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TRENDS, SHOCKS AND PREDICTIONS IN THE PRICE DEVELOPMENT OF FOOD-GRADE WHEAT

Jakub Horák*
School of Expertness and Valuation, Institute of Technology and Business, České Budějovice 37001, Czech Republic
Department of Economics, Management and Marketing, Institute of Technology and Business, Prešov 08001, Slovakia
E-mail: horak@mail.vstecb.cz; horak@vste.sk

Jiří Kučera
School of Expertness and Valuation, Institute of Technology and Business, České Budějovice 37001, Czech Republic
E-mail: kuceraj@mail.vstecb.cz

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Abstract: Both farmers and end consumers are concerned with how wheat prices have evolved, the factors that have shaped them, and how they are likely to develop in the future, as this knowledge supports informed purchasing and selling decisions. This study examines the trends in food-grade wheat prices in the Czech Republic from January 2010 to November 2024 and provides a forecast for the period from December 2024 to December 2025. The analysis employs content analysis, linear regression, and neural network modeling. Content analysis revealed that the steepest increase in wheat prices occurred between 2021 and 2022, when the country was simultaneously recovering from the COVID-19 pandemic and experiencing the impacts of the war in Ukraine. During this period, the wheat price reached 8,654 CZK/t, the highest value in the time series. Regression analysis indicates a gradual upward trend in wheat prices. The final stage of analysis, conducted using Statistica software, applies regression and forecasting with artificial neural networks, specifically multilayer perceptron (MLP) and radial basis function (RBF) models. Ten of the best-performing networks are used for forecasting. For validation, actual price data from December 2024 to February 2025 are included. The MLP models approximate these values most closely, whereas the RBF models tend to underestimate them. The findings of this study provide valuable insights for financial decision-making—such as whether to purchase immediately

* Corresponding author: Jakub Horák. *E-mail: horak@mail.vstecb.cz; horak@vste.sk*

or postpone buying – as well as practical guidance for farmers preparing for upcoming wheat price developments.

Keywords: Agriculture; wheat; forecast; price trend; commodity.

JEL CODES: C45, C53, Q11.

1. Introduction

The supply of commodities to society is one of the key pillars of a modern economy. Significant fluctuations in commodity prices can strongly influence not only macroeconomic development but also the stability of production sectors, social security, and the overall standard of living (Zhang et al., 2022). The commodity market plays a crucial role in international industrial chains and sustainable development. Within this framework, the price of wheat represents a decisive factor affecting the decisions of farmers, traders, investors, and consumers (Mutiawani et al., 2016).

Agriculture occupies an irreplaceable position in both social and economic development, making price stability in agricultural products essential. As Wang et al. (2022) emphasize, sharp increases or decreases in prices heighten production risks and undermine the stability of the global agricultural market. Wheat price fluctuations create uncertainty for both producers and consumers, and these fluctuations are further amplified by global trade linkages, particularly in less developed economies where markets do not operate under conditions of perfect competition (Madaan et al., 2019). Wheat price volatility depends heavily on production levels, global demand variability, and access to key markets, which altogether increase the vulnerability of the sector (Ravi Kumar et al., 2024). To mitigate these risks, measures such as production subsidies, price regulations, and support for small-scale farmers have been recommended (Chen et al., 2018). Beyond tracking historical developments, however, accurate forecasting has become increasingly important. Jiang et al. (2023) show that modern prediction tools—including deep learning and ensemble algorithms—achieve high levels of accuracy. Proper market timing based on such forecasts can significantly affect the profitability of agricultural enterprises (Geetha et al., 2024; Pozdílková et al., 2021).

Wheat prices are shaped by a wide range of factors, including weather conditions, climate change, macroeconomic dynamics, and extraordinary global events. In recent years, major shocks have been caused by the COVID-19 pandemic, the war in Ukraine, and the global food crisis (Tandogan, 2024). These events have heightened uncertainty in financial markets and disrupted the balance between supply and demand (Kotyza et al., 2021; Smutka et al., 2019). The result is increased volatility in agricultural commodity prices, with wheat holding a unique position given its cultivation across most regions of the world. Its price dynamics thus have direct implications for national economies and the formulation of public policies (Martin & Minot, 2022).

Despite extensive literature on wheat price volatility in global markets, research on wheat price forecasting in Central Europe—particularly the Czech Republic—remains limited. Most existing studies concentrate on developing countries or major exporters, while applications of advanced forecasting tools such as neural networks to smaller, open economies are relatively rare. Moreover, comparative research that evaluates traditional regression models alongside modern machine learning methods within one integrated framework is lacking. In view of rising market uncertainty, geopolitical instability, and climate-related challenges, refining forecasts of future wheat prices has become increasingly important.

This study seeks to address this research gap by providing practically applicable insights for agricultural producers, the food industry, and policymakers. Its aim is to identify trends in food-grade wheat prices in the Czech Republic between 2010 and 2024 and to forecast their development until the end of 2025 using both traditional regression approaches and advanced neural network models. The study also evaluates the predictive accuracy of these methods and aims to deliver forecasts that can support informed decision-making in an environment marked by high volatility and external shocks.

To achieve this objective, the following research questions were set:

RQ1: How did wheat prices evolve between 2010 and 2024 in the Czech Republic?

RQ2: What events had the most significant impact on wheat prices in the Czech Republic between 2010 and 2024?

RQ3: What price trends can be expected for wheat by December 2025?

2. Literary Research

Wheat is an important staple food worldwide, contributing significantly to the daily intake of energy, fiber, and micronutrients. Higher consumption of whole grains reduces the risk of diabetes, cardiovascular disease, and colon cancer, although specific wheat components may trigger adverse reactions such as celiac disease and wheat allergy (Brouns et al., 2019). Traditional winter wheat cultivation methods face limitations, particularly in terms of insufficient land utilization and low efficiency in water and nitrogen use, which constrain sustainability. A new method employing low seedbed cultivation has therefore been developed to improve land use and wheat productivity (Si et al., 2023). Appropriate mineral fertilization and plant protection technologies are essential for wheat cultivation, directly influencing both yield quantity and quality (Buczek et al., 2020). Studies show that intensifying cultivation practices increases grain yield as well as protein, gluten, phosphorus, and magnesium content, but also elevates iron, zinc, and manganese levels.

Given wheat's significance as a global commodity, effective price modeling is vital for both economic and social development. Identifying the key factors in econometric modeling of wheat prices supports more effective government policies and price interventions. Such factors include demand, supply, climate change, and natural resource availability (Sahinli, 2021). Wheat stands at the center of global food security, and extreme price fluctuations can create broader social risks, especially in terms of food security and human well-being. In Pakistan, for example, wheat is not only a staple crop but also contributes approximately 10.3% to agriculture, which itself accounts for 2.2% of GDP. Based on macroeconomic instability and climate change, prices have been predicted using recurrent neural networks with long-term memory, showing a gradual decline in wheat prices until 2030, a trend posing significant risks for the economy (Subhan et al., 2022). Understanding the relationship between production costs and market prices also allows farmers to better anticipate market direction and minimize business risks. Farmers may decide to sell before harvest, immediately afterward, or to store grain and sell later. When the market price aligns with operating costs, farmers often suspend sales and hold stocks in anticipation of higher prices, demonstrating a strong positive correlation between operating costs and market price (Jankovic et al., 2020). The strategic role of Russia and Ukraine as major wheat exporters highlights the vulnerabilities of global food security. The ongoing conflict has disrupted production and exports, pushing up prices in import-dependent countries (Mottaleb et al., 2022). Their study showed that, on average, a 1% decline in global wheat trade increases the producer price by 1.1%, while a 1% rise in producer price reduces annual per capita wheat consumption by 0.59%. A 50% reduction in wheat exports from Russia and Ukraine could increase wheat prices by as much as 15%. Although Russia and Ukraine dominate global export volumes, price adjustments are more closely aligned with those in France, the United States, and Canada. French wheat prices in particular have been shown to transmit price signals more effectively to other export markets than U.S. prices (Svanidze & Duric, 2021).

A number of studies have focused specifically on wheat price forecasting and modeling. Theofilou et al. (2025) conducted a systematic review of machine learning, deep learning, ensemble, and time series models, concluding that hybrid deep learning methods achieved lower error rates than traditional approaches.

Manogna et al. (2025) compared ARIMA, SVR, XGBoost, MLP, RNN, LSTM, GRU, and ESN models on 23 agricultural commodities (including wheat) and found that LSTM and GRU achieved superior performance, particularly in capturing complex temporal dynamics. Abid et al. (2025) reported that deep belief networks (DBN) outperformed GRU in predicting wheat prices during the Russia–Ukraine conflict, despite GRU showing the lowest error rates. Similarly, Nayak et al. (2025) applied hybrid Transformer architectures combined with metaheuristic algorithms (GWO, WOA, PSO) for agricultural price forecasting, finding that automatic hyperparameter optimization enhanced both accuracy and generalizability.

Xu and Zhang (2023) employed an auto-regressive neural network to predict weekly wholesale prices of edible oils in China, demonstrating high predictive accuracy even during substantial price fluctuations. Wang (2023a) used an improved RBF neural network model for short-term forecasting of agricultural product prices, showing that it outperformed traditional statistical methods by effectively capturing nonlinear time series patterns. Hao et al. (2020) applied linear regression models with robust loss functions and regularization techniques (LASSO, Ridge, Elastic Net) to forecast oil prices, confirming that carefully specified regression remains a stable and reliable forecasting tool. Butler et al. (2021) tested multilayer perceptron (MLP) neural networks for short-term oil price prediction, finding that they consistently outperformed conventional methods, particularly for one- to three-day horizons. Together, these studies demonstrate the complementary value of regression analysis for trend identification and neural networks for modeling nonlinear dynamics.

Although not centered on wheat, additional insights can be gained from related commodities. Shobande and Shodipe (2021) examined corn price rigidity in the United States from 1930 to 2017, using USDA and Federal Reserve data. Employing the Calvo price rigidity model within a new Keynesian equilibrium and applying DSGE-VAR simulation, they found that corn price inflation persisted at roughly 2% annually, driven primarily by expected inflation and the output gap. Random shocks caused only partial price declines, with prices reverting to long-term equilibrium. Their findings further highlight that domestic policies often have limited influence on international commodity prices, while interventions can distort markets and worsen yields.

A concise summary of these studies is provided in Appendix 1.

3. Material and Methods

Figure 1 summarizes the main steps of the research design of this study—from data collection and preparation, through model selection, to the prediction procedure itself. Each step is described in detail in the following sections.

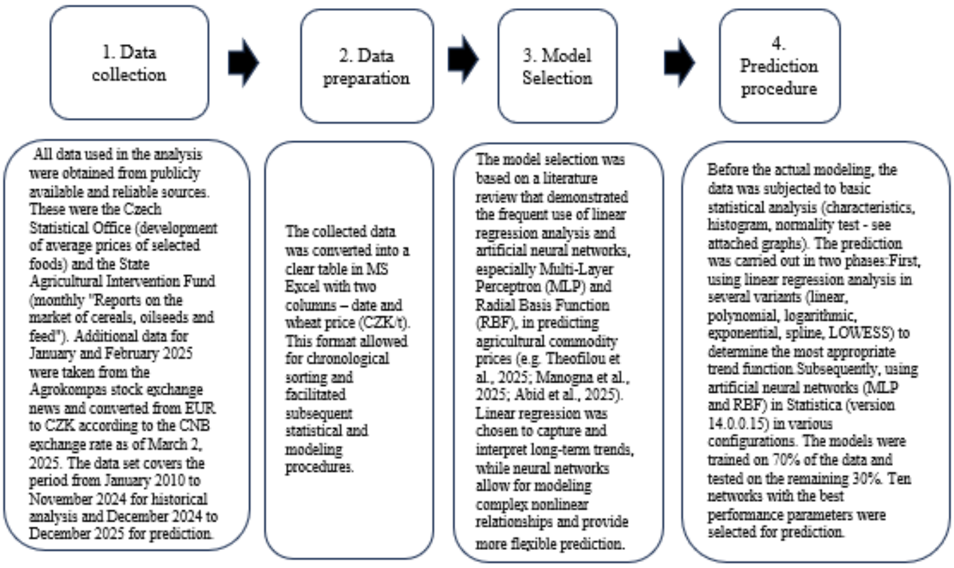

Figure 1. Diagram of the main steps of the research study process
Source: Authors.

3.1. Material

The required data were obtained through content analysis from the web portals of the Czech Statistical Office and the State Agricultural Intervention Fund. To evaluate the development of food-grade wheat prices, information was drawn from the *Average Price Developments of Selected Foodstuffs* graph (Czech Statistical Office, 2024) and from monthly wheat price data contained in the *Cereals, Oilseeds and Feedstuffs Market Report* (State Agricultural Intervention Fund, 2023). For wheat, prices were recorded in CZK per tonne as of the first day of each month. Data were collected for the following months: April 2011, September 2011, February 2012, June 2013, August 2013, January 2014, May 2015, July 2015, January 2016, April 2017, September 2017, January 2018, May 2019, October 2019, February 2020, May 2020, July 2022, October 2022, March 2023, April 2023, September 2023, February

2024, July 2024, December 2024, and January 2025. To determine wheat prices for January and February 2025, data from the Exchange Data website (Akrokompas, 2025) were used. These prices were converted from euros to Czech crowns using the exchange rate on 2 March 2025 (25.0634 CZK/EUR).

For the analysis, data covering the entire period from 2010 to early 2025 were selected in order to capture both long-term trends and short-term fluctuations in wheat prices. Representative months were chosen each year to provide a sufficient number of observations for building a time series while ensuring even temporal distribution. Values from the first days of selected months were prioritized to minimize the effect of intra-month price shocks and to maintain consistency across records. The chosen number and distribution of data points also reduced the risk of overfitting in neural networks, which can occur when working with excessive datasets, while still providing a robust basis for forecasting future price developments.

The content analysis was conducted between 1 February and 10 March 2025, covering the period from January 2010 to November 2024. Reports describing events that influenced wheat price movements were obtained primarily from press releases of the Ministry of Agriculture (2025). Additional relevant information included reports on climatic conditions (e.g., natural disasters), foreign trade in agricultural commodities, agricultural subsidies, and related topics. Other important sources for this analysis included the Czech Television portal (2025), *Aktuálně.cz*, the Confederation of Commerce and Tourism of the Czech Republic, and the Association of Private Agriculture of the Czech Republic.

3.2. Methods

Following the content analysis, the data were processed into tables and figures using Microsoft Excel. To identify wheat price trends, monthly prices were entered into a spreadsheet and used to generate a graph illustrating the development of wheat prices. The methods employed for data examination included linear regression analysis and neural network modeling.

Linear regression analysis was applied to evaluate how different functional curves could smooth the commodity time series. It was also used to generate forecasts; however, these were not forward-looking predictions but rather estimates based on historical data. Several types of regression functions were tested, including linear, polynomial, logarithmic, exponential, Distance Weighted Least Squares, Negative Exponential Weighted Least Squares, spline, and LOWESS. Function calculations were performed according to the formulas provided in Appendix 2.

Two types of neural networks were employed for time series prediction: multilayer perceptron (MLP) and radial basis function (RBF) models. These represent relatively simple architectures of artificial neural networks but often yield strong results in time series forecasting. Their main advantages are lower computational complexity and easier implementation, while still achieving high predictive accuracy (Yi et al., 2023).

For linear regression analysis, all regression functions standardly available in the Statistica software package were applied. These functions range from simple (e.g., linear, exponential) to more advanced (e.g., Distance Weighted Least Squares), enabling a comprehensive verification of the predictive capacity of regression models (Vochozka et al., 2019).

Although linear regression analysis and neural networks such as MLP and RBF are valuable tools for time series prediction, they also present certain limitations. Linear regression assumes a constant relationship between variables, making it less capable of capturing complex nonlinear dynamics and more sensitive to outliers. Neural networks, by contrast, can model nonlinear relationships, but their performance depends heavily on the quality and scope of training data as well as appropriate architectural design. Both approaches are based on historical data, which means that unexpected external shocks—such as geopolitical crises or natural disasters—may significantly affect results. Thus, each prediction represents a simplification of reality, but nevertheless provides a valuable foundation for decision-making.

All data analyses and modeling were conducted in the Statistica software environment. Statistica is widely used due to its user-friendly and intuitive graphical interface, which allows users to perform predictive analyses without advanced IT skills. It also offers a broad suite of analytical tools, ranging from data preparation and modeling (e.g., regression and neural network services) to workflow automation and integration with R or Python. This combination of simplicity, clarity, and functionality makes Statistica a suitable platform for replicating and extending predictive analyses in broader research contexts. In this regard, Demidova et al. (2016) highlight the value of Statistica for both students and researchers, as it facilitates data management, data mining, and machine learning without requiring programming knowledge, thereby providing an accessible environment for scientific work.

The data were obtained exclusively from publicly available sources and were processed in accordance with the ethical principles of scientific research. Their use followed the principles of transparency, verifiability, and accurate interpretation, with no violation of copyright or manipulation of content. All sources of information are properly documented in the bibliography.

The following figure (Figure 2) provides a graphical summary of the dataset used, including basic descriptive statistics and distribution characteristics. This visual overview increases transparency during data preparation and allows for a quick assessment of any anomalies or irregularities before applying predictive models.

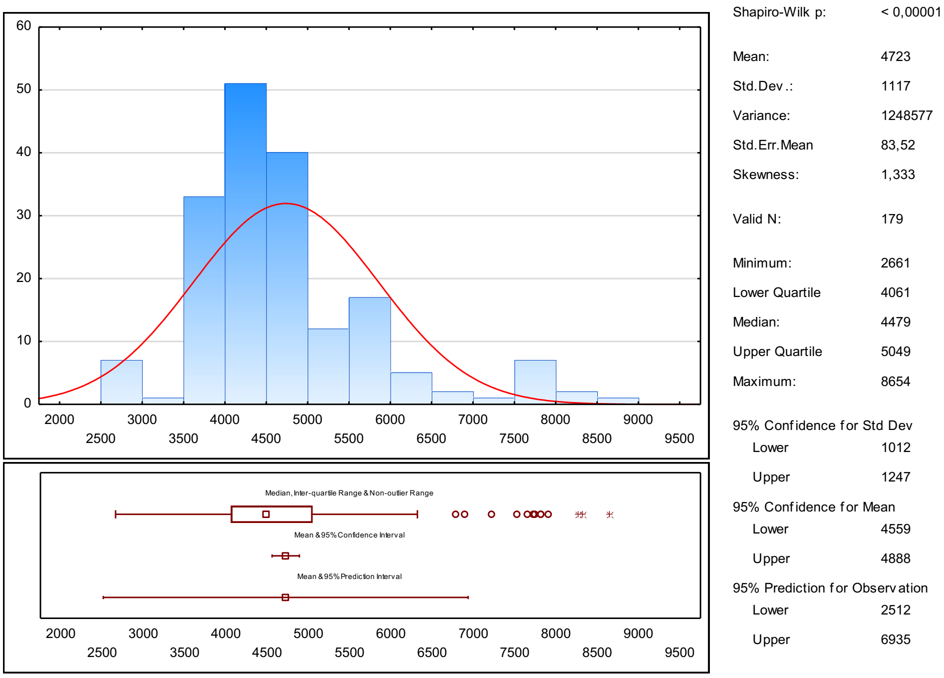

Figure 2. Graphical summary of the dataset
Source: Authors.

A Normal P-plot was created to verify the assumption of normality of the data. Figure 3 shows a comparison between the observed cumulative probabilities and the expected values under a normal distribution. The closer the plotted points are to the diagonal line, the greater the degree of agreement with the assumption of normality.

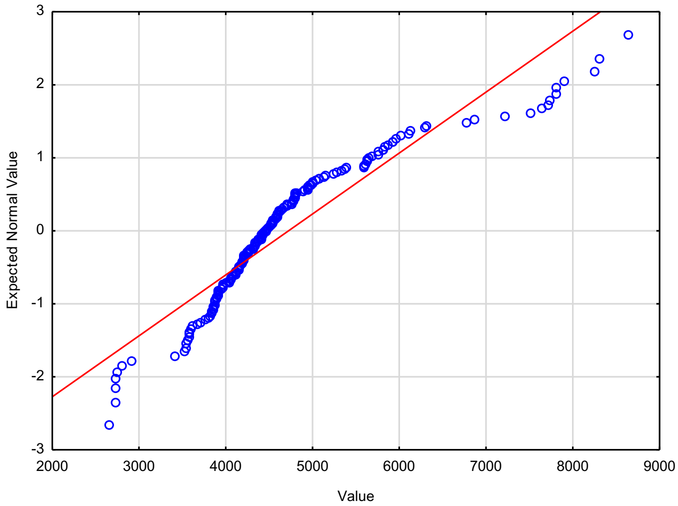

Figure 3. Normal P-plot of the dataset
Source: Authors.

4. Results

In this part of the research, the individual analyses described above are carried out. The results are presented in accordance with the research questions. First, the historical development of wheat prices in the Czech Republic from 2010 to 2024 is analyzed. This is followed by the identification of key events that significantly influenced price developments in this period. Finally, wheat price predictions until December 2025 are presented based on linear regression analysis and neural networks.

RQ2: What events had the most significant impact on wheat prices in the Czech Republic between 2010 and 2024?

4.1. Externalities affecting wheat prices

The content analysis indicates that climatic conditions have exerted a significant influence on wheat prices over the years. In 2010, prices rose due to excessive rainfall in July, whereas in 2012, a severe drought had a pronounced effect on wheat markets. In 2024, flooding—described as a once-in-a-century event—also disrupted wheat production.

The global economic crisis of 2007–2015 contributed to rising prices of agricultural commodities, including wheat. In 2011, flood relief subsidies and harvests falling short of demand were key drivers of price increases. In 2014, wheat exports grew by CZK 3.3 billion, while production simultaneously expanded owing to a record harvest of 8.8 million tonnes.
The armed conflict between Russia and Ukraine was a major factor behind the surge in wheat prices in 2022, when prices on global exchanges reached a record high of CZK 9,000 per tonne. This increase was further reinforced by rising energy and fertilizer costs. In 2023, prices began to decline, largely due to a surplus of grain in the Czech Republic, where wheat stocks increased by 40% year-on-year (Association of Private Agriculture, 2023).

RQ1: How did wheat prices evolve between 2010 and 2024 in the Czech Republic?

4.2. Wheat price trend

Table 1 gives descriptive statistics on food-grade wheat prices.

Table 1. Descriptive statistics of food-grade wheat

Descriptive statistics	Food-grade wheat
Mean	4723.363128
Standard error of the mean	83.51819924
Median	4479
Mode	5634
Standard deviation	1117.397351
Sample variance	1248576.839
Minimum	2661
Maximum	8654
Count	179
Confidence level (95,0 %)	164.8132182

Source: Authors. Based on the data in CZSO (2024) and the State Agricultural Intervention Fund (2023).

The table indicates that the minimum price of wheat for the period under review was 2,661 CZK/t, the maximum price was 8,654 CZK/t, and the modus (the most frequent price) was 5,634 CZK/t. Other statistics, such as mean, error of the mean, median, standard deviation, sampling variance, count, and confidence level, are also presented.

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Figure 4 shows the development of the price of food-grade wheat from 2010 to 2024.

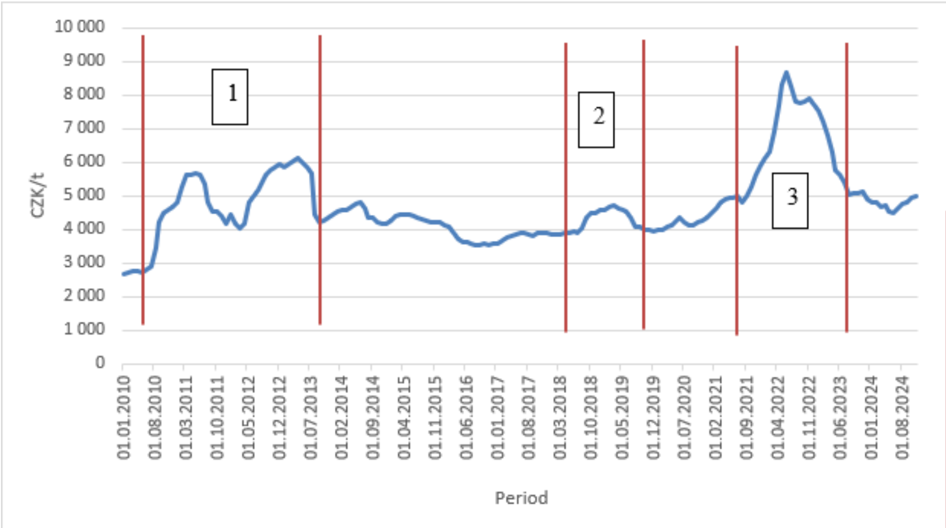

Figure 4. Price trend of food-grade wheat
Source: Authors based on the SZIF (2025) data.

As of 1 January 2010, the wheat price was the lowest, at 2,661 CZK/t, and by 1 June 2011 it had risen to 5,634 CZK/t. There were significant fluctuations between 2011 and 2013, with the price in March 2012 at 4,057 CZK/t and in 2013 at 6,033 CZK/t. Between 2014 and 2020, the price was stable, ranging between 3,500 and 4,500 CZK/t. At the beginning of 2021, the wheat price started to rise sharply, reaching a peak of 8,654 CZK/t in June 2022. This increase was followed by a decline to 5,010 CZK/t on 1 November 2024. The turning points include 2010-2011, when the effects of rainfall and fuel price increases may have been present, and the period 2021-2023, when the wheat price was affected by the COVID-19 pandemic, the war conflict in Ukraine, and the energy crisis.

RQ3: What price trends can be expected for wheat by December 2025?

4.3. Linear regression analysis

The following scatter plots show the relationship between the price of food wheat in CZK/t and the time. The x-axis always describes the period under review from its beginning, i.e., 2010, until the end of 2025, and the y-axis indicates the price of the commodity. The blue dots in the figure indicate the individual wheat prices at different times. Figure 5 also shows dotted red lines indicating the prediction range or confidence interval of 95%, i.e., how the values should move according to the function, and that they are highly likely to lie between. The regression function -6167.0264+0.2539x in Figure 2 is shown by the solid red line. Based on the value of +0.2539x, a slight increase in the price of wheat can be observed in the long run. The figures indicate that there were significant fluctuations in 2011, 2021, and 2022.

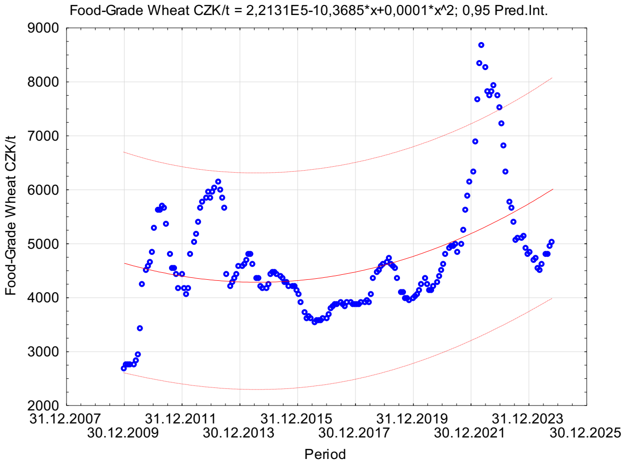

Figure 5. Linear regression
Source: Authors.

Figure 6 shows the polynomial function y = -6167.0264+0.2539*x. +0.2539x again characterizes an increasing curve. Like the figure above, the polynomial functions are given by dotted red lines to indicate the range of prediction within which the values should vary. The red curve of the function deviates significantly from the actual values (blue dots).

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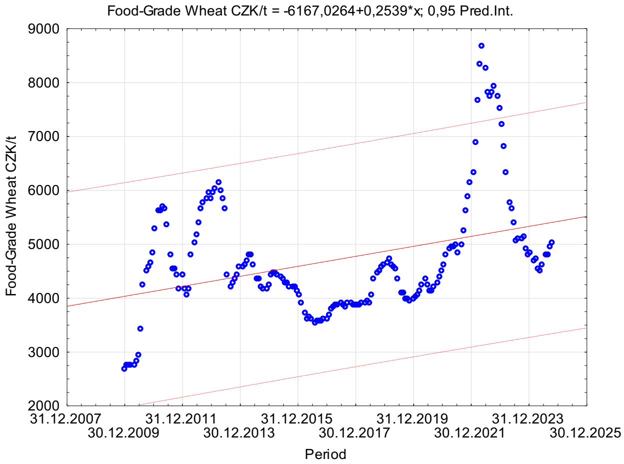

Figure 6. Polynomial regression
Source: Authors.

Figure 7 represents a logarithmic regression where the red curve shows a significant deviation from the actual values, so it is not well-suited for regression.

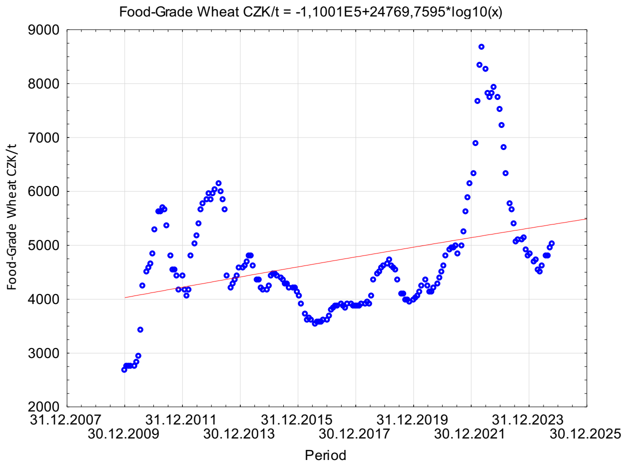

Figure 7. Logarithmic regression
Source: Authors.

This type of regression is recommended more for data changes that slow down over time, but here, a gradual increase in prices is assumed. Its function is expressed as y = -1.1001E5+24769.7595*log10(x).

The exponential regression is presented in Figure 8. This model assumes that the price of wheat increases exponentially over time, but it is only appropriate if a sharp rise is expected, which is not the case here. The exponential function is expressed as y = 505,1102*exp(5,1544E-5*x)

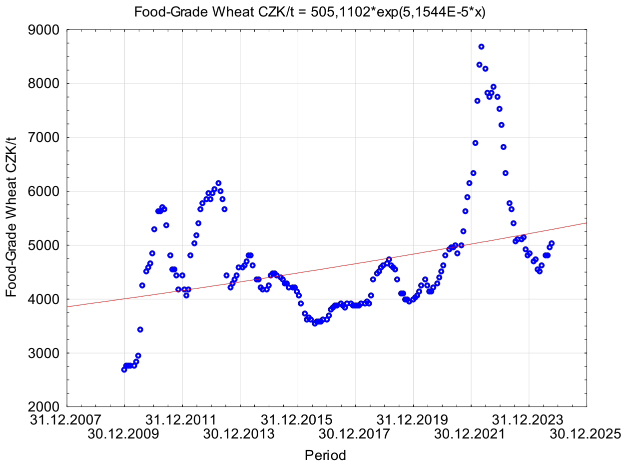

Figure 8. Exponential regression
Source: Authors.

Figure 9 shows the Distance Weighed Least Squares function, which again follows the trend in prices and takes more account of local variability in the data than linear regression models, but local extremes are not included in the curve.

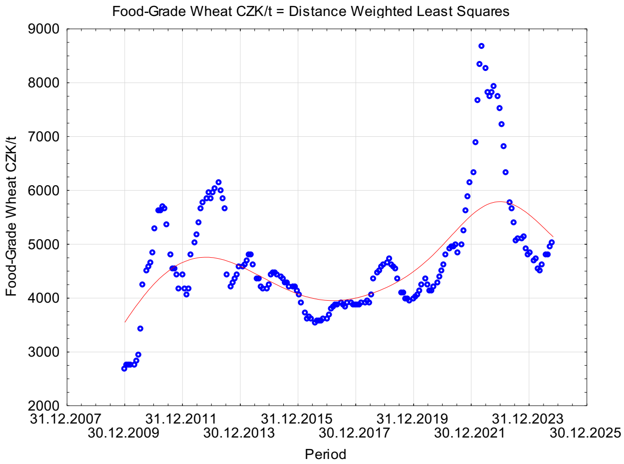

Figure 9. Distance Weighted Least Squares
Source: Authors.

Figure 10 shows the Negative Exponential Weighted Least Squares function, which exponentially smooths the previous function.

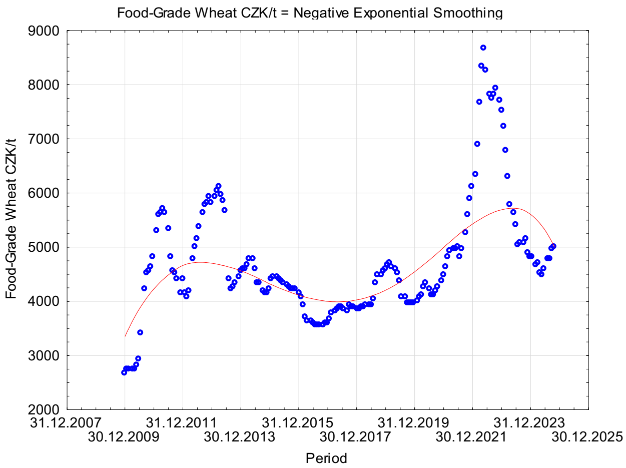

Figure 10. Negative Exponential Weighted Least Squares
Source: Authors.

Figure 11 representing the spline regression even reproduces the individual blue points completely, i.e., local minima and maxima are included, but in some sections, the values are too outlying for this function.

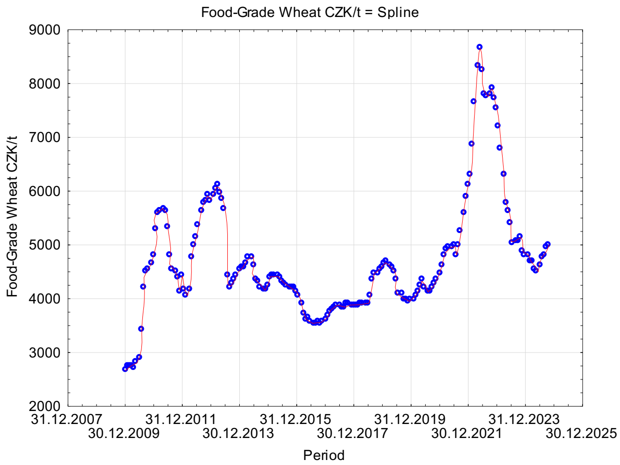

Figure 11. Spline Regression
Source: Authors.

The LOWESS function in Figure 12 does not respect local extremes. The actual values approach or only intersect the red curve in some places.

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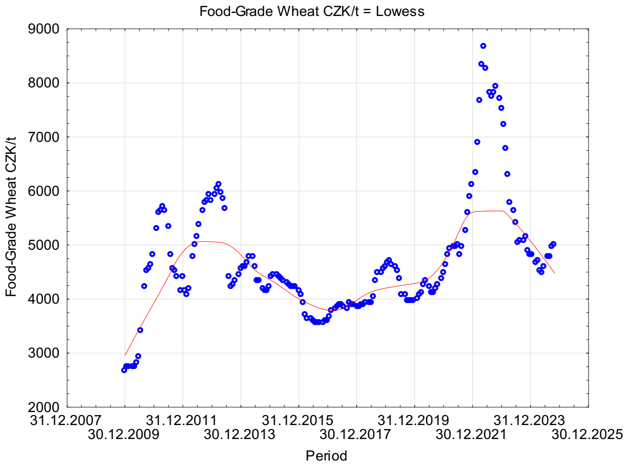

Figure 12. LOWESS
Source: Authors.

4.4. Neural networks

The following neural network calculations are performed primarily for the purpose of wheat price forecasting, but also to further investigate the evolution of prices.
Table 2 shows the ten best neural networks for food-grade wheat. The data are monthly and cover the period from 2010 to 2024. The table includes the MLP and the RBF models. The ninth column lists the functions used in the hidden layer of the neural networks, i.e., Gaussian, logistic, and tangent. The last column includes the activation functions of the output neutron, namely identity, sine, and logistic functions. SOS or Sum of Squares (sum of squares of errors) shows the errors in the regression models. Of all the networks examined, the RBF 1-50-1 network with index 6 performed the best, achieving the highest accuracy on the training models (0.990362) and test data (0.97683), and with the lowest training error (10405.91). On the other hand, the worst performing network is the RBF 1-32-1 with index 8, training model 0.975224, and test data 0.974205.

Table 2. Overview of the active networks (wheat – monthly data 2010-2024)

Index	Net. name	Training perf.	Test perf.	Training error	Test error	Training algorithm	Error function	Hidden activation	Output activation
1	RBF 1-37-1	0.985037	0.974797	16111.63	37335.78	RBFT	SOS	Gaussian	Identity
2	MLP 1-42-1	0.983314	0.977239	17963.48	32590.93	BFGS 338	SOS	Logistic	Sine

3	MLP 1-38-1	0.978194	0.976356	23418.32	33942.43	BFGS 205	SOS	Tanh	Identity
4	MLP 1-45-1	0.987682	0.97387	13327.29	37967.07	BFGS 314	SOS	Logistic	Logistic
5	RBF 1-50-1	0.977843	0.976059	23771.4	37530.33	RBFT	SOS	Gaussian	Identity
6	RBF 1-50-1	0.990362	0.97683	10405.91	32941.75	RBFT	SOS	Gaussian	Identity
7	RBF 1-37-1	0.987831	0.975186	13135.08	36493.63	RBFT	SOS	Gaussian	Identity
8	RBF 1-32-1	0.975224	0.974205	27806.69	37934.94	RBFT	SOS	Gaussian	Identity
9	MLP 1-39-1	0.981118	0.97662	20294.58	33786.46	BFGS 173	SOS	Tanh	Identity
10	RBF 1-46-1	0.983811	0.978313	17439.77	31670.75	RBFT	SOS	Gaussian	Identity

Source: Authors.

The most significant part of the table is analysed in more detail by means of correlation coefficient analysis (Table 3). The first column lists the network names, the second and third columns show the correlation coefficients on the training and test data, respectively. The training data illustrate how well the network can fit the model to the historical data, and the test data measure the network's ability to predict new values. All these neural networks approach the value of 1, achieve high coefficients, and are therefore sufficiently able to predict wheat prices. The coefficient values in both sets are around 0.97, and the best results are achieved by the RBF 1-50-1 network in row 6, which reached the highest coefficient in both training and test sets.

Table 4 presents the MLP and RBF networks and their statistical characteristics, such as minima and maxima, for each dataset during training and testing of the model. The table shows both the values for prediction and the values of the residuals. The minimum predicted values for the training and test models are between 2,247 and 3,303 CZK/t, which shows the lower end of the price range. On the other hand, the maximum predicted values range from 8,026 to 8,412 CZK/t, which corresponds to the probable price peaks in the data. The lower part of the table contains the mentioned residuals, i.e., the prediction error values. The 5th RBF model 1-50-1 has a very high maximum residual in the training data with a value of 1,021.6, so in some cases, prices may be strongly overestimated. The MLP 1-42-1 model shows the lowest maximum value of 346, indicating its more reliable and stable predictions. The standardized residuals can identify whether the errors are within the normal range, and if the values are close to 0, then the input data are consistent with the predicted values.

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Table 3. The statistics of predictions (Wheat – monthly data 2010-2024)

Statistics	1. RBF 1-37-1	2. MLP 1-42-1	3. MLP 1-38-1	4. MLP 1-45-1	5. RBF 1-50-1	6. RBF 1-50-1	7. RBF 1-37-1	8. RBF 1-32-1	9. MLP 1-39-1	10. RBF 1-46-1
Minimum prediction (Train)	2687.05	2393.68	2246.84	2773.77	2710.58	2521.13	2715.3	2655.5	2412.28	2699.69
Maximum prediction (Train)	8121.22	8103.73	8396.2	8060.28	8278.77	8396.93	8093.17	8390.78	8266.06	8056.28
Minimum prediction (Test)	3302.78	2523.24	2469.74	2807.13	2695.82	2751.09	2971.64	2764.8	2517.31	2747.23
Maximum prediction (Test)	8151	8072.9	8291.6	8036.35	8152.49	8412.28	8026.29	8235.71	8177.69	8028.79
Minimum residual (Train)	-866.705	-448.325	-575.197	-493.361	-859.074	-575.932	-512.118	-686.473	-534.121	-537.375
Maximum residual (Train)	434.088	344.817	486.163	404.414	1021.62	475.164	462.741	603.447	346.863	1311.14
Minimum residual (Test)	-566.805	-711.812	-734.892	-923.941	-911.344	-666.365	-673.014	-727.341	-748.814	-297.172
Maximum residual (Test)	828.674	662.18	497.863	666.31	501.515	708.573	636.169	597.771	476.307	1040.99
Minimum standard residual (Train)	-6.828	-3.345	-3.759	-4.274	-5.572	-5.646	-4.468	-4.117	-3.749	-4.069
Maximum standard residual (Train)	3.42	2.73	3.177	3.503	6.626	4.658	4.038	3.619	2.435	9.928
Minimum standard residual (Test)	-2.933	-3.943	-3.989	-4.742	-4.704	-3.671	-3.523	-3.734	-4.074	-1.67
Maximum standard residual (Test)	4.289	3.668	2.702	3.42	2.589	3.904	3.33	3.069	2.591	5.849

Source: Authors.

The trend of the wheat price from 2010 to 2024 can be seen in Figure 13. Almost all neural networks were able to follow the actual price movement throughout the period under study, except for the RBF 1-37-1 network, which deviated from the actual movement at several intervals. As in the graphs above tracking the wheat price evolution, the largest price fluctuation is noticeable at the end of the period, and the lowest price was at the beginning of the period.

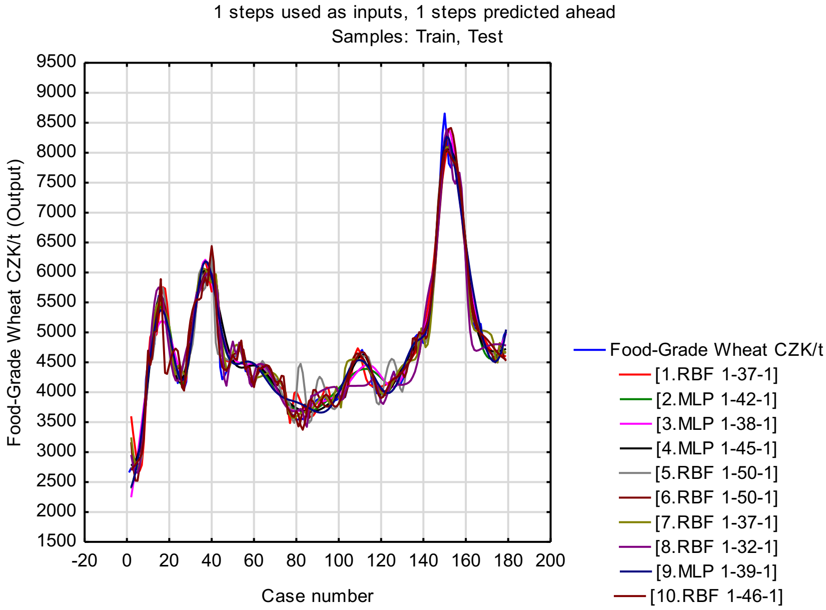

Figure 13. Wheat price trend
Source: Authors.

Table 4 shows the wheat price prediction from December 2024 to December 2025. Again, the different columns correspond to the different neural networks used for forecasting. At first sight, the highest predicted prices and significant fluctuations were given by the 9th network (MLP 1-39-1), while the RBF networks show more stable and lower predictions. The most stable networks are the 5th and 6th RBF 1-50-1, with the values of 4,652.677 (which is constant all the time) and 4,507 (which changes only minimally). Based on the analysis performed, a gradual increase in prices is expected during 2025. The lowest price at the end of the forecast period (4,514.209 CZK/t) is predicted by the 1st network, and the highest price is predicted by the 9th network (16,544.47 CZK/t). The last column shows the actual prices from

December 2024 to February 2025. The actual wheat prices recorded so far confirm the predicted upward trend. The actual price is closest to the prediction of the MLP 1-38-1 network, whereas all the RBF networks underestimated the price.

Table 4. The predicted and actual wheat prices

Date	1. RBF 1-37-1	2. MLP 1-42-1	3. MLP 1-38-1	4. MLP 1-45-1	5. RBF 1-50-1	6. RBF 1-50-1	7. RBF 1-37-1	8. RBF 1-32-1	9. MLP 1-39-1	10. RBF 1-46-1	Real price
01.12.2024	4577.18	5249.73	5193.94	4749.51	4652.68	4512.25	4655.67	4753.63	5617.9	4520.89	5081
01.01.2025	4566.59	5381.72	5316.63	4764.7	4652.68	4510.42	4636.01	4737	6012.67	4516.05	5 739.51
01.02.2025	4556.78	5518.68	5447.8	4780.69	4652.68	4509.3	4620.14	4718.32	6488.35	4514.58	5 714.45
01.03.2025	4548.77	5645.41	5572.84	4795.8	4652.68	4508.68	4608.78	4699.84	6994.32	4515.34	
01.04.2025	4540.98	5787.75	5717.83	4813.25	4652.68	4508.27	4599.03	4677.82	7646.23	4517.7	
01.05.2025	4534.57	5926.31	5864	4830.84	4652.68	4508.05	4591.96	4655.16	8375.43	4520.84	
01.06.2025	4529.07	6069.13	6020.44	4849.78	4652.68	4507.93	4586.6	4630.6	9236.3	4524.42	
01.07.2025	4524.78	6205.94	6176.45	4868.87	4652.68	4507.86	4582.9	4605.94	10177	4527.82	
01.08.2025	4521.29	6344.89	6341.87	4889.4	4652.68	4507.83	4580.22	4579.78	11261.6	4531.03	
01.09.2025	4518.62	6480.49	6511.02	4910.8	4652.68	4507.81	4578.4	4553.17	12458.5	4533.8	
01.10.2025	4516.69	6607.83	6677.81	4932.37	4652.68	4507.8	4577.23	4527.23	13718.3	4536	
01.11.2025	4515.22	6734.77	6852.9	4955.6	4652.68	4507.8	4576.44	4500.42	15114.8	4537.81	
01.12.2025	4514.21	6852.65	7024.61	4979.05	4652.68	4507.79	4575.95	4474.68	16544.5	4539.14	

Source: Authors.

Figure 14 demonstrates the forecasted prices using neural network curves. The horizontal x-axis shows the forecast period from December 2024 to December 2025, and the vertical y-axis represents prices in CZK/t. The yellow curve represents the actual wheat price for the period from December 2024 to February 2025. This illustration better demonstrates that in December, the actual price is closest to the 3rd neural network MLP 1-38-1. In January 2025, it shifted slightly away from this network and closer to the 9th MLP 1-39-1, but this network separated from all networks in February and was the furthest away from the actual price curve. In February, the actual price moved back towards the 3rd neural network.

Figure 14. The predicted and actual wheat prices
Source: Authors.

To assess the reliability of the predictions made, 95% confidence intervals were calculated for individual months of 2025, based on two different approaches.

Table 5. Forecasted wheat prices for 2025 with 95% confidence intervals by two methods

Date	Average forecast	CI (residuals) – lower	CI (residuals) – upper	CI (models) – lower	CI (models) – upper
01.12.2024	4,848.34	4,219.70	5,476.98	4,580.61	5,116.07
01.01.2025	4,909.45	4,280.81	5,538.09	4,553.45	5,265.44
01.02.2025	4,980.73	4,352.09	5,609.37	4,519.20	5,442.26
01.03.2025	5,054.25	4,425.60	5,682.89	4,481.07	5,627.42
01.04.2025	5,146.15	4,517.51	5,774.80	4,429.61	5,862.70

01.05.2025	5,245.98	4,617.34	5,874.63	4,369.34	6,122.63
01.06.2025	5,360.70	4,732.05	5,989.34	4,295.10	6,426.29
01.07.2025	5,483.02	4,854.38	6,111.67	4,210.83	6,755.22
01.08.2025	5,621.06	4,992.42	6,249.70	4,110.38	7,131.74
01.09.2025	5,770.53	5,141.89	6,399.17	3,996.27	7,544.79
01.10.2025	5,925.39	5,296.75	6,554.04	3,873.26	7,977.52
01.11.2025	6,094.84	5,466.20	6,723.49	3,734.20	8,455.49
01.12.2025	6,266.53	5,637.88	6,895.17	3,589.55	8,943.50

Source: Authors.

Note:
CI (residuals) – intervals based on historical model error (constant width, reliable for "normal" behaviour).
CI (models) – intervals derived from variance among 10 models in a given month (width increases when models differ significantly)

The table presents forecasted monthly wheat prices for 2025, including 95% confidence intervals calculated by two different approaches – based on residual analysis and based on variability among individual models.
The intervals derived from residuals (CI – CI-residuals) show a relatively constant width across all months, reflecting the assumption that the historical prediction error remains stable over time. This approach is reliable in periods without significant market disturbances, as it directly builds on past model performance.
In contrast, the intervals derived from the variability of models (CI – models) tend to widen considerably in the later months of the forecast horizon. This behaviour indicates an increasing divergence among the ten models used for prediction as the forecast extends further into the future. The growing interval width captures the fact that uncertainty naturally increases with the length of the forecast period, and the presence of larger discrepancies between models reflects potential sensitivity to different input assumptions or training conditions.
From a practical perspective, narrower residual-based intervals may underestimate uncertainty in volatile or shock-prone markets, while the model-variability-based intervals provide a more conservative and cautious estimate of potential price outcomes. The comparison of both approaches thus offers a more comprehensive picture of prediction reliability, allowing decision-makers to weigh stability against precaution when interpreting forecast results.

To complement the analysis, the residuals of the retained neural network models were also evaluated. The residuals graph (Figure 15) allows us to assess how accurately the models capture the actual price development and to identify any systematic deviations of predictions from real values.

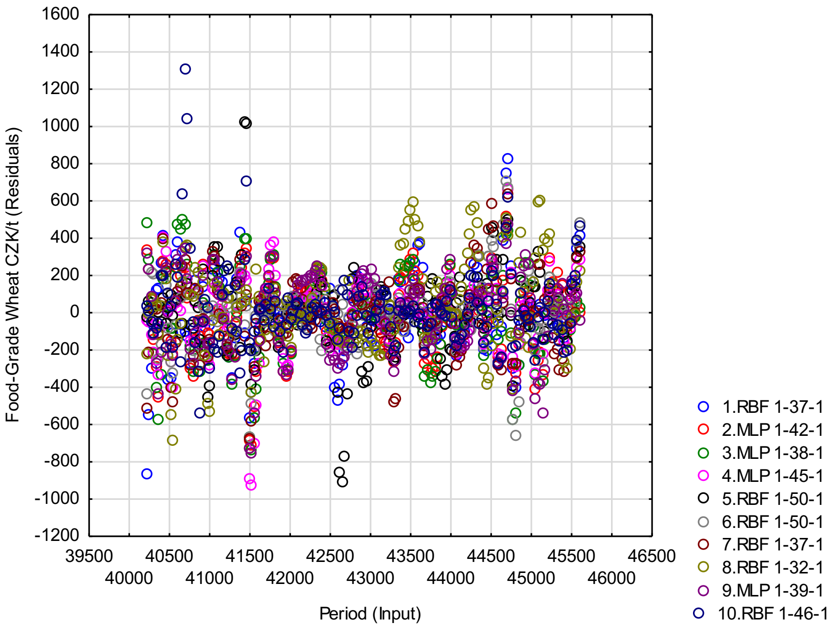

Figure 15. Residuals of retained neural network models
Source: Authors.

The plot of residuals of the retained networks shows the differences between actual and predicted prices of food wheat (in CZK/t) for different neural network models (MLP and RBF).

The residuals range mostly from approximately −1000 to +1000 CZK/t, which indicates that the deviations of predictions from the actual values are relatively flat around zero and do not show a significant systematic trend. This is a good sign, because the absence of significant systematic deviation means that the models do not tend to underestimate or overestimate prices in the long term.

The variance of the residuals is roughly constant over the entire time period (X-axis – input period), which supports the assumption of homoskedasticity, which is important for the reliability of the predictions. However, occasional extreme values (outliers) indicate the influence of unexpected external factors that the models were unable to capture.

Overall, the graph confirms that both types of neural networks (MLP and RBF) achieve similar accuracy, with MLP tending to show slightly less residual variance, which may contribute to more accurate predictions.

Based on the analysis, it can be concluded that models based on linear regression analysis and neural networks show different levels of prediction accuracy. In the framework of linear regression analysis, it was shown that the use of all available functions in statistical software provides a wide range of results, with only some functions approaching the real development of the wheat price. In particular, the spline function achieved a very accurate copying of the real development. This result can be explained by the fact that the spline function is made up of a set of partial polynomials connected at nodal points, which allows it to respond flexibly to local changes in the time series. Thanks to this, it can accurately model both long-term trends and short-term fluctuations caused by, for example, climatic events or geopolitical factors, which global linear or polynomial models cannot do to the same extent.

In the case of neural networks, two types were tested – MLP (Multi-Layer Perceptron) and RBF (Radial Basis Function). Both models demonstrated the ability to reproduce historical development and provide relevant predictions, but more accurate results were achieved with MLP. The reason is the MLP architecture, which uses multiple layers of neurons and nonlinear activation functions, allowing it to capture more complex, nonlinear patterns and interdependencies between factors affecting the price of wheat. The price development of this commodity is conditioned by a combination of long-term trends, seasonal influences, and sudden shocks (e.g., weather changes, trade policies, geopolitical events), which MLP can better model and generalize. In contrast, RBF, although characterized by fast convergence and good accuracy in modeling smooth functions, has a limited ability to adapt to significantly nonlinear and highly variable data, which can lead to lower prediction accuracy in dynamic market conditions.

The results, therefore, indicate that for predicting wheat prices in conditions characterized by a combination of trends and sudden fluctuations, it is more appropriate to use MLP neural networks or spline functions within regression analysis, as both of these approaches can more effectively capture complex market dynamics.

5. Discussion

Based on the analyses performed and the results achieved, the formulated research questions can now be answered, and the study objective thus set can be fulfilled.

RQ1: How did wheat prices develop in the Czech Republic in the years 2010–2024?

The results indicate that wheat prices during the period under review experienced several pronounced shifts. The lowest price was recorded on 1 January 2010 at 2,661 CZK/t. Between 2010 and 2013, prices fluctuated considerably, after which they stabilized and remained at roughly the same level until 2021. Beginning in 2021, prices rose sharply, peaking at 8,654 CZK/t on 1 June 2022, before declining to 5,010 CZK/t as of 1 November 2024. This trajectory confirms that climatic conditions, global demand, and geopolitical factors played a decisive role in shaping the dynamics of this commodity.

RQ2: What events had the most significant impact on wheat prices in the Czech Republic between 2010 and 2024?

The most significant events influencing wheat prices included the global economic crisis of 2007–2015, which reduced commodity exports and altered demand patterns. In 2010, excessive rainfall caused an increase in wheat prices, while in 2012 prices rose as a result of extreme drought. In 2011, the opening of new markets (e.g., cooperation with Ukraine) and, later in 2015, the growth of wheat exports by CZK 3.3 billion played a role. Harvest volumes and demand also proved decisive: in 2011, prices increased because production fell short of demand, whereas in 2014 prices declined due to abundant production of 8.8 million tonnes.
The sharp increase in prices during 2021–2022 was associated with the effects of the pandemic, geopolitical tensions, and rising production costs. The year 2022 was particularly pivotal: the war in Ukraine and the surge in energy and fertilizer prices drove prices even higher (Goyal & Steinbach, 2023). Prices were also influenced by the overpopulation of field voles and the broader impacts of the energy crisis. From 2023 onwards, prices began to decline, mainly due to a surplus of wheat and duty-free imports from Ukraine into the EU. This development demonstrates that wheat prices were shaped by a combination of natural disasters, economic crises, political decisions, and global market forces, consistent with the findings of Sahinli et al. (2021).

RQ3: What price trends can be expected for wheat until December 2025?

Neural network methods, specifically MLP and RBF models, were employed to address this research question. The predictions showed that the minimum expected values for the training and testing models ranged from 2,247 CZK/t to 3,303 CZK/t, while the maximum values reached between 8,026 CZK/t and 8,412 CZK/t. For 2025, prices are expected to rise, with the minimum predicted value at 4,514 CZK/t and the maximum at 16,544 CZK/t. These findings contradict Subhan et al. (2022), who forecast a decline in wheat prices by 2030.

When comparing predicted prices with actual data for December 2024 and January and February 2025, the MLP 1-38-1 model most closely approximated the observed values, whereas all RBF networks consistently underestimated prices. These discrepancies are also evident in the confidence intervals, which highlight the degree of model uncertainty. Intervals derived from residuals provided relatively stable ranges for normal price behavior, while intervals based on variance across models widened during periods of greater divergence in predictions. The results also confirm that the spline function within the linear regression analysis provided the best fit to historical data, reflecting its flexibility in approximating nonlinear price movements. Among the neural networks, MLP models outperformed RBF models, likely due to their superior capacity to capture complex nonlinear relationships in the data. It should be emphasized, however, that the predictions are based on monthly data and therefore do not account for short-term fluctuations that might emerge in daily data. The models also do not reflect unexpected shocks—such as extreme weather events or sudden geopolitical changes—that could significantly alter future outcomes.

The strength of this study lies in the combined application of multiple methods (linear regression, MLP, and RBF neural networks), which allows for a comparison of predictive capabilities across approaches. The results provide insights into historical price developments and offer specific estimates for the future. Nonetheless, limitations include the reliance on monthly data and the inherent uncertainty associated with all predictions. Future research should focus on retraining the best-performing networks with updated data to improve accuracy. Hybrid approaches that integrate neural networks with other time series forecasting methods may also be considered to leverage the advantages of both.

In connection with these results, it is relevant to mention studies that addressed similar topics. Manogna et al. (2025), for example, analyzed 23 agricultural commodities using daily data from 2010–2024 and compared ARIMA, SVR, XGBoost, and various neural network architectures, including MLP, RNN, LSTM, GRU, and ESN. They found that deep neural networks, particularly LSTM and GRU,

achieved the lowest prediction errors due to their ability to capture nonlinearities and temporal dependencies. Wang (2023b) focused on predicting agricultural product prices such as garlic and pork using an improved RBF model, which outperformed traditional statistical approaches in short-term forecasting. Foroutan et al. (2024) examined the prices of WTI and Brent crude oil and precious metals (gold and silver) using 16 machine learning and deep learning models, including TCN, BiGRU, LSTM, and CNN. They found that TCN performed best for oil and silver, while BiGRU was the most effective for gold price forecasting; tree-based models such as LightGBM also served as strong benchmarks.
Guindani et al. (2024) studied short-term agricultural commodity price prediction and showed that relatively simple neural networks, with approximately 20 neurons and two lags, provided the highest accuracy for one-day forecast horizons, suggesting that even small architectures can be highly effective under specific conditions. Pandit et al. (2024) developed a hybrid CEEMDAN-TDNN approach for monthly agricultural price prediction and demonstrated its superiority over alternative models using Diebold–Mariano and Friedman tests. Bora et al. (2024) focused on multi-step forecasting of agricultural commodity prices and confirmed that deep neural networks maintained higher accuracy than traditional models even at longer horizons. Qiu et al. (2024) took a different perspective, predicting polyester yarn prices using multiple linear regression and the Holt–Winters model. Their findings showed that, with proper specification, linear regression can serve as a transparent, interpretable, and robust baseline model for comparison with more complex approaches.

6. Conclusions

Wheat, as a fundamental agricultural commodity, plays a crucial role in daily life, and accurate price identification and forecasting are essential to ensure a stable supply and to mitigate adverse market impacts. The aim of this paper was to analyze wheat price trends in the Czech Republic from 2010 to 2024 and to forecast their development through December 2025.
The analysis of price dynamics during 2010–2024 revealed that the Czech wheat market exhibits marked cyclical fluctuations, shaped by a combination of natural, economic, and geopolitical factors. In the early years of the period (2010–2013), frequent price volatility was observed, driven by developments in world markets, shifts in domestic and foreign demand, and the effects of extreme climatic events such as excessive rainfall and drought. This was followed by a relatively stable phase lasting until 2021. From 2021 onward, prices rose sharply, peaking in June 2022 at

8,654 CZK/t. This increase resulted from a combination of factors, including restrictions on international trade due to the COVID-19 pandemic, rising energy and input costs, and, most importantly, the outbreak of the war in Ukraine. Since 2023, prices have gradually declined, partly due to surplus supply and liberalized imports of Ukrainian wheat into the EU.

The forecasting component of the study applied multilayer perceptron (MLP) and radial basis function (RBF) neural networks to estimate wheat prices through December 2025. The MLP 1-38-1 model achieved a lower average deviation from actual prices in the testing period compared to RBF models, indicating its superior ability to capture nonlinear relationships in the data. Both models predict continued growth in wheat prices in 2025, with an estimated range between 4,514 CZK/t and 16,544 CZK/t. This wide interval reflects the high degree of uncertainty inherent in commodity market forecasts, driven by unstable climatic conditions, fluctuating global demand, and geopolitical shocks.

The results align with the conclusions of many recent empirical studies, which likewise identify climate anomalies, economic crises, and political decisions as key determinants of agricultural commodity prices. (A synthesis and comparison with selected contemporary studies will be added here.)

Although all research questions were addressed, several limitations should be acknowledged. The analysis relied on monthly data for 2010–2024, which may have smoothed short-term shocks and reduced sensitivity to abrupt market changes. The relatively short prediction horizon (through 2025) also limits the ability to capture long-term structural transformations. Moreover, the neural network models applied—MLP and RBF—require extensive historical data, are sensitive to input quality, and may be prone to overfitting if not properly optimized.

From a practical perspective, the findings offer useful input for agricultural and trade policy, particularly in the areas of market stabilization and food security. For risk management, it is essential to consider the effects of climate variability, geopolitical crises, and shifts in international trade in order to prevent sharp price shocks and to support more informed purchasing and selling strategies. Within the Czech Republic and the EU, potential policy measures include the creation of strategic reserves, diversification of export markets, and the development of financial hedging instruments against price volatility.

Future research should extend this work in two main directions. First, retraining the best-performing neural networks with new data could further enhance predictive accuracy. Second, integrating neural networks with other time series forecasting approaches—such as econometric or hybrid models—may help capture the complex dynamics of cereal markets more effectively. These steps could contribute to the development of a more robust forecasting tool, supporting strategic decision-making by producers, traders, and policymakers alike.

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Author Contributions
J.H. conceived the study and was responsible for the design and development of the data analysis, using software, writing the original draft, project administration, and supervision. J.K. was responsible for the formal analysis, visualization, literature review, writing, review and editing, and funding.

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Appendix

Appendix No. 1. The most important empirical studies

Author	Methods used	Main findings	Research gap	Study limitations
Theofilou et al. (2025)	Systematic review + ML methods	Insufficient use of ensemble learning in wheat price prediction	Lack of comparison between models in different regions	Focused primarily on rice and corn

Harish Nayak et al. (2025)	Metaheuristics + AI	Accurate prediction of commodity prices thanks to hybrid algorithms	Detailed testing on a specific crop, like wheat, is lacking	The study includes multiple commodities, not specifically wheat
Shobande & Shodipe (2021)	DSGE-VAR model	Corn prices adjust by only 2% per year, and state interventions harm the market.	Listed for corn – wheat missing	Does not address global influences, data only up to 2017
Manogna et al. (2025)	Deep learning	Improving the accuracy of commodity price predictions	Does not address economic implications. Improving the accuracy of commodity price predictions	No geographical scope specification
Abid et al. (2025)	AI models	The conflict has strongly affected commodity prices	No predictions for the future, just descriptions	Focused more on war shock than structural trends
Xu, X., Zhang, Y. (2023)	Auto-regressive neural network	Provided accurate predictions of weekly wholesale edible oil prices even under high volatility, confirming the suitability of NN for commodity forecasting	Application of the approach to other commodity markets	Focused only on the edible oil market in China; limited to weekly data
Wang, Y. (2023)	Improved RBF neural network	Outperformed traditional statistical methods, effectively capturing nonlinear time series behavior in agricultural product prices	Extension to a broader range of agricultural and non-agricultural commodities	Tested on a limited set of agricultural products; short prediction horizon
Hao, X., Li, X., Zhang, H. (2020)	Linear regression (LASSO, Ridge, Elastic Net) with robust loss functions	Demonstrated that properly specified linear regression is a stable and reliable tool for economic forecasting	Potential integration with nonlinear models for improved accuracy	Focused only on crude oil prices; did not test alternative AI models
Butler, S., Han, S., Piotr, P. (2021)	Multilayer feed-forward neural network (MLP)	Achieved better results than conventional	Exploration of longer prediction horizons	Focused only on crude oil prices; did not test

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		models in short-term crude oil spot price direction prediction (1–3 days)	and other commodity markets	alternative AI models

Source: Authors.

Appendix No. 2. Calculations of functions according to the given formulas

$$Y = a + bx, \tag{1}$$

where: Y – predicted value; x – independent variable; a – absolute member (intersection with the y-axis); b – regression coefficient (gradient of the line). Polynomial regression is a linear function extended by higher powers of the independent variable.

$$Y = a + b_1x + b_2x^2 + b_3x^3 + \cdots + b_nx^n, \tag{2}$$

where n refers to the degree of the polynomial. A logarithmic regression will examine how the variable x affects y on a logarithmic scale. The formula is shown below:

$$Y = a + b\,ln(x), \tag{3}$$

where ln(x) will be the natural logarithm of the input variable. Exponential regression will be used for data with exponential growth or decline. The formula is as follows:

$$Y = ae^{bx}, \tag{4}$$

where e will be Euler's number. The Distance Weighted Least Squares method will assign weights to data points according to the distance from the predicted point. The wi weights take into account the precision or importance of each measurement.

$$S_w(\beta_0, \beta_1) = \sum_{i=1}^{n} w_i\,(y_i - \hat{y}_i)^2 = \sum_{i=1}^{n} w_i\,(y_i - \beta_0 - \beta_1 x_i)^2 \tag{5}$$

The Distance Weighted Least Squares and Negative Exponential Weighted Least Squares will then exponentially smooth the values. This method is primarily intended for short-term time series forecasting. For the negative expression, weights are applied to the previous equations, where α is a constant and t_i is time:

$$w_i = e^{-\alpha t_i}, \tag{6}$$

Spline regression will divide the data into segments and use a different polynomial function for each of them. The formula is below:

$$y = \sum_{c_1+\cdots+c_p=0}^{k} \beta_{c_i \ldots c_p} \prod_{i=1}^{p} x_i^{c_i} + \sum_{s=1}^{p} \sum_{t_s=1}^{a_s} \beta_k^t (x-\delta)^k + \varepsilon \tag{7}$$

The last method of the regression function is LOWESS (Locally Weighted Scatterplot Smoothing). It will produce a smooth curve using a weighted regression function:

$$\hat{y}(x) = \hat{\beta}_0 + \hat{\beta}_1 x \tag{8}$$

The neural network method will be applied to forecast the commodity prices. Neural networks can be understood as mathematical methods inspired by the functioning of the human brain, and they form the foundation of artificial intelligence. This method is used not only to predict trends (forecasting) but also for pattern recognition and dealing with complex problems. The forecast will be carried out by means of Statistica software version 14.0.0.15 from TIBCO Software Inc. (2020), into which the commodity prices will be uploaded. An MLP (Multi-Layer Perceptron) model will be applied for the calculation of the prediction, which is one of the most commonly used types of neural networks and the information in it passes only in one direction (from input to output), i.e. the input layer receives the historical prices of the commodity, the hidden layers between input and output recognize the complex relationships in the data and the output layer gives the predicted price. The mathematical expression of the MLP model is shown in (9):

$$y(\vec{x}) = \sigma(\sum_{i=0}^{n} w_i x_i) \tag{9}$$

Another model will be an RBF (Radial Basis Function), which focuses on measuring the distance between data points and neuron centres, so each neuron represents a centre, and the input data is then compared to these centres, and the closer the input is to the centre, the higher weight it then gets in the prediction. The mathematical expression of the RBF model is as follows:

$$y(\vec{x}) = e - (\frac{||\vec{x} - \vec{c}||}{b})^2 \tag{10}$$

Then, the data are divided into a training set representing 70% of the data and a test set (the remaining 30% of the data). Once the model is set up, the training model will be run to find the optimal weights between neurons. The process will be repeated until the desired accuracy of the data is achieved. For the research, 1,000 neural networks will be used, of which only the ten networks showing the best characteristics will be retained. The hidden layer of the MLP will contain 2 to 50 neurons, and the hidden layer of the RBF will also contain 2 to 50 neurons. Logistic, identity, tangent, exponential, and sine functions will be used to activate the hidden and output layers of the MLP. The calculated wheat price predictions will be compared to the actual prices, and the difference will be represented by residuals.

Appendix No. 3. Activation functions of the hidden and output layers of the MLP and the RBF

Function	Definition of the function	Range of the function
Logistic	$P(t) = \frac{1}{1+e^{-1}}$	$(0; 1)$
Identity	a	$(-\infty; +\infty)$
Tangent	$tgx = \frac{\sin x}{\cos x}$	$(-\infty; +\infty)$
Exponential	e^{-a}	$(0; +\infty)$
Sine	$\sin(a)$	$[0; 1]$

Source: Šuleř & Machová (2020).