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ARTICLE

Price Volatility and Prediction of Rapeseed as a Market Commodity

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ABSTRACT

The price movement of agricultural commodities is decisive for producers and consumers. Rapeseed is one of the essential sources of proteins, vegetable oil and biofuels in European agriculture. Predicting and analysing its price movement is vital for effective economy, considering climate change, growing demand and geopolitical uncertainty. The article aims to analyse the rapeseed price movement in the Czech Republic from January 2010 to November 2024, forecasting the further price trend through December 2025 based on historical data. We used content analysis, linear regression, MLP and RBF neural networks for the predictions. The data come from publicly available monthly statistics of agricultural commodity prices. Our results show a steadily growing trend in rapeseed prices, peaking at 19,887 CZK/t in 2022, when the effects of the COVID-19 pandemic and war in Ukraine had dramatically swayed the price movement. Regression analysis confirmed an increasing trend, revealing a period with an accelerated price hike between 2020 and 2022. We used MLP and RBF neural networks for forecasts. MLP indicated the most accurate results with the values closest to the real prices between December 2024 and February 2025, while RBF neural structures tended to underestimate reality. The predicted movement suggests that the rapeseed price will be growing, which may affect the behaviour on purchasing, selling or warehousing this strategic commodity.

Keywords: Price Movement; Price Prediction; Rapeseed; Neural Networks; Agriculture

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1. Introduction

Agricultural commodities are vital for the functioning of modern society, offering a large assortment of goods to feed people and ensure sustainable economic growth. The price fluctuation of these commodities may severely undermine macroeconomic stability, manufacturing processes and the standard of living [1]. The commodity market plays a key role in global competition and industrial chains, badly suffering from any global-scale economic instability.

Commodity prices are essential for farmers, merchants, investors and consumers to decide upon producing, selling or buying, which requires a real-time analysis [2]. Agriculture is indispensable for social and economic development, relying heavily on political and economic stability [3].

Marked deviations in agricultural commodity prices increase risk, threatening the stability of domestic and global markets. Economic policy should focus primarily on analysing the price rise of consumer goods. The government is responsible for price regulation to curb violent market fluctuations and protect producers and consumers [4]. Price variations are especially punishing to developing economies, whose market mechanisms may encounter serious obstacles [5]. The impacts of price fluctuations are reflected in business relationships, employment rates and globalization dynamics [6].

In recent years, climate change has been a major factor influencing the volatility of agricultural commodity prices. Extreme events such as long-term droughts, floods or unusual temperature fluctuations have a significant impact on yields and increased market risk. The result is not only greater uncertainty for farmers, but also higher volatility in global markets, as price movements are quickly transmitted between regions through world trade. Public policy therefore plays a significant role—states and the European Union are introducing risk management tools, such as crop insurance or support mechanisms within the Common Agricultural Policy. While these interventions cannot eliminate fluctuations themselves, they can mitigate their negative impacts on producers' incomes and market stability [7].

Highly susceptible to meagre commodity portfolios, agricultural markets are vulnerable to price variations, changes in global demand or trade barriers [8]. Stable markets benefit from various aids like production supports, grants, price regulations and subsidies for countryside producers and consumers [9].

As price fluctuations are unavoidable, future price movements should be accurately predicted. Modern methods based on machine learning and deep learning algorithms (e.g. neural networks) have proved successful in modelling time series and estimating future trends [10]. A timely prediction helps farmers better plan sales strategies and decide when to enter the market to generate the highest profits [11,12].

External factors like climate changes, macroeconomic conditions or political and health crises also significantly affect the rapeseed price movement. The recent years have seen striking price fluctuations triggered by an escalating global food crisis, the COVID-19 pandemic and war in Ukraine [13]. These unfortunate incidents severely disrupted supply and demand, causing an increase in price fluctuation in global markets.

As an essential global oil plant, rapeseed cultivation requires advanced techniques, i.e. replacing obsolete technologies with modern equipment to increase yields and ensure distribution. Recent research suggests that chlorophyll levels contained in plants may encourage rapeseed planting and monitor its growth in real time [14]. The cultivation of rapeseed has been enhanced many times since 1970, e.g. by removing erucic acid, lowering glucosinolate content, increasing seed yield and quality and developing resistance against diseases. Although these improvements made rapeseed one of the most globally produced oil plants, such bred oilseed rape significantly reduced the genetic variety of winter rapeseed [15]. The long process of domestication gave rise to three ecotypes—winter, half-winter and spring plants, with different requirements for low temperatures for bloom initiation [16]. Given increased agricultural input and yield, raising winter rapeseed is more eco-friendly than the spring oilseed plants [17]. Growing rapeseed is nitrogen-intensive and the amount of applied nitrogen significantly influences the number of blossoms. Rapeseed is a source of oil and proteins in food and industrial sector, as a medicine or decoration as it comes in various colours [18]. All its parts (bloom, seeds, stalk, leaves and roots) are usable, even as biowaste for feeding animals or further recycling. Seeds, the most important part of the plant, are used in oil manufacturing. Tofanica [19] describes rapeseed as an essential economic and eco-friendly renewable source. The oilseed plant is primarily used as a natural resource of oil and proteins in the food industry. Its stalks are a valuable source of cellulose fibers in the paper-making sector.

Forecasting crop and rapeseed yields has recently involved unmanned airplanes and spectral sensor technologies, shooting plants in the stage of seedling, budding, blooming and seedpod. The correlation analysis and observation of main components [20] helped predict the crop yields using random forest regression, multiple linear regression and support vector machine learning, revealing strong potential of the airplanes to accurately forecast large-scale crop yields compared to traditional methods [20]. From 2007 to 2019, the rapeseed and sunflower saw the most enormous increase in selling prices triggered by buoyant demand for these products when Romania joined the European Union and new agricultural market opened [21]. Simotova et al. [22] analysed the price movement of wheat and rapeseed in 2017–2022, reflecting the impact of the COVID-19 pandemic on the commodities. The correlation and descriptive analysis revealed a low linear correlation between commodity prices and emergencies.

Although tricky, predicting the prices of agricultural commodities is an important task largely contributing to a sustainable management of agricultural production, market decision-making and economic policies. An accurate estimate of the future price movement allows efficient fund allocation, risk management and strategic planning [23]. The recent years have seen the development of advanced analytical tools, including combined machine learning models overcoming the limitations of traditional statistical approaches. Sun et al. [24] confirmed that integrating multiple models like regressive analysis, Gray model, time series analysis or neural networks (ANN) leads to a more accurate prediction of absolute values and future trends.

From machine learning methods, we mostly use ANN, LSTM and CNN neural networks, Random Forest or supporting vectors. They accurately model non-linear relationships, consider complex connections between input variables and involve factors like weather, production data and trade volumes [25,26]. Dharmayanti et al. [27] suggest using multiple linear regression for price predictions including subtractions and production volumes, helping farmers make decisions.

LSTM models may also involve a dual input (DIA-LSTM), enabling to process multiple variables within time series including meteorological data to make the forecasts more robust [27]. Combined approaches incorporate external factors like climate changes, water shortage or inflation into two-phase hybrid models to simulate futures prices [28,29]. Macroeconomically, predictive models forecast food and overall inflation better than traditional reference prototypes [30,31]. The study argues that although the commodity prices may fuel inflation, they are highly unreliable for predicting overall inflation rates.

Neural networks remain the most popular tool for predictions. Thanks to their adaptability to data variability, they are more accurate than common economic models [32,33]. Significantly boosting the economic income and maintaining market stability, forecasting is imperative for farmers, traders, investors and policy makers.

Therefore, this article aims to analyse the price movement of rapeseed in the Czech Republic from January 2010 to November 2024 and to predict its trend through December 2025. In order to achieve the stated aim and increase the reliability of the study, the following research questions (RQ) are formulated:

RQ1: Was the price of rapeseed volatile or stable in the Czech Republic from 2010 to 2024?

RQ2: Did the COVID-19 pandemic and the war in Ukraine between 2022 and 2024 play a significant role in the price movement of the rapeseed?

RQ3: Can the price movement of the repassed be expected to grow through December 2025?

2. Literature Review

Agricultural production and commodity markets represent a key segment of the world economy, which has long been exposed to significant risks. These risks arise both from natural factors and from market conditions and the political environment. In recent decades, climate change, biodiversity loss, and increasing market globalization have been added to traditional risks, jointly amplifying price volatility and complicating the prediction of agricultural commodity developments [34–36]. Building a theoretical framework therefore requires an examination of economic models of risk and empirical studies that have investigated these phenomena. The first significant contributions to the issue of risk and uncertainty were made by economists Arrow [37] and Pratt [38], who laid the foundations for the analysis of risk aversion and the optimal allocation of the risk burden. These works became the starting point for the development of theories later applied in agricultural economics. Akerlof's study [39] is a fundamental work for understanding information asymmetry, showing how the lack of information can affect market efficiency and lead to price distortions. These theoretical approaches remain the basis for modeling risks in agricultural markets. This assumption of theoretical approaches immediately provides space for reflection in accordance with the hypothesis that rapeseed prices will show relatively stable growth until 2022 despite the remote price.

H1. *The price of the rapeseed was growing steadily and stably from 2010 to 2022 before the COVID-19 pandemic and the war in Ukraine occurred in 2022.*

Since the 1970s, agricultural economists have developed specific models for analyzing crop yields. Just and Pope [40] and later Antle [41] introduced methods that allowed better capturing of yield distributions and evaluating ex-ante risk management strategies. Their work emphasized that simple analysis based on mean and variance is insufficient, because extreme values at the lower end of the distribution can significantly affect production stability [42–46]. From this, a long-standing theoretical framework for price stability emerges, which is again the subject of hypothesis H1.

In recent decades, increasing attention has been paid to the impacts of climate change and spatial variability. Ray et al. [45] demonstrated that in many regions yield growth is stagnating, which increases the risk of underproduction. Similarly, Lobell [46] and Nelson et al. [47] warned that rising temperatures and more frequent extreme events have the potential to disrupt production stability significantly. Statistical evidence of the negative impacts of climate change on cereal yields was provided by Gammans et al. [48], while Bukovsky and Mearns [49] showed that climate shifts also affect comparative advantages and land use patterns. These studies demonstrate that climate risks have both production and market consequences. These findings from the literature thus support our hypothesis, which proposed that unforeseen events such as the COVID-19 pandemic and the war in Ukraine had a dramatic impact on the price of rice.

H2. *The COVID-19 pandemic and the war in Ukraine did provide a dramatic effect on the price movement of the rapeseed between 2022 and 2024.*

In addition to climate change, spatial variability also plays a crucial role. Jones et al. [50], Amundson et al. [51], and Stevens [52] highlighted that soil fertility and agro-climatic conditions vary substantially between regions, making it difficult to develop uniform yield models. A recent review by Frew et al. [53] showed that contemporary agriculture faces simultaneous shocks across "breadbasket" regions, with immediate implications for global food prices. Assuming these findings, it is possible to establish an argument that commodity prices react jumping to combinations of natural and geopolitical shocks.

Another important area of research concerns the role of technology and innovation. Ciliberto et al. [54] showed how the introduction of genetically modified varieties in the USA increased productivity and reduced yield risk. Fuglie and Walker [55] analyzed economic incentives in breeding and emphasized the different roles of the public and private sectors. These studies confirm that innovations can function as a stabilizing tool, but their impact is differentiated by region and commodity. This area will certainly open space for consideration in support of hypothesis, that the price of rapeseed in the construction industry is growing, and this is due to innovative and technological factors.

H3. *The price movement of the rapeseed is expected to grow through December 2025.*

Public policy plays an equally important role. Zhang et al.[56] showed that reforms of the EU Common Agricultural Policy led to the expansion of public support instruments for risk management, particularly through insurance schemes and mutual funds. This confirms that, in addition to market mechanisms, institutional intervention remains a crucial factor in stabilizing farmers' incomes. This conclusion again follows on from the previous statement, as it suggests that price developments until 2025 will depend not only on the market, but also on public policy measures.

In summary, research on agricultural risks has gradually shifted from general economic models of risk to sophisticated empirical studies that account for spatial variability, climate change, and market globalization. This theoretical framework provides a necessary basis for analyses of price volatility and predictions of agricultural commodity developments. The results of previous studies clearly show that the combination of natural and market risks will continue to pose a major challenge.

3. Materials and Methods

3.1. Data

We use content analysis to collect relevant data from online sources, including the websites of the Czech Statistical Office and the State Agricultural Intervention Fund, observing the price movement of the rapeseed from the monthly reports like the Report on the breakfast cereal, oil plant and fodder market issued by the State Agricultural Intervention Fund[57]. In this case, we analyse the time series of prices in CZK per tonne, relating to the first day of the month.

The data involve the following monthly issues: 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. We use Burzovní zpravodajství[58] websites to calculate rapeseed prices for January and February 2025, converting the resulting values in Euro to CZK according to the exchange rate applicable to 2nd March 2025 (25.0634 CZK/EURO).

We conduct the content analysis from 1st February 2025 to 10th March 2025, focusing on the period between January 2010 and November 2024. We analyse the reports of the Ministry of Agriculture[59], exploring the events affecting the price movement of rapeseed like observable climatic phenomena (natural disasters), the international trade with agricultural products, grant policies and other impactful circumstances. Other sources involve news portals ČT24[60], Atuálně.cz, the Czech Association of Trade and Tourism or Czech Association of Private Agriculture.

3.2. Methods

Upon conducting the content analysis, the gathered data are processed in MS Excel into tables and graphical depictions. Aligning the monthly values into the table allows us to observe the price movement of rapeseed, forming a graph illustrating a trend of its price dynamics. We use linear regression analysis and neural networks for the data analysis.

The procedure involves linear regression analysis, exploring the accuracy of the given function to mimic the time series of the given commodity. The method also includes a price movement prediction based on available historical data, rather than forecasting future values. The analysis involves testing various types of regressive functions like linear, polynomial, logarithmic, exponential, Distance Weighted Least Squares, Negative Exponential Weighted Least Squares, spline and LOWESS. The functions are calculated from the formulas below:

$$Y = a + bx, \quad (1)$$

where:

Y —predicted value;

x —independent variable;

a —absolute value (intersection with y axis);

b —regressive coefficient (line direction)

Polynomial regression is basically an expanded linear function by higher powers of the independent variable.

$$Y = a + b_1x^1 + b_2x^2 + b_3x^3 + \ldots + b_nx^n, \quad (2)$$

where n means a polynomial degree

Logarithmic regression explores the influence of x variable on y on a logarithmic scale. The formula is as follows:

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

Where ln(x) is a natural logarithm of the input variable.

Exponential regression is used for exponentially growing or decline. The formula is as follows:

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

Where e is Euler's number

Using the weighted least squares, we assign weighs to the data points according to the distance from the predicted point. The weights w_i consider the accuracy or importance of each measurement.

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

The negative exponential weighted least squares exponentially smooths the values, accurately predicting short-term time series. We use the weights where α is a constant and t_i is time for a negative expression of Formula 7.

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

Spline regression divides the data into segments with a different polynomial function. The formula is a s follows:

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

LOWESS (Locally Weighted Scatterplot Smoothing) smooths the curve using a weighted regressive function.

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

Accurately predicting the prices of the agricultural commodity, artificial neural networks involve a mathematical tool inspired by the human brain to create a fundamental component of artificial intelligence. Neural networks forecast trends, devise formulas and solve complex equations. In this research, we use Statistica software 14.0.0.15 developed by TIBCO Software Inc. (2020) to upload the commodity price data.

We apply MLP (Multi-Layer Perceptron) model to make a prediction, one of the most globally used types of neural networks. The model acquires data into the network through an input layer, passing through one or more hidden layers processing and interconnecting the data, and continuing into an output layer which makes the final prediction. The information is a one-way flow—from the input to the output. The input layer loads historical prices of the commodity, hidden layers analyse their interrelationships, and the output layer predicts the price. The mathematical formula of the MLP is as follows:

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

RBF (Radial Basis Function) focuses on measuring the distance between the data points and neural centres, i.e. each neuron represents a centre compared with the input data points. The inputs closer to the centre weigh more in the final prediction. The formula is as follows:

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

The dataset involves two parts: a training set comprising 70% of the total data and test set including 30%. When our model is configurated, we launch the training phase, optimizing weighted parameters between the neurons. The cycle repeats until we achieve the required prediction accuracy. Our analysis generates 1,000 neural networks, of which the ten best structures will continue in our experiment.

The number of neurons in hidden layers oscillates between 2 and 50 in both –MLP and RBF. We use various functions for activating hidden and output layers in the MLP model, including a logistic, identity, tangents, exponential and sinus functions (**Table 1**). The final predicted rapeseed prices are compared with real values. the differences between these two datasets are labelled as residues.

Table 1. Activation functions of hidden and output layers of MLP and RBF.

Function	Definition	Extension
Logistic	$P(t) = \frac{1}{1+e^{-1}}$	$(0;1)$
Identity	a	$(-\infty;+\infty)$
Tangents	$tgx = \frac{\sin x}{\cos x}$	$(-\infty;+\infty)$
Exponential	e^{-a}	$(0;+\infty)$
Sinus	$\sin(a)$	$[0;1]$

Source: Šuleř and Machová [61].

4. Results

The following part presents the conducted analyses.

4.1. Externalities Involved in the Price Movement of Rapeseed

The content analysis suggests climate changes, international trade and regulatory interventions as decisive factors influencing the price movement of the rapeseed. In 2011, the Czech Republic started to cooperate with Ukraine in renewable energy sources, using the plant for making biofuels. The partnership opened new export opportunities, dramatically changing price dynamics.

The rapeseed price topped 17,685 CZK/t on the Parisian stock market in 2021, narrowly defeated by China where the price soared to 19,000 CZK/t. Given the increasing demand for rapeseed oil and decline in sowing areas, the Czech prices settled at 10,885 CZK/t. Abiding by the EU environmental regulations, cultivable acreage witnessed a decrease by 11%.

February 2022 saw an outbreak of the war in Ukraine and a subsequent energy crisis, observing a further increase in input costs and the rapeseed price soar to 19,000 CZK/t. Although 2023 marked a price stabilization, the repercussions of the previous crises were still globally felt. The prices were subject to water availability, duty-free import and cultivators' preferences, who favoured less labour-intensive crops, including rapeseed.

4.2. Rapeseed Price Movement

Table 2 suggests the general data characteristics including the descriptive statistics of rapeseed prices.

Table 2. Descriptive statistics of rapeseed.

Descriptive Statistics	Rapeseed
Mean value	10,841.60894
Mean value error	163.2973323
Median	10,313
Modus	11,830
Standard deviation	2184.769405
Variance	4,773,217.352
Minimum	6799
Maximum	19,887
Number	179
Confidence interval (95.0%)	322.2478346

Source: author [62].

Table 2 suggests that the minimum price of rapeseed was 6799 CZK/t and over the monitored period, reaching the maximum of 19,887 CZK/t. The most frequent value (modus) was 11,830 CZK/t. other indicators include the mean value, error mean value, median, standard deviation, variance, number of observations and confidence interval.

Figure 1 illustrates the price movement of rapeseed from 2010 to 2024.

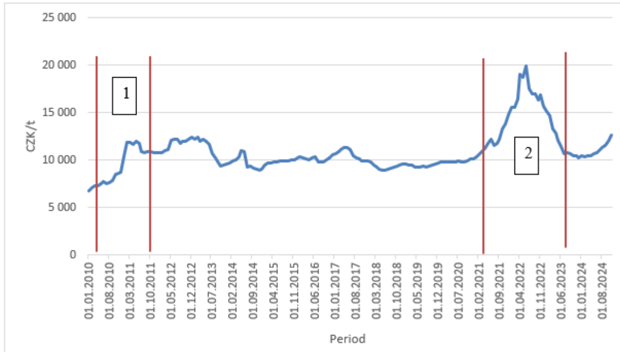

Figure 1. Price movement rapeseed.

Source: author data [33].

Figure 1 shows the lowest price 6,799 CZK/t at the beginning of the monitored period. The rapeseed price did not see an increase to 11,830 CZK/t until March 2011, settled until 2020. The period between 2013 and 2014, and 2016 and 2017 saw only mild fluctuations to witness a price hike in 2021, soaring from 10,342 CZK/t to 19,887 CZK/t in June 2022. The price suffered a decline to 10,263 CZK/t in December 2023 to see a slight rise to 12,608 CZK/t in November 2024. The period between 2021 and 2023 witnessed the most violent fluctuations, reflecting the aftermaths of the COVID-19 pandemic, war in Ukraine and increased input costs. At the beginning of the period, the price rise mimicked the economic crisis.

4.3. Linear Regression Analysis

The following scatterplots illustrate the price movement of rapeseed in CZK/t in time. The x axis represents the monitored period and y axis the price value. The blue dots mimic the price value over the monitored periods, while the dashed red lines in **Figure 2** set the limits for the predicted prices. The full red line illustrates the function. Scatterplot 2 (linear function) suggests a steady price rise in time based on the formula y = 13,453.4018 + 0.5665 x. None of the scatterplots 2, 3, 4 and 5 reflect reality, significantly deviating from the real price movement. None of the functions incorporate local minimums and maximums.

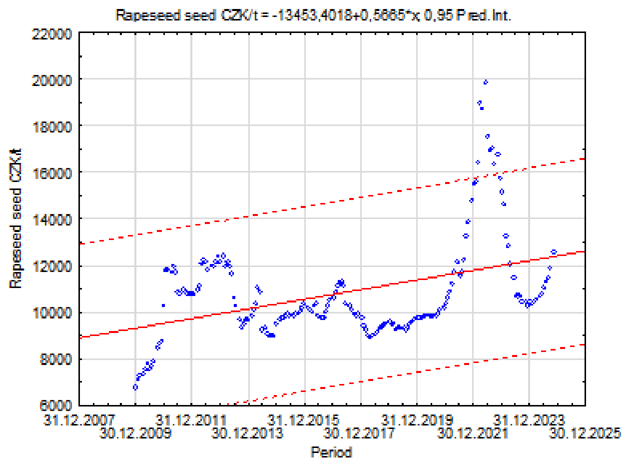

Figure 2. Price movement rapeseed.

Linear regression.

Although the curvature makes the polynomial regression in **Figure 3** more flexible than the linear function, it does not have to be suitable for long-term predictions. Its function is y = 2.6666E5−12.5141*x+0.0002*x^2 .

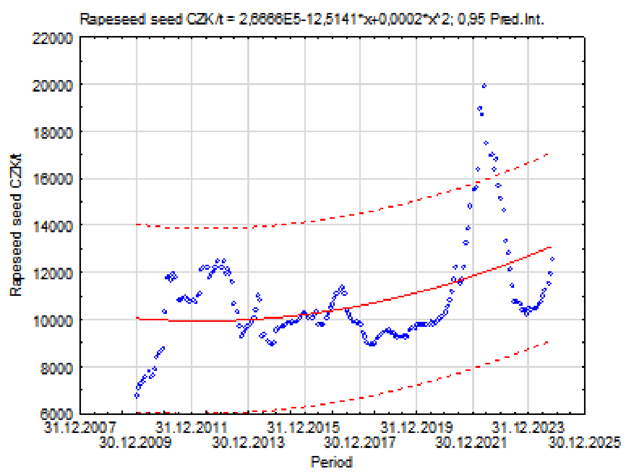

Figure 3. Polynomial regression.

The same as the linear function, the logarithmic function y = −2.4641E5+55537.7196*log10(x) in **Figure 4** fails to detect violent price fluctuations.

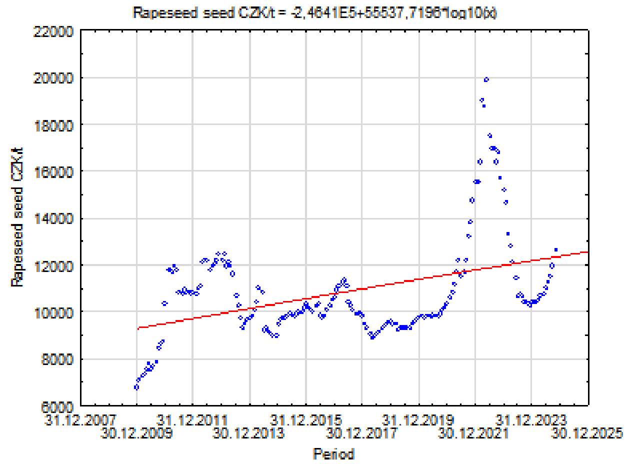

Figure 4. Logarithmic regression.

Although the exponential function y = 1312.5204*exp(4.8826−5*x) depicted in **Figure 5** is usually suitable for the accelerating price rise in time, the function failed to identify local extremes.

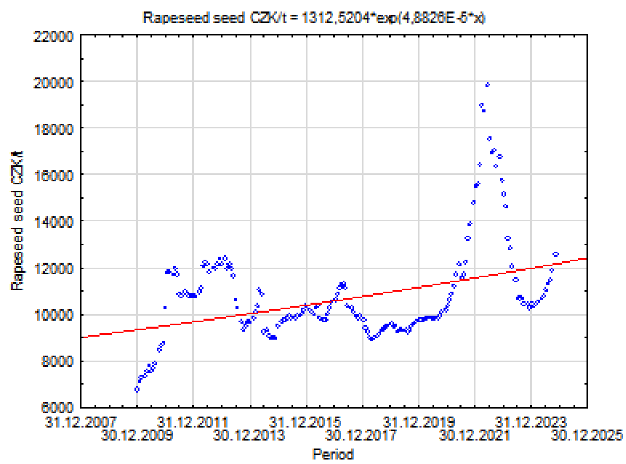

Figure 5. Exponential regression.

The weighted least square method (**Figure 6**), negative exponential weighted least square method, spline regression and LOWESS track the real price movement the closest.

The negative exponential weighted least square method in **Figure 7** smooths the data, contrasted to the Distance Weighted LS method.

Spline regression in **Figure 8** accurately tracks the price movement of the rapeseed, eclipsing distant vales.

LOWESS function in **Figure 9** indicates a substantial distance between the blue dots and red curve of the function between 2021 and 2023.

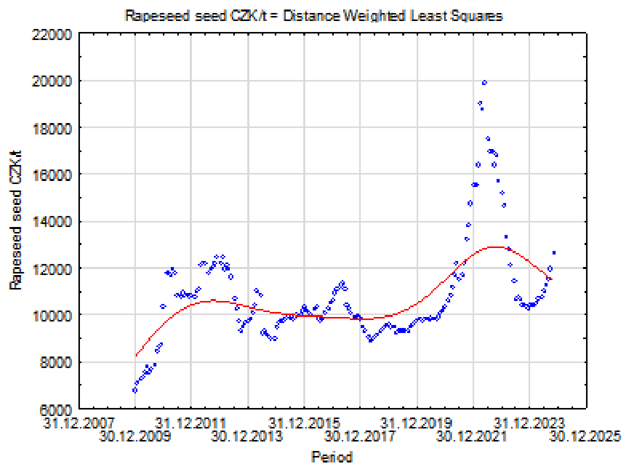

Figure 6. Distance Weighted Least Squares.

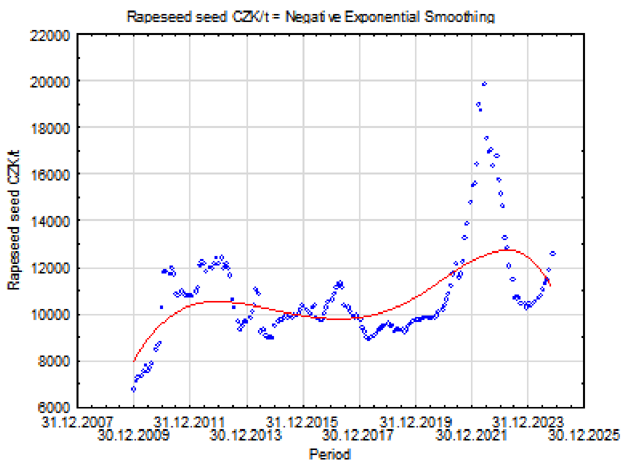

Figure 7. Negative Exponential Weighted Least Squares.

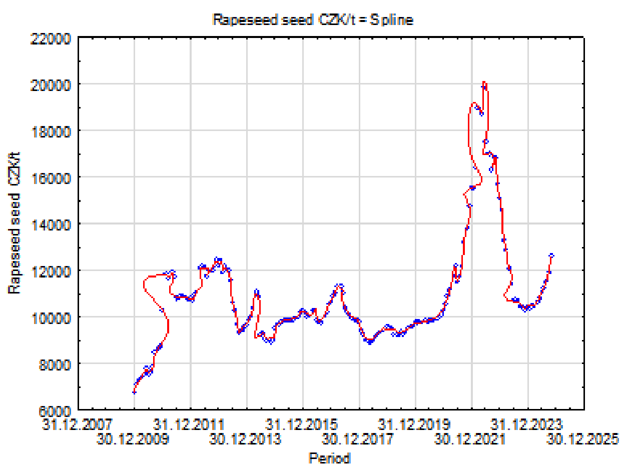

Figure 8. Spline regression.

The curves in **Figures 6, 7** and **9** do not mimic local extremes, preserving their specific shape.

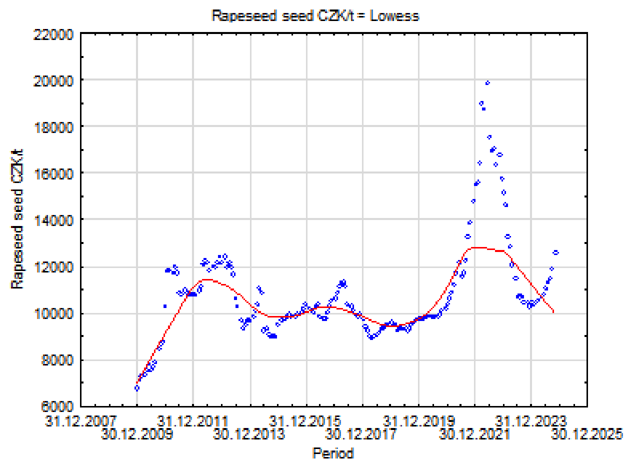

Figure 9. LOWESS.

4.4. Neural Networks

We did the following calculations of neural networks to predict rapeseed prices and closely inspect its price movement.

Table 3 outlines ten active neural networks of the RBF and MLP model which indicated the most accurate forecasts. We also used the monthly data relating to the period from 2010 to 2024. The hidden layer involves Gaussian, tangents and logistic functions. The main activating functions involve identities, sinus, logistic and exponential. The test data run the best on RBF 1-50-1 0.983216 and MLP 1-28-1 0.984374 networks, indicating their best adaptability to the test data. MLP 1-28-1 99076 shows the most accurate predictions and the lowest test error. MLP 1-31-1 displays the worst results in 0.972586 training network, while its test network goes down in flames as well.

Table 4 demonstrates correlation coefficients of the rapeseed on training and test data. The values of all ten neural networks approach 1, indicating an accurate prediction of rapeseed prices. The first RBF network 1-50-1 0.987181 showed the best training correlation coefficient, whereas the ninth MLP network 1-31-1 0.972586 indicated the worst result. The best training coefficient was in the eight MLP structure 1-28-1 0.984374, and the worst was detected in the sixth RBF network 1-23-1 0.980191.

Table 3. The overview of active networks (Rapeseed—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 1-50-1	0.987181	0.983216	48,341.7	114,670.6	RBFT	SOS	Gaussian	Identity
2	MLP 1-41-1	0.975612	0.980227	91,431.7	126,821.3	BFGS 288	SOS	Tanh	Sine
3	MLP 1-39-1	0.979745	0.982851	76,116.1	112,198.9	BFGS 271	SOS	Tanh	Identity
4	MLP 1-34-1	0.979506	0.981536	77,089.6	123,017.8	BFGS 211	SOS	Tanh	Logistic
5	MLP 1-34-1	0.974009	0.980578	97,855.2	126,026.5	BFGS 234	SOS	Tanh	Exponential
6	RBF 1-23-1	0.980232	0.980191	74,288.3	130,654.4	RBFT	SOS	Gaussian	Identity
7	MLP 1-20-1	0.975442	0.981303	92,725.9	120,626.1	BFGS 401	SOS	Logistic	Logistic
8	MLP 1-28-1	0.974756	0.984374	95,005.5	99,076	BFGS 192	SOS	Logistic	Exponential
9	MLP 1-31-1	0.972586	0.98032	102,686.1	126,253.3	BFGS 196	SOS	Tanh	Exponential
10	MLP 1-38-1	0.97595	0.980309	90,187.2	126,534.5	BFGS 267	SOS	Logistic	Identity

Table 4. Correlation coefficient (Rapeseed—monthly data 2010–2024).

Net. Name	Train	Test
1.RBF 1-50-1	0.987181	0.983216
2.MLP 1-41-1	0.975612	0.980227
3.MLP 1-39-1	0.979745	0.982851
4.MLP 1-34-1	0.979506	0.981536
5.MLP 1-34-1	0.974009	0.980578
6.RBF 1-23-1	0.980232	0.980191
7.MLP 1-20-1	0.975442	0.981303
8.MLP 1-28-1	0.974756	0.984374
9.MLP 1-31-1	0.972586	0.98032
10.MLP 1-38-1	0.97595	0.980309

Table 5 suggests the prediction statistics of the MLP and RBF networks. The minimum predicted values range from 6996.32 to 7290.17 CZK/t and the maximum statistics from 17,782.31 to 18,426.76 CZK/t. The test model shows minimum predicted values from 7124 to 7618.48 CZK/t, while the maximum ones oscillate between 17,805.99 and 18,407.7 CZK/t. The fourth MLP network 1-34-1 amounting to 2081.01 demonstrates the highest maximum residue, indicating a risk of an extreme overestimation of rapeseed prices. The lowest maximum residue is reflected in the first RBF 1-50-1 1147.58, implying more reliable prediction.

Table 5. Prediction statistics (Rapeseed—monthly data 2010–2024).

Statistics	1.RBF 1-50-1	2.MLP 1-41-1	3.MLP 1-39-1	4.MLP 1-34-1	5.MLP 1-34-1	6.RBF 1-23-1	7.MLP 1-20-1	8.MLP 1-28-1	9.MLP 1-31-1	10.MLP 1-38-1
Minimum prediction (Train)	7218.2	6996.32	7199.93	7290.17	7124.12	7185.92	7124	7124	7177.1	7142.93
Maximum prediction (Train)	17,851.42	17,936.32	18,127.86	17,782.31	17,986.44	18,000.9	17,908.94	18,426.76	18,043.47	17,946.44
Minimum prediction (Test)	7618.48	7260.34	7286.87	7299.02	7124.52	7355.7	7124	7124	7209.12	7199.25
Maximum prediction (Test)	18,175.8	17,912.75	18,223.1	17,805.99	17,860.48	18,169.3	17,900.16	18,407.7	17,914.41	17,973.19
Minimum residual (Train)	−993.55	−843.89	−871.61	−869.49	−940.27	−926.73	−847.28	−1203.59	−994.56	−790.03
Maximum residual (Train)	1147.58	1593.49	1313.8	1502.16	1884.53	1361.43	1521.91	1426.88	1847.45	1539.18
Minimum residual (Test)	−901.61	−1157.12	−1067.54	−1011.65	−1058.05	−1258.78	−1225.95	−1140.39	−935.18	−974.57
Maximum residual (Test)	1718.45	1974.25	1663.9	2081.01	2026.52	1717.7	1986.84	1479.3	1972.59	1913.81
Minimum standard residual (Train)	−4.52	−2.79	−3.16	−3.13	−3.01	−3.4	−2.78	−3.9	−3.1	−2.63
Maximum standard residual (Train)	5.22	5.27	4.76	5.41	6.02	5	5	4.63	5.77	5.13
Minimum standard residual (Test)	−2.66	−3.25	−3.19	−2.88	−2.98	−3.48	−3.53	−3.62	−2.63	−2.74
Maximum standard residual (Test)	5.07	5.54	4.97	5.93	5.71	4.75	5.72	4.7	5.55	5.38

Figure 10 suggests the rapeseed price movement between 2010 and 2024. The neural networks mimicked the curve of the real price movement almost throughout the monitored period, indicating very adaptable models. The most significant deviation occurred in case number 140–160, when the real price movement substantially outpaced the neural structures. RBF network 1-50-1 shows the most significant oscillations. The diagram proposes that the rapeseed price hit the trough at the beginning of the monitored period, witnessing the sharpest fluctuations in the end.

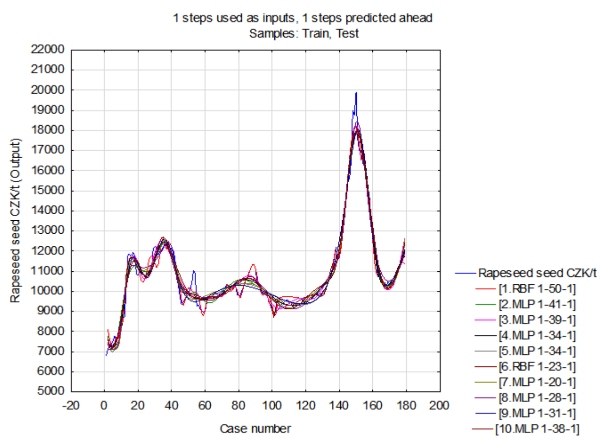

Figure 10. Rapeseed price movement.

Table 6 illustrates the rapeseed price prediction from December 2024 to December 2025. MLP networks forecast higher prices than RBF structures. While MLP structures tend to grow in time, with the third MLP 1-39-1 peaking at 21,994.39 CZK/t at the end of the observed period, RBF networks show a decreasing trend, with the first RBF 1-50-1 falling to 9726.83 CZK/t. The last column displays real prices from December 2024 to February 2025. The price saw a slight decline in January 2025 compared to December to witness an increase in February. MLP networks better predict real prices, while RBF structures tend to underestimate the actual value.

Table 6. Rapeseed prices—prediction vs. reality.

Date	1.RBF 1-50-1	2.MLP 1-41-1	3.MLP 1-39-1	4.MLP 1-34-1	5.MLP 1-34-1	6.RBF 1-23-1	7.MLP 1-20-1	8.MLP 1-28-1	9.MLP 1-31-1	10.MLP 1-38-1	Real Price
01 December 2024	11,068.07	12,592.9	13,691.33	12,533.24	13,135.09	11,941.01	13,899.54	12,548.99	12,574.94	13,242.8	12,886
01 January 2025	10,852.92	12,863.78	14,276.04	12,787.6	13,599.65	12,001.39	14,691.18	12,933.91	12,873.42	13,703.16	12,707.1
01 February 2025	10,630.79	13,136.54	14,890.9	13,044.47	14,087.94	12,036.75	15,521.29	13,357.94	13,175.37	14,183.67	12,907.7
01 March 2025	10,440.26	13,383.65	15,470	13,277.52	14,545.88	12,048.69	16,262.86	13,776.04	13,449.02	14,634.08	
01 April 2025	10,252.97	13,657.22	16,135.08	13,535.51	15,067.16	12,042.03	17,021.77	14,279.49	13,750.91	15,150.12	
01 May 2025	10,102.07	13,921.19	16,800.46	13,784.04	15,581.02	12,018.34	17,647.16	14,808.98	14,040.11	15,666.29	
01 June 2025	9979.37	14,192.44	17,508.25	14,038.58	16,116.02	11,979.15	18,150.63	15,401.63	14,334.11	16,216.54	
01 July 2025	9890.69	14,452.81	18,210.73	14,281.7	16,631.81	11,930.06	18,496.74	16,020.95	14,612.49	16,765.07	
01 August 2025	9825.56	14,719.06	18,952.68	14,528.66	17,156.39	11,870.95	18,728.39	16,710.01	14,892.53	17,348.24	
01 September 2025	9781.73	14,981.87	19,708.98	14,770.4	17,665.75	11,806.37	18,864.08	17,450.72	15,163.75	17,947.92	
01 October 2025	9754.32	15,232.4	20,452.75	14,998.62	18,137.79	11,741.28	18,935.01	18,218.34	15,417.02	18,543.94	
01 November 2025	9736.82	15,486.81	21,231.84	15,227.85	18,597.44	11,673.69	18,971.45	19,065.61	15,668.63	19,176.03	
01 December 2025	9,726.83	15,728.21	21,994.39	15,442.74	19,009.02	11,609.85	18,987.59	19,939.29	15,901.91	19,803.43	

Figure 11 depicts the curves of predictions made by neural networks. The yellow curve marks the real rapeseed price from December 2024 to February 2025.

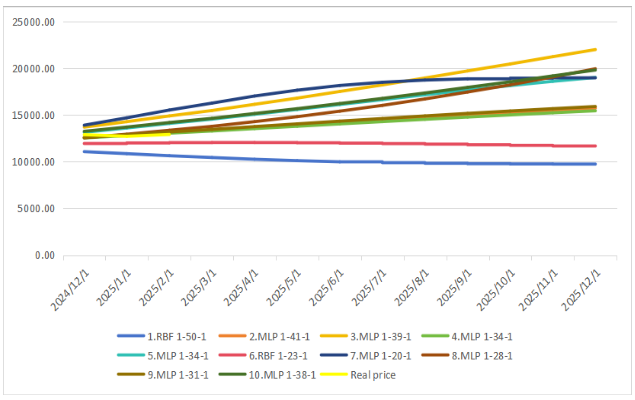

Figure 11. Predicted vs. real prices.

In December 2024, the curves are close, increasingly diverging from one another in time. The first RBF 1-50-1 marks the furthers and most underestimated rapeseed value shown in **Figure 11**, whereas the second MLP 1-41-1, fourth MLP 1-34-1 and ninth MLP 1-31-1 are the closest to the real price. The three networks mimic the same trend throughout the period. Although the eighth neural network MLP 1-28-1 also reliably tracked the real price, it began to overestimate the actual value as of March 2025.

5. Discussion

Based on the findings and analyses performed, we can answer the following research questions and assess the validity of the formulated hypotheses.

RQ1: Was the price of rapeseed volatile or stable in the Czech Republic from 2010 to 2024?

H1. *The price of the rapeseed was growing steadily and stably from 2010 to 2022 before the COVID-19 pandemic and the war in Ukraine occurred in 2022.*

The price of rapeseed showed more moderate fluctuations than the other monitored commodities. At the beginning of the monitored period, it reached a low of 6,799 CZK/t, while in March of the following year it increased to 11,830 CZK/t. In the years 2011–2020, the price remained relatively stable, oscillating around 10,000 CZK/t. However, from January 2021 onwards, there was a sharp increase, which peaked in June 2022 at 19,887 CZK/t. This significant increase reflected increased demand for rapeseed oil, shrinking sown areas and rising production costs. After reaching a peak, it was followed by a decline to 10,263 CZK/t in December 2023. Towards the end of the monitored period, prices recovered slightly, reaching 12,608 CZK/t in November 2024.

This result shows that the price of rapeseed has been relatively stable in the long term, although there have been sharp fluctuations in certain periods. Hypothesis H1 was confirmed, as stable growth until 2022 was indeed evident, with a major turning point only occurring in connection with the pandemic and the war in Ukraine.

RQ2: Did the COVID-19 pandemic and the war in Ukraine between 2022 and 2024 play a significant role in the price movement of the rapeseed?

H2. *The COVID-19 pandemic and the war in Ukraine did provide a dramatic effect on the price movement of the rapeseed between 2022 and 2024.*

The development of rapeseed prices in the period 2010–2024 was influenced by a number of factors, including climate change, geopolitical events and changes in agricultural policy. Significant droughts or excessive rainfall significantly affected the harvest and thus the price level. Since 2021, strict environmental measures have also contributed to the price increase, leading to a reduction in rapeseed acreage, while growing demand for rapeseed oil has further increased prices. In 2022, additional factors have added to these pressures—in particular, the armed conflict in Ukraine and rising input prices such as energy and fertilizers. These determinants have resulted in exceptionally high rapeseed prices. However, the following year saw a sharp decline in prices, enabled by favorable weather conditions, a good harvest and the replacement of labor-intensive crops (e.g. fruits and vegetables) with oilseeds. Prices stabilized towards the end of the period under review.

The analysis clearly shows that extreme weather events and geopolitical events act as key price triggers. Hypothesis H2 was confirmed, as the COVID-19 pandemic and the war in Ukraine had a dramatic and immediate impact on rapeseed price developments in 2022–2024.

RQ3: Can the price movement of the repassed be expected to grow through December 2025?

H3. *The price movement of the rapeseed is expected to grow through December 2025.*

Neural networks, specifically MLP and RBF models, were used to predict the development of rapeseed prices. The data were divided into training and testing sets, and the ten best neural structures were used. The minimum predicted values in the training model ranged from 6996.32 CZK/t to 7290.17 CZK/t, while the test prototype showed values from 7124 CZK/t to 7618.48 CZK/t. The maximum predicted values in the training model ranged from 17,782.31 CZK/t to 18,426 CZK/t and in the test model between 17,805.99 CZK/t and 18,407.7 CZK/t. One of the MLP models showed the highest residuals, which suggests that the prediction may be overestimated.

The results showed that MLP models tend to predict higher prices and an upward trend, while RBF models only predicted a slight increase or decrease. The highest predicted rapeseed price was 21,994.39 CZK/t and the lowest value was 9726.83 CZK/t at the end of the monitored period in December 2025. A comparison of the predictions with the actual values in the first months of 2025 showed that MLP models approached the real values better than RBF models, which tended to underestimate prices.

Based on these results, it can be expected that the rapeseed price will fluctuate in the interval of 9700–22,000 CZK/t in 2025, while remaining sensitive to existing market and geopolitical factors. Hypothesis H3 was therefore confirmed, although with some limitations, as the prediction models differed in their accuracy and RBF models in particular showed weaker prediction ability.

Based on the above results, it can be concluded that the development of rapeseed prices is sensitive in the long term to a combination of climatic conditions, geopolitical events and market demand. In addition to these factors, it is also necessary to take into account the impacts of trade and agricultural policies, which may significantly influence market developments in the future. The future introduction of US tariffs on imports of agricultural products from the EU, including rapeseed, could fundamentally disrupt the export opportunities of European producers and lead to downward pressure on prices within the EU, while on markets outside Europe there could be room for other competitors. These trade restrictions could thus contribute to higher price volatility and increase the uncertainty of predictions. The issue of public interventions in the management of agricultural risks, in particular through the EU Common Agricultural Policy, also plays an important role. Policy instruments such as subsidies, compensation or support mechanisms for farmers may act as a stabilizer of price developments in the future and mitigate the impacts of adverse events on the market. The final synthesis thus expands the answers to the questions posed and at the same time underlines what was formulated in the theoretical framework—namely that the long-term development of agricultural commodity prices is the result of a complex interaction of natural conditions, international politics, market demand and public administration interventions.

6. Conclusions

Rapeseed is a vital agricultural commodity in the food processing industry and its proper valuation is imperative for a stable agricultural sector and an end user. The thesis aimed to identify the price movement of rapeseed in the Czech Republic between 2010 and 2024, predicting its movement through December 2025.

The research aim was fulfilled using content analysis, linear regression and neural networks. The content analysis revealed that the rapeseed price fluctuated less than other observed commodities over the monitored period, indicating the lowest price in 2010 (6799 CZK/t) and the highest in 2022 (19,887 CZK/t). The key factors influencing the price movement involved the COVID-19 pandemic, armed conflict in Ukraine and extreme climatic conditions like drought or floods. These observable phenomena reduce the availability of materials, production capacity and the final market price.

The price prediction for December 2024–December 2025 involved MLP and RBF neural network models, so the predicted price movement veered off in a different direction depending on the network type. MLP networks predicted an increase, while RBF decrease in rapeseed prices. The predicted value peaked at 21,994 CZK/t in December 2025 (3rd MLP 1-39-1), hitting the bottom of 9,726 CZK/t (1st RBF 1-50-1). The real prices available for the first months of 2025 were the closest to the 2nd, 4th and 9th MLP networks, indicating a high prediction accuracy of the respective types.

The results suggest that a future price movement is hard to predict and depends on many externalities. In practice, neural networks may be used as a supplementary instrument for producers and other agricultural players to make good decisions.

Our thesis is limited by a short time span of monitoring (2010–2024), making predictions only through 2025. We also used only monthly data, ignoring daily fluctuations. Future research should involve an extended observable period or comprehensive temporal data. Our findings were also affected by extraordinary events between 2020 and 2022, significantly disrupting regular market conditions and potentially biasing the predictions.

Finally, it should be emphasized that the price development of rapeseed in the future will not be determined only by short-term market factors, but to a large extent also by broader structural influences, in particular climate change, geopolitical events and public interventions. As has already been outlined several times, climate change brings a higher risk of extreme events, such as long-term droughts, flash floods or uneven rainfall totals, which can significantly reduce yields and thus directly affect the price level. Similarly, geopolitical factors, such as the possible introduction of US tariffs on imports of agricultural products from the EU, can significantly disrupt market stability and increase pressure on domestic producers. In this context, government interventions also play an important role, both at national and European level, especially within the framework of the EU Common Agricultural Policy. Climate risk insurance support programmes, subsidies for production diversification or intervention purchases can act as a tool to mitigate price shocks and contribute to stabilising the market environment. It will therefore be necessary to systematically include these climatic and political determinants in future prediction models so that they best reflect real conditions and provide useful information for decision-making by producers and policymakers.

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Not applicable.

Data Availability Statement

All publicly available data used in the article have been referenced in Section "3.1. Data". Specific websites for the materials are listed in the references section.

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Conflicts of Interest

The author declares no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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