https://doi.org/10.17221/121/2023-AGRICECON

Impacts of the war on prices of Ukrainian wheat

Lenka Novotná, Zuzana Rowland, Svatopluk Janek*

Institute of Technology and Business in České Budějovice, České Budějovice, Czech Republic

**Corresponding author: 27559@mail.vstecb.cz*

Citation: Novotná L., Rowland Z., Janek S. (2023): Impacts of the war on prices of Ukrainian wheat. Agric. Econ. – Czech, 69: 404–415.

Abstract: The Russian-Ukrainian armed conflict significantly affected wheat production and its export from Ukraine, mainly during the war outbreak. Since both countries rank among the major global wheat producers, the warfare disrupted wheat supplies, hastily pushing the prices. Based on the analysed data, we carried out research using multilayer perceptron networks. The findings suggest the biggest price increase between February and March 2022, witnessing wheat prices at about 1 400 USD per t. We predict a decline to the pre-war values until the end of 2025, estimating its rates between 600 USD and 800 USD per t. This price slump may involve signing an agreement on unblocking Ukrainian seaports, which would restore wheat exports. Yet, our survey is confined to historical data, which do not suggest any dramatic event that would alarmingly sway wheat prices.

Keywords: correlation analysis; regression; Ukraine; war conflict; wheat price

The Russian invasion of Ukraine seriously harmed the European and global economies, weakening food markets and agriculture. The aggression of the Russian Federation towards Ukraine in February 2022 severely disrupted the global geopolitical layout, jeopardising Western Europe and violating norms of general international law that govern relationships between civilised states (Villasmil-Espinoza et al. 2022). The armed conflict has also seriously damaged wheat supplies, as both countries are its key exporters.

Wheat is the primary commodity negotiated on the global food market (Franch et al. 2021). Ukraine, often called 'European granary' has the lion's share of total wheat production and export (Fenghe 2020), producing almost 10% of the global yield of 765 million t (Hyles et al. 2020).

Both Russia and Ukraine supply more than 30 countries that are net importers of wheat with at least 30% of their total wheat imports. According to the Food and Agriculture Nations, global food prices have reached an all-time high in real terms. Food supply problems are far beyond Ukraine‘s borders. Russia suspended exports of grain and white and raw sugar to former Soviet states, and suspended exports of wheat, rye, barley and maise to neighbouring states

https://doi.org/10.17221/121/2023-AGRICECON

of the Eurasian Economic Union, including Armenia, Belarus, Kazakhstan and Kyrgyzstan. Furthermore, port operations in Ukraine are unusable for commercial activities and very high insurance premiums for vessels have affected exports via the Black Sea. However, following the agreement signed between Ukraine and Russia, it seems that a solution has been found for exports from Ukraine through safe corridors (Tortajada and Biswas 2022).

The armed conflict between two agricultural powers has negative global socio-economic impacts, undermining world food security (Ben Hassen and El Bilali 2022). Export and production volumes in Ukraine fell since the war prevented harvesting all wheat sown before the conflict. The crops could be harvested only in areas under Kyiv's control, as the military occupation laid other farmlands waste. Last spring, Ukraine sowed land about one-quarter smaller than before the Russian invasion. The blockade of the Black Sea ports is another contributing factor to a decline in exports, confining Ukraine to a limited shipment of produced wheat. Russian aggression created a need for rethinking the socio-economic value of agriculture and open trade to secure food and stability in vulnerable regions (Hellegers 2022). We must also realise that not only armed conflicts may severely damage crops and international trade.

In the midst of the war in Ukraine, grain and barley prices rose dramatically. Both Russia and Ukraine are large exporters of grain products, and with the ongoing war, volatility is already evident in the market. A number of factors may have contributed to the increase in wheat prices, such as workers leaving their farms to assist in Ukrainian efforts, as well as parts of fertile fields that were destroyed by tanks and military vehicles (McDonald 2022).

The huge production of Ukrainian grain is causing problems in the surrounding markets. Interrupted deliveries are redirected to neighbouring markets. The Polish government initially supported the EU's plans to move surplus grain but instead of a smooth transition to global markets, the excess supply pushed down prices in Europe, provoking massive protests from Polish farmers. Thus, the Polish government decided to restrict Ukrainian imports in order to protect its own markets (Brzeziński 2023).

On top of the war, climate change also affects wheat production and export in Ukraine. Heatwaves, tropical nights, frost, and drought involve crucial factors threatening the local wheat yields in the reproduction and grain bagging phase (Schierhorn et al. 2021).

The Russian invasion and climate change severely disrupt global markets with agricultural commodities, pressing on wheat supplies and food prices. Higher impacts are globally felt given the roaring world trade (Hellegers 2022). We assume that production cuts and a decline in exports will dramatically raise wheat prices and its products.

On top of wheat production and export, the conflict in Ukraine has completely wrecked the country's economy. Regions severely afflicted by enemy actions or invaded localities generate almost 20% of the Ukrainian GNP (Gross National Product). The first three months of the war in Ukraine saw a sharp economic slump. Introducing fundamental tax reforms to mitigate massive economic upheavals led to severe income tax cuts (Irtyscheva et al. 2022). The aim of this paper is to examine the impact of the war in Ukraine on wheat production and exports in the country. The methodology explains the procedure that led to the results published below. The results of the work are presented and discussed in the second part of the article.

We aim to explore the impacts of the war in Ukraine on the country's wheat production and export on wheat price in European markets.

The conflict could partly influence the price of produced wheat, including a failure to sow enough land, frustration of harvesting pre-war crops, etc. The research questions are as follows:

RQ_1: How does the war affect the wheat price in Europe?

Because of the war, the wheat price violently fluctuated. After the conflict ends, the price may reflect many determining factors. The second research question is as follows:

RQ_2: What could be the wheat price movement in European markets through 2025?

Literary research. The research involves multilayer perceptron (MLP) neural networks for predicting the wheat yield per district. The analysis indicates that new activation functions generate better results than the 'S-shaped' output activation function of neural structures for agricultural datasets (Bhojani and Bhatt 2020). Methods including a decision tree, Bayesian, Lazy, Meta and Function classifiers, MLPs, radial basis functions (RBF) and probabilistic neural networks suggest analysing the ventral part of seeds using coloured space textures (Ropelewska 2019). The goal of Niedbała et al. (2019) and other authors was to create multi-criteria models for the prediction and simulation of winter wheat yields using MLP. The findings showed models' great utility in large-area agriculture, including precision agriculture, as a cru-

https://doi.org/10.17221/121/2023-AGRICECON

cial element for effective decision-making. To predict the effectiveness of hybrid wheat, Shamsabadi et al. (2022) used multivariate statistics and two MLP neural network systems. MLP analysis showed the validation accuracy from 0.96 for phenotype data to 0.99 for combined data.

Regression methods of machine learning, climate records and time series of satellite photos reliably estimated yields of Australian wheat, meeting the requirements for accurate mapping of yield gaps and their hotspots. These gaps provide fertile ground for further agricultural research (Kamir et al. 2020).

The authors aimed at a methodology for incorporating seasonal fluctuations into time series smoothing, achieving more accurate and clearer time series smoothing by involving variables like the year, month, date and weekday of measuring (Vochozka et al. 2019).

External regressors of time series best learn the relationship between the time series and categorical class labels using a regression-modified modern TSC Rocket al.orithm, ensuring higher total accuracy than other algorithms (Tan et al. 2021). Liu and Yin (2021) analysed partially linear regression time series models with correlated errors using polynomial splines and weighted least squares, achieving better results than ignoring the correlation. Kumar et al. (2022) effectively and accurately estimated and predicted crop yields using the MERRA-2 model, satellite gauge and MODIs-Terra satellite data and regression and time series models. They revealed relevant data measurable with actual datasets. Matkovic-Stojsin et al. (2018) conducted a randomised complete block design experiment using ten wheat genotypes to assess variability and the relationship between various elements of wheat yields. The gradual regression suggests that 87.1% of the grain weight per ear type wheat variety mimics the model ignoring the ear length.

Correlation analysis is a standard and highly informative descriptive statistical tool for studying relationships between variables within two- and multidimensional data (Rodrigues and Mahmoudvand 2016). A two-dimensional correlation analysis involves visualising correlated variables inside multidimensional data in time using a complex cross-correlation for assessing the degree of association between xerophytic wheat (Harrington et al. 2000). Splitting correlation coefficients into direct and indirect effects revealed profound favourable impacts of caryopses on ears and fresh biomass on grain yields during severe drought (Shimelis et al. 2019). A scholarly correlation study on genetic variability, heredity, heat tolerance index, phenotype and genotype for 250 elite bread wheat genotypes unveiled significant genotype differences in all characteristics (Elbashier et al. 2019). The analysis explored a correlation, regression and curve analysis using 39 bread wheat genotypes during two seasons, finding a positive correlation between grain yield, all ears/plants and the number of grains (Fouad 2018).

Correlation allows us to examine whether causation exists, using causal analysis as support (Gejingting et al. 2019). Xiong et al. (2018) examine the volatile correlations between economic policy uncertainty (EPU) and Chinese stock market returns, suggesting the massive impact of fundamental EPU changes on stock market returns. Bradauskiene et al. (2021) studied the relationship between wheat consumption and coeliac disease (CD). Although Pearson's correlation coefficient revealed a close positive equivalence between eating wheat and biopsy predomination of confirmed CD on the continental scale, the nationwide survey did not find any striking parallel. Brown rust on the leaves seriously affects wheat production and causes economic losses around the world. In this study, an evaluation was carried out of a locally developed collection of wheat cultivars consisting of 133 varieties. Various multivariate analyses, including analysis of dispersion (ANOVA), correlation analysis, analysis of major components and cluster analysis, were performed to assess varietal response under rust conditions. Analysis of variance showed that all truths have a highly significant difference for all characters. Pearson's correlation coefficients revealed that grain yield per plant was positively correlated with most yield attributes but negatively correlated with disease severity (Sabar et al. 2021). Pearson's test for exploring the correlation between the microstructure, pores and hydration characteristics of wheat bran on vegetable, tissue and cellular gauge modified by an air-flowing impact mill showed that the water retention capacity of wheat bran remarkedly correlated with the cellular and tissue micropore percentage (Li et al. 2022).

Complex causal models and analyses involving huge correlation matrices are more common in social sciences than simple causal models with one correlation coefficient (Trafimow 2017). Song et al. (2018) framed causal relationships by combining collective intelligence with modern machine learning methods, devising an efficient technique for causal analysis of open data.

We use a correlation analysis for the first research question, while the second will involve regression time series using multilayer perceptron networks.

https://doi.org/10.17221/121/2023-AGRICECON

MATERIAL AND METHODS

The paper is focused on all European wheat markets. Every single country publishes prices of wheat day by day, and we do not know if prices in European markets are correlated. Therefore, it is necessary to find a reference market. Norland (2016) claims that wheat prices in all European (and non-European) markets are highly correlated to US Wheat Futures. Therefore, to answer our questions, we inspected daily closing wheat prices on US Wheat Futures. We used data on wheat prices from September 10, 2012, to November 9, 2022, taken from official websites of Investing.com financial platform (Investing.com 2022). The prices were expressed in bushels.

Impacts of war on European wheat prices. We applied the Wolfram Mathematica software to process the data, using artificial neural networks to assess the impacts of the war on wheat prices. The calculations involved looking for differences in predicting a possible wheat price movement from the war outbreak to November 9, 2022, reflecting the pre-war and existing wheat price movement. February 24, 2022, is the critical date, marking the Russian infringement of Ukrainian borders.

The time series involved neural networks, multilayer perceptron structures in particular, using data from September 10, 2012, to February 23, 2022. The neural network's layout is as follows:

i) The input layer included a single vector, a date, expressed in days passed from January 1, 1900.

ii) The first hidden layer of neurons comprised a linear layer equally transmitting the signal according to the weight of the variable, including the date of the wheat trade as an input variable.

iii) The second hidden layer of neurons contained an elementwise layer of non-linearity in a neural network. This experiment randomly chose a function for transmitting the signal between the first and third hidden layer of neurons when creating the networks.

Hyperbolic tangent:

$$f(x) = \tanh x = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{1}$$

Sinus:

$$f(x) = \sin x \tag{2}$$

ReLU (rectified linear unit):

$$R(x): R \to R_0^+ \tag{3}$$

Logistic function:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{4}$$

iv) The third hidden layer of neurons also involved the elementwise layer, corresponding to the second hidden layer, including the experiment.

v) The fourth hidden layer of neurons again comprised a linear function, generating the calculation for the output layer.

vi) The output layer generated closing wheat prices as the output.

The experiment involves ADAM optimisation algorithm, producing 1 000 neural networks. The Pearson's correlation coefficient derived from factual data of the time series movement (existing wheat price) and predicted wheat prices between Septeber 10, 2012, and February 23, 2022, picked the best structure (Figure 1).

Then, we made a prediction for the period from February 24, 2022, to November 9, 2022, where the difference between the predicted and existing wheat price movement for the respective period answered our research question.

Pearson's correlation coefficient derived from the predicted and existing wheat price movement over the given period informed us of the impact of the war on the commodity price.

The wheat price movement in European markets through 2025. The second research question involved methods for designing the model in the first question. The only difference was the observed period, using data from September 10, 2012, to November 9, 2022, and predicting the wheat price movement through 2025.

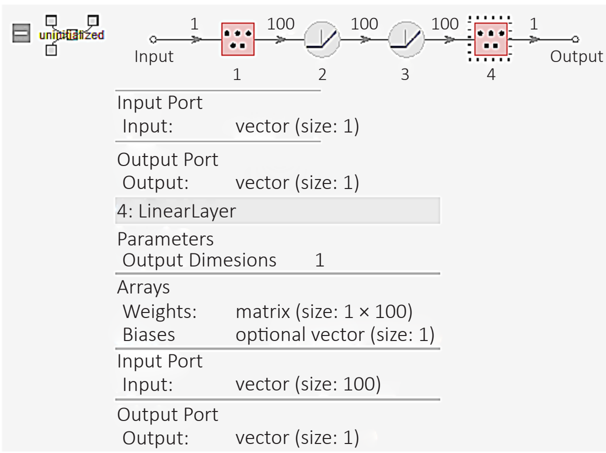


Figure 1. Output dimensions: 1 neural network

Source: Authors' elaboration

https://doi.org/10.17221/121/2023-AGRICECON

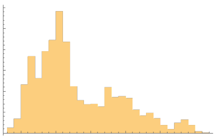
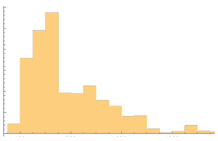
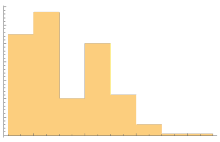
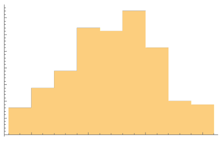
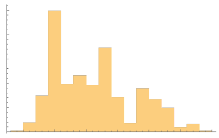
RESULTS

Table 1 suggests the basic characteristics of the existing time series. The data on the US Wheat Future prices reflect the official websites of Investing.com financial platform (Investing.com 2022), including market prices of trading days of the commodity.

Table 1 implies that minimum wheat prices hit the trough before and in the first nine months of the conflict, peaking at about 361 USD per t. Although the onset of the war inflated the price minimum to 731.5 USD per t, predictions suggest a decline of the post-invasion price rise as of November 10, 2022. We spotted the price maximum during the first nine months after the invasion, topping 1 425.25 USD per t, exceeding maximum pre-war prices by about 40%.

Impacts of the war on European wheat prices. Figure 2 illustrates the existing wheat price from September 10, 2012, to February 23, 2022, and its prediction from February 24, 2022, to November 9, 2022. The blue curve

Table 1. Dataset characteristics

Samples	Pre-war wheat price	Wheat price until Nov 9, 2022	Post-invasion wheat price to Nov 9, 2022	Post-invasion predicted wheat price until Nov 9, 2022	Predicted price from Nov 10, 2022
Minimum	361.000	361.000	731.500	690.230	597.992
Maximum	925.880	1 425.250	1 425.250	859.901	887.588
Median	523.250	530.500	873.750	770.943	702.122
Mean	561.053	588.991	928.077	770.621	711.925
Distribution	14 265.500	25 033.600	22 224.600	1 518.760	3 991.300
Histogram					

Source: Investing.com (2022)

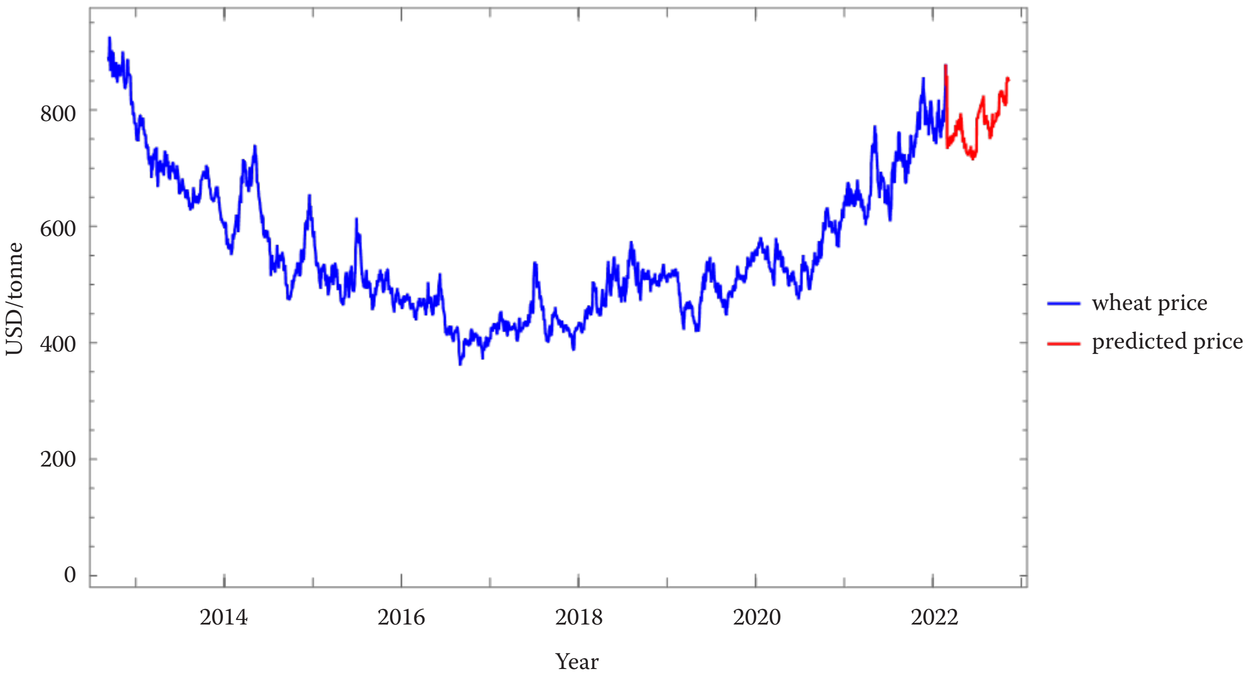


Figure 2. Total wheat price and its prediction

Source: Investing.com (2022)

https://doi.org/10.17221/121/2023-AGRICECON

in Figure 2 depicts the real wheat price, while the red trajectory is its prediction until November 2022. The values hit the top between 2012 and 2014, declining to 400 USD per t since then and restoring the original rates between 2020 and 2022. We predict the wheat price to be between 700 USD and 800 USD per t for 2022.

Figure 3 illustrates the real wheat prices from January 1, 2021, to February 23, 2022, and its prediction from February 24, 2022, to November 9, 2022. Figure 3 follows the pattern of the previous graph, cutting the blue curve (the existing wheat price) shorter. Although the plot demonstrates marked price fluctuations, the monitored period (2021–2022) shows a growing trend. The red trajectory tracks the predicted price from February 2022 to November of the same year. We estimate the price peak in February and then a slump with subtle variations.

Figure 4 suggests absolute residuals of wheat prices from September 10, 2012, to February 23, 2022. Figure 4 indicates the highest residual distribution in the half of 2015, ranging between –60 USD and 30 USD per t. We can spot the slightest variations from 2016 to 2018 and between 2019 and 2022, stretching between –30 USD to 30 USD per t.

Figure 5 depicts the time series of wheat prices from January 1, 2022, to January 9, 2022, and its prediction from February 24, 2022, to January 9, 2022. The blue curve in Figure 5 tracks the wheat price, indicating the highest values in March when the numbers topped 1 400 USD. On the other hand, the rates reached the trough in January, February and August, falling to about 800 USD. The red trajectory demonstrates the predicted price, making the highest estimate at the beginning of the period, peaking at about 900 USD per t. From March to June, the values are steady, slightly growing in July. The predicted prices range from 700 USD to 900 USD per t.

The correlation coefficient –1 shows inverse and +1 direct proportion. A zero correlation indicates no significant statistical linearity between the two variables. Our research found a correlation coefficient of –0.601014, indicating an inverse relationship between the war in Ukraine and wheat prices, i.e. partial reliance.

The wheat price movement at European markets thru 2025. Figure 6 depicts the existing wheat price from September 10, 2012, to November 9, 2022, and its prediction from November 10, 2022, to December 31, 2025. The blue curve in Figure 6 tracks the wheat price, topping 1 400 USD per t in 2022. The massive price rise is possibly due to the Russian-Ukrainian conflict since Ukraine, a prominent wheat exporter, had to cut production for a long. The orange colour imitates the prediction from 2022 to 2025, ranging from 600 USD to 800 USD per t without any wild fluctuations.

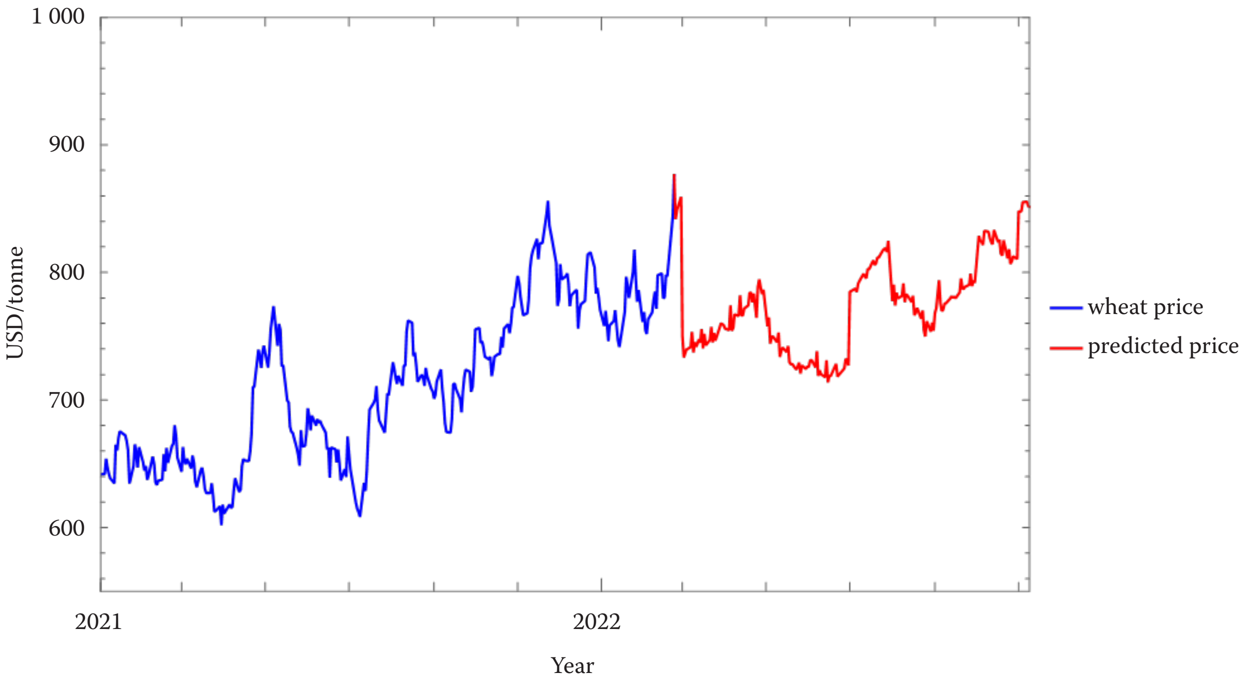


Figure 3. Partial existing wheat price and its prediction

Source: Investing.com (2022)

https://doi.org/10.17221/121/2023-AGRICECON

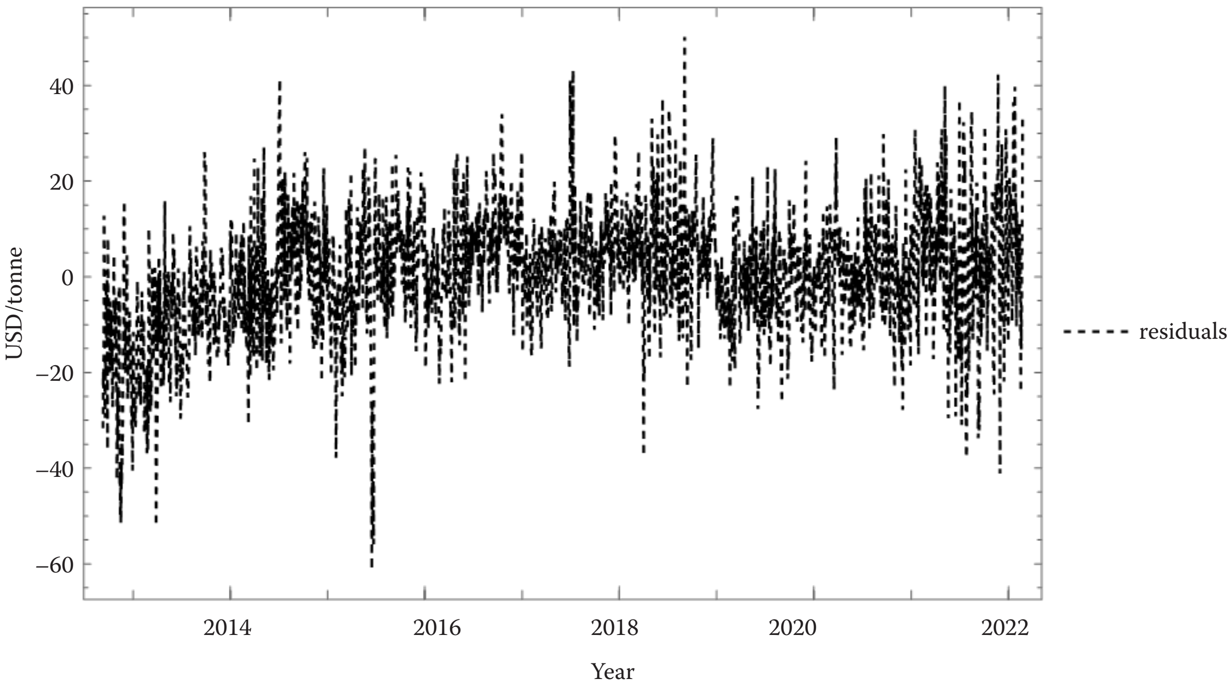


Figure 4. Residuals from September 10, 2012 to February 23, 2020

Source: Investing.com (2022)

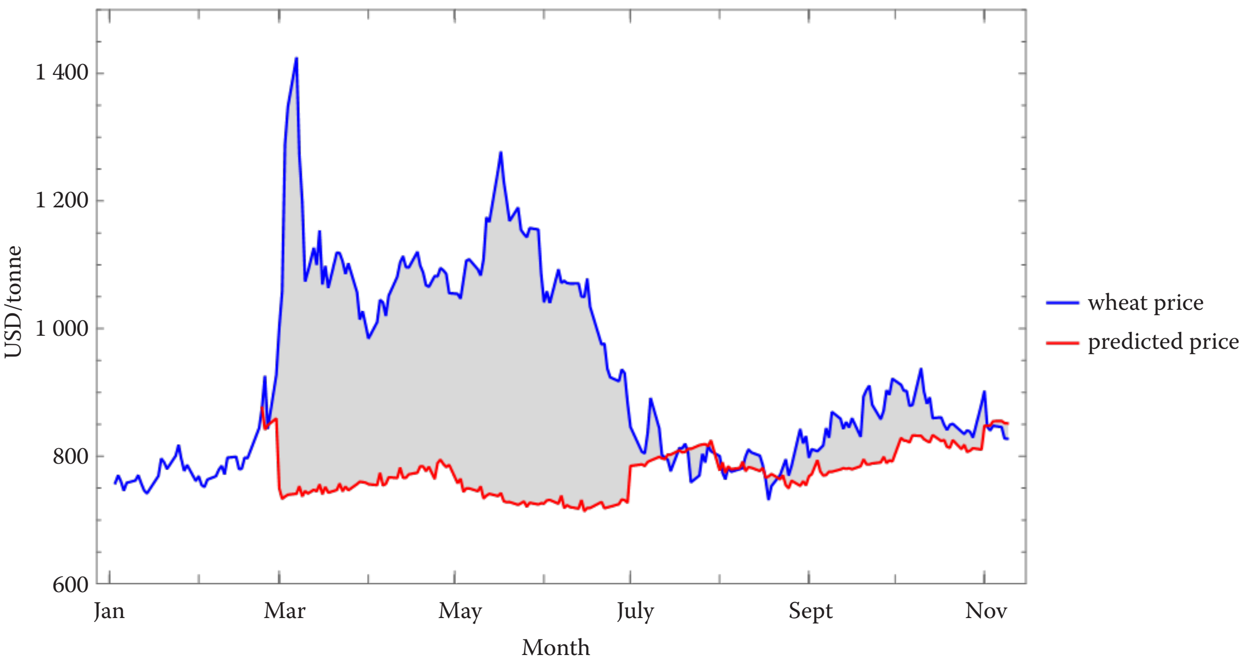


Figure 5. Time series of wheat prices from January 1, 2022 to December 9, 2022 and its prediction from February 24, 2022 to December 9, 2022

Source: Investing.com (2022)

https://doi.org/10.17221/121/2023-AGRICECON

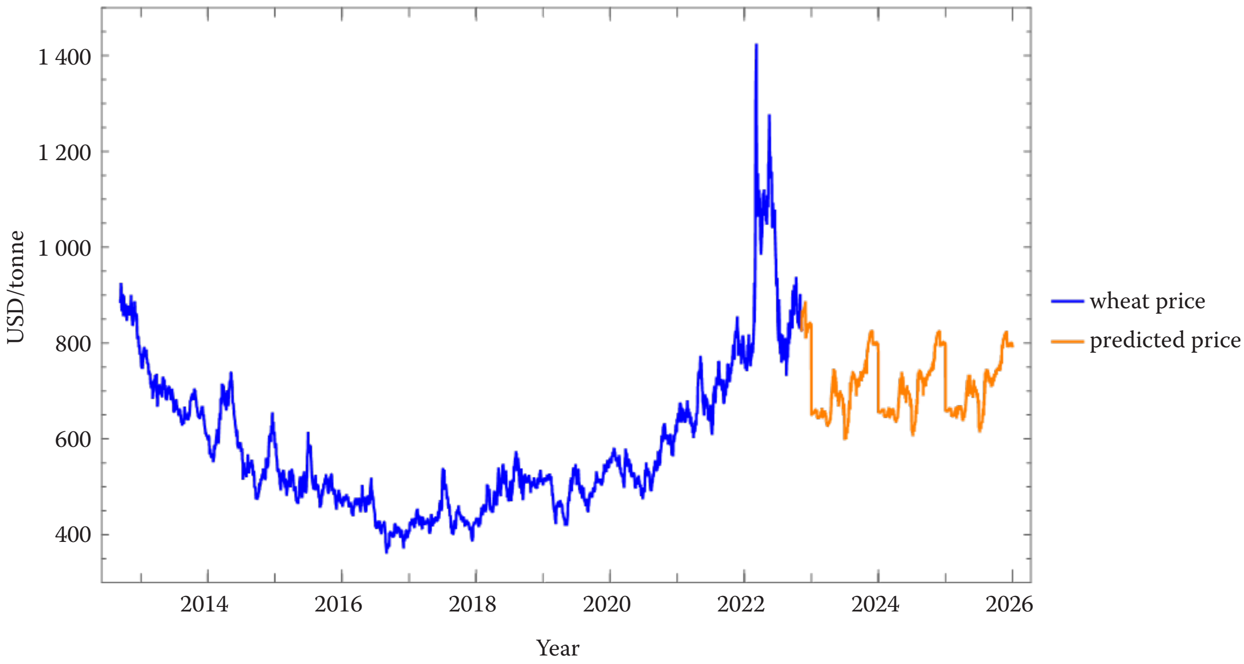


Figure 6. Existing and predicted wheat price through 2025

Source: Investing.com (2022)

Figure 7 illustrates the prediction from November 10, 2022, to December 31, 2025. Figure 7 suggests predicted wheat prices from November 2022 to 2025, hitting the cap in 2022, followed by a slump to 650 USD per t. The end of 2023, 2024 and 2025 will witness the price peaking at 800–850 USD per t, whereas the low-

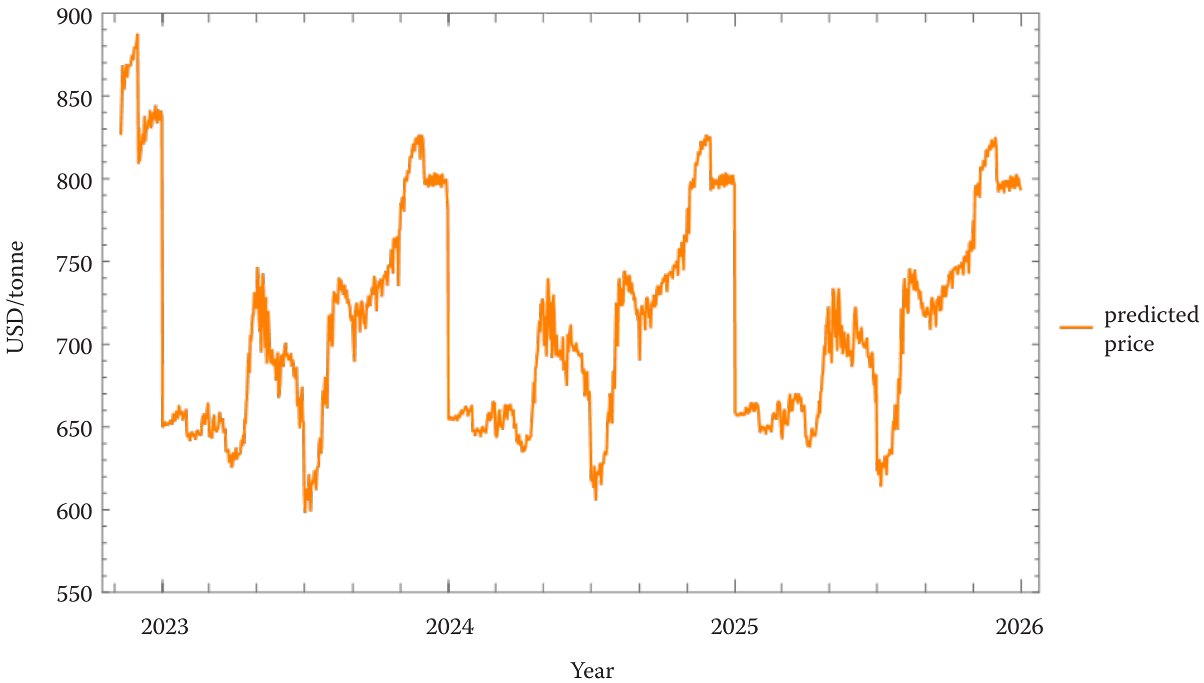


Figure 7. Price prediction

Source: Investing.com (2022)

https://doi.org/10.17221/121/2023-AGRICECON

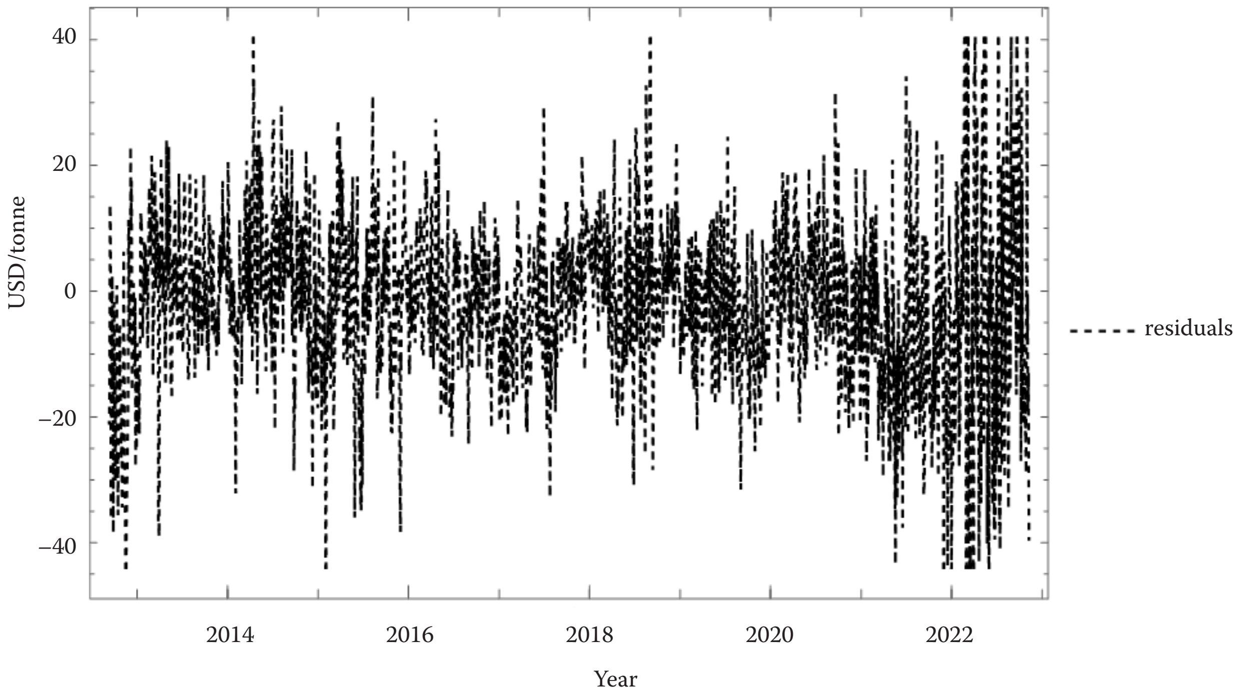


Figure 8. Residuals from September 10, 2012 to November 9, 2022

Source: Investing.com (2022)

est values will occur in the middle of 2023, 2024 and 2025, mildly fluctuating. We can say that the predicted price from 2023 to 2025 will be very similar.

Figure 8 depicts residuals from September 10, 2012, to November 9, 2022. Figure 8 suggests a remarkably wide residual range over the monitored period, indicating the hugest amplitude in 2022, stretching from –40 USD to 40 USD per t.

DISCUSSION

Our findings allowed us to answer the research questions.

***RQ*$_1$: How does the war affect the wheat price in Europe?** The Russian-Ukrainian conflict has significantly affected wheat prices, seeing the biggest increase in the beginning. The invasion made Ukrainian farmers uncertain about timely sowing the fields and good harvest. The war profoundly disrupted Ukrainian food production, as Moscow blocked most Ukrainian sea shipments. Relentless attacks on energy infrastructure considerably complicated field works, destroying granaries or wheat processing plants. The estimated Ukrainian wheat production profoundly plummeted between 2022 and 2023, triggering inflated prices and disruptions in the global food supply chain. From March to May 2022, the average wheat price sharply soared compared to COVID-19 and pre-COVID values (Nasir et al. 2022). A study on food price shocks during the COVID-19 pandemic and the Ukrainian Crisis revealed a double global wheat price rise due to price isolation, causing increased volatility in both periods – falling and rising prices (Martin and Minot 2022).

The war in Ukraine threatened to block 9% of global wheat exports, triggering rampant price inflation. On top of that, year-to-year variability and frequent poor harvests caused by climate change may always reduce wheat exports by an additional five to seven million tonnes, overburdening global markets (Nóia Júnior et al. 2022).

***RQ*$_2$: What could be the wheat price movement in European markets through 2025?** The wheat price will fall to pre-war values by the end of 2025, ranging from 600 USD to 800 USD per t. Our prediction involved many determining factors, including an agreement on unblocking Ukrainian seaports for renewing the exports. Although the Russian-Ukrainian war significantly affected the wheat price, there are also other driving forces behind the fluctuation, such as climate change, lack of moisture, soil erosion, energy prices, pandemic, etc.

Dried and ground coffee cherry used instead of flour is a possible way to fight growing grain prices, shipping

https://doi.org/10.17221/121/2023-AGRICECON

costs and broken supply chains caused by the Russian-Ukrainian conflict and climate change (Eckhardt et al. 2022). Violent climate changes and energy crises made fertiliser supply chains unstable to complement the Russian invasion in inflating gas prices and reducing fertiliser supplies. The aggression may significantly aggravate the energy crisis and the situation in global wheat supply chains (Halecki and Bedla 2022).

CONCLUSION

Our research aimed to find if the war in Ukraine affects wheat production and export, and predict the future price movement in European markets through 2025. The Pearson correlation coefficient revealed inverse proportion, i.e. wheat prices reflect the war only partially. The correlation between the wheat price and the Russian-Ukrainian conflict is –60.1%, indicating an inverse relationship between these variables. It means that adverse situations in Ukraine triggered inflation of wheat prices in Europe. It is only a correlation between the actual price of wheat and the predictive price. From this conclusion, predictions about the relationship between the war in Ukraine and the price of wheat are only partial.

The beginning of the military invasion of Ukraine in February 2022 deeply affected the commodity rates. Since Russia and Ukraine rank among the leading wheat producers, the conflict has adverse worldwide impacts. The lack of supplies commanded exorbitant prices, topping 1 400 USD per t between February and March. Ukrainian exported wheat also reflects the prevailing situation in the country. Moscow's persisting blockage of Ukrainian shipments, relentless attacks on energy infrastructure and assaults on granaries and wheat processing plants severely damage local farm work. The war disrupted Ukrainian food production, the global supply chain and trade, causing rampant inflation in food prices.

On top of the war in Ukraine, fluctuating wheat prices echo the repercussions of the COVID-19 pandemic, from which the country is still recovering. Other decisive factors involve climate change, lack of moisture and soil erosion.

Using artificial neural networks, multilayer perceptron networks in particular, we predicted a fall in the wheat price to the pre-war values through 2025. The price slump will reflect the agreement on unblocking Ukrainian seaports, restoring the global export of Ukrainian wheat.

Based on the discoveries, we fulfilled our research aim. Yet, the unresolved armed Russian-Ukrainian conflict may give rise to unpredictable scenarios that could reverse our findings, e.g. a cease-fire could restart the limited wheat production in both conflicting countries, markedly biasing our results.

REFERENCES

Ben Hassen T., El Bilali H. (2022): Impacts of the Russia-Ukraine war on global food security: Towards more sustainable and resilient food systems? Foods, 11: 2301.

Bhojani S.H., Bhatt N. (2020): Wheat crop yield prediction using new activation functions in neural network. Neural Computing and Applications, 32: 13941–13951.

Bradauskiene V., Vaiciulyte-Funk L., Martinaitiene D., Andruskiene J., Verma A.K., Lima J.P.M., Serin Y., Catassi C. (2021): Wheat consumption and prevalence of celiac disease: Correlation from a multilevel analysis. Critical Reviews in Food Science and Nutrition, 63: 18–32.

Brzeziński B. (2023): Ukraine's bumper grain exports rile allies in eastern EU. Available at https://www.politico.eu/article/ukraine-grain-glut-cause-poland-support-waver-war-russia/ (accessed Apr 19, 2023)

Eckhardt S., Franke H., Schwarz S., Lachenmeier D.W. (2022): Risk assessment of coffee cherry (cascara) fruit products for flour replacement and other alternative food uses. Molecules, 27: 8435.

Elbashier E.M., Elbashier E.M.E., Idris2 S.E., Tadesse W., Tahir I.S.A., Ibrahim A.E.S., Elhashimi A.M.A., Saad S.I., Idris A.A., Mustfa H.M. (2019). Genetic variations, heritability, heat tolerance indices and correlations studies for traits of bread wheat genotypes under high temperature. International Journal of Climate Change Strategies and Management, 11: 672–686.

Fenghe Z. (2020): Analysis of the current situation of agricultural trade development between China and Ukraine. Agricultural and Resource Economics, 6: 23–36.

Fouad H. (2018): Correlation, path and regression analysis in some bread wheat (*Tritcum aestivum* L.) genotypes under normal irrigation and drought conditions. Egyptian Journal of Agronomy, 40: 133–144.

Franch B., Vermote E., Skakun S., Santamaria-Artigas A., Kalecinski N., Roger J.C., Becker-Reshef I., Barker B., Justice C., Sobrino J.A. (2021): The ARYA crop yield forecasting algorithm: Application to the main wheat exporting countries. International Journal of Applied Earth Observation and Geoinformation, 104: 102552.

Gejingting X., Ruiqiong J., Wei W., Libao J., Zhenjun Y. (2019): Correlation analysis and causal analysis in the era of big data. IOP Conference Series: Materials Science and Engineering, 563: 042032.

Halecki W., Bedla D. (2022): Global wheat production and threats to supply chains in a volatile climate change and energy crisis. Resources, 11: 118.

https://doi.org/10.17221/121/2023-AGRICECON

Harrington P.D.B., Urbas A., Tandler P.J. (2000): Two-dimensional correlation analysis. Chemometrics and Intelligent Laboratory Systems, 50: 149–174.

Hellegers P. (2022): Food security vulnerability due to trade dependencies on Russia and Ukraine. Food Security, 14: 1503–1510.

Hyles J., Bloomfield M.T., Hunt J.R., Trethowan R.M., Trevaskis B. (2020): Phenology and related traits for wheat adaptation. Heredity, 125: 417–430.

Investing.com (2022): Investing.com. Available at https://www.investing.com (accessed May 12, 2022).

Irtyshcheva I., Kramarenko I., Sirenko I. (2022): The economy of war and postwar economic development: World and Ukrainian realities. Baltic Journal of Economic Studies, 8: 78–82.

Kamir E., Waldner F., Hochman Z. (2020): Estimating wheat yields in Australia using climate records, satellite image time series and machine learning methods. ISPRS Journal of Photogrammetry and Remote Sensing, 160: 124–135.

Kumar P., Choudhary A., Joshi P.K., Prasad R., Singh S.K. (2022): Multiple crop yield estimation and forecasting using MERRA-2 model, satellite-gauge and MODIS satellite data by time series and regression modelling approach. Geocarto International, 37: 16590–16619.

Li Y., Wang L., Wang H., Li Z., Qiu J., Wang L. (2022): Correlation of microstructure, pore characteristics and hydration properties of wheat bran modified by airflow impact mill. Innovative Food Science and Emerging Technologies, 77: 102977.

Liu Y., Yin J. (2021): Spline estimation of partially linear regression models for time series with correlated errors. Communications in Statistics – Simulation and Computation: 1–15.

Martin W., Minot N. (2022): The impacts of price insulation on world wheat markets during the 2022 food price crisis. Australian Journal of Agricultural and Resource Economics, 66: 753–774.

Matkovic Stojsin M., Zecevic V., Petrovic S., Dimitrijevic M., Micanovic D., Banjac B., Knezevic D. (2018): Variability, correlation, path analysis and stepwise regression for yield components of different wheat genotypes. Genetika, 50: 817–828.

McDonald J. (2022): Ukraine influences wheat prices world-wide. Available at https://www.kbzk.com/news/local-news/ukraine-influences-wheat-prices-world-wide (accessed Nov 22, 2023)

Nasir M.A., Nugroho A.D., Lakner Z. (2022): Impact of the Russian–Ukrainian conflict on global food crops. Foods, 11: 2979.

Niedbała G., Nowakowski K., Rudowicz-Nawrocka J., Piekutowska M., Weres J., Tomczak R.J., Tyksiński T., Álvarez Pinto A. (2019): Multicriteria prediction and simulation of winter wheat yield using extended qualitative and quantitative data based on artificial neural networks. Applied Sciences, 9: 2773.

Nóia Júnior R.S., Ewert F., Webber H., Martre P., Hertel T.W., van Ittersum M.K., Asseng S. (2022): Needed global wheat stock and crop management in response to the war in Ukraine. Global Food Security, 35: 100662.

Norland E. (2016): Record price gap between U.S. and European wheat. CME Group. Available at https://www.cmegroup.com/education/featured-reports/record-price-gap-between-us-and-european-wheat.html (accessed Jan 5, 2023)

Rodrigues P.C., Mahmoudvand R. (2016): Correlation analysis in contaminated data by singular spectrum analysis. Quality and Reliability Engineering International, 32: 2127–2137.

Ropelewska E. (2019). Classification of wheat kernels infected with fungi of the genus *Fusarium* using discriminative classifiers and neural networks. Chilean Journal of Agricultural Research, 79: 48–55.

Sabar G., Jabran M., Hussain A., Hussain S., Sabir W., Zulkiffal M., Ahmed M.S., Joyia F.A., Ali M.A. (2021): Field-based assessment of genetic diversity for leaf rust resistance and yield attributes in the locally developed wheat cultivars using multivariate analysis. Pakistan Journal of Agricultural Sciences, 58: 1813–1823.

Schierhorn F., Hofmann M., Gagalyuk T., Ostapchuk I., Müller D. (2021): Machine learning reveals complex effects of climatic means and weather extremes on wheat yields during different plant developmental stages. Climatic Change, 169: 39.

Shimelis H.A., Shamuyarira K.W., Mathew I., Tsilo T.J. (2019): Correlation and path coefficient analyses of yield and yield components in drought-tolerant bread wheat populations. South African Journal of Plant and Soil, 36: 367–374.

Shamsabadi E.E., Sabouri H., Soughi H., Sajadi S.J. (2022): Using of molecular markers in prediction of wheat (*Triticum aestivum* L.) hybrid grain yield based on artificial intelligence methods and multivariate statistics. Russian Journal of Genetics, 58: 603–611.

Song J., Oyama S., Kurihara M. (2018): A framework for crowd-based causal analysis of open data. In: 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Myiazaki, Japan, Oct 7–10, 2018: 2188–2193.

Tortajada C., Biswas A.K. (2022): The price of grain, the global supply chain, and the invasion of Ukraine. Available at https://www.policyforum.net/the-price-of-grain-the-global-supply-chain-and-the-invasion-of-ukraine/ (accessed Nov 22, 2023)

https://doi.org/10.17221/121/2023-AGRICECON

Trafimow D. (2017): The probability of simple versus complex causal models in causal analyses. Behavior Research Methods, 49: 739–746.

Tan C.W., Bergmeir C., Petitjean F., Webb G.I. (2021): Time series extrinsic regression: Predicting numeric values from time series data. Data Mining and Knowledge Discovery, 35: 1032–1060.

Villasmil-Espinoza J.J., Leheza Y., Holovii L. (2022): Reflections for the interdisciplinary study of the Russian Federation's invasion of Ukraine in 2022. Cuestiones Políticas, 40: 16–24.

Vochozka M., Horák J., Šuleř P. (2019): Equalizing seasonal time series using artificial neural networks in predicting the Euro–Yuan exchange rate. Journal of Risk and Financial Management, 12: 76.

Xiong X., Bian Y., Shen D. (2018): The time-varying correlation between policy uncertainty and stock returns: Evidence from China. Physica A: Statistical Mechanics and Its Applications, 499: 413–419.

Received: April 6, 2023
Accepted: October 2, 2023