Food price dynamics in Turkey's agricultural export market with selected machine learning approaches

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Abstract

Price fluctuations significantly impact supply and demand mechanisms, particularly in agriculture and food production. These effects are often persistent and challenging to adapt directly, making it crucial for agrarian countries to understand the factors driving these changes. This research focuses on calculating a specific food price index related to Turkish food exports, with the goal of evaluating the factors contributing to volatility in this index. Using data from 1991-2022, the analysis employed selected machine learning methodologies to project potential policy interventions. The support vector regression (SVR) predictions revealed that rising prices of exportable products are driven by various factors, including cost items, food price inflation, unemployment levels (as an indicator of income), and exchange rates. The predictions closely aligned with the actual calculated variables, suggesting that variations in aggregate price levels, exchange rates, and technology-related and import-dependent costs are critical for observation and evaluation. These factors appear to play a more significant role in determining price inflation for Turkish agricultural and food products.

Keywords: *Food trade, Food prices, Machine learning, Turkey.*

1. Introduction

Prices of goods and services are critical indicators of a country's economic well-being and societal welfare. Among these, food prices hold particular significance as they constitute a substantial component of aggregate price levels. The Food and Agriculture Organization (FAO) regularly announces food prices, providing a global benchmark that complements domestic price data or Consumer Price Index (CPI), a key measure of inflation that reflects the cost of living and purchasing power of a population. This bilateral relationship between food prices and CPI is well-documented, with evidence suggesting that food prices exert a stronger influence on CPI than other goods (Oral *et al.*, 2023).

Inflation in agricultural commodity prices often outpaces overall CPI, driven by rising input costs that significantly affect production

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outputs. This dual effect highlights the complexity of inflationary pressures in the agricultural sector (Canbay, 2023). The implications are particularly profound for countries like Turkey, where agriculture plays a vital role in both domestic consumption and international trade. Turkey is a significant producer of a wide range of agricultural products, including some tropical and sub-tropical items (Gunes *et al.*, 2017). The country's agricultural sector has evolved from traditional dry farming to more sophisticated irrigated and controlled production systems, which have enhanced its export potential (Yucer, 2020).

The impact of food and agricultural prices on macroeconomic stability is more pronounced in producer countries, where these goods serve as both consumer staples and commercial exportable products (Page, 2013). This dual role underscores the importance of understanding the factors driving price volatility. In recent years, numerous studies have examined the dynamics of food prices in Turkey, often focusing on the relationship between agricultural producer prices (PP) and CPI. For instance, Canbay (2023) conducted a panel causality analysis across selected developing economies, including Brazil, India, Indonesia, Turkey, and South Africa. The study found that in Turkey, rising agricultural prices contribute to higher consumer prices, while inflation tends to suppress agricultural prices. Interestingly, the study revealed diverse impacts across other countries, highlighting the complex interplay between inflation and agricultural prices globally.

Further investigations into Turkey's food price deviations, spanning data from 1992 to 2022, have employed various quantitative methods. For example, Ozcan (2023) utilized Augmented Dickey-Fuller (ADF) tests to assess price bubbles in datasets from the FAO, OECD, and IMF, identifying significant deviations in FAO and IMF datasets. Meanwhile, Ozdurak (2021) explored the interplay between Turkey's national agricultural price index, the FAO index, and exchange rates from 2000 to 2020 using a Vector Autoregression (VAR) approach. The findings indicated that domestic price increases have a more substantial impact on the FAO index, while short-term exchange rate depreciations negatively influence agricultural imports.

Given the importance of these findings, this study aims to detect and analyze variations in Turkey's food prices from 1991 to 2022, with a particular focus on exportable agricultural products. By employing alternative machine learning methodologies, this research seeks to investigate the effects of macroeconomic and global factors on food price volatility, offering new insights that could inform policy interventions and economic strategies.

2. Methodology

Inflation in agricultural and food commodity prices has been closely monitored through announcements by national statistical organizations and global entities such as the FAO. This research aimed to develop a unique index specifically for exportable agricultural products of Turkey. The food price index was adjusted based on the export proportions of various product groups, including cereals, meat and dairy products, oil products, and sugar. Subsequently, the variation in this index was analyzed in relation to several macroeconomic factors, including the FAO's Food Price Index for Turkey (FFPI). Other influential factors considered in this research included macroeconomic cost data and global economic indicators. The analysis spanned a 31-year period from 1991 to 2022.

The Food Price Index specific to Turkey (FPT) was developed using a formula that incorporates data on exportable food products and their respective prices:

(1) $FPT = \sum \{a_i/b_j*(P_i/P_j)\}$

a_i= the export share of product i in the relevant product group j

b_j= the export share of product group j in the total agricultural and food exports

P_i= the price index of product i

P_j = the price index of the product group that the product takes place in.

Product groups (j) and products (i) used to calculate the index for Turkey was as following due to FAO databases.

Cereal	Meat	Milk	Oil Products	Sugar
• Wheat • Barley • Maize • Millet • Oat • Rye • Sorghum • Rice	• Cattle: bone – without bone – fresh – frozen chilled • Buffalo – beef • Turkey meat • Sheep (sheep + chilled/ frozen • Chicken	• Raw milk – cattle • Raw milk – cow; condensed + operated: raw buffalo milk + butter + cheese • Sheep – cream	• Groundnut • Olive • Maize • Soya • Sunflower • Sesame • Cotton seed • Safflower	• Sugar beet

Therefore, this weighted index enabled is an indicator reflecting the shares of Turkish exportable agricultural products. The specific calculated export based FPT (y_i) for Turkey was run against the following variables (x_i):

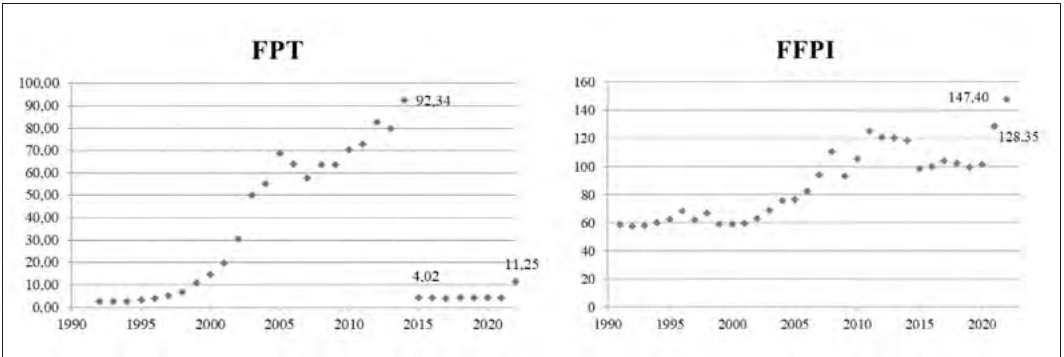
- Food Price Index announced by TUIK for Turkey – PPF_TR
- Producer Price Indices (TUIK)
  a) Petroleum and Gas Prices – PGP
  b) Agricultural Machinery Prices – AMP
- Share of People Employed (%) (ILO) – R_EMP
- Number of People Unemployed (thousands) (ILO) – UNEMP
- Exchange Rate (Dollar/ TL) – EXC
- FAO Food Price Index – (FAO) – FFPI

Prior to the analysis, the calculated export-based index that is the dependent variable (FPT), and the announced FPI for Turkey (FFPI) were demonstrated in the Figure 1.

The continuously rising food prices are evident on the right-hand side of the data, but a sharp decline in the calculated index after 2014 warrants attention, particularly in relation to agricultural exports. Over the 31-year period, the index for exportable products increased in 22 years. The fluctuation in the Food Price Index (FPT) between 2004 and 2008 seems to correlate with rising imports of agricultural products and inputs, reflecting the varying significance of these products within the FPT index (Anonymous, 2008). The observed fall in 2014, followed by a subsequent stabilization, also appears to be linked to import patterns (Orkunoglu Sahin, 2022). As a result, rising food commodity prices contributed to a reduction in exports.

Despite the declining trend in many segments of exportable products, demand for major crops such as cereals and vegetables in Turkey increased, influencing agricultural prices and price indices. The FAO index for Turkey rose by 15%

Figure 1 - Calculated Index (FPT) and FAO Index for Turkey (FFPI) (1991-2022).



Source: Authors' calculation and findings based on FAO (2022) and TUIK (2022) datasets.

from 2021 to 2022 and by 46% from 2020 to 2022. Particularly the COVID-19 pandemic led to an increase in exports for Turkey in 2021 and 2022, following the elimination of trade barriers imposed during the early stages of the pandemic and bolstered by increased producer support (Altay, 2024). Given these trends, this study aimed to analyze the variations using machine learning methodologies. To differentiate data projection tasks in analytics, machine learning methodologies such as multiple linear regression (MLR), support vector regression (SVR), and artificial neural networks (ANN) were employed.

Firstly, multiple linear regression (MLR) methodology derived from Gaussian analytical perspective focuses on finding a linear equation of potentially effective factors (x_i) which provides estimates that are close to the real values of the dependent variable (y_i) as shown below (Sheynin, 1999).

$$f(x_i) = y_i = \sum \beta_i * x_i + u_i$$

Food price index is the dependent variable in our case. The proximity of estimates to observed/real values of y_i is measured with the sum of squared errors ($\sum u_i^2$) of estimation in the econometric literature (Narula and Wellington, 1977). With minimum deviation, the probability of finding a more explanatory linear relationship between variables and increasing the accuracy of the estimates and forecasts of the economic data becomes more eligible. In other words, minimum errors mean maximum proximity between estimated and calculated food price indices.

In accordance with recent statistical progress, the regression methodology was implemented by dividing the sample into training and testing sets, consistent with MLR and machine learning practices. Train and test approach refers to learning the data tendencies from a randomly separated portion/percentage of the available dataset and forecasting the relationship with the remaining observations. With training the data, the probability of minimizing the sum of squared errors increases. Wide deviations can be removed with training and reaching robust and consistent estimates with higher fit of regression becomes more eligible (Dietterich, 1995). Additionally, overfitting reduces as the data is processed more than once to eliminate extreme values (Allgaier and Pryss, 2024). Besides, more training can be suggested for larger dataset as testing sample would be large enough to capture the unseen projections. More testing is more efficient for smaller datasets and mostly 80-20% of train-test-split approach is being used in the literature (Manda *et al.*, 2021).

Secondly, support vector regression (SVR) model predicts the weights of input components (w) of the estimation vector (x_i) that affect corresponding output (y_i).

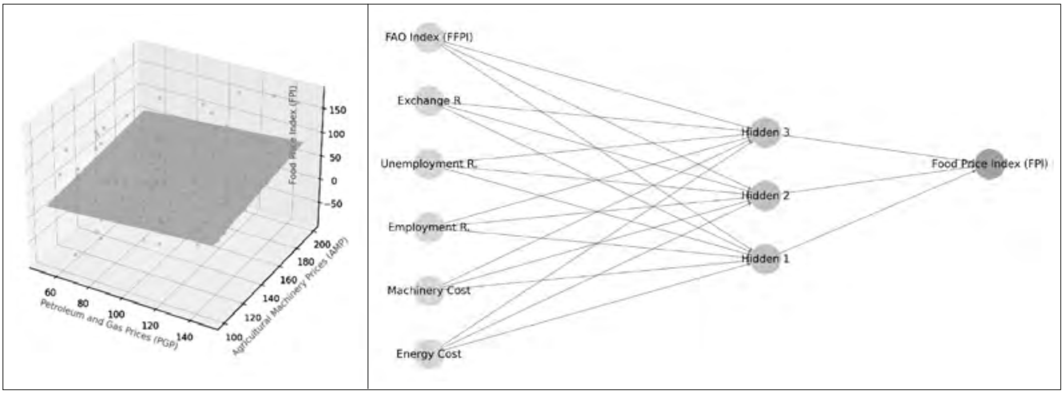
$$f(x_i) = y_i = \sum w * x_i + b$$

SVR was introduced mostly to solve non-linear problems with regression (Montesinos López e*t al.,* 2022) and it is an extension of SVM (support vector machine) that has been used for non-linear classification since its introduction for computer science algorithms (Cortes and Vapnik, 1995). The objective of SVR is again minimization of the errors, but differentiating feature is using a hyperplane and elimination of the commonalities in the error terms (Beniwal *et al.*, 2023). Hyperplane is the line, plane or more than 3D spaces that differentiates data depending on the number of factors or inputs explaining the expected food price index (y_i).

SVR does not enforce linear process and look for a kernel that guarantees the optimization rather than minimization (Jayaswara *et al.*, 2023). The supervised machine learning algorithm classifies without using default hyperparameters and uses a kernel function for forecasting (Awad and Khanna, 2015). Kernel function enables analysis of non-linear data and inference on multi-dimensional problems. It can be classified as linear, polynomial, radial basis function (RBF) and sigmoid kernel. RBF kernel helps trial of different non-linear scenarios to find the best fitting equation. Sigmoid functions are more alike neural network implementations. Mostly, RBF kernel is used to interpret data with more than two dimensions or with at least 3D hyperplanes (Cortes, and Vapnik, 1995; Simian *et al.*, 2020).

Thirdly, artificial neural network (ANN) approach is used to forecast potential networks between inputs that yield the best fit for the out-

Figure 2 - Demonstration of SVR hyperplane (a) and ANN relationships between input and output layers (b).



put with a revealing approach regarding hidden layers of input correlations (Najem et al. 2024). The hidden layers are the non-described and invisible factors affecting the neural relationship between inputs and outputs. In other words, there are factors that were not defined prior to the analysis, and ANN approach aims to portray these factors and their relationship with both sides of the equation meaning inputs and outputs. The number of layers is related to the complexity of the relationship and dimensions of the question (Siddique Afraaz and Vijayaramachandran, 2020). The networking approach suitable for machine learning was developed within a stock price prediction study conducted for Shanghai Stock exchange (Wen *et al.*, 2024).

Therefore, three Machine Learning methodologies explained technically above were used in this research to estimate and predict the factorial relationship that provides information on food price index (FPT) calculated for Turkey. Interpretation of price changes with recently used approaches appeared as a complementary objective for the current research. The analyses were conducted in Python Anaconda Ide. The ratios for training and testing the data were 80% and 20% respectively for all methodologies.

To summarize, the major difference between these algorithms is the dimension of the estimated food price index and processing of the data. The multi-variables are used to estimate a linear relationship and show a linear graph of findings in MLR. The relationship lay-out of SVR and ANN processes are demonstrated below.

In SVR, more dimensions are included for multi-variables, and a hyperplane is estimated. In ANN prediction, available – measured inputs are weighted with different approaches and additional invisible algorithms are produced to reach the single output, the food price index. Estimation and predictions of three algorithms were demonstrated in the following section.

3. Results

3.1. *Multiple Linear Regression Results (MLR)*

MLR was implemented alongside machine learning algorithms. Initially, the factors were estimated at their original levels. However, the anticipated multicollinearity between variables was assessed using Variance Inflation Factors (VIF) following the level estimation. The results in Table 1 indicated that the VIF values for all variables were notably high, with agricultural

Table 1 - VIF of independent variables.

Variables	*PPF_TR*	*PGP*	*AMP*	*EXC*	*UNEMP*	*R_EMP*	*FFPI*
VIF	794.39	89.14	1,364.97	115.09	123.76	90.41	58.81

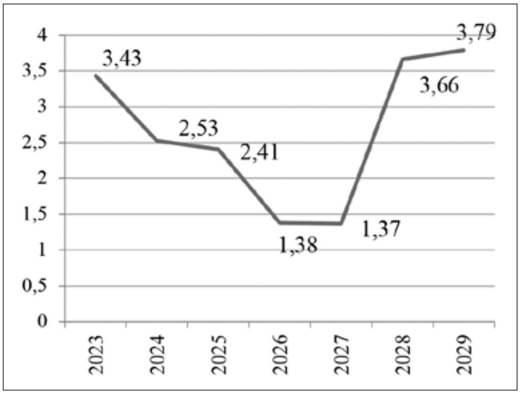
Source: Authors' calculation and findings based on FAO (2022) and TUIK (2022) datasets.

machinery prices being the most non-linear variable, followed by the FAO index for Turkey, the unemployment rate, and exchange rates.

Before applying linear adaptation, the data was initially estimated with a moderate R^2 of 79%, but the Mean Squared Error (MSE) was 261.96 and this indicated a low fit. The VIF values remained high even after logarithmic transformation, necessitating a reduction in variables for more accurate projection. Consequently, multicollinearity among the variables was not sufficiently addressed through linear transformation alone, prompting the consideration of additional methods. Lasso and Ridge regularizations were proposed to mitigate multicollinearity. The transformed logarithmic variables were estimated using Ridge modification, with a reduction in highly collinear variables, such as the announced Food Price Index (PPF_TR) and the share of employment (R_EMP). Ridge regression constrains the sum of squares of the parameters, minimizing the likelihood of an L2 penalty (Thevaraja *et al.*, 2019). The goodness of fit for this log-ridge estimation improved to 80%, and the MSE was reduced to 0.36. An antilog calculation to infer odds ratios revealed that the highest contributors to the export-based index (FPT) were the announced prices and the agricultural machinery price index.

Following Ridge modeling, Lasso regularization was implemented. Lasso drives the ineffective parameter estimates to zero, whereas Ridge regression allows for the interpretation of all variables by distributing the collinearity effect among factors (Yang and Wen, 2018). The change in the export-based FPT was most significantly influenced by agricultural machinery prices, with an estimated impact of 1.77, followed by exchange rates. However, the rising exchange rate resulted in a relatively smaller increase in the index, with an odds ratio of 0.28.

Figure 3 - MLR – Ridge Predictions for FPT (2023-2029).



Source: Authors' calculation and findings based on FAO (2022) and TUIK (2022) datasets.

The fit of this estimation was 63%, with an MSE of 0.68. These estimates suggest that MLR-RIDGE may be a more effective approach. Accordingly, the FPT was projected for the next seven years using MLR-RIDGE estimates and demonstrated in Figure 3.

The calculated index was 11.25 in 2021 and decreased to 4.82 in 2022. Based on these reference figures, the decline is expected to continue until 2028. However, the reduction in exports does not appear to support a rising index within the current methodology. In other words, there is no short-term expectation for a significant increase in the index. This does not imply that prices will decrease; rather, prices are expected to continue rising, but at a slower pace.

3.2. *Support Vector Regression Prediction (SVR)*

SVR was implemented for level and log-transformed versions of the factors. Kernels of estimation were linear and radial basis function (RBF) for level and polynomial kernel was

Table 2 - SVR Results for FPT estimation.

	LEVEL		*LOG*		
	LINEAR	*RBF*	*LINEAR*	*RBF*	*POLY*
MSE	3 545	1 333.26	0.97	0.28	1.56
R^2	-1.78	-0.05	0.47	0.85	0.15

Source: Authors' calculation and findings based on FAO (2022) and TUIK (2022) datasets.

added for the logarithmic estimation. The R^2 and MSE comparisons of initial modelling were demonstrated below. The constant of the prediction was taken as 10.

The RBF kernel mostly produces smooth and flexible regression curves for multidimensional data that adapt well to the training data with lower MSE and higher R^2 (Cortes, and Vapnik, 1995). Besides, negative R^2 of level estimations directly sign improper fit of the model. The best inference could be made with RBF kernel estimation of SVR modelling with log-transformation. The fit of predictions can be evaluated by the graphical representation. The overlap between the calculated export-based index and the predicted FPT is evident in Figure 4.

The average difference between the actual and predicted values over the tested 7 years is -0.29, with a mean squared error of 0.28 as indicated in Table 2. This suggests a slight depreciation in the calculated food index anticipated for the future. Given that the radial basis function aims to minimize the differences between real and predicted values, it can be concluded that the predictions are compatible with the actual values.

Figure 4 - Fit of SVR – RBF predictions (2016-2022).

Source: Authors' calculation and findings based on FAO (2022) and TUIK (2022) datasets.

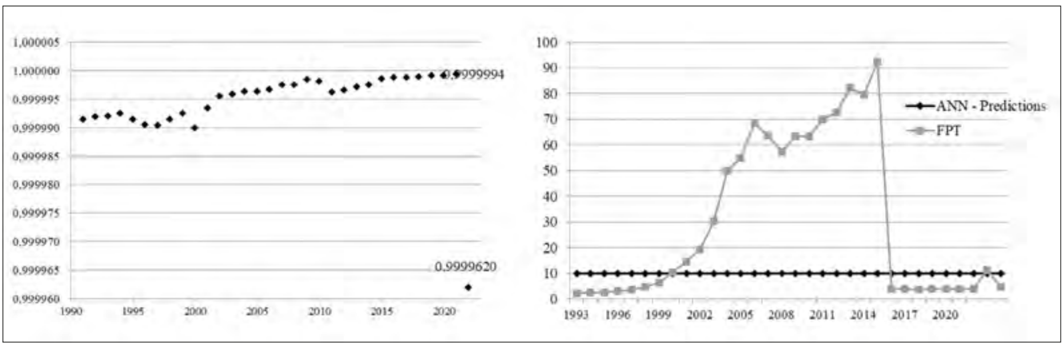
3.3. *Artificial Neural Networks Prediction (ANN)*

The reduced model was employed to determine if there is a neural relationship between the inputs and outputs. With two independent variables, the non-linear model was structured with three layers and one output. The predictions aligned well with the log-transformed data. As the model underwent repeated training, the fit of the data improved. The number of training cycles was set at 10,000 epochs, due to the limited sample size of 32 years. If the sample for the secondary data was large enough or pre-trained data was utilized, the number of trials to converge might be smaller (Zhang *et al.*, 2017). This approach suggests repeated training for higher fit without overfitting the estimates (Maliar *et al.*, 2021).

The predictions indicate a compatible index between 9 and 10 over the past 31 years, as shown on the left pane of Figure 5.

The calculated FPT and ANN predictions were closely aligned between 1991 and 2000, with a similar proximity observed after 2014. These periods of adjustment correspond to rising exports and the existing capacity to meet domestic demand. However, significant variation was noted during the first decade of the 2000s.

Figure 5 - ANN Predictions and FPT for 1991-2022.



Source: Authors' calculation and findings based on FAO (2022) and TUIK (2022) datasets.

Given the outputs, predictions for the future are better aligned with SVR and ANN models for estimating the specific export-based Food Price Index on an annual basis.

4. Discussion

Energy use is an integral part of agricultural production. Both the costs of production and agricultural value added are affected by the energy price volatility globally. This is especially valid for importing countries as machinery costs rise in a cyclical manner (Beckmann *et al*., 2020). Rising energy use appeared to affect agricultural production positively, while the energy cost had negative impact due to 1971 and 2003 annual data for Turkey (Karkacier *et al.*, 2006). As a significant supplier, oil price shocks used to stimulate industrial production in Iran. However, agricultural production had reduced, calling for more imports due to quarterly measures between 1989 and 2006 (Farzanegan and Markwardt, 2009).

Research on the economic impact of energy costs in BRICS countries portrayed that rising oil prices and sudden shocks increases marginal cost of production and reduces productive capacities of countries that are dependent on energy imports (*Nasir et al*., 2018). Accordingly, oil importing China and India have been worse off with rising prices, while exporters Russia and Brazil experienced rising export revenues in exchange of rising local production costs, the former being more significant. The impacts of international financial fluctuations on spot prices of wheat were analysed for Egypt between 1998 and 2017 (Ahmed, 2021). The research portrayed the uprising impact of futures prices in Paris (CBOT) and USA (MATIF) markets on prices of Egyptian wheat market, which is import-dependent.

In a complementary way, the reasoning behind rising production costs is related to changing availability and costs of financial inputs. Not surprisingly, the financial volatility is related to national currency volatility. Depreciating Chinese Wuan led to rising costs of energy inputs and this indeed led to rising interest rates and rising aggregate production costs in every economic activity line (Kim *et al.*, 2017). With a different perspective, unavailability of resources accompanied with low awareness and extensive information poses risks for importing countries as many African countries. An example is from Tunisia, with limited water and technological inputs and market instability due to international dependency (Thabet *et al*., 2024). The negative impact of strict Tunisian currency devaluation on prices has also been visible after 2012. The research suggests promotion of smart agriculture and reduction of import dependency. Additionally, insurance and post-harvest management systems need to be promoted among Tunisian farmers.

It is also essential to evaluate the changing costs and depreciating Turkish Lira and their multiple effects. Although cost items generally drive-up prices in economic terms, the technology-related costs examined here were largely mitigated by the negative impact of the appreciating Dollar against Turkish Lira. The depreciation of currency and the associated increase in exports resulted in variations in the calculated and predicted indices over the study period. Therefore, the index formed based on exportable products was more affected by exchange rate fluctuations, while the indirect impact of exchange rates on energy and machinery costs was less significant. This also can be related to import dependency for other inputs as well. The rising costs observed in 2020 and 2021 were consistent with the increasing price indices used in the study.

The predictions confirmed a continuous fall in the export-based index from 2016 to 2019, followed by a sharp increase. The index more than doubled between 2020 and 2021, rising by 143%, with a further 20% increase from 2021 to 2022. These inverse shifts are attributable to the COVID-19 pandemic, as observed globally, and to exchange rate fluctuations specific to Turkey. The variations in the predictions, calculated values, and FAO-announced figures were consistent throughout the sample, reflecting both country-specific and global factors.

The predicted index variations can be viewed as a reflection of Turkey's experience during the COVID-19 pandemic. Major impacts on food markets included supply chain disruptions and trade interruptions, which affected prices, as confirmed in recent studies (Kubatko *et al.*, 2023). Similar effects have been observed in other countries, including the USA and Canada, highlighting the global nature of the pandemic's impact (Alabi and Ngwenyama, 2023). In Australia, primary data research revealed significant increases in the costs and prices of healthy nutrition, including fresh products, since 2019 (Lewis *et al.*, 2023). Recent findings for Turkey also underscore the impact of COVID-19, as well as other challenges such as oil price fluctuations and export conditions related to the Russian - Ukrainian conflict (Urak, 2023).

Rising food prices in response to external factors are a significant contributor to these fluctuations. FAO-announced food prices, which indicate food price inflation, appeared to increase the export-based index. The expected bilateral relationship between inflation and prices was evident. Alongside rising prices, the reduction in food exports since 2014 can be seen as a contributing factor to the fall in the index. This global trend has had a more pronounced effect on countries like Turkey. In an evaluation of Turkish-Chinese exports, both countries reported rising prices, increasing costs, and declining exports (Kazancoglu *et al.*, 2023). However, the fall in exports since 2014 is more closely linked to rising costs and an insufficient or declining supply of the major products examined in this study. Additionally, the stable exchange rate before 2013 stimulated agro-food imports, and this effect seems to have persisted amid global challenges (Ozdurak, 2023).

5. Conclusion

The study aimed to uncover the relationship between agricultural and food price determinants and a specific export-based index for Turkey. The calculated index, representing key exportable products and product groups, was evaluated against various production and trade-related factors. Using machine learning approaches, particularly Support Vector Regression (SVR), the model effectively captured 31 years of data. Significant correlations were identified between the specific food price index and input costs, such as energy and machinery, as well as exchange rates, which were negatively correlated with the index. Conversely, the index was found to rise in tandem with the unemployment rate and FAO-announced scores. This indicates that while rising technical costs and an appreciating Dollar tend to reduce food prices, increased unemployment or declining income levels lead to higher prices.

It is crucial to pre-evaluate the potential effects of macroeconomic challenges on agricultural production and pricing mechanisms. To better understand these effects, further research is needed, both on a comparative basis and through primary responses from producers. It is also important to consider the effects of exchange rates, unemployment, and income levels on agricultural and food commodity prices. While reducing demand inflation may not directly lower product prices, cost inflation has been more significant in agro-economic markets, impacting prices for end consumers. Since prices also influence economic growth through inflation, multidimensional policymaking and support mechanisms are necessary for Turkey and comparable countries. Although direct intervention in prices may be challenging, managing costs through effective investment in agricultural technology and inputs is essential. This conclusion is supported by the stronger effect of cost inflation on aggregate prices and using alternative evaluation approaches.

Specific inferences for Turkey are related to information and support mechanisms rather than direct market interventions. For critical products the public authority imposes minimum prices to protect both sides of the internal market. But these direct interventions are limited to products like wheat, hazelnut, tea and tobacco. A rising import-dependency is observed for wheat. Therefore, it is aimed to support reduction import dependency for wheat, while subsidization of remaining products mostly aims to protect export-competitiveness. Although it is not possible to support every single actor, public authorities have utilized other sorts of support with extension activities. There are significant funding tools available for producers and their unions. Ministry of Industry and Technology offers specific funding opportunities to small and medium sized enterprises and supports integration of smallholder actors. The farmers and other relevant agricultural operators also have direct funding opportunities provided by the Development Agencies. The major challenge here is reaching information rather than its availability. The organization of operators has been developing sincerely. However, reaching small units and assisting them at least towards cost efficiency need to be empowered. The extension officers are approved and monitored by the Ministry of Agriculture and Forestry. The ministry supports the producer unions, boards of agriculture and supra-structures of these NGOs to employ and monitor extension officers with further emphasis since 2010.

The two sides of agricultural trade are all effective in Turkish farm input and export product markets. The need to adjust import prices and at least maintain export revenues are attached to financial monitoring and guidance. All operators need to be informed on this extent as well. There it seems that empowerment of information systems is more essential under volatile conditions and these operators, especially the sector representatives, need to be supported in information dissemination processes.

These interpretations relying on technical findings can be extended to different sources of products or product group-based analyses can be streamed to use efficiency of techniques. However, it is important to keep in mind that the agricultural operators need to be informed about future economic expectations related to the awaited exchange rate fluctuations and input prices. These findings also emphasized that future projections on inflationary fluctuations are essential for production planning. Accordingly, the need for more focused index-based studies and dissemination of their findings are essential for assuring supplies.

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