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A Hybrid Simple Moving Average and XGBoost Approach for Enhanced Wheat Commodity Price Forecasting

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Abstract: The forecasting of wheat commodity prices plays a crucial role in mitigating financial risks for stakeholders across the agricultural supply chain. In this study, the predictive performance of three models—Simple Moving Average (SMA), Extreme Gradient Boosting (XGBoost), and a hybrid SMA-XGBoost model—was evaluated to determine their efficacy in capturing both linear trends and complex nonlinear patterns inherent in wheat price data. A 10-lag structure was employed to integrate historical dependencies and seasonal fluctuations, thereby enhancing the accuracy of trend identification. The dataset was partitioned into training (75%) and testing (25%) subsets to facilitate an objective performance assessment. The XGBoost model, known for its capability in modelling nonlinear dependencies, demonstrated the highest forecasting precision, achieving a Mean Absolute Percentage Error (MAPE) of 1.64%. The hybrid SMA-XGBoost model, which leveraged the complementary strengths of both SMA and XGBoost, yielded a MAPE of 1.75%, outperforming the standalone SMA model, which exhibited a MAPE of 2.60%. While the hybrid model displayed slightly lower accuracy than XGBoost, it offered greater stability and robustness by effectively balancing trend extraction and nonlinear adaptability. These findings highlight the hybrid approach as a viable alternative to purely machine learning-based forecasting methods, particularly in scenarios requiring resilience to diverse market fluctuations. The proposed methodology provides a valuable tool for policymakers, agricultural producers, and market analysts seeking to enhance decision-making strategies and optimize risk management within the agricultural sector.

Keywords: Forecasting; Simple Moving Average (SMA); Extreme Gradient Boosting (XGBoost); Hybrid modelling; Agricultural price prediction

1 Introduction

Accurate forecasting of wheat commodity prices is crucial for policymakers, traders, and stakeholders to mitigate risks and make informed decisions, especially in the context of volatile global markets and supply chain disruptions. The five largest wheat-producing countries—China, India, Russia, the USA, and France—are both exporters and importers of wheat [1–3]. While the global wheat market is denominated in metric tonnes, it is primarily traded alongside corn on the Chicago Board of Trade (CBOT) in the US markets [4–6]. Most analysts take into account the factors and drivers of wheat supply and demand, with a clear understanding of the price context in the market environment [7–9]. A key element in forecasting wheat price fluctuations is the relationship between supply and demand. In the global marketplace [10–12], forecasting in wheat trading involves considering multiple variables. One important factor is the climate conditions of the producing countries [13–15]. Additionally, wheat production can be influenced by government policies and advancements in agricultural technologies [16–18]. Analysts often rely on statistical models and historical data to predict near-future price changes [19–21]. Wheat yield is also impacted by global climate change, making it an important external factor in forecasts [22–24]. Global economic factors, such as population growth and changing consumer preferences, also affect demand. Fast-developing nations, in particular, tend to see increased wheat demand [25, 26], along with a rise in wheat-based products [27–29]. Moreover, wars or political instability in wheat-producing countries can disrupt the supply chain [30–33]. All these elements must be considered when forecasting wheat prices and trade volumes [34–36].

Figure 1. The map stressing China, India, Russia, the United States, and France

An effective forecasting model is critical to helping market participants make decisions, as shown in Figure 1 above for the countries China, India, Russia, the United States, and France. Prediction assists governments, traders, farmers, and enterprises in minimizing risk and developing trade plans [37–39]. Management tools that are predictive in nature based on the study of the physical, econometric, behavioural, and other aspects of wheat markets (wheat supply, demand, prices, etc.) would assist companies to optimize their profits and minimize their losses [40–42]; and, accurate forecasting ensures the availability of wheat to fulfil global demands [43–45]. Research and development in forecasting methods still transforms in solving difficulties in the wheat market [46, 47]. From the international perspective, wheat products undergo multiple trials that could impact availability, pricing and market access. The issue encompasses not just financial perspectives, but also external ones such as trade policies and climate conditions [48, 49]. In the last few years, climate change has emerged as an important factor determining wheat production over a range of countries [50, 51]. That being the case, market participants must understand the various variables that impact the commodity [52]. Given the complexities and uncertainties in wheat price forecasting, there is a pressing need for more robust and adaptive models that can integrate historical trends with machine learning techniques to enhance prediction accuracy and decision-making for market participants.

The condition makes the world's wheat supply unstable and uncertain. As a result, the price of wheat in the world market has shown significant volatility [53, 54]. The analysis of wheat commodity prices may use fundamental elements. Geopolitical instability, however, leads basic analysis to depend too much on uncertainty at each given moment. Production and demand data often do not reflect the real situation during times of political crisis [55–59]. As a result, an agile approach may be necessary considering variable market conditions [60, 61]. The utilization of geopolitical algorithms and economic data within the SSA framework results in less accurate pricing predictions. The major limitation of the model is that it does not suit non-stationary data or data affected by external events [62]. Thus, there is an urgent need to develop more complex prediction models [63, 64]. The ARIMA model, which focuses on patterns present in the past, performs better for stable trends. The approach is still less effective in the case of sudden market swings, as is occasionally the case with wheat products. Random Forests and Extreme Gradient Boosting (XGBoost) models have great potential; however, they are sparsely applied to model wheat commodity forecasts and prediction [65, 66]. In dynamic market situations, the model can process more complicated data and yield more accurate predictions [67–69]. The high price fluctuations as well as the importance of wheat as a world food staple commodity were some of the factors that largely motivated the research. The XGBoost method can be employed to examine extensive datasets on agricultural input pricing, global demand, and diverse economic components [70, 71]. This study aims to develop a hybrid forecasting model that integrates SMA and XGBoost to improve the accuracy of wheat price predictions, addressing the limitations of traditional statistical models in capturing market volatility and external disruptions.

2 Methodology

Metropolitan University in Manhattan, Kansas the study utilized the comprehensive methodological matrix spanning advanced machine learning algorithms and traditional statistical methods to study price variances across USD-coins in the wheat price and to accurately interpret market patens. We employed a methodological approach that combines linear and non-linear modelling to provide comprehensive trend analysis using historical price data. The proposed combination of SMA and XGBoost attempted to solve the problems of short-term dependency and noise in price data, while taking into account the volatility of the market situation which was fluctuations in stock prices due to events occurring around the world. Although SMA provides a simple and interpretable trend estimation, it is limited in capturing sudden market shifts and non-stationary patterns, whereas XGBoost, a powerful gradient boosting algorithm, excels at handling complex, non-linear dependencies but may require extensive hyperparameter tuning and computational resources.

The study's dataset included daily historical wheat commodity prices from 2013 to 2024, making it an excellent data set to analyse market trends, price variations and time series. The Austrian dataset provides a systematic analysis of price volatility in wheat during aspects such as supply chain disruptions, global events, and economic uncertainty. Another dataset contained 1,175 data points with daily prices from January 2, 2020, through September 6, 2024. In that time, the outbreak of COVID-19, world economic crises, agricultural production also causes fluctuations in prices. By utilizing this dataset, a broad range of essential market trends could be studied, thereby yielding informative insights when building prediction models that can aid legislators and market analysts. It facilitated the investigation of long-term and short-term market trends by study such as volatility trends like rising and falling price trends over a selected period. According to contemporary conditions, modern forecasting techniques could be used based on daily data between 2020 and 2024. Utilizing 10-lag framework short-term dependencies within price changes were detected enabling the model to better capture existing market conditions and mitigate noise. This provided high-quality and reliable secondary data sources to build forecasting models. The study provided SMA and XGBoost—more precisely, with respect to the wheat market sensitivity to global and economic events—for the first time in the commodity price forecasting literature [72].

Forecasts of wheat prices must be both reliable and accurate, therefore, both statistical and machine learning methodologies are evaluated capable of identifying linear and non-linear trends. The method ensured a full understanding of market dynamics, thus addressing the complexity of commodity price fluctuations driven by a short-term dependency and external information. Analysis of time series data is fundamental to understanding and anticipating trends in key commodities, especially those essential to world food systems. Employing state-of-the-art methods, the research analysed critical events on agricultural markets with a specific focus of the essential role that wheat plays in ensuring food security. The research was influenced by many factors, including major price fluctuations and the importance of sustainable development policies. SMA is used to find historical data average over a given period. When we deal with a time series, the SMA for a certain period is the mean of previous values. The method was used frequently in data analysis to identify short-term and long-term trends. Time Series Data Preparation: It refers to the collection of data points at a consistent interval over a specific time span. Analysing day-to-day stock prices, each number represented the price of that stock at a given point in time. Data is hugely important for looking at trends and patterns over time. The SMA, as delineated for a designated period, n, was calculated as follows [73]:

$$SMA_n(t) = \frac{1}{n} \sum_{i=1}^{n-1} u_{t-i} \tag{1}$$

For the XGBoost model, the SMA presented further features. Through lower short-term volatility, the SMA clarified data. Combining the SMA itself with the historical values of the source data produced the SMA feature dataset. For example, for periods t can use values and as input features can use, $u_{t-1}, u_{t-2}, \ldots, u_{t-n}$, SMA with periods of 10, 20, 30 etc. Back in the early 2010s, XGBoost was a relatively popular machine learning method, especially in data science competitions such as Kaggle. Its strength was its high accuracy and efficiency, making it capable of dealing with multiple data types. It also enhanced gradient boosting methods by combining several improvements that made them more efficient and stronger than standard gradient boosting methods. Here was an in-depth explanation regarding XGBoost along with its key features. XGBoost was a gradient boosting method with an aggregated approach where new "weak" models were incrementally created, the next model correcting the prediction errors of the previous. These models were called additive models, in that all attempted to improve the previous forecast and integral accuracy. XGBoost minimizes general error on the educational set by adopting an iterative method, thus growing model accuracy. Furthermore, the method demonstrated processing efficiency and assisted in minimization of overfitting. XGBoost has become the go-to algorithm in machine learning to improve expected accuracy. Assuming we intended to estimate the target value y based on a set of features x, the prediction at iteration t was articulated as:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t\left(x_i\right) \tag{2}$$

where,

$\hat{y}_i^{(t)}$: prediction for the first data in the t^{th} iteration.

$f_t\left(x_i\right)$: model or tree in the t^{th} iteration.

XGBoost's objective function consisted of two main elements. The first component was the loss function $L(y, \hat{y})$ which calculates the error between the actual value y and the model's prediction $\hat{y}$. The function measured the difference between predicted and actual values in order to guide the model toward the lowest prediction error. The second component was the regularization term $\Omega\left(f_t\right)$, which introduced a penalty for model complexity. Regularization prevented too complicated structures that can cause overfitting, hence preserving model simplicity. XGBoost's goal function balanced generalizability with accuracy by varying the two components. Models that performed remarkably on training data and also generalizing successfully to new data needed equilibrium. The function was:

$$Obj = \sum_{i=1}^{n} L\left(y_i - \hat{y}_i^{(t)}\right) + \sum_{i=1}^{k} \Omega\left(f_k\right) \tag{3}$$

In regression, the loss function frequently employed Mean Squared Error (MSE):

$$L(y, \hat{y}) = \frac{1}{n} \sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2 \tag{4}$$

Log-loss, or binary cross-entropy, was frequently employed for classification purposes. Regularization was a penalization component that regulates the model's complexity. Regularization in XGBoost was expressed as:

$$\Omega\left(f_t\right) = \gamma \mathrm{T} + \frac{1}{2} \lambda \sum_{j=1}^{T} w_j^2 \tag{5}$$

T: the number of leaves in the tree.

w_j: weight on j^{th} leaf.

γ and λ: hyperparameters to control the size and power of regularization.

For every iteration, the XGBoost approximated loss function changes with second-order Taylor expansion for model updates. By incorporating the Hessian along with the gradient, the technique additionally allowed the model to assess both the direction and magnitude of adjustments it needed to make. With second-order information, XGBoost could make more accurate updates, which resulted in faster convergence and improved accuracy. The Hessian showed the curvature, and the gradient explained the slope of the error, so both gave complete knowledge of reducing the loss. The model was trained on iterations; each time we made it maximise to reduce the error. The use of second-order information was one of the biggest advantages of XGBoost over traditional gradient boosting methods. For simple models, first-order gradient information was adequate, but second-order Taylor expansion enabled XGBoost to capture more complex data patterns. The new accuracy allowed the model to be faster and better at assignments of reading the intricate network of relationships in data. Hence, this made XGBoost very suitable for high-dimensional datasets, as precise changes were key. This method proved to be more effective for many math learning competitions and applications. The objective function in the t^{th} iteration can be approached as follows:

$$Obj^t \approx \sum_{i=1}^{n} \left[g_i f_t\left(x_i\right) + \frac{1}{2} h_i f_t\left(x_i\right)^2\right] + \Omega\left(f_t\right) \tag{6}$$

The gradient $\left(g_i\right)$ was the first derivative of the loss function to the previous prediction:

$$g_i = \frac{\partial L\left(y_i, \hat{y}_i^{(t-1)}\right)}{\partial \hat{y}_i^{(t-1)}} \tag{7}$$

The hessian $\left(h_i\right)$ was the second derivative of the loss function to the previous prediction:

$$h_i = \frac{\partial^2 L\left(y_i, \hat{y}_i\right)}{\partial \hat{y}_i^2} \tag{8}$$

Gradients indicated the essential direction of change, whereas the Hessian represented the optimal magnitude of change needed to minimize errors. Each decision tree in XGBoost had leaf nodes that retained prediction values for the data assigned to those nodes. On each leaf node (j), the optimal weight (w_j) calculated as follows:

$$w_j = -\frac{\sum_{i\in I_j} g_i}{\sum_{i\in I_j} h_i + \lambda} \tag{9}$$

I_j: datasets that fall on the j^{th} leaf.
$\sum_{i\in I_j} g_i$: number of gradients for data on that leaf.
$\sum_{i\in I_j} h_i$: the number of hessians for the data on the leaf.
λ: regulatory parameters that control the weight value so that it is not too large.

XGBoost uses computed gain to quantify the value of a split at a node. Gain represented the improvement of the objective function obtained from splitting the node into two new leaf nodes. XGBoost evaluated the gain to see if a split would provide better performance for the model. The calculation ensured that only beneficial splits, which reduced error or improved prediction accuracy, were made. Gain score: In order to find out the best split while training the model, the gain score was a key parameter that was used to construct a model's architecture. If the benefit was large enough, we did the split; otherwise, we avoided unnecessary complexity in the model. This approach allowed XGBoost to build an optimal tree structure by choosing splits that greatly improved prediction performance. The gain score was mathematically represented as:

$$Gain = \frac{1}{2}\left(\frac{\left(\sum_{i\in I_L} g_i\right)^2}{\sum_{i\in I_L} h_i + \lambda} + \frac{\left(\sum_{i\in I_R} g_i\right)^2}{\sum_{i\in I_R} h_i + \lambda} - \frac{\left(\sum_{i\in I} g_i\right)^2}{\sum_{i\in I} h_i + \lambda}\right) - \gamma \tag{10}$$

where,
I_L and I_R: datasets on the left and right branches post-splitting.
$\sum_{i\in I_L} g_i$ and $\sum_{i\in I_R} g_i$: number of gradients on left and right leaves.
γ: regularization parameter that controls the number of leaves (a larger gamma value will reduce the number of leaves formed).

The iterative method allowed the model to learn from its mistakes, with each tree concentrating on a specific part of the error. The predictions of various trees were then combined as the model evolved to deliver a robust ensemble. The method yielded a fairly accurate model capable of detecting complex trends in the data. The techniques allow XGBoost to generate accurate and general forecasts. XGBoost calculated the gradient and Hessian for every observation (errors) according to the forecasts in the previous model, and this makes the slope and curvature of the error obvious. The data utilized the gradient and Hessian values to create a decision tree that attempts to minimize residual error, thus informing the actual construction of the tree. The method improved accuracy at each stage by allowing for the precise modifications of the model. After the tree structure had been built, XGBoost optimized the weights of each leaf by applying a specific formula that ensured the output of each leaf sufficiently corrected the errors identified. Adding the new model to the existing ensemble as well as contributing to reducing the overall prediction error. This allowed it to better correct errors from prior passes, yielding a more accurate prediction. The original basis of XGBoost was efficient summarization, which was implemented by stepwise augmenting predictions with new models that built upon the errors of earlier predictions. Consequently, each model has a unique role that enhanced the overall performance. The structured process of continuously improving assured the optimizing of the model and helped it serve better and fight off any future competition. The final product was a prediction model that was quite accurate and evolved continuously from previous versions. XGBoost uses a systematic, ordered approach that nicely balances generalizing ability and exactness.

XGBoost has one of its most important hyperparameters, the learning rate (η), which defines how much each tree contributes to the model. Instead, a lower learning rate returned a better model over the dataset, but maximum performance was dependent on a greater number of trees. The maximum depth was an important factor influencing model complexity; it limited the depth of each tree. If it were very high, the model may have been more prone to overfitting; however, with greater maximum depth, it would be able to detect more complicated patterns. The subsample value indicates the percentage of data selected randomly to create each tree. The method added uncertainty to the model-building process and also reduced overfitting by using a sub-sample of the data for each iteration. The model complexity management also depended critically on γ and λ representing regularizing terms. Avidly penalizing overly complex trees, the criteria assured excellent model performance on held-out data. By combining these hyperparameters, users were able to achieve the proper trade-off between accuracy and resilience, thereby making XGBoost a powerful and configurable tool. Then the XGBoost was trained with the basic equation [74, 75]:

$$\hat{b}_i = \sum_{l=1}^{L} f_l\left(x_i\right) \tag{11}$$

where,

x_t was a feature vector for the sample of t and f_l was a decision tree to- l.

Using MSE as the loss function for regression the model was optimized [76]:

$$M(b,\hat{b}) = \frac{1}{n}\sum_{i=1}^{n}\left(b_i - \hat{b}_i\right)^2 \tag{12}$$

The results of the SMA and XGBoost models were combined by incorporating their respective projections. One approach to achieve this is by assigning weights to both forecasts:

$$\hat{b} = z_1 \times SMA(t) + z_2 \times \hat{b}_{XGBoost}(t) \tag{13}$$

where,

z_1 and z_2 were the weights for XGBoost and the SMA, respectively, and can be changed according to how well the model performs.

3 Results

The findings of the study showed that some of the forecasting models were able to capture the complexities of wheat price data, thereby emphasizing the importance of their home strengths and weaknesses. The analysis highlighted the reliability and accuracy of all methods, which may yield significant information for agriculture sector market analysis and exploration. Using a hybrid approach that combines XGBoost models with the SMA, they generated useful insight into new knowledge concerning wheat price predictions. The hybrid model significantly reduced forecasting errors due to XGBoost, which is better at identifying features with intricate patterns, and SMA, which lowers short-term volatility. The development allowed for wiser decisions to be made regarding market tactics and agriculture policies.

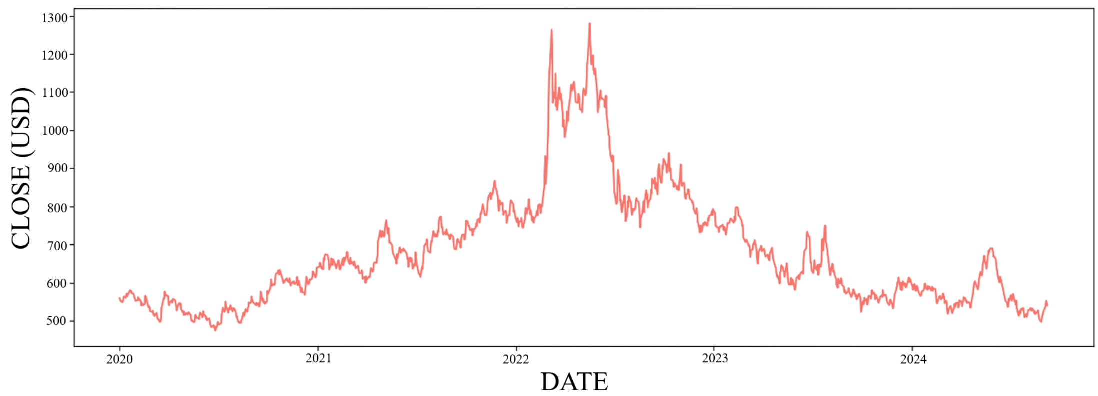

Figure 2. The time series graph of the closing price

Presumably a stock or cryptocurrency, Figure 2 depicted a time series of an asset priced in USD's closing price between early 2020 and mid-2024. The vertical axis shows the price range—from \$400 to \$1200—while the horizontal axis shows a year-by-year look, which allows for the ability to observe long-term trends. Between \$500 and \$700, the price of this asset did not change much from 2020 to 2021, and it remained on an upward trajectory with low volatility. Mirroring consistent market conditions through the range, the incremental growth represented value accretion unencumbered by material price volatility. Between 2021 and 2022, the asset had a noticeable rise in price above \$1200. Whether through external events or an increased excitement from investors, as the bulk rise suggested, increased market speculation and seethe. A major correction followed the apex that brought the price down to approximately \$700 by the end of 2022. The collapse may also have reflected changing market conditions that included profit-taking or outside economic events that shifted investor mood. Unlike previous oscillations that were more erratic, the asset has settled into a narrow range of \$500 to \$700 as of 2023. As the initial euphoria wore off and investors began re-evaluating the asset's fundamentals, the phase had indicated a return to sustainable price levels. The boom-and-bust cycle of 2021–2022 showed the importance of caution in speculative markets, as asset prices were heavily affected by internal and external developments.

Figure 3 displayed a comparison of two datasets labelled "Training Data" and "Testing Data" by way of a time series line graph to further elucidate temporal trends and facilitate comparison between training and testing phases. The line, which was designed as "Date," was scaled along the X-axis from 2020 to 2024 and provided a longitudinal view of changes to a variable normally associated with secondary financial measures like stock prices. "Closing

[USD] on Y-axis varied from $400 to $1300." The range highlighted the market volatility: To the downside, lower values indicated potential lows, to the upside, higher values signified market all-time highs. The study was proved useful for financial predictions, revealing the significant transformations in the profile of the waves: The peaks, troughs and the stable periods. The red line on the graphic shows training data from early 2020 too mid to late 2023. The era's statistics registered significant volatility, typical of the type of big swings found in a dynamic market. Price increases were huge from 2021 to 2022, largely driven by market bubbles or spikes initiated by external events, including speculation. What followed after the highs was a correcting period marked with the red line — the period when market balance changed and the prices fell significantly. The trend stressed what a big demand for sophisticated analytical techniques to model historical data to forecast future trends and the difficulty of forecasting in an uncertain market. With several prices most not crossing $700, the blue line, as it appears testing data from late 2023 to 2024, exhibited a shorter time period and demonstrated significantly less volatility. Perhaps in line with the tumble of speculative heights, the lower and more continuous range indicated a trend toward steadiness in the market. The blue line's stability - prices were consolidating towards a viable price band aided by economic developments or lower speculative demand — suggested that the phase of market activity was cyclic and there was significant disparity between training data and test data for this exercise underlining the importance of predictive modelling for financial behavioural analytics followed by an emphasis for downturn in market conditions leading up to an event and underwater considerations affecting deviations from normal distributions in the data.

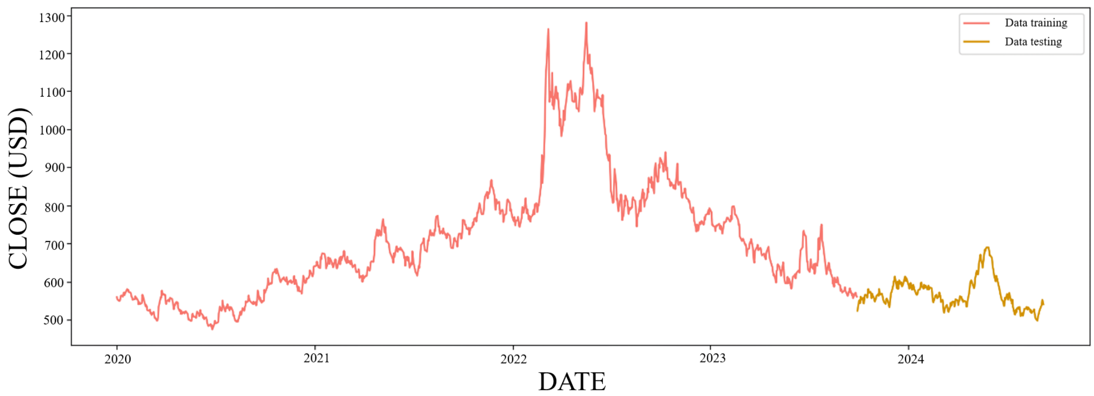

Figure 3. Training red data and testing yellow data

Table 1. The performance comparison of three prediction models

Model	MSE	RMSE	MAE	MAPE (%)
SMA	403.750	20.094	15.029	2.605
XGBoost	135.863	11.656	9.416	1.643
Hybrid SMA-XGBoost	173.845	13.185	10.022	1.750

The analysis of wheat price forecasting methods was used and three main models were compared: SMA, XGBoost, and Hybrid SMA-XGBoost. The results of the quantitative analysis of the accuracy measures, i.e., MSE, RMSE, MAE, and MAPE, provided a comprehensive assessment of the advantages and limitations of each model. Table 1 showed that the SMA model underperformed compared to the other models, with a MSE of 483.75 and a MAPE of 2.60%. It may imply that the SMA exhibited lower capabilities in identifying complex non-linear patterns in the wheat price data. SMA was able to determine the underlying linear trends while smoothing out short-term fluctuations, but its inability to detect the variance of more complex data was a huge disadvantage. As a result of this, using the SMA alone did not provide a sufficient basis on which to predict the movement in commodity prices, moving it past the requirement for more in-depth analysis. Despite this, SMA played a pivotal role in laying the foundation for hybrid approaches that amalgamated traditional and modern processes. XGBoost has shown impressive results, with a minimum MSE of 135.86 and a MAPE of 1.64%. XGBoost showed the best skill in recognising non-linear and complex data patterns and achieving precise predictions. This highlights the ability of the model to make use of complex interdependencies between variables. The RMSE of 11.65 signifies that the predictions were more stable and consistent as compared to SMA. The XGBoost model was consistently generating signals specifically for the complicated data of wheat price volatility. In comparison, the SMA-XGBoost hybrid model had a balanced performance with a MSE of 173.85 and a MAPE of 1.75%. MAPE was better than the value for XGBoost, but the model was less sensitive because it combined the power of SMA to identify linear trends with the effectiveness of XGBoost in terms of handling non-linear trends. Results show the hybrid model successfully combines a larger scope of data while preserving accuracy. In contexts with both long-term trends and short-term fluctuations in the data, the strategy was particularly relevant. The hybrid model is a good compromise to gain a balance of precision, stability, and adaptability in wheat price analysis.

Improve the prediction of commodity prices with complex data using three different models: A result of complementary conventional and modern approaches to conferencing meets close. The findings revealed that machine learning approaches, specifically XGBoost, achieved superior performance by capturing non-linear relationships between variables, while conventional models like SMA provided a strong foundation for linear trend detection. A hybrid model incorporating these two approaches holds much promise in terms of achieving an acceptable trade-off between accuracy and stability. From the data, understanding the properties of the data, long-term trends, and short-term fluctuations are essential for generating trustable predictions, the research findings showed. Particularly for commodity price volatility driven by both global and economic events, a hybrid strategy provided a useful means of solving the problem. Analytical techniques and modern technology are used to improve price forecasting, which provides essential information for policy-makers and market agents when markets are less stable.

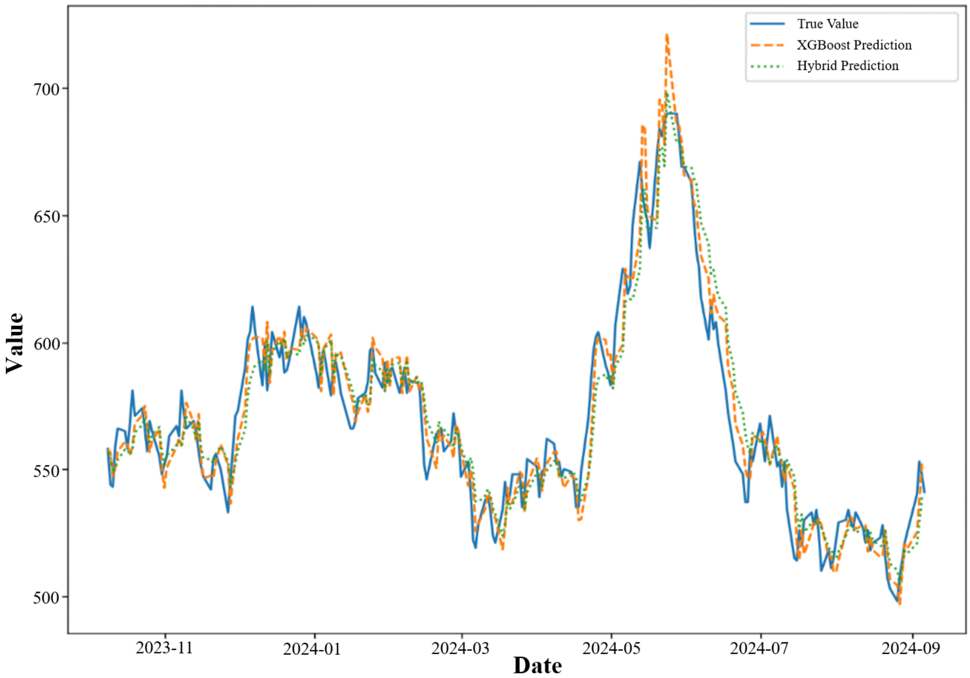

Figure 4. The graphic time series

Figure 4 shown above is a time series plot of True Value v/s XGBoost Prediction and Hybrid Prediction. This comparison also gave a visual evaluation of the predictive accuracy of each model over time. The next slide offers a comparison between True Value and projections, the pros and the cons of each model. The trend analysis threw light on how predictively valid and reliable both approaches were; in that all ways, both methods could elicit the basic trends in the data. Comparing the differences was imperative for assessing the prediction power of each model on dynamic variations in the dataset. The True Value was signified by a blue line enacting true data points from late 2023 through September 2024, painting the picture of considerable change suggesting a very high momentum, dynamical phenomenon cutting through our region of the parameter space. The peak in mid-2024, which is the highest value in the data set, was a key value to check model accuracy. The prediction by XGBoost, marked with an orange dashed line, followed the True Value closely, except when it overestimated values close to the peak. The anomalies indicated that, while XGBoost was reasonably effective, it had difficulty with notable anomalies. The Hybrid Prediction, shown in a green dotted line, was remarkably in tune with the True Value, especially at significant peaks and troughs, showcasing the integrated approach of the model in handling complex shifting patterns. The two models were both comparable to the true value, although the hybrid model showed a better tendency to follow trends, making this model a more appropriate choice for the dataset. This study emphasized that models should be selected according to the characteristics of the underlying data, and the hybrid model emerged as the preferred model for this application.

Figure 5 shows the closing price in USD (averaged on a daily basis) for the period from September 11, 2024 to September 19, 2024. Dates appeared along the x-axis, displaying a chronological order separated by two-day intervals, and the y-axis, bearing with the heading "Prediction of Daily Close", represented predicted values between approximately $600 and $1200. The hierarchical structure was excellent for visualizing price movements over time, which was important to assess market conditions. By providing a visual outline of how prices may vary, the graph ultimately helped stakeholders make more informed financial decisions by drawing attention to substantial differences within a compact timeline. There was significant polarization in pricing expectations on September 11, projecting a price of some $600. This was followed by a sharp increase, with an estimated $1200 by September 13, signifying a rapid shift in market expectations. After reaching the summit, the expected prices stayed flat at $1200 until September 19, when we have a consolidation phase. Aside from small fluctuations, the prevailing trend continued, suggesting an era of market stability had begun after the initial blast. The red dots represent the predicted closing prices for each day, with a dotted red line connecting them to emphasize the trend over time, showcasing both the adaptability of the model to different market conditions and its efficacy in spotting significant market trends.

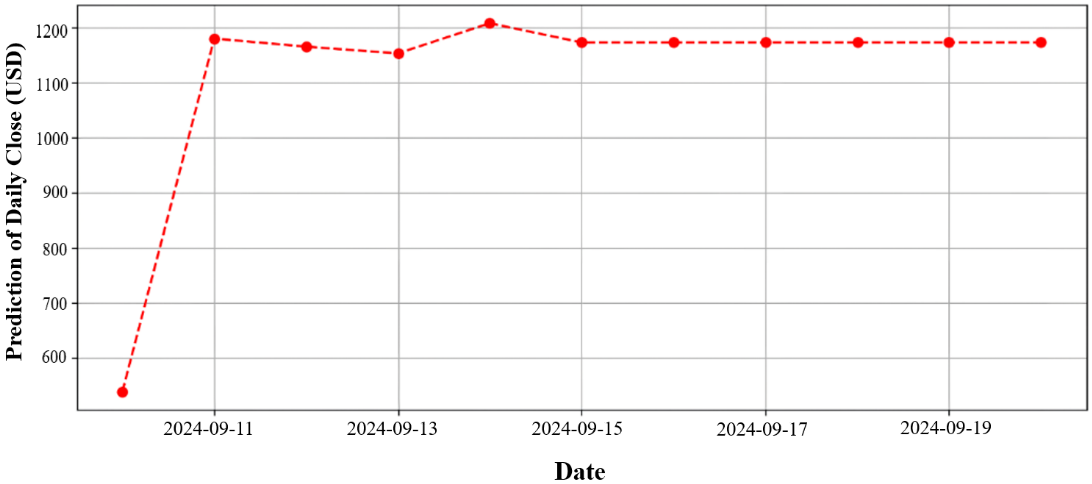

Figure 5. The daily closing price prediction

4 Discussion

The results will add to our knowledge of how asset prices behave over time and will have implications for models of financial forecasting. The study contributes to econometrics by analysing price impacts using time series data and predictive algorithms. One of the core observations is the cyclical nature of asset prices usually in terms of phases of price growth and decline, periods of high mobility and periods of relative stability. This cyclical pattern aligns with current trends in financial markets, consisting of various upcoming cycles of economic expansion (booms), followed by their inevitable correction. This cyclical nature is reflected in the large price increases during the 2021-2022 period, followed by a steep decline and price normalization. This is what we call a speculative bubble, and it is a period of time characterized by a significant increase in the price of certain assets due to increased demand and speculative investment, followed by a period of correction when the market realities show up. The boom-bust cycle highlights how both internal market dynamics and external economic conditions can lead to significant fluctuations in asset prices, with important implications for investors and policymakers in terms of the underlying volatility and unpredictability of financial markets. Figure 5: An analysis of the training and testing data used in this study highlights the importance of historical data in predicting trends under volatile market conditions from 2020 to 2023. Analysts have built and improved their forecasting models by identifying patterns of price increases and decreases, including significant peaks and troughs. These previous findings are critical for informing a more precise forecasting model during the testing phase. As for late 2023 to 2024, data shows volatility has significantly dropped — possibly identifying a period of market stability or retracement following a series of years marked by wild fluctuations. Separating training from testing phases serves as an important touchstone for ascertaining model reliability, providing an accurate understanding of predictive model performance in a more stable market climate. This finding emphasises the need for continuous historical trend analysis to properly assess how fluctuations in price impacted previous market conditions to make appropriately informed decisions. These observations of both observed reduction in price volatility and collection of new fundamental data are thought to reflect a market that has matured, where prices track sustainable levels instead of speculative peaks. The authors evaluate the performance of the different prediction models using several performance metrics, including MSE, RMSE, MAE, and MAPE. During the investigation, the XGBoost model consistently outperformed the SMA and Hybrid models in all metrics assessed in this study. XGBoost shows powerful performance for considering complex, non-linear associations in financial data. The hybrid model, therefore, includes elements of both standards and approaches to cross-stitching; however, its degree of success is not comparable to the individual accuracy of XGBoost. These results emphasize the efficacy of using XGBoost-type machine learning models for financial forecasting, especially when faced with datasets that are complex and also when identifying short- and long-term trends. The hybrid model outperforms the conventional SMA, suggesting that combining different approaches will exploit better models, especially in cases where high data volatility does not have much impact on forecast accuracy. The analysis shows that the XGBoost model performs well in situations where predictive accuracy is critical, thus confirming its importance in financial prediction. The paper focuses on forecast outputs in terms of the daily closing prices for September 2024, which shows how the models were able to accurately predict short-term price movements. The prediction for the next few periods implies initial dynamics of an upward price movement and then a consolidation phase, characteristic of a market when sharp fluctuations are generally followed by stabilization. This expected outcome is appropriate, given the model's responsiveness to data trends, and suggests the market might enter a stable phase after experiencing extreme volatility. This information is especially valuable for short-term traders and financial analysts as it aids in ascertaining the expected price direction and the possible price consolidation periods. The likely initial spike in price with subsequent stability indicates the model is sensitive to early market indicators, which appear to be measured against numerous outside influences such as regulations and changes in investor behaviours. The ability to adapt to changing markets very quickly shows that improved predictive models are required to handle and explain the fundamental randomness of markets. Through methodologies to specify and assess variations in this dynamic domain, the research demonstrates that potential effectuation of the trading of assets (e.g., simulated instruments) needs better forecasting approaches to be adopted for effective dispersion and decision formulation. The study emphasizes the value of regular updates to predictive models given the growing complexity and volatility of market environments. This highlights the shortcomings of the traditional approach, which fails to capture various complexities, and the strength of the hybrid model that utilises a mixture of simple models (i.e., SMA) and complex machine learning algorithm (i.e., XGBoost). Combined methods improve the accuracy of forecasting by using more than one methodology and help stakeholders to make better decisions. This will be especially important in sectors like agriculture, where prices are heavily influenced by weather variations, political factors, and market fluctuations. Tariff and quota hybrid models are flexible tools to address changing market conditions, ultimately improving global food security and stability in agricultural markets. It is suggested that fundamental methods and advanced algorithms be mixed together for commodities whose prices change a lot and for research on hybrid forecasting.

SMA and XGBoost model integration allows for a holistic evaluation of the forecast accuracy for crops like wheat. While SMA effectively quenches short-term volatility, it often misses out on price changes brought on by extreme weather or geopolitical events. XGBoost is one of the most powerful machine learning methods, which can efficiently handle large datasets and nonlinearities to increase prediction accuracy. An optimal balance between accuracy and stability is achieved through a hybrid method that combines the models. The approach has benefits for agricultural market stakeholders like legislators, merchants, and producers who rely on accurate forecasting to make informed decisions. The results demonstrate that integrating machine learning and forecasting models can lead to meaningful inferences about the intricacies of price volatility and improve the methodologies of market predictions. Traditional models like SMA may also be unable to adapt to rapidly changing markets. The results are quite interesting; machine learning methods result in much higher accuracy, and the winner is XGBoost. The hybrid method is a proposed method of combining the classical approach with an advanced one to obtain good forecasting results. Including machine learning methods for improved forecasts is an area where future forecasts should head, especially in volatile sectors such as agriculture. Using advanced forecasting techniques can help stakeholders better navigate market uncertainty and bring about more stability overall. The results highlight the need for more sophisticated modelling of the effects of multiple factors on agricultural prices and, in turn, the need to create a more resilient global food system," the authors of the study wrote.

5 Conclusions

This research sheds light on the prospects of some hybrid models that show the most promising results in wheat commodity prices forecasting, such as the hybrid of SMA and XGBoost models. While the S/M is a robust basis for trend analysis, it can overlook some of the more non-linear and complex patterns that arise due to extreme weather or geopolitical events. As a result, XGBoost is particularly successful in dealing with large datasets and complex patterns in these examples, which substantially improves the prediction performance. Combining such methods allows the hybrid model to more effectively balance stability with accuracy in order to guide agricultural market players. Results show that the hybrid method markedly improves forecasting accuracy, specifically in high-variability settings like agriculture. This model demonstrates more accurate outcomes relative to traditional methods, which has profound implications for the market actors, including farmers, traders, and policymakers, to manage risk and devise marketing strategies. Price forecasting improves planning for production, distribution, and consumption, enhancing world food security. It will provide market participants with a proven predictive tool for market fluctuations, creating increased stability and an improved regulatory environment for the market.

This research expands the body of work in data science and finance by combining nutritional trend analysis with contemporary machine learning methodologies. The study adds to the literature by presenting a novel method of dealing with volatility in agricultural markets. And the results also open doors to the model's usage in other sectors sharing volatility characteristics such as energy or logistics and thereby increasing its relevance and suitability in different market environments. This study notes the constraints of the hybrid model, in particular that its reliance on historical data combined with its limited real-time data integration reduces its adaptability to unforeseen market scenarios. Real-time data integration, advanced machine learning approaches, and expanding the universality of the model to cover additional commodities and markets will be explored in follow-up research. Hybrid methodology enhances forecasting accuracy and revolutionizes risk management and decision-making processes in the agricultural sector, promoting market stability and securing a more sustainable food supply chain globally.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] A. Dadrasi, M. Chaichi, A. Nehbandani, A. Sheikhi, F. Salmani, and A. Nemati, "Addressing food insecurity: An exploration of wheat production expansion," *PLoS ONE*, vol. 18, no. 12, p. e0290684, 2023. https://doi.org/10.1371/journal.pone.0290684

[2] J. Fu and G. Tong, "The state of grain trade between China and Russia: Analysis of growth effect and its influencing factors," *Agriculture*, vol. 13, no. 7, p. 1407, 2023. https://doi.org/10.3390/agriculture13071407

[3] G. Wang, B. Li, and X. Liu, "Evolution of global grain trade network and supply risk assessment based on complex network," *New Medit*, vol. 22, no. 4, pp. 43–55, 2023. https://doi.org/10.30682/nm2304c

[4] P. Langridge, M. Alaux, N. F. Almeida, K. Ammar, M. Baum, F. Bekkaoui, and et al., "Meeting the challenges facing wheat production: The strategic research agenda of the global wheat initiative," *Agronomy*, vol. 12, no. 11, p. 2767, 2022. https://doi.org/10.3390/agronomy12112767

[5] V. Petkov, "The international market of wheat and the food security," *J. Econ. Public Financ.*, vol. 9, no. 3, pp. 83–91, 2023. https://doi.org/10.22158/jepf.v9n3p83

[6] O. Skoromna, "Current trends of the world wheat market: Demand and supply," *Rev. Transp. Econ. Manag.*, vol. 7, no. 23, pp. 230–239, 2023. https://doi.org/10.15802/rtem2022/258054

[7] A. G. A. Cariappa, B. Kathayat, S. Karthiga, and R. Sendhil, "Price analysis and forecasting for decision making: Insights from wheat markets in India," *Indian J. Agric. Sci.*, vol. 90, no. 5, pp. 979–984, 2020. https://doi.org/10.56093/ijas.v90i5.104376

[8] A. Thakur, P. Ray, K. K. Acharya, A. Das, R. Jaiswal, U. Ravishankar, R. Raju, and R. Sendhil, "Price dynamics in Indian wholesale wheat markets: Insights and implications," *Indian J. Agric. Sci.*, vol. 91, no. 8, pp. 1219–1225, 2021. https://doi.org/10.56093/ijas.v91i8.115880

[9] N. Udhayan, A. D. Naik, and G. M. Hiremath, "Market arrivals and price behavior of wheat in major markets of India," *Asian J. Agric. Ext. Econ. Sociol.*, vol. 41, no. 10, pp. 378–386, 2023. https://doi.org/10.9734/ajaees/2023/v41i102181

[10] Z. Li, Z. Zhang, and X. Guo, "Wheat futures price prediction based on GA-VMD-CS-LSTM model," *BCP Bus. Manag.*, vol. 26, pp. 102–109, 2022. https://doi.org/10.54691/bcpbm.v26i.1830

[11] F. Shafipour, M. Shamsi, and R. Babazadeh, "Optimum prediction and forecasting of wheat demand in Iran," *Int. J. Appl. Manag. Sci.*, vol. 13, no. 2, pp. 141–151, 2021. https://doi.org/10.1504/IJAMS.2021.10039601

[12] L. Zomchak and T. Kukhotska, "Wheat market price dynamics in Ukraine: Quantitative exploration and forecasting," *Eur. J. Econ. Manag.*, vol. 9, no. 4, pp. 14–22, 2023. https://doi.org/10.46340/eujem.2023.9.4.2

[13] D. Beillouin, B. Schauberger, A. Bastos, P. Ciais, and D. Makowski, "Impact of extreme weather conditions on European crop production in 2018," *Philos. Trans. R. Soc. B Biol. Sci.*, vol. 375, no. 1810, p. 20190510, 2020. https://doi.org/10.1098/rstb.2019.0510

[14] N. Marmai, M. Franco Villoria, and M. Guerzoni, "How the Black Swan damages the harvest: Extreme weather events and the fragility of agriculture in development countries," *PLoS ONE*, vol. 17, no. 2, p. e0261839, 2022. https://doi.org/10.1371/journal.pone.0261839

[15] Z. Shi, H. N. Huang, Y. J. Wu, Y.-H. Chiu, and S. J. Qin, "Climate change impacts on agricultural production and crop disaster area in China," *Int. J. Environ. Res. Public Health*, vol. 17, no. 13, p. 4792, 2020. https://doi.org/10.3390/ijerph17134792

[16] A. A. Chandio, Y. A. Nasereldin, D. L. T. Anh, Y. Tang, G. R. Sargani, and H. Zhang, "The impact of technological progress and climate change on food crop production: Evidence from Sichuan—China," *Int. J. Environ. Res. Public Health*, vol. 19, no. 16, p. 9863, 2022. https://doi.org/10.3390/ijerph19169863

[17] S. Gahlot, T.-S. Lin, A. K. Jain, S. B. Roy, V. K. Sehgal, and R. Dhakar, "Impact of environmental changes and land management practices on wheat production in India," *Earth Syst. Dyn.*, vol. 11, no. 3, pp. 641–652, 2020. https://doi.org/10.5194/esd-11-641-2020

[18] C. Song, X. Huang, O. Les, H. Ma, and R. Liu, "The economic impact of climate change on wheat and maize yields in the North China Plain," *Int. J. Environ. Res. Public Health*, vol. 19, no. 9, p. 5707, 2022. https://doi.org/10.3390/ijerph19095707

[19] M. R. Islam and N. Nguyen, "Comparison of financial models for stock price prediction," *J. Risk Financ. Manag.*, vol. 13, no. 8, p. 181, 2020. https://doi.org/10.3390/jrfm13080181

[20] A. W. Li and G. S. Bastos, "Stock market forecasting using deep learning and technical analysis: A systematic review," *IEEE Access*, vol. 8, pp. 185 232–185 242, 2020. https://doi.org/10.1109/ACCESS.2020.3030226

[21] A. Medvedev and A. Medvedev, "Forecasting financial markets using advanced machine learning algorithms," *E3S Web Conf.*, vol. 403, p. 08007, 2023. https://doi.org/10.1051/e3sconf/202340308007

[22] C. Wan, P. Dang, L. Gao, J. Wang, J. Tao, X. Qin, B. Feng, and J. Gao, "How does the environment affect wheat yield and protein content response to drought? A meta-analysis," *Front. Plant Sci.*, vol. 13, p. 896985, 2022. https://doi.org/10.3389/fpls.2022.896985

[23] H. Zhang, Y. Tang, A. A. Chandio, G. R. Sargani, and M. A. Twumasi, "Measuring the effects of climate change on wheat production: Evidence from Northern China," *Int. J. Environ. Res. Public Health*, vol. 19, no. 19, p. 12341, 2022. https://doi.org/10.3390/ijerph191912341

[24] Y. Zhang, X. Qiu, T. Yin, Z. Liao, B. Liu, and L. Liu, "The impact of global warming on the winter wheat production of China," *Agronomy*, vol. 11, no. 9, p. 1845, 2021. https://doi.org/10.3390/agronomy11091845

[25] C. Abys, S. Skakun, and I. Becker-Reshef, "The rise and volatility of Russian winter wheat production," *Environ. Res. Commun.*, vol. 4, no. 10, p. 101003, 2022. https://doi.org/10.1088/2515-7620/ac97d2

[26] X. Wang, W. Qiang, S. Niu, A. Growe, S. Yan, and N. Tian, "Multi-scenario simulation analysis of grain production and demand in China during the peak population period," *Foods*, vol. 11, no. 11, p. 1566, 2022. https://doi.org/10.3390/foods11111566

[27] L. Deroover, Y. Tie, J. Verspreet, C. M. Courtin, and K. Verbeke, "Modifying wheat bran to improve its health benefits," *Crit. Rev. Food Sci. Nutr.*, vol. 60, no. 7, pp. 1104–1122, 2020. https://doi.org/10.1080/10408398.2018.1558394

[28] K. Harris, F. Overcash, D. Belobrajdic, and J. Slavin, "Perspective: Utilizing high amylose wheat flour to increase dietary fiber intake of children and adolescents: A health by stealth approach," *Front. Public Health*, vol. 10, p. 817967, 2022. https://doi.org/10.3389/fpubh.2022.817967

[29] H. Wieser, P. Koehler, and K. A. Scherf, "The two faces of wheat," *Front. Nutr.*, vol. 7, p. 517313, 2020. https://doi.org/10.3389/fnut.2020.517313

[30] W. Halecki and D. Bedla, "Global wheat production and threats to supply chains in a volatile climate change and energy crisis," *Resources*, vol. 11, no. 12, p. 118, 2022. https://doi.org/10.3390/resources11120118

[31] S. Jagtap, H. Trollman, F. Trollman, G. Garcia-Garcia, C. Parra-López, L. Duong, and et al., "The Russia-Ukraine conflict: Its implications for the global food supply chains," *Foods*, vol. 11, no. 14, p. 2098, 2022. https://doi.org/10.3390/foods11142098

[32] W. Leal Filho, M. Fedoruk, J. H. P. P. Eustachio, J. Barbir, T. Lisovska, A. Lingos, and C. Baars, "How the war in Ukraine affects food security," *Foods*, vol. 12, no. 21, p. 3996, 2023. https://doi.org/10.3390/foods12213996

[33] M. A. Nasir, A. D. Nugroho, and Z. Lakner, "Impact of the Russian–Ukrainian conflict on global food crops," *Foods*, vol. 11, no. 19, p. 2979, 2022. https://doi.org/10.3390/foods11192979

[34] F. M. Davenport, S. Shukla, W. Turner, C. Funk, N. Krell, L. Harrison, G. Husak, D. Lee, and P. Peterson, "Sending out an SOS: Using start of rainy season indicators for market price forecasting to support famine early warning," *Environ. Res. Lett.*, vol. 16, no. 8, p. 084050, 2021. https://doi.org/10.1088/1748-9326/ac15cc

[35] T. Vollmer, H. Herwartz, and S. von Cramon-Taubadel, "Measuring price discovery in the European wheat market using the partial cointegration approach," *Eur. Rev. Agric. Econ.*, vol. 47, no. 3, pp. 1173–1200, 2020. https://doi.org/10.1093/erae/jbz040

[36] A. Wolanin, G. Mateo-García, G. Camps-Valls, L. Gómez-Chova, M. Meroni, G. Duveiller, Y. Liangzhi, and L. Guanter, "Estimating and understanding crop yields with explainable deep learning in the Indian Wheat Belt," *Environ. Res. Lett.*, vol. 15, no. 2, p. 024019, 2020. https://doi.org/10.1088/1748-9326/ab68ac

[37] Y. Jia, A. Anaissi, and B. Suleiman, "ResNLS: An improved model for stock price forecasting," *Comput. Intell.*, vol. 40, no. 1, p. e12608, 2024. https://doi.org/10.1111/coin.12608

[38] D. K. Padhi, N. Padhy, A. K. Bhoi, J. Shafi, and S. H. Yesuf, "An intelligent fusion model with portfolio selection and machine learning for stock market prediction," *Comput. Intell. Neurosci.*, vol. 2022, p. 7588303, 2022. https://doi.org/10.1155/2022/7588303

[39] D. C. Yıldırım, I. H. Toroslu, and U. Fiore, "Forecasting directional movement of Forex data using LSTM with technical and macroeconomic indicators," *Financ. Innov.*, vol. 7, p. 1, 2021. https://doi.org/10.1186/s40854-020-00220-2

[40] P. Peng, Y. Li, D. Li, Y. Guan, P. Yang, Z. Hu, Z. Zhao, and D. Liu, "Optimized economic operation strategy for distributed energy storage with multi-profit mode," *IEEE Access*, vol. 9, pp. 8299–8311, 2021. https://doi.org/10.1109/ACCESS.2020.3047230

[41] R. A. B. da Silva, H. Pandorfi, G. L. P. de Almeida, and N. V. da Silva, "Optimizing the profit of an agricultural company through the application of genetic algorithms," *Int. J. Comput. Appl.*, vol. 183, no. 24, pp. 39–42, 2021. https://doi.org/10.5120/ijca2021921613

[42] A. Zielińska-Chmielewska, J. Kaźmierczyk, and I. Jaźwiński, "Quantitative research on profitability measures in the polish meat and poultry industries," *Agronomy*, vol. 12, no. 1, p. 92, 2021. https://doi.org/10.3390/agronomy12010092

[43] J. Cao, Z. Zhang, F. Tao, L. Zhang, Y. Luo, J. Han, and Z. Li, "Identifying the contributions of multi-source data for winter wheat yield prediction in China," *Remote Sens.*, vol. 12, no. 5, p. 750, 2020. https://doi.org/10.3390/rs12050750

[44] Y. Wang, Z. Zhang, L. Feng, Q. Du, and T. Runge, "Combining multi-source data and machine learning approaches to predict winter wheat yield in the conterminous United States," *Remote Sens.*, vol. 12, no. 8, p. 1232, 2020. https://doi.org/10.3390/rs12081232

[45] A. Pang, M. W. L. Chang, and Y. Chen, "Evaluation of random forests (RF) for regional and local-scale wheat yield prediction in Southeast Australia," *Sensors*, vol. 22, no. 3, p. 717, 2022. https://doi.org/10.3390/s22030717

[46] J. Han, Z. Zhang, J. Cao, Y. Luo, L. Zhang, Z. Li, and J. Zhang, "Prediction of winter wheat yield based on multi-source data and machine learning in China," *Remote Sens.*, vol. 12, no. 2, p. 236, 2020. https://doi.org/10.3390/rs12020236

[47] N. Udhayan, A. D. Naik, and G. M. Hiremath, "Market integration among major wheat markets in India," *Asian J. Agric. Ext. Econ. Sociol.*, vol. 41, no. 10, pp. 317–324, 2023. https://doi.org/10.9734/ajaees/2023/v41i102174

[48] N. S. Fradgley, J. Bacon, A. R. Bentley, G. Costa-Neto, A. Cottrell, J. Crossa, and et al., "Prediction of near-term climate change impacts on UK wheat quality and the potential for adaptation through plant breeding," *Glob. Change Biol.*, vol. 29, no. 5, pp. 1296–1313, 2023. https://doi.org/10.1111/gcb.16552

[49] J. Hristov, I. P. Domínguez, T. Fellmann, and C. Elleby, "Economic impacts of climate change on EU agriculture: Will the farmers benefit from global climate change?" *Environ. Res. Lett.*, vol. 19, no. 1, p. 014027, 2024. https://doi.org/10.1088/1748-9326/ad0e34

[50] O. S. Obembe, N. P. Hendricks, and J. Tack, "Decreased wheat production in the USA from climate change driven by yield losses rather than crop abandonment," *PLoS ONE*, vol. 16, no. 6, p. e0252067, 2021. https://doi.org/10.1371/journal.pone.0252067

[51] M. Qin, E. Zheng, D. Hou, X. Meng, F. Meng, Y. Gao, P. Chen, Z. Qi, and T. Xu, "Response of wheat, maize, and rice to changes in temperature, precipitation, CO_2 concentration, and uncertainty based on crop simulation approaches," *Plants*, vol. 12, no. 14, p. 2709, 2023. https://doi.org/10.3390/plants12142709

[52] D. N. L. Pequeno, I. M. Hernández-Ochoa, M. Reynolds, K. Sonder, A. M. Milan, R. D. Robertson, and et al., "Climate impact and adaptation to heat and drought stress of regional and global wheat production," *Environ. Res. Lett.*, vol. 16, no. 5, p. 054070, 2021. https://doi.org/10.1088/1748-9326/abd970

[53] J. Guo and T. Tanaka, "Examining the determinants of global and local price pass-through in cereal markets: Evidence from DCC-GJR-GARCH and panel analyses," *Agric. Food Econ.*, vol. 8, no. 1, p. 27, 2020. https://doi.org/10.1186/s40100-020-00173-1

[54] M. Svanidze and I. Đurić, "Global wheat market dynamics: What is the role of the EU and the Black Sea wheat exporters?" *Agriculture*, vol. 11, no. 8, p. 799, 2021. https://doi.org/10.3390/agriculture11080799

[55] Z. Gebeltová, P. Hálová, K. Malec, K. Bartoňová, V. Blažek, M. Maitah, and et al., "Geopolitical risks for Egypt wheat supply and trade," *Front. Sustain. Food Syst.*, vol. 7, p. 1137526, 2023. https://doi.org/10.3389/fsufs.2023.1137526

[56] E. Hein, W. P. Meloni, and P. Tridico, "Welfare models and demand-led growth regimes before and after the financial and economic crisis," *Rev. Int. Polit. Econ.*, vol. 28, no. 5, pp. 1196–1223, 2021. https://doi.org/10.1080/09692290.2020.1744178

[57] D. Krawczyk, V. Martynets, Y. Opanasiuk, and I. Rekunenko, "Socio-economic development of European countries in times of crisis: Ups and downs," *Sustainability*, vol. 15, no. 20, p. 14820, 2023. https://doi.org/10.3390/su152014820

[58] X. Lv, H. Zhang, Y. Zhang, and J. Li, "Spatial correlation evolution and driving factors of wheat production in China based on social network analysis," *Agronomy*, vol. 13, no. 2, p. 515, 2023. https://doi.org/10.3390/agronomy13020515

[59] Y. Sun, S. Zhang, F. Tao, R. Aboelenein, and A. Amer, "Improving winter wheat yield forecasting based on multi-source data and machine learning," *Agriculture*, vol. 12, no. 5, p. 571, 2022. https://doi.org/10.3390/agriculture12050571

[60] A. Sopelana, M. Kunc, O. Rivera, J. Aranceta, and A. R. Castellanos, "Modelling the dynamics of organisational change in a Spanish industrial cooperative," *J. Oper. Res. Soc.*, vol. 73, no. 3, pp. 455–466, 2022. https://doi.org/10.1080/01605682.2020.1860659

[61] A. Zeiselmair and S. Köppl, "Constrained optimization as the allocation method in local flexibility markets," *Energies*, vol. 14, no. 13, p. 3932, 2021. https://doi.org/10.3390/en14133932

[62] S. Kundu, "TemporalGSSA: A numerically robust R-wrapper to facilitate computation of a metabolite-specific and simulation time-dependent trajectory from stochastic simulation algorithm (SSA)-generated datasets," *J. Bioinform. Comput. Biol.*, vol. 20, no. 4, p. 2250018, 2022. https://doi.org/10.1142/S0219720022500184

[63] V. M. T. de Jong, K. G. M. Moons, M. J. C. Eijkemans, R. D. Riley, and T. P. A. Debray, "Developing more generalizable prediction models from pooled studies and large clustered data sets," *Stat. Med.*, vol. 40, no. 15, pp. 3533–3559, 2021. https://doi.org/10.1002/sim.8981

[64] K. S. Sandhu, D. N. Lozada, Z. Zhang, M. O. Pumphrey, and A. H. Carter, "Deep learning for predicting complex traits in spring wheat breeding program," *Front. Plant Sci.*, vol. 11, p. 613325, 2021. https://doi.org/10.3389/fpls.2020.613325

[65] A. Morales and F. J. Villalobos, "Using machine learning for crop yield prediction in the past or the future," *Front. Plant Sci.*, vol. 14, p. 1128388, 2023. https://doi.org/10.3389/fpls.2023.1128388

[66] Y. E. Roell, A. Beucher, P. G. Møller, M. B. Greve, and M. H. Greve, "Comparing a random forest based prediction of winter wheat yield to historical yield potential," *Agronomy*, vol. 10, no. 3, p. 395, 2020. https://doi.org/10.3390/agronomy10030395

[67] D. N. Gono, H. Napitupulu, and Firdaniza, "Silver price forecasting using extreme gradient boosting (XGBoost) method," *Mathematics*, vol. 11, no. 18, p. 3813, 2023. https://doi.org/10.3390/math11183813

[68] V. Srivastava, V. K. Dwivedi, and A. K. Singh, "Cryptocurrency price prediction using enhanced PSO with extreme gradient boosting algorithm," *Cybern. Inf. Technol.*, vol. 23, no. 2, pp. 170–187, 2023. https://doi.org/10.2478/cait-2023-0020

[69] K. Tissaoui, T. Zaghdoudi, A. Hakimi, O. Ben-Salha, and L. B. Amor, "Does uncertainty forecast crude oil volatility before and during the COVID-19 outbreak? Fresh evidence using machine learning models," *Energies*, vol. 15, no. 15, p. 5744, 2022. https://doi.org/10.3390/en15155744

[70] Y. Liu, C. Yang, K. Huang, and W. Liu, "A multi-factor selection and fusion method through the CNN-LSTM network for dynamic price forecasting," *Mathematics*, vol. 11, no. 5, p. 1132, 2023. https://doi.org/10.3390/math11051132

[71] W. Masiza, J. G. Chirima, H. Hamandawana, and R. Pillay, "Enhanced mapping of a smallholder crop farming landscape through image fusion and model stacking," *Int. J. Remote Sens.*, vol. 41, no. 22, pp. 8739–8756, 2020. https://doi.org/10.1080/01431161.2020.1783017

[72] P. J. A. Kleinman, S. Spiegal, J. R. Rigby, S. C. Goslee, J. M. Baker, B. T. Bestelmeyer, and et al., "Advancing the sustainability of US agriculture through long-term research," *J. Environ. Qual.*, vol. 47, no. 6, pp. 1412–1425, 2018. https://doi.org/10.2134/jeq2018.05.0171

[73] Q. Xue, Y. Ling, and B. Tian, "Portfolio optimization model for gold and bitcoin based on weighted unidirectional dual-layer LSTM model and SMA-slope strategy," *Comput. Intell. Neurosci.*, vol. 2022, p. 1869897, 2022. https://doi.org/10.1155/2022/1869897

[74] W. Li, Y. Yin, X. Quan, and H. Zhang, "Gene expression value prediction based on XGBoost algorithm," *Front. Genet.*, vol. 10, p. 1077, 2019. https://doi.org/10.3389/fgene.2019.01077

[75] P. Zhang, Y. Jia, and Y. Shang, "Research and application of XGBoost in imbalanced data," *Int. J. Distrib. Sens. Networks*, vol. 18, no. 6, p. 15501329221106935, 2022. https://doi.org/10.1177/15501329221106935

[76] J. Qi, J. Du, S. M. Siniscalchi, X. L. Ma, and C. H. Lee, "On mean absolute error for deep neural network based vector-to-vector regression," *IEEE Signal Process. Lett.*, vol. 27, pp. 1485–1489, 2020. https://doi.org/10.1109/LSP.2020.3016837