Enhancing Wheat Price Forecasting Accuracy through Prophet Based Models*

Dmytro Zherlitsyn[1,†], Volodymyr Kharchenko[2,*,†], Hanna Kharchenko[3,†]

[1] University of National and World Economy, 1303 Sofia, Bulgaria
[2] National University of Life and Environmental Science of Ukraine, 03189 Kyiv, Ukraine
[3] Glasgow Caledonian University, G4 0BA, Glasgow, UK

Abstract

Accurate forecasting of agricultural commodity prices, especially wheat prices, is critical for stabilizing food markets and informing strategic decisions across supply chains. This study investigates optimal forecasting methodologies for wheat prices using Facebook's Prophet Tool. While Prophet's default configuration uses base forecasting patterns, its performance is significantly enhanced through hyperparameter optimization, including custom Fourier terms for crop-specific seasonality and adaptive changepoint detection to capture market shocks. To address residual volatility during geopolitical or climatic disruptions, the proposed framework integrates Prophet with gradient boosting algorithms for error correction, forming a hybrid model. The hybrid Prophet-ML approach further improves the accuracy of forecasting models. Empirical results, quantified through MAE, RMSE, and mean absolute percentage error (MAPE) metrics, underscore the framework's robustness in reconciling structural time series patterns with nonlinear market dynamics.

Keywords

Wheat prices, Prophet, Forecasting, Machine learning, Time series, Hyperparameter tuning, Price volatility, Seasonality, Trend[1]

1. Introduction

Accurate forecasting is a key problem of socio and economic analysis. It enables understanding development trends, risk assessment, and preparation for potential changes across economic sectors. In the globalization and IT era, economic instability and rapid technological shifts, effective forecasting underpins strategic decision-making at governmental, corporate, and societal levels, fostering stability, innovation, and adaptability to future challenges.

Forecasting market indicators, particularly resource and commodity prices, is vital for economic development. Agricultural commodities such as wheat are core information about global food market trends, and price fluctuations significantly support and impact economies. Accurate price forecasting enhances production cycle management, trade potential evaluation, and price stabilization policies [15].

Contemporary analytical methods, including machine learning, econometric models, and specialized algorithms, improve forecasts' accuracy, reliability, and efficiency. Socio and economic data forecasting requires robust mathematical and statistical models capable of predicting market indicators, such as agricultural prices, in complex and dynamic environments.

Prophet, a time series forecasting tool developed by Meta (formerly Facebook), integrates statistical power with the ability to handle seasonal and irregular fluctuations characteristic of socio-economic processes [16].

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[1*] Corresponding author.
[†] These authors contributed equally.
d.zherlitsyn@unwe.bg, dmitro.zherlitsin@mipolytech.education (Dmytro Zherlitsyn); vkharchenko@nubip.edu.ua (Volodymyr Kharchenko); hanna.kharchenko@gcu.ac.uk (Hanna Kharchenko).
0000-0002-2331-8690 (Dmytro Zherlitsyn); 0000-0001-5067-7181 (Volodymyr Kharchenko); 0000-0002-0705-447X (Hanna Kharchenko)

Thus, forecasting is an analytical tool and a foundation for formulating policies and corporate strategies to ensure stability, sustainable development, and economic growth.

Prophet is a time series forecasting tool developed by Meta (formerly Facebook), specifically designed to handle datasets exhibiting seasonality, trend patterns, and irregularities such as missing values or anomalies - typical characteristics of socio-economic processes [31]. The library integrates seamlessly with Python and R programming ecosystems, offering compatibility with interactive environments like Jupyter Notebook for data visualization, cloud based platforms such as Google Colab for code execution without local setup, and integrated development environments (IDEs) like PyCharm, VSCode, and Spyder for advanced implementations. Prophet is typically used alongside foundational Python libraries, including Pandas for data manipulation, NumPy for numerical computations, and Matplotlib for visualization [9, 10, 21, 25, 36].

While Prophet provides a robust framework for forecasting, other methodologies remain relevant in socio-economic analysis. For instance, the ARIMA (AutoRegressive Integrated Moving Average) model is a classical approach that is practical for datasets with linear trends and seasonal components but is limited in handling complex seasonality or external shocks [3]. Linear regression and its variants are widely used to model relationships between variables, such as commodity prices and macroeconomic indicators, enabling the quantification of external factor impacts [11]. Machine learning techniques, including Random Forest, Gradient Boosting, and Support Vector Machines (SVM), excel in capturing non-linear interactions among multiple variables, particularly in large-scale datasets [27]. Factor models, which assess price dynamics through influential variables like climatic conditions or market demand-supply shifts, further complement these approaches [2, 18].

2. Literature Review

Forecasting represents a critical analytical tool for understanding social and economic trends, assessing risks, and preparing for systemic changes. Time series forecasting has evolved significantly by integrating machine learning techniques and specialized tools like Facebook's Prophet, which address limitations inherent in traditional econometric methods.

Adhikari and Agrawal [1] provide a foundational framework for time series modelling, emphasizing the need for adaptable approaches in handling complex datasets. Building on this, Taylor and Letham [32] introduced Prophet, an open-source tool designed to model trends, seasonality, and external factors in socio and economic data. Its robustness in handling missing values and irregular intervals has been validated across diverse applications, from financial markets to public health crises. For instance, Zivot and Wang [37] highlight the challenges of modelling volatile financial time series, while Martin and Anderson [20] demonstrate the critical role of price forecasting in mitigating agricultural market disruptions caused by export restrictions.

The limitations of classical methods like ARIMA in managing noisy, large-scale datasets have driven interest in machine learning. Lim and Zohren [17] survey deep learning applications in time series forecasting, noting their capacity to uncover non-linear patterns without prior assumptions. Gupta et al. [8] extend this to agricultural economics, showing how machine learning models capture external factor influences on commodity prices. Prophet's practical utility is further evidenced by Parsa et al. [26], who combine it with anomaly detection for industrial time series analysis, and Menculini et al. [7, 23], who demonstrate its competitive performance against ARIMA and deep learning in food price forecasting.

Recent applications underscore Prophet's versatility. Hossain et al. [22] apply it to predict catchment-level rainfall using climate model data in environmental science. Shen et al. [12] adapted it for multi-pollutant air quality forecasting in Seoul. Angelo et al. [24] highlight its superiority over ARIMA in Bitcoin price prediction, attributing this to its handling of volatility. Public health implementations include Satrio et al. [4] and Sah et al. [29], who use Prophet for COVID-19 case forecasting, proposing hybrid models to improve accuracy.

Agricultural economics studies reveal Prophet's sector-specific value. Kharchenko et al. [13, 14] focus on investment forecasting for Ukrainian agribusinesses, while Kostaridou et al. [16] compare their performance with traditional models in Greek tomato markets. In transportation, Agyemang et al. [5] integrate change point detection for accident prediction, and Saeed et al. [28] apply it to container freight rate forecasting.

Emerging applications in energy systems [34] and network traffic management [35] further demonstrate Prophet's adaptability. These studies affirm that combining mathematical rigor with modern computational tools enhances forecasting precision, enabling data-driven decision making across economic, environmental, and public health domains.

Contemporary research underscores the significance of integrating mathematical approaches with advanced technologies in forecasting socio-economic processes. Combining robust statistical methods and innovative computational tools like Prophet enhances forecasting accuracy, reliability, and practicality. Integrating advanced forecasting techniques provides valuable support for strategic decision-making, enabling stakeholders to manage economic, environmental, and public health challenges proactively. However, future studies should focus on the practical application of the methods and tools, e.g., Prophet Python Forecasting tools, to robust analytical results, improve accuracy, and respond to global uncertainties.

Thus, this study aims to forecast wheat prices using a combination of Prophet and machine learning tools, focusing on assessing their performance in modelling complex dynamic trends.

3. Methodology

This study utilizes the Federal Reserve Economic Data (FRED) source. These platforms provide complementary data streams essential for analysing agricultural commodity price dynamics. FRED (Federal Reserve Economic Data), maintained by the Federal Reserve Bank of St. Louis, offers access to over 700,000 economic and financial indicators, including historical prices for key agricultural commodities such as wheat. These data are critical for identifying long-term market trends and volatility patterns [6].

Daily wheat price data in USD per kilogram are sourced from Markets Insider, a comprehensive financial news platform offering real-time and historical market data essential for capturing short-term market fluctuations and providing granular insights into price movements [19].

The dataset analysed in the paper covers wheat prices from two periods: monthly price records from January 1990 to November 2024 and daily price records from January 2014 to January 2025. Data preprocessing steps included standardizing date formats and addressing missing values.

The descriptive statistics for the wheat price dataset, providing insights into the central tendencies, variability, and distribution characteristics of the prices, are summarized in Table 1.

The descriptive statistics (Table 1) show several notable characteristics of wheat prices over the observed periods. From 1990 to 2024, monthly wheat prices show an average price of approximately 160.66 USD per metric ton, with a median slightly lower at 151.80 USD, indicating a mild positive skewness (1.00). The relatively high standard deviation (67.46) suggests considerable variability in monthly wheat prices over the long-term period. Kurtosis near zero (0.07) indicates that the distribution of monthly prices is near normal, with neither pronounced peaks nor extreme outliers.

Table 1
Descriptive Statistics for Wheat Prices

Statistic	Monthly Prices, USD/tn (1990–2024)	Daily Prices, USD/ kg. (2014–2024)
Mean	160.66	209.50
Median	151.80	194.50
Standard Deviation	67.46	57.87
Kurtosis	0.07	2.94

Skewness	1.00	1.15
Range	273.45	298.25
Minimum	75.06	140.00
Maximum	348.51	438.25
Count	419	2642
Confidence Level (95.0%)	6.48	2.21

Daily wheat prices, observed from 2014 to 2025, exhibit a higher average price of 209.50 USD per metric ton, with a median of 194.50 USD per kg, further suggesting skewness (1.15) and a noticeable deviation from the monthly averages. The daily dataset has a higher kurtosis (2.94), indicating a heavier tail distribution with more frequent price spikes or drops. The range (298.25) with a minimum of 140.00 USD and a maximum of 438.25 USD indicates significant price volatility within the daily measured period.

The distributional differences between series have important implications for forecasting. The monthly data's near-normal distribution and lower kurtosis suggest it may be more suitable for traditional time series models that assume Gaussian errors. However, the daily series' properties and higher skewness indicate that models accounting for fat tails and asymmetric distributions might be more appropriate for short-term forecasting. Thus, our subsequent analysis will also compare the predictive performance of both series to determine their relative forecasting merits under different market conditions.

To achieve the research aim, the authors employed a comprehensive methodological approach based on the classical Prophet framework for time series analysis. The Prophet library utilizes mathematical models that combine trend, seasonality, and holiday effects for time series forecasting. The general forecasting model in Prophet can be expressed as [30, 33]:

$$y(t)=g(t)+s(t)+h(t)+\epsilon_t \tag{1}$$

where:

$y(t)$ is the forecast value at time t;

$g(t)$ is the trend component (long-term change);

$s(t)$ is the seasonal component (cyclic variations such as annual or weekly fluctuations);

$h(t)$ captures holiday effects (impact of special events or holidays);

ϵ_t is random error (noise or uncertainty in the data) .

The trend component in Prophet can be modeled either as linear [30, 33]:

$$g(t) = \beta_0 + \beta_1 t \tag{2}$$

where:

β_0 is the initial trend level β_1 indicates the trend change rate or as logistic growth:

$$g(t)=\frac{C}{1+\exp\left(-\left(\beta_0+\beta_1 t\right)\right)} \tag{3}$$

where:

C is the maximum trend level (carrying capacity),

β_0 is the trend offset,

β_1 represents the growth rate t is the time factor.

The logistic trend proves particularly valuable for modelling processes with natural limits (e.g., maximum production capacities).

Seasonal components are modeled using Fourier series decomposition [30, 33]:

$$s(t)=\sum_{k=1}^{K}\left(a_k\cos\left(\frac{2\pi kt}{P}\right)+b_k\sin\left(\frac{2\pi kt}{P}\right)\right) \tag{4}$$

where:

P is the seasonal period (e.g., P=365 for yearly seasonality);

a_k and b_k are coefficients determining the amplitude and phase of seasonality for each harmonic *k;*

k represents the number of harmonics used to model seasonality.

This decomposition effectively captures seasonal patterns (annual, weekly, etc.).

Holiday effects may be modelled through additional parameters [30, 33]:

$$h(t)=\sum_{j=1}^{M} I(t,j)\delta_j \tag{5}$$

where:

$I(t,j)$ is an indicator function (1 if time t corresponds to holiday j, 0 otherwise)

δ_j represents the effect size for holiday j

The error component $\in_t$ is typically modelled as normally distributed [30, 33]:

$$\epsilon_t \;\; N(0,\sigma^2) \tag{6}$$

where σ^2 error's variance.

It should be noted that for Prophet object, parameter estimation is typically performed using maximum likelihood estimation (MLE). This approach optimizes model parameters by maximizing the likelihood of observed data, ensuring reliable trend and seasonality detection. The resulting model demonstrates robust forecasting capabilities, effectively handling seasonal variations, holiday effects, and underlying trends in the data.

4. Results and Discussion

The study's first stage aims to evaluate the performance of Facebook's Prophet algorithm for forecasting monthly wheat prices (USD/ton) from 1992 to 2024. Three modelling approaches were implemented to address the challenges of agricultural commodity price prediction: a baseline model with default parameters, a customized model incorporating domain-specific adjustments, and a hyperparameter-optimized model. The analysis focuses on the comparative performance of these approaches, with particular emphasis on their ability to capture structural trends, seasonal patterns, and exogenous shocks inherent to global wheat markets.

Model 1. Prophet modelling object with default Parameters produced unsatisfactory results, failing to account for the dataset's unique characteristics. Visual inspection revealed systematic deviations between predicted and observed values. The model inadequately captured long-term price trends and intra-annual cyclicality, resulting in a mean absolute percentage error (MAPE) exceeding 20% during validation. This poor performance stemmed from inappropriate assumptions about seasonality components and insufficient flexibility.

Model 2. Customized Parameterization of the Prophet() object is as follows:

- Disabling irrelevant daily and weekly seasonality while preserving annual periodicity;
- Explicit specification of monthly cycles (30.5-day period, Fourier order=5);
- Enhanced changepoint detection (n=60) to better reflect historical market shocks;
- Annual seasonality modelling using 12 Fourier terms to capture, for example, planting-harvest cycles.

These adjustments improved model fidelity substantially (Figure 1).

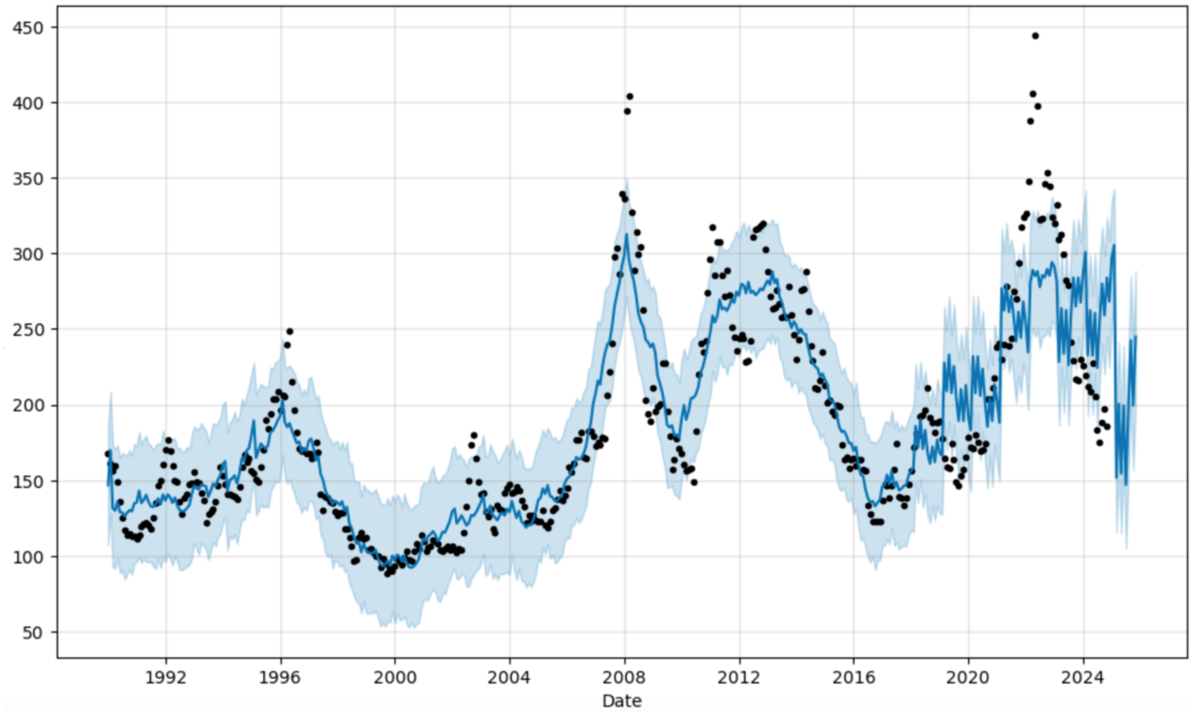

Figure 1: Prophet-Forecasted Monthly Wheat Prices (1992–2024) with Custom Seasonality Parameters, USD/tn.

Key performance metrics of the Model 2 demonstrate marked enhancement:
MAPE reduced to 11%
RMSE decreased to $30.82/ton
R^2 increased to 0.79

The customized model identified major price dynamics, including decadal-scale inflation trends and biennial production cycles. However, residual analysis revealed persistent underestimation of extreme price spikes during geopolitical crises, suggesting opportunities for further refinement through exogenous variable integration.

Model 3. Optimized Hyperparameters of the Prophet() object. The study employed a grid search approach to systematically evaluate combinations of key parameters, including the trend flexibility parameter (changepoint_prior_scale), seasonality formulation (seasonality_mode), and Fourier orders for yearly and monthly seasonal components. The optimal configuration identified - changepoint_prior_scale=0.5, seasonality_mode='multiplicative', and Fourier orders of 12 (yearly) and 15 (monthly) - reflects the inherent complexities of wheat price dynamics. The high changepoint_prior_scale value suggests substantial variability in trend shifts. Multiplicative seasonality scales seasonal effects with the trend magnitude. It aligns with the observed amplification of price fluctuations during periods of high market volatility, such as harvest cycles or export restrictions.

The result of the hyperparameter optimization defines the following:
‘changepoint_prior_scale': 0.5,
'seasonality_mode': 'multiplicative',
'yearly_fourier_order': 12,
'monthly_fourier_order': 15.

For example, a yearly Fourier order of 12 captures nuanced annual seasonality, potentially linked to planting and harvesting schedules; the monthly order of 15 accommodates irregular short-term variations, such as mid-month price adjustments due to policy changes or speculative trading.

The results of the Model 3 application are shown in Figure 2.

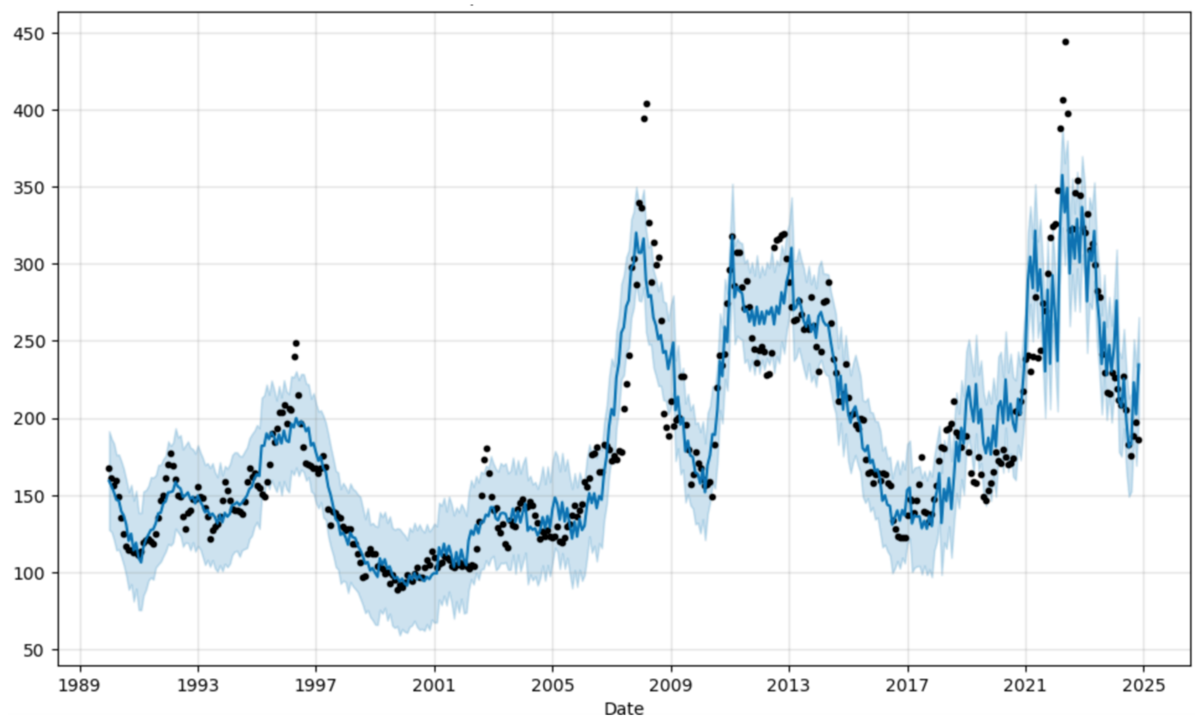

Figure 2: Prophet-Forecasted Monthly Wheat Prices (1992–2024) with Hyperparameters' optimized model, USD/tn.

Key performance metrics of the Model 3 are:

MAPE reduced to 9%

RMSE decreased to $24.81/ton

R^2 increased to 0.87

Comparative analysis with previously estimated Prophet configurations revealed that the optimized model reduced the mean absolute percentage error (MAPE) to 9%. The model's coefficient of determination (R^2 = 0.87) further demonstrates its ability to explain 87% of the variance in historical wheat prices, underscoring the efficacy of hyperparameter tuning. Despite these advancements, residual errors persist, as evidenced by a root mean squared error (RMSE) of 24.81 USD/tn. These residuals highlight some of Prophet's limitations in modelling data fluctuation, a common feature of agricultural and other markets where volatility during periods of uncertainty, such as droughts, trade restrictions, wars, and so on. For instance, the model underestimates price spikes observed during 2008 (global financial crisis) and 2022 (agricultural export restrictions from Russia), characterized by abrupt variance shifts. The lack of the Prophet tools can be solved using a hybrid framework. For example, integrating Prophet with classical Machine learning models is proposed to address this gap. This approach will be discussed later.

The second phase of this investigation focused on analysing daily wheat price data (see Table 1).

Model 4. A customized Prophet model configuration was implemented to capture the inherent patterns in high-frequency agricultural commodity markets (based on monthly data hyperparameter tests). The model was initialized with yearly seasonality explicitly disabled, as preliminary tests indicated that intra-year patterns were better captured through manually specified Fourier terms rather than the default approximation of annual seasonality. Weekly and daily seasonal components were also deactivated, as their inclusion did not improve model performance and risked introducing noise in the daily price forecasting context.

The changepoint prior scale parameter was set to 5.0 to enhance the model's sensitivity to abrupt trend changes. This modification allowed the model to better adapt to structural breaks in the price series while maintaining robustness against overfitting.

The seasonal components were explicitly modelled through custom Fourier series expansions. A yearly seasonality term of 365.25 days and a Fourier order of 12 were incorporated to account for annual cyclical patterns. Additionally, a monthly seasonality component with a period of 30.5 days and a Fourier order of 5 was included to capture finer-grained periodic fluctuations potentially linked to mid-month market adjustments.

The results of the Model 4 application are depicted in Figure 3.

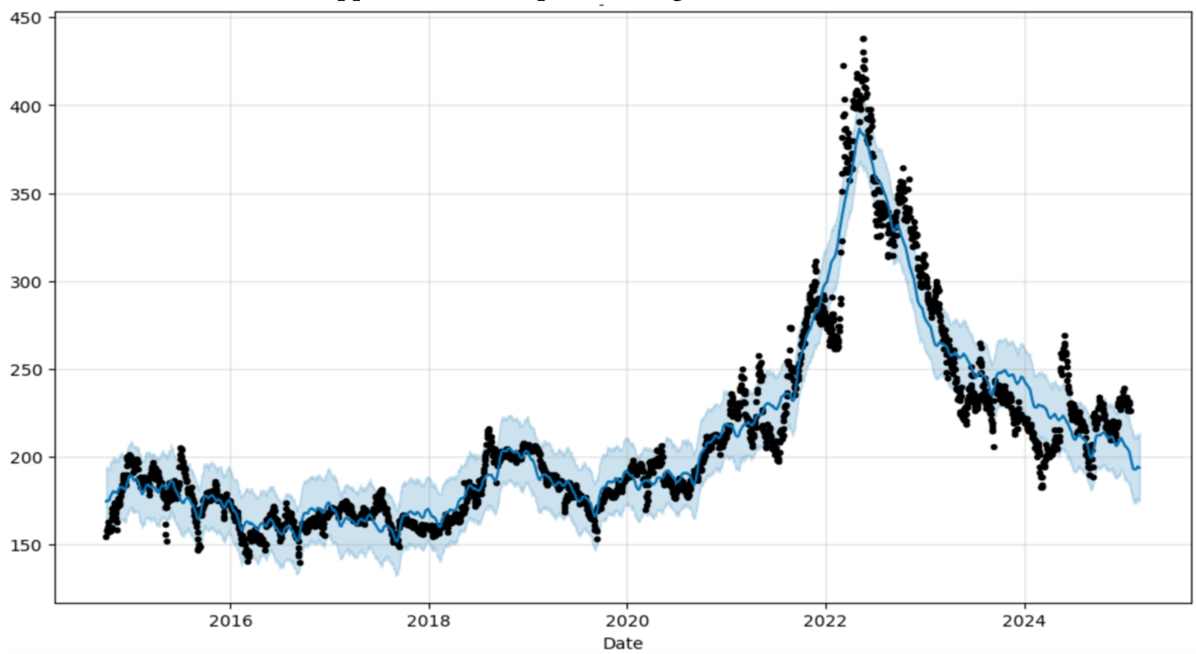

Figure 3: Prophet-Forecasted Daily Wheat Prices (2014–2025) with custom-defined parameters model, USD/kg.

Key performance metrics of the Model 4 are:

MAPE: 5%

RMSE: 14.40 USD/kg

R^2: 0.93

Figure 3 shows that the price trajectory exhibits fluctuations, characteristic of agricultural commodities influenced by short-term supply-demand imbalances, climatic variability, and geopolitical events. Notably, the model captures a steady upward trend from 2020 to mid-2022. The forecasted values beyond 2024 suggest a stabilization phase. However, the actual price fluctuation is high.

Model 4, configured with custom-defined parameters, demonstrates significant improvements in forecasting accuracy relative to monthly data models. Although daily data are less consistent with the normal statistical distribution, the Prophet's tools can be used for forecasting with higher accuracy. This is most likely due to the tool's settings focused on recording daily changes. At the same time, intra-month interpolation is used in monthly forecasts. However, analysis of Figure 3 shows that Model 4 also does not cope very well with periods of high volatility and sudden changes in trends (after 2024). That is why we will consider the hybrid approach, which uses machine learning models for the model's residuals.

Model 5 integrates the Prophet model (customized for daily data in Model 4) with a machine learning-based residual correction mechanism. Residuals from Model 4 — representing unexplained variance — were estimated using a stacked ensemble of gradient-boosting algorithms (XGBoost, LightGBM, and CatBoost), meta-learned through a Ridge regression model. This approach leverages the complementary strengths of Prophet’s structural time series decomposition and the ensemble’s capacity to model nonlinear, high-frequency noise.

Figure 4 illustrates the daily wheat price dynamics from 2016 to 2024, comparing observed values, Prophet-based forecasts (Model 4), and adjusted forecasts generated by a hybrid Prophet-ML framework (Model 5).

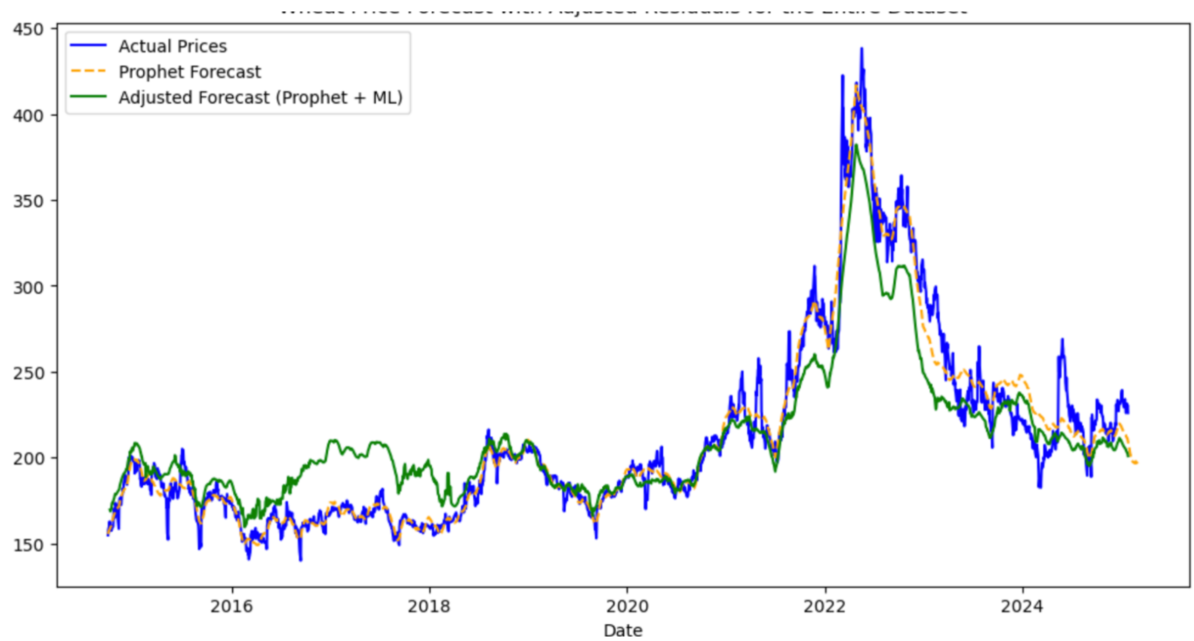

Figure 4: Prophet & ML-Forecasted Daily Wheat Prices (2014–2025) with a custom-defined parameters model and ML correction of the residuals. USD/kg.

The hybrid model achieved a mean absolute percentage error (MAPE) of 8.1% and an R^2 score of 0.84. While these metrics suggest a marginal increase in MAPE compared to Model 4 (MAPE = 5%, R^2 = 0.93), the hybrid framework demonstrates better performance in capturing transient volatility, as evidenced by its alignment with extreme price movements in Figure 4.

Thus, Model 5 represents a pragmatic advancement in agricultural price forecasting, addressing Prophet's limitations in volatility capture through machine learning-driven residual correction. While its MAPE suggests modest degradation in overall accuracy, its ability to replicate high-frequency fluctuations provides actionable insights for stakeholders navigating volatile markets.

Discussion. For further discussion, the authors applied Python AutoARIMA, RandomForestRegressor, XGBRegressor tools, as described in [36], to the same data sets. Comparison with the results reveals that the new Prophet-based models deliver superior performance over classical approaches. Classical AutoARIMA yielded a MAPE of 12.29% for monthly data and a negative R^2 (-2.11). A Random Forest model improved the accuracy (MAPE 9.37%) and achieved a modest R^2 of 0.23. In contrast, the optimized Prophet model in our study attained a substantially lower MAPE (9%) and a high R^2 of 0.87, indicating a dramatic gain in both accuracy and explanatory power. The advantage of the Prophet's complex approach is even more pronounced for daily forecasts. The AutoARIMA baseline on daily prices produced substantial errors (MAPE 34.67%) with no predictive power ($R^2 \approx -10.02$). Even an ensemble machine learning method (Random Forest + XGBoost) achieved only a MAPE of 8.71%, with R^2 still negative at -0.36. By contrast, the new hybrid Prophet-ML model maintained a comparably low MAPE while boosting R^2 to 0.93, reflecting superior accuracy and a much-improved ability to capture variance and volatility in wheat prices. These results demonstrate that the hybrid approach offers significantly enhanced forecasting accuracy and robustness, especially under volatile market conditions, compared to classical ARIMA and standalone ML benchmarks. The substantial error reduction and improved R^2 in the Prophet-ML forecasts further validate the proposed methodology and underscore the practical value of integrating Prophet with machine-learning-based residual correction for reliable wheat price forecasting.

However, it should be noted that classical forecasting models [36] were used without hyperparameter optimization and did not use neural network models (like LSTM), which determines further study directions. However, it should also be noted that approaches based on Prophet models combine relatively high accuracy, simplicity, clarity, and interpretability of the result, further increasing their practical value. For example, although LSTM models often give more accurate forecasts, they are challenging to interpret practically.

5. Conclusion

Accurate forecasting of agricultural commodity prices remains pivotal for economic stability, policy formulation, and strategic decision-making in volatile markets. This study evaluated the efficacy of Facebook's Prophet algorithm in modelling wheat price dynamics across monthly (1990–2024) and daily (2014–2025) datasets, emphasizing customization and integration with machine learning (ML) to address inherent limitations.

Key findings demonstrate that Prophet's default configuration is unsuitable for agricultural market structural trends and seasonal patterns. However, tailored parameterization—such as adjusting Fourier terms for seasonality, optimizing changepoint detection, and employing multiplicative seasonality—significantly enhanced performance. For monthly data, hyperparameter tuning reduced MAPE to 9% and improved R^2 to 0.87, while daily forecasting achieved a MAPE of 5% and R^2 of 0.93. Despite these advancements, residual errors during extreme events (e.g., geopolitical crises, financial crises, and so on) underscore Prophet's challenges in capturing abrupt volatility.

The hybrid Prophet-ML framework addressed this gap by leveraging gradient-boosting ensembles to correct residuals, improving alignment with high-frequency fluctuations. Although marginally increasing MAPE to 8.1%, the hybrid model better replicated transient price spikes, offering actionable insights for stakeholders navigating volatile markets.

These results highlight Prophet's adaptability across temporal resolutions but emphasize the necessity of domain-specific customization and complementary ML integration. Limitations persist in modelling exogenous shocks (e.g., droughts, trade wars), suggesting the need for incorporating external variables (e.g., climate data, policy changes) in future work. Further research could explore advanced ML architectures, real-time data integration, and cross-commodity analyses to bolster predictive robustness.

In conclusion, this study demonstrates the practical applicability of the Prophet model as a scalable tool for forecasting agricultural commodity prices, particularly wheat. The results emphasize the benefits of integrating Prophet with machine learning methods, where the hybrid approach improves the model's ability to capture volatility and nonlinear market dynamics. Nevertheless, despite the substantial enhancement in predictive accuracy, certain limitations remain, particularly considering external factors such as weather anomalies, political interventions, and global supply chain disruptions. Addressing these challenges requires including exogenous variables and applying advanced deep learning models, such as LSTM networks, capable of modelling long-term dependencies in complex time series data. At the same time, balancing predictive accuracy with model interpretability is essential to ensure practical applicability in decision-making processes. Further research should also focus on developing dynamic weighting mechanisms that optimize the trade-off between trend stability and sensitivity to abrupt market changes, as well as the systematic application of cross-validation techniques to improve the robustness of forecasting models.

Declaration on Generative AI

While preparing this work, the authors used GPT-4 and Grammarly tools to check grammar and spelling. After using these tools, they reviewed and edited the content as needed and took full responsibility for the publication's content.

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