependent on heavy industry and energy which was built on fossil fuels. After that, the price of maize had a pendulum trend, where the price of maize kept moving down and back up to the same values. It was not until the value of 7000 (1987) that there was a larger drop in the price of maize, and in the following few months, the price of maize returned to its original value. Another price shock (this time upwards) came in the 1990s when the Soviet Union was disintegrating and the Cold War, which lasted from 1947-1991, was reaching its end. Around 1995-96, the price peaked, and immediately after that, the price of maize began to fall sharply again. Another very significant price shock came between 2007-09, when there was not only a global financial crisis, but also the so-called tortilla crisis in Mexico, which caused the price of maize to skyrocket in 2007. The price of maize went up like this also due to flooding and increasing demand from ethanol producers, only to have the price plummet down subsequently. A price correction came during the following recession, but then there was even more rapid growth, driven by foreign demand and also by the catastrophic drought of 2011-2013. Scorching heat, a lack of moisture, and increasing demand kept prices more or less above $6 a bushel during this period. Between 2015 and 2020, the price of maize kept a constant trend. Then the Covid 19 pandemic came, but in Figure 5 we can see that the pandemic had almost no effect on the price of maize. On the contrary, the war in Ukraine, which occurred in February 2022, had an immense effect on the price of maize. In the figure, we can see that the price of maize skyrocketed. Only now, in recent months, the price of maize has started to fall back to its original value. We will subsequently see what the future holds for maize prices. Table 6 presents the future development of the maize price for the predicted 30 trading days.

Table 6: Maize price prediction for 30 trading days

Date	1.MLP 1-14-1	2.MLP 1-17-1	3.MLP 1-20-1	4.MLP 1-19-1
04.08.2023	5.5	5.38	5.21	5.48
07.08.2023	5.49	5.37	5.2	5.48
08.08.2023	5.49	5.36	5.19	5.47
09.08.2023	5.48	5.35	5.17	5.46
10.08.2023	5.47	5.34	5.16	5.45
11.08.2023	5.46	5.31	5.12	5.43
14.08.2023	5.45	5.3	5.11	5.42
15.08.2023	5.44	5.29	5.1	5.41
16.08.2023	5.44	5.28	5.08	5.4
17.08.2023	5.43	5.27	5.07	5.39
18.08.2023	5.41	5.25	5.03	5.37
21.08.2023	5.4	5.24	5.02	5.36
22.08.2023	5.4	5.23	5	5.35
23.08.2023	5.39	5.22	4.99	5.35
24.08.2023	5.38	5.21	4.98	5.34
25.08.2023	5.36	5.18	4.93	5.31
28.08.2023	5.36	5.17	4.92	5.3
29.08.2023	5.35	5.16	4.91	5.3
30.08.2023	5.34	5.15	4.89	5.29
31.08.2023	5.34	5.14	4.88	5.28
01.09.2023	5.33	5.13	4.86	5.27
04.09.2023	5.32	5.11	4.84	5.25
05.09.2023	5.31	5.1	4.82	5.25
06.09.2023	5.3	5.1	4.81	5.24
07.09.2023	5.3	5.09	4.79	5.23
08.09.2023	5.29	5.08	4.78	5.22
11.09.2023	5.27	5.05	4.73	5.2
12.09.2023	5.27	5.04	4.72	5.19
13.09.2023	5.26	5.03	4.7	5.18
14.09.2023	5.25	5.02	4.69	5.17

5.MLP 1-19-1	6.MLP 1-15-1	7.MLP 1-17-1	8.MLP 1-14-1	9.MLP 1-20-1	10.MLP 1-20-1
6.46	6.23	6	5.09	5.69	5.37
6.46	6.23	6	5.08	5.69	5.36
6.46	6.23	5.99	5.06	5.68	5.35
6.46	6.23	5.99	5.05	5.68	5.34
6.46	6.23	5.98	5.04	5.67	5.33
6.46	6.23	5.97	5	5.66	5.3
6.46	6.23	5.97	4.98	5.65	5.29
6.46	6.23	5.97	4.96	5.65	5.28
6.46	6.23	5.97	4.95	5.64	5.27
6.46	6.23	5.96	4.94	5.64	5.26
6.46	6.23	5.95	4.89	5.62	5.23
6.45	6.23	5.95	4.88	5.62	5.22
6.45	6.23	5.95	4.86	5.61	5.21
6.45	6.23	5.95	4.85	5.61	5.2
6.45	6.23	5.94	4.83	5.6	5.19
6.45	6.23	5.93	4.79	5.59	5.16
6.45	6.23	5.93	4.77	5.58	5.15
6.45	6.23	5.93	4.76	5.58	5.14
6.45	6.23	5.92	4.74	5.57	5.13
6.45	6.23	5.92	4.73	5.57	5.12
6.45	6.23	5.92	4.71	5.56	5.11
6.45	6.23	5.91	4.68	5.55	5.09
6.45	6.23	5.91	4.67	5.55	5.08
6.45	6.23	5.91	4.65	5.54	5.07
6.45	6.23	5.9	4.63	5.54	5.06
6.45	6.23	5.9	4.62	5.53	5.05
6.45	6.23	5.89	4.57	5.52	5.01
6.45	6.23	5.89	4.56	5.51	5
6.45	6.23	5.88	4.54	5.51	4.99
6.45	6.23	5.88	4.53	5.5	4.98

Source: Authors

Table 6 presents the movement of the price of maize in the period from 4/8/2023 to 14/9/2023. It can be seen that the first four neural networks have a downward trend and that at the beginning of the period, they all predict a price of around 5-5.5 dollars per bushel. As the month progresses, the price goes down. What is interesting about the fifth neural network is that it has the same value of 6.46 until 18/8/2023, and the following day it has a value of 6.45 and it maintains this value until the end of the monitored period. In turn, the sixth neural network has the same value throughout the observed period. The remaining neural networks have the same downward trend as the first four neural networks. The table also shows which neural networks predict a higher maize price and which ones predict a lower price. The fifth, sixth, and seventh neural networks predict a higher price of maize, while the third and eighth neural networks predict a lower price of maize. Table 7 presents the real maize prices for August and September 2023.

Table 7: Real maize price

Date	Real price of maize
04.08.2023	4.8475
07.08.2023	4.8225
08.08.2023	4.8575
09.08.2023	4.81
10.08.2023	4.8325
11.08.2023	4.755
14.08.2023	4.7475
15.08.2023	4.64
16.08.2023	4.695
17.08.2023	4.73
18.08.2023	4.79
21.08.2023	4.6925
22.08.2023	4.665
23.08.2023	4.7625
24.08.2023	4.7225
25.08.2023	4.695
28.08.2023	4.785
29.08.2023	4.695
30.08.2023	4.6175
31.08.2023	4.61
01.09.2023	4.6525
04.09.2023	4.6475
05.09.2023	4.71
06.09.2023	4.715
07.09.2023	4.7075
08.09.2023	4.685
11.09.2023	4.7125
12.09.2023	4.6325
13.09.2023	4.64
14.09.2023	4.625
15.09.2023	4.7525

Source: Authors

In Table 7 we can see what the real price of maize was in the observed period. This monitored period started on 4/8/2023 and ended on 14/9/2023. It is evident that the price of maize was almost constant throughout the monitored period. In the beginning, the price hovered around 4.85 dollars per bushel, and over some time it went down. On 16/8/2023, the price of maize started to rise slightly again, and after a few days it fell a little lower again, but as you can see in the table, this drop and rise in the price always differed only in a few tenths. There was no major price shock throughout the observed period. Table 8 below shows the residuals between the real maize price and the predicted price.

Table 8: Residuals between the real and the predicted price

Date	1.MLP 1-14-1	2.MLP 1-17-1	3.MLP 1-20-1	4.MLP 1-19-1	5.MLP 1-19-1	6.MLP 1-15-1	7.MLP 1-17-1	8.MLP 1-14-1	9.MLP 1-20-1	10.MLP 1-20-1
04.08.2023	-0.65	-0.53	-0.36	-0.63	-1.61	-1.38	-1.15	-0.24	-0.84	-0.52
07.08.2023	-0.67	-0.55	-0.38	-0.66	-1.64	-1.41	-1.18	-0.26	-0.87	-0.54
08.08.2023	-0.63	-0.50	-0.33	-0.61	-1.60	-1.37	-1.13	-0.20	-0.82	-0.49
09.08.2023	-0.67	-0.54	-0.36	-0.65	-1.65	-1.42	-1.18	-0.24	-0.87	-0.53
10.08.2023	-0.64	-0.51	-0.33	-0.62	-1.63	-1.40	-1.15	-0.21	-0.84	-0.50
11.08.2023	-0.71	-0.56	-0.37	-0.68	-1.71	-1.48	-1.22	-0.25	-0.91	-0.55
14.08.2023	-0.70	-0.55	-0.36	-0.67	-1.71	-1.48	-1.22	-0.23	-0.90	-0.54
15.08.2023	-0.80	-0.65	-0.46	-0.77	-1.82	-1.59	-1.33	-0.32	-1.01	-0.64
16.08.2023	-0.75	-0.59	-0.39	-0.71	-1.77	-1.54	-1.28	-0.26	-0.94	-0.57
17.08.2023	-0.70	-0.54	-0.34	-0.66	-1.73	-1.50	-1.23	-0.21	-0.91	-0.53
18.08.2023	-0.62	-0.46	-0.24	-0.58	-1.67	-1.44	-1.16	-0.10	-0.83	-0.44
21.08.2023	-0.71	-0.55	-0.33	-0.67	-1.76	-1.54	-1.26	-0.19	-0.93	-0.53
22.08.2023	-0.74	-0.57	-0.34	-0.69	-1.79	-1.57	-1.29	-0.20	-0.95	-0.55
23.08.2023	-0.63	-0.46	-0.23	-0.59	-1.69	-1.47	-1.19	-0.09	-0.85	-0.44
24.08.2023	-0.66	-0.49	-0.26	-0.62	-1.73	-1.51	-1.22	-0.11	-0.88	-0.47
25.08.2023	-0.67	-0.48	-0.23	-0.61	-1.76	-1.54	-1.24	-0.09	-0.90	-0.47
28.08.2023	-0.58	-0.39	-0.14	-0.52	-1.67	-1.45	-1.15	0.02	-0.80	-0.37
29.08.2023	-0.65	-0.47	-0.22	-0.61	-1.76	-1.54	-1.24	-0.06	-0.89	-0.44
30.08.2023	-0.72	-0.53	-0.27	-0.67	-1.83	-1.61	-1.30	-0.12	-0.95	-0.51
31.08.2023	-0.73	-0.53	-0.27	-0.67	-1.84	-1.62	-1.31	-0.12	-0.96	-0.51
01.09.2023	-0.68	-0.48	-0.21	-0.62	-1.80	-1.58	-1.27	-0.06	-0.91	-0.46
04.09.2023	-0.67	-0.46	-0.19	-0.60	-1.80	-1.58	-1.26	-0.03	-0.90	-0.44
05.09.2023	-0.60	-0.39	-0.11	-0.54	-1.74	-1.52	-1.20	0.04	-0.84	-0.37
06.09.2023	-0.59	-0.39	-0.09	-0.53	-1.74	-1.52	-1.20	0.06	-0.83	-0.36
07.09.2023	-0.59	-0.38	-0.08	-0.52	-1.74	-1.52	-1.19	0.08	-0.83	-0.35
08.09.2023	-0.61	-0.40	-0.10	-0.54	-1.77	-1.55	-1.22	0.06	-0.85	-0.37
11.09.2023	-0.56	-0.34	-0.02	-0.49	-1.74	-1.52	-1.18	0.14	-0.81	-0.30
12.09.2023	-0.64	-0.41	-0.09	-0.56	-1.82	-1.60	-1.26	0.07	-0.88	-0.37
13.09.2023	-0.62	-0.39	-0.06	-0.54	-1.81	-1.59	-1.24	0.10	-0.87	-0.35
14.09.2023	-0.63	-0.40	-0.07	-0.55	-1.83	-1.61	-1.26	0.09	-0.88	-0.36
Total value	-19.78	-14.45	-7.20	-18.34	-52.11	-45.40	-36.66	-2.91	-26.41	-13.84
Mean	-0.66	-0.48	-0.24	-0.61	-1.74	-1.51	-1.22	-0.10	-0.88	-0.46
Median	-0.66	-0.49	-0.25	-0.62	-1.74	-1.52	-1.22	-0.10	-0.88	-0.47

Source: Authors

Table 8 presents the residuals between the actual maize price and the predicted maize price. In this case, the 8th neural network performed best. Most values came close to the actual price of maize here. Specifically, the following days were concerned: 18/08/2023 and then the period from 23/08/2023 to 14/09/2023. Next, the 3rd neural network performed excellently. Many days came very close to the actual price of maize. These days were: 28/8/2023 and then the period from 5/9/2023 to 14/9/2023. The 5th, 6th and 7th neural networks came out as the worst ones. These were the most distant from the real price. What we can also see in the table is the fact that the residuals between the real and predicted price were almost minimal. This means that almost all of the neural networks that predicted the price of maize hit the real price.

5 Discussion of results

A lot of countries grow maize and export it in the international market. Maize is an important export item, which contributes to trade balance of maize producing countries. Maize international trade has a significant economic influence on a global level. Maize is an important crop for farmers in the whole world. Growing and selling maize is an important influence on the income and profitability of agricultural enterprises.

It is possible to answer all the determined research questions based on results obtained with the help of time series analysis and neural network method.

RQ1: How did the price of maize develop in dependence on the world events in the commodity market from 1959 to 2023?

This issue was solved with the help of neural networks when a time series of data collected from 1959 to 2023 was created. This price development is displayed in Figure 5, where it is notable that all the retained neural networks were able to copy the real movement of maize price almost in the same way. Since the data have been taken in the past 64 years, it may be observed that the tendency of maize price resembled a pendulum. It is also shown that maize prices had almost constant values at the beginning of the monitored period. We can record only small price fluctuations that neural networks failed to detect. A more significant price shift occurred from the value of 3 300 onwards in the 1970s. After that the price of maize had a pendulum tendency, the price constantly moved down and back to the same values. Only when it reached the value of 7,000 (1987) there was a bigger drop in the price of maize, which gradually returned to its original value in the several following months. The next price shock (upwards this time) occurred in the 1990s when the Soviet Union was in the process of disintegration. There was a peak around 1995-96 and the price began to fall sharply right after that. The next significant price shock was between 2008-09 during the financial crisis, the consequence of which was the rocketing of maize price and a subsequent sharp fall of the price. It was immediately followed by another price shock, which remained till 2013 when another drop in maize prices occurred. There was a trend of constant maize prices from 2015 to 2020. It was followed by the COVID-19 pandemic; however, it is notable from Figure 5 that the pandemic little influenced the prices of maize. In contrast, the war in Ukraine, which started in February 2022, influenced the prices of maize enormously. The Figure shows there was a rocket rise in maize prices. The price of maize is falling back to its original values now. The future price of maize is yet to be seen.

RQ2: How successful is artificial intelligence in the prediction of maize price for 30 consecutive trading days?

Research question 2 dealt with the residue between the predicted maize price and the real price of maize. This difference is so-called validation and it is a difference between the predicted price and the real price. This validation is shown in Table 8. It is obvious from our results that the 8^{th} neural network worked the best and most of its values came near the real price of maize. There were the following days specifically in the case of this network: 18/8/2023, and a later period from 23/8/2023 to 14/9/2023. The next excellent result was the 3^{rd} neural network, which included many days that came very near the real price of maize. There were the following days: 28/8/2023, and the following period from 5/9/2023 to 14/9/2023. The worst results were in the 5^{th}, 6^{th}, and 7^{th} neural networks, which came furthest from the real price. It is notable in that table that the residue between the real and predicted prices was minimal, it can be claimed that almost all the neural networks, which predicted the price of maize, predicted the price correctly.

The summary is that all the 10 retained MLP networks for maize were able to copy the curve of real price development of this commodity, and, therefore, they can be deemed reliable and applicable in practice. This statement is confirmed by the research of Shahhosseini et al. (2021) who found that machine learning (ML) can provide adequate predictions faster and more flexibly in comparison with simulation crop modelling. However, one machine learning model can be surpassed by a 'selection' of models (machine learning sets), which can reduce the distortion of predictions, variance, or both, and is able to reflect data distribution better. Shahhosseini et al. (2021) explored machine learning for predicting maize yields in three states of crop belt (Illinois, Indiana and Iowa). Shahhosseini et al. (2021) determined that a suggested optimized weighted set and an average set are the most accurate models with RRMSE 9.5%. Roznik et al. (2023) examined the accuracy of predicting maize yields with the help of machine learning with the use of satellite and meteorological data. They further researched the incremental value of these predictions for expanding world agricultural supply and demand estimates (WASDE). They collected publicly available data from 1984 to 2021 to illustrate the potential of machine learning methods with the use of the XGBoost algorithm. Roznik et al. (2023) found out that the XGBoost model had approximately the same results, however, failed to surpass WASDE prediction of maize yields for a 12-year period beyond the set. Roznik et al. (2023) further indicate that XGBoost machine learning models can create quite accurate predictions of crop yields. It is evident that artificial neural networks and machine learning are ideal tools for predicting maize prices, as demonstrated by the aforementioned authors.

5 Conclusion

Changes in the extent of maize cultivation in different regions of the world can influence global supply. Furthermore, fluctuations in currency exchange rates can affect maize prices because it is often traded in dollars. Political events and government decisions can influence agricultural production, trade, and maize prices. The price of oil and its impact on transportation costs and fertilizer production can also affect maize prices because oil is a key raw material for chemical fertilizers. Overall, maize prices are the result of a complex and dynamic mix of these factors. Therefore, prices can change rapidly and are difficult to predict with certainty.

This work aimed to create and analyse a model based on neural networks for predicting maize yields and to identify its position in the commodity market. For this reason, research questions were formulated to achieve the set goal. Research question 1 was addressed using neural networks to create a time series of data for the period from 1959 to 2023. Research question 2 dealt with residuals between predicted maize prices and actual maize prices, which were then evaluated using Statistica software, employing artificial neural network methodology. Furthermore, a prediction of maize prices was made for the next 30 trading days, revealing that maize prices did not exhibit any extreme fluctuations. The prices of all networks during the observed period either slightly increased or decreased, but no significant price shock was recorded for any of the networks. After prediction, a validation of actual maize prices against predicted prices was conducted, with the best-performing model being the 8th neural network, as it was the only one that closely approached a value of zero. The overall finding was that the residuals between actual and predicted maize prices were almost minimal, indicating that the neural networks used for maize price prediction almost accurately reflected actual prices.

Based on the results obtained, it was concluded that over the past sixty-four years, maize prices have predominantly risen. It is evident that during the historical price evolution, there have been many fluctuations caused by various factors, such as financial crises or various armed conflicts around the world. One of the limitations of the work is the lower number of neural structures. The more neural structures there are, the more accurate the results. If neural networks can further improve predictions, it may lead to greater accuracy in estimating maize yields, which is a key factor in decision-making in agriculture and commodity trading. Another limitation of this work is the limited scope of commodities, as only one commodity was examined. It would be better to examine maize prices in relation to other commodities. This article differs from others in that it focuses on the specific application of neural networks in predicting maize yields, which may be unique and targeted at the agricultural sector. It also utilizes a specific dataset related to maize yields, reflecting all international conflicts and crises over the past sixty-four years.

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Primary Paper Section: A

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