

Review

Predicting Prices of Staple Crops Using Machine Learning: A Systematic Review of Studies on Wheat, Corn, and Rice

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Abstract: According to the FAO, wheat, corn, and rice are staple crops that support global food security, providing 50% of the world's dietary energy. The ability to predict accurately these key food crop agricultural commodity prices is important in stabilizing markets, supporting policymaking, and informing stakeholders' decisions. To this aim, machine learning (ML), ensemble learning (EL), deep learning (DL), and time series methods (TS) have been increasingly used for forecasting due to the rapid development of computational power and data availability. This study presents a systematic literature review (SLR) of peer-reviewed original research articles focused on forecasting the prices of wheat, corn, and rice using machine learning (ML), deep learning (DL), ensemble learning (EL), and time series techniques. The results of the study help uncover suitable forecasting methods, such as hybrid deep learning models that consistently outperform traditional methods, and they identify important limitations in model interpretability and the use of region-specific datasets, highlighting the need for explainable and generalizable forecasting solutions. This systematic review adheres to the PRISMA 2020 reporting guidelines.

Keywords: agriculture; commodities; wheat; corn; maize; rice; paddy; price; prediction; machine learning; deep learning; ensemble learning; time series



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1. Introduction

Agriculture plays a critical role in the global economy, serving as the backbone of food security, livelihoods, and trade. In 2022, the global share of agriculture value added in GDP was 4.3%, accounting for a total amount of USD 3.8 trillion [1,2]. In many developing nations, agriculture is a cornerstone of the economy, and it contributes as much as 25% of their GDP and an even larger share of employment, providing income to a large segment of the population [3]. In most developed countries, agriculture, albeit a small percentage of GDP, is a key economic sector, as made clear by agricultural policies, such as the EU Common Agricultural Policy, the US Farm Bill, Japan's Agricultural Policy, and Australia's APAP, among others, providing subsidies and price support. In this context, the World Bank Group states, "Agricultural development is one of the most powerful tools to end extreme poverty, boost shared prosperity, and feed a projected 10 billion people by 2050" [4].

Among all agricultural crops, three stand out as the world's primary staple foods, with their cultivation combined providing over half of global dietary energy [1]. Wheat, corn (also referred to as maize in some parts of the world), and rice (also referred to as paddy in some parts of the world) are key global export commodities, and they are vital for human consumption, livestock feed, and biofuel. Their role makes them central to agricultural

policy, international trade, and food system stability. Fluctuations in their production and price have consequences for both consumers and producers. Evenson and Gollin, in their research [5], note that with grain prices near or at historical lows, the world's average caloric intake increased, leading to gains in health and life expectancy, but at the same time, concerns have been raised since the level of intensive cultivation needed leads to biodiversity loss, soil degradation, chemical pollution, aquifer depletion, and soil salinity. While striving to mitigate these risks, the goal is to increase the production of wheat, corn, and rice in the years to come to feed the projected 10 billion people by 2050.

Agricultural commodities are being traded in global markets. This comes with risks and benefits for all parties involved. On one side, market mechanisms can help establish fair prices by allowing farmers and agribusinesses to “lock” prices through futures contracts and options, stabilize their income, and support long-term planning. On the other side, the commodity markets can be influenced by speculative activity and thus make prices highly volatile and decoupled from fundamentals. Additionally, smallholder farmers in some developing countries may lack the infrastructure, information, or financial skills to utilize and benefit from the market systems [6]. The price volatility in agricultural commodities poses significant challenges for farmers, traders, consumers, and policymakers alike. Sudden and unpredictable changes in prices can destabilize income, disrupt planning for farmers, and lead to food insecurity, social unrest, and inflation [7]. Volatility also adds additional levels of complexity in policymaking, as governments struggle to design safety nets for the uncertain conditions farmers and society face. Price swings are led by weather events, pests and diseases, geopolitical tensions, trade restrictions, and financial speculation [8]. Therefore, managing price volatility is essential to building stable and equitable food systems [7].

In response to the risks posed by price volatility, farmers, policymakers, traders, agribusinesses, researchers and practitioners have used advanced forecasting methods to improve price prediction. Agricultural markets have complex behavior that is characterized by non-stationarity, non-normality, and non-linearity in both supply (arrivals) and price data. This poses significant challenges for traditional statistical forecasting models. These difficulties are further compounded by external volatility from climate events, market speculation, and policy interventions. Such dynamics limit the effectiveness of classical approaches. Traditional econometric models such as ARIMA (Autoregressive Integrated Moving Average) and SARIMA (Seasonal Autoregressive Integrated Moving Average), have been used for time-series forecasting, but the limitations they have in handling data that is non-linear and high-dimensional, have led to a shift to other approaches [9]. Machine learning (ML), ensemble learning (EL), and deep learning (DL) methods are powerful alternatives. These techniques can capture complex patterns in large and diverse datasets. These models are increasingly being applied to forecast commodity prices using as input historical price time series, weather data, production statistics, and even textual information from news and social media to analyze the market's sentiments. Accurate forecasting can help farmers, traders, investors, and policymakers make educated decisions, leading to efficient agricultural markets [10,11], but the volatility presents enormous problems to them [3].

This study aims to systematically evaluate the application of ML, EL, DL, and time series techniques to agricultural commodity price prediction. This SLR intends to identify the used techniques in the commonly studied commodities of wheat, corn, and rice, along with their challenges and limitations, through analysis of original research articles. The goal is to provide a comprehensive understanding of the state of the field, highlight gaps in the literature, and propose directions for future research. The contributions of this study are as follows:

- i. This study provides a comprehensive analysis of common machine learning, ensemble learning, deep learning, and time series techniques used in agricultural commodity price prediction.
- ii. It offers insights into the unique prediction requirements of agricultural commodities forecasting.
- iii. This study investigates key challenges and limitations in agricultural price forecasting, including data availability, model interpretability, and computational complexity.

This review focuses specifically on wheat, corn, and rice due to their status as the world's most important staple crops, as together, they provide more than half of the global dietary energy supply. These commodities are central to food security and widely traded and studied, making them an appropriate and impactful focus for a systematic review of forecasting methods.

2. Research Methodology

In order to define the primary focus of this study, which is to evaluate and draw lessons from the existing research in the prediction of specific agriculture commodity prices, we employ a systematic review approach guided by methodologies outlined in Elberzhager et al. [11] and Ishaq et al. [12], as shown in Figure 1. Based on their frameworks, we formulated the relevant research questions and developed robust search strategies. This systematic approach enabled us to identify and analyze the relevant literature in the field.

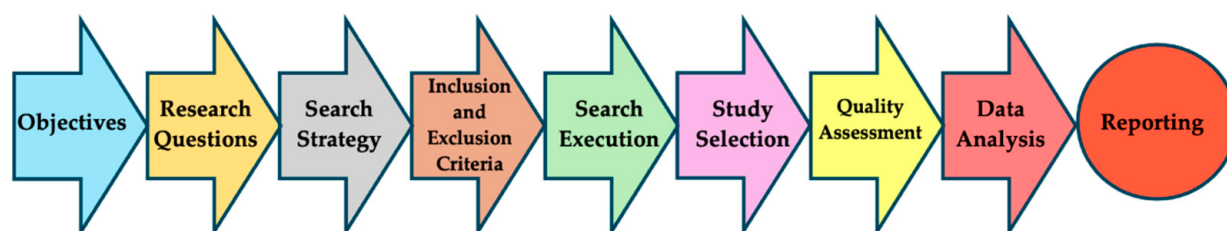


Figure 1. Research methodology.

2.1. Research Questions and Research Objectives

Three key research objectives and corresponding research questions were formed to guide the structure of this systematic literature review. These aimed to evaluate the forecasting methods applied in the selected agricultural commodity price prediction, explore the limitations of these approaches, and explain the rationale for focusing specifically on wheat, corn, and rice as globally significant staple crops. The objectives and questions are summarized in Table 1.

Table 1. Research objectives and question.

Research Objective (RO)	Research Question (RQ)	Motivation
RO1: To identify and categorize the machine learning, ensemble learning, deep learning, and time series techniques used in agricultural commodity price prediction and to provide a descriptive overview of the publication trends, geographical distribution, and subject focus of the research field.	RQ1: What forecasting techniques have been applied in predicting the prices of agricultural commodities such as wheat, corn, and rice?	To understand the landscape of computational methods used in agricultural price forecasting and examine how the literature has evolved over time and space.

Table 1. *Cont.*

Research Objective (RO)	Research Question (RQ)	Motivation
RO2: To investigate the challenges and limitations encountered in the implementation of these forecasting models.	RQ2: What are the key challenges and limitations reported in the literature regarding data quality, model complexity, interpretability, and computational demands?	To highlight the obstacles and limitations faced by researchers and practitioners in developing accurate and reliable forecasting models.
RO3: To focus the review on staple crops that are central to global food security.	RQ3: Why are wheat, corn, and rice chosen as the target commodities for this review?	To justify the scope of the study based on the essential role of these crops in global diets and markets.

2.2. Search Strategy

The Following search string has been used to find relevant articles to conduct this study.

TITLE-ABS-KEY ((“machine learning” OR “deep learning” OR “reinforcement learning” OR “neural networks” OR “random forests” OR “support vector machines” OR “support vector regression” OR “SVR” OR “LSTM” OR “Bayesian networks” OR “hybrid models” OR “ensemble techniques” OR “gradient boosting” OR “AutoML” OR “extreme learning machine” OR “ELM” OR “decision trees” OR “KNN” OR “k-nearest neighbors” OR “principal component analysis” OR “PCA” OR “recurrent neural networks” OR “RNN”)

AND

(“wheat” OR “maize” OR “corn” OR “rice” OR “paddy”)

AND

(“price prediction” OR “price forecasting” OR “future price” OR “price trends” OR “market forecasting” OR “commodity price forecasting” OR “price volatility” OR “price dynamics” OR “real-time price forecasting” OR “long-term price forecasting” OR “short-term price forecasting”))

In the query used above, SVR is Support Vector Regression, LSTM is Long Short-Term Memory, RNN is Recurrent Neural Network, RF is Random Forest, KNN is k-Nearest Neighbors, and VAR is Vector Autoregression.

The search for original research articles in the field of agriculture commodity price prediction involved collecting articles from Scopus.

The Scopus database was selected for the comprehensive and consistent indexing of peer-reviewed journals in computer science, engineering, and agricultural sciences. This choice supported the reproducibility and transparency of the review and ensured that high-quality original research articles were included. The search was conducted in January 2025 and included studies published up to 31 December 2024. No additional databases, registries, websites, or gray literature were consulted.

The choice to use a single database may limit the breadth of the literature covered; we acknowledge this limitation and suggest that future reviews expand their scope to include other databases, such as Web of Science and Google Scholar. Similar approaches have been adopted in other recent SLRs (e.g., Lee [13]; Ramandanis and Xinogalos [14]; Karger and Kureljusić [15]; Lundberg et al. [16]).

A total of 75 articles were retrieved initially.

The following filters were applied:

- Language: English
- Document type: Journal articles only

These filters ensured that the review focused on high-quality, peer-reviewed studies published in English.

2.3. Study Selection

The selection of relevant studies followed a structured multi-stage process based on the criteria summarized in Table 2:

1. Title Screening. Articles with titles clearly unrelated to price prediction or machine learning were excluded.
2. Abstract Screening. The remaining articles were reviewed at the abstract level to assess their relevance to agricultural price forecasting using machine learning methods. Papers that did not meet the core focus were excluded at this stage.
3. Full-Text Review. Full texts of the remaining articles were reviewed in detail to ensure alignment with the inclusion criteria and overall objectives of the review. Only studies with a direct focus on forecasting the prices of wheat, corn, or rice using machine learning or time series techniques were retained.

Table 2. Study selection criteria.

Criteria	Inclusion	Exclusion
Study Type	Peer-reviewed journal articles indexed in Scopus	Non-peer-reviewed articles, editorials, opinion pieces, gray literature, conference papers
Commodity Focus	Studies focusing on agricultural commodities: wheat, corn (maize), or rice (paddy)	Studies on non-agricultural commodities (e.g., metals, energy) or financial markets
Techniques	Studies using machine learning, deep learning, time series models, or hybrid forecasting methods	Studies using only traditional statistical methods (e.g., simple regression) or no forecasting
Focus on Price Prediction	Studies explicitly focused on price forecasting or prediction	Studies focused on unrelated topics (e.g., yield, soil, climate) without price prediction
Language	Published in English	Published in other languages
Indexing	Indexed in Scopus	Not indexed in Scopus

After applying this process, a final set of 50 studies was selected for in-depth analysis.

This systematic review adhered to the PRISMA 2020 reporting guidelines. Two reviewers independently performed the screening of the titles, abstracts, and full texts. Any disagreements were resolved through discussion. The studies were grouped according to the forecasting techniques identified (ML, EL, DL, TS) and the selected agro-commodities (wheat, corn, rice). No formal risk of bias assessment was performed, as the review focused on descriptive and comparative analysis of forecasting methods. This review was not registered, and no protocol was prepared.

Figure 2 below presents the PRISMA 2020 flow diagram of the study selection process.

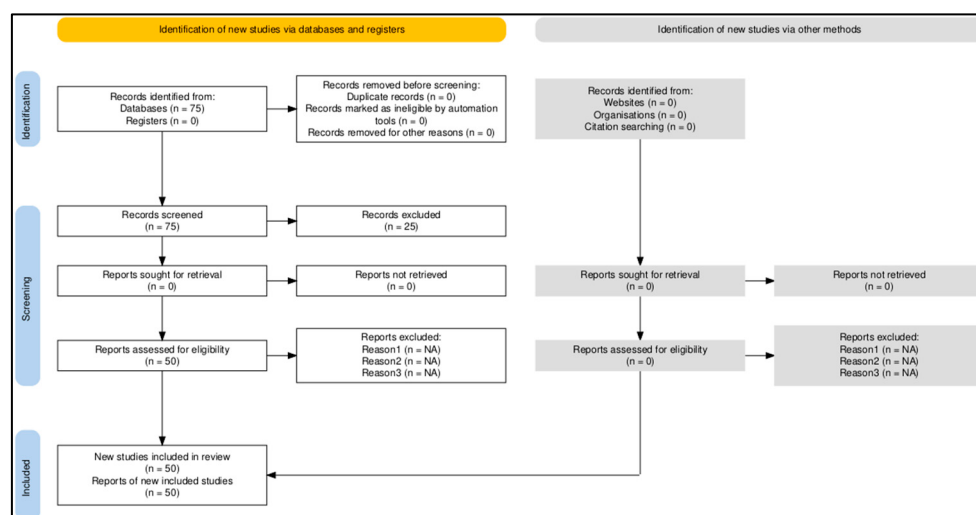


Figure 2. PRISMA 2020 flow diagram illustrating the study selection process. Diagram generated using the online PRISMA2020 Shiny App developed by Haddaway et al., 2022 [17], available at: https://estech.shinyapps.io/prisma_flowdiagram/ (accessed on 10 June 2025).

3. Analysis of Original Research Articles

Data extraction was performed manually from each article by one reviewer and verified by a second. The extracted data included the publication year, country, commodity, model type, dataset, technique, findings, and limitations. No assumptions were made about missing data. Since no quantitative synthesis was performed, effect sizes and confidence intervals were not calculated. Risk of bias was not formally assessed. No effect estimates or measures of heterogeneity were calculated. The review does not assess the certainty of evidence (using tools such as GRADE).

The analysis of original research articles explores the various techniques employed in wheat, corn, and rice price forecasting, focusing on machine learning, ensemble learning, deep learning, and time series methods as shown in Figure 3. Each approach is examined for its strengths and limitations in predicting price trends across different commodities.

3.1. Descriptive Analysis of the Selected Studies

A total of 50 studies were selected based on the inclusion criteria.

Figure 4 presents the distribution of the papers by country. China holds the research lead with 17 articles published, followed by the United States and India with 8 and 8 articles, respectively.

Figure 5 displays the numbers of articles published each year. Starting in 2020, research interest has grown rapidly in the past four years.

Figure 6 shows the percentage of papers published by subject area. Computer Science holds the lead with 27 published papers (22.4%), followed by Mathematics with 15 (12.9%), Economics/Econometrics/Finance with 13 (11.2%), and Agricultural/Biological Sciences with 11 (9.5%).

3.2. Machine Learning Techniques

Many techniques of machine learning have been applied to predict commodity prices in agriculture using different methodologies, as illustrated in Table 3, to improve predictive accuracy. The indirect influence of crude oil on food prices was examined by Esmaeili and Shokoohi [18] in a study using Principal Component Analysis (PCA) to study co-movement between the food prices of seven major food commodities (eggs, meat, milk, oilseeds, rice, sugar, and wheat) and macroeconomic indices (including crude oil price, CPI, Food

Production Index, and GDP). They found that crude oil prices did not directly affect the primary food price component, but they had an impact on the food production index, and in this way, they indirectly affected food prices. Finally, Traoré et al. [19] applied machine learning methods to ascertain whether nonlinear effects and asymmetries in price transmission were present and showed that local rice prices in Dakar are being affected by world prices and are more sensitive to world price increases than to price declines.

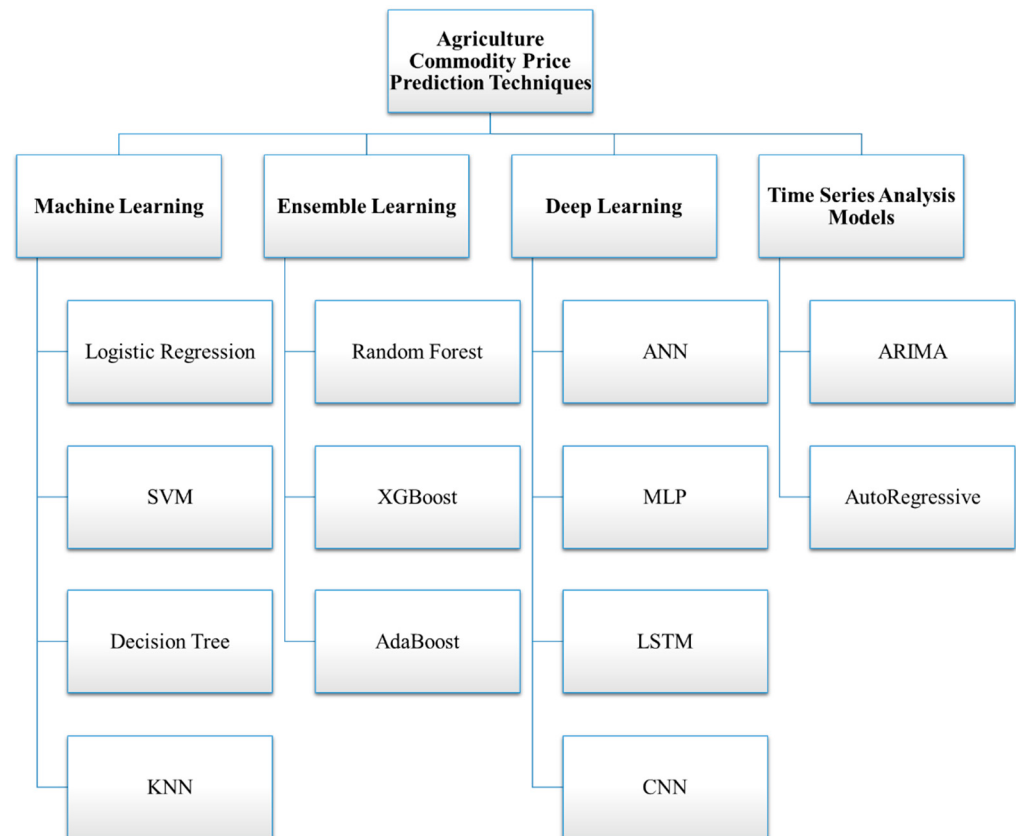


Figure 3. Taxonomy of the agriculture commodity price prediction techniques.

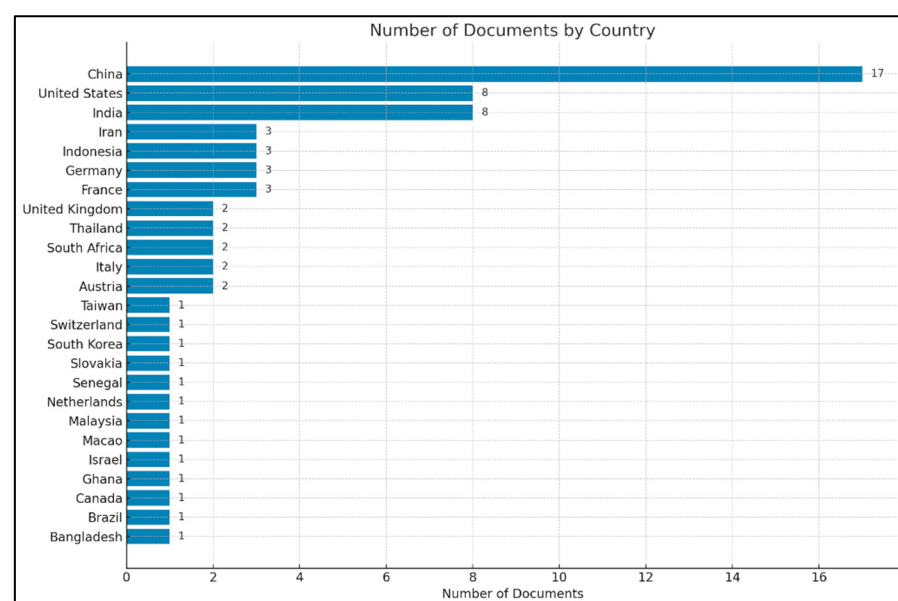


Figure 4. Distribution of papers by country.

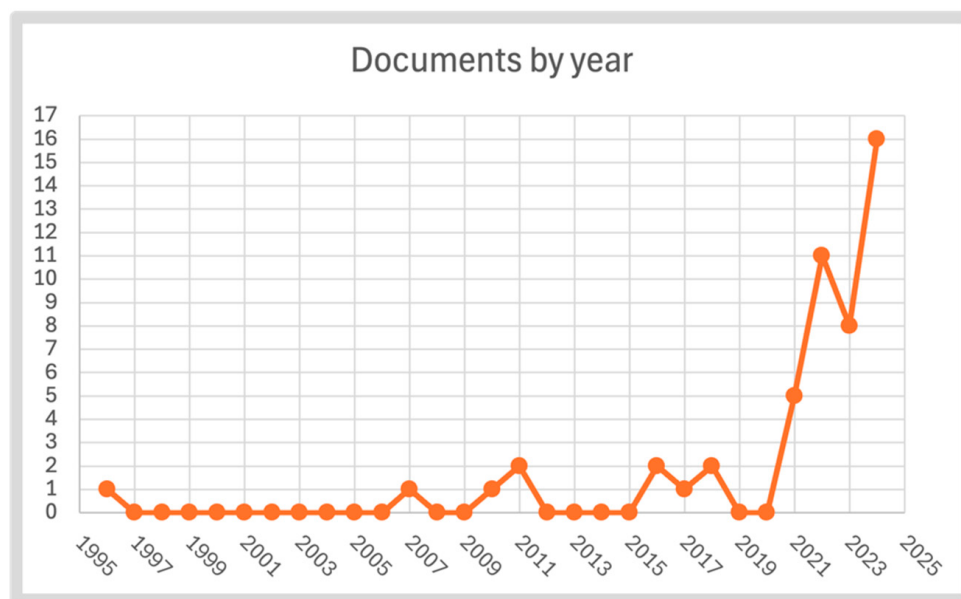


Figure 5. Published articles per year.

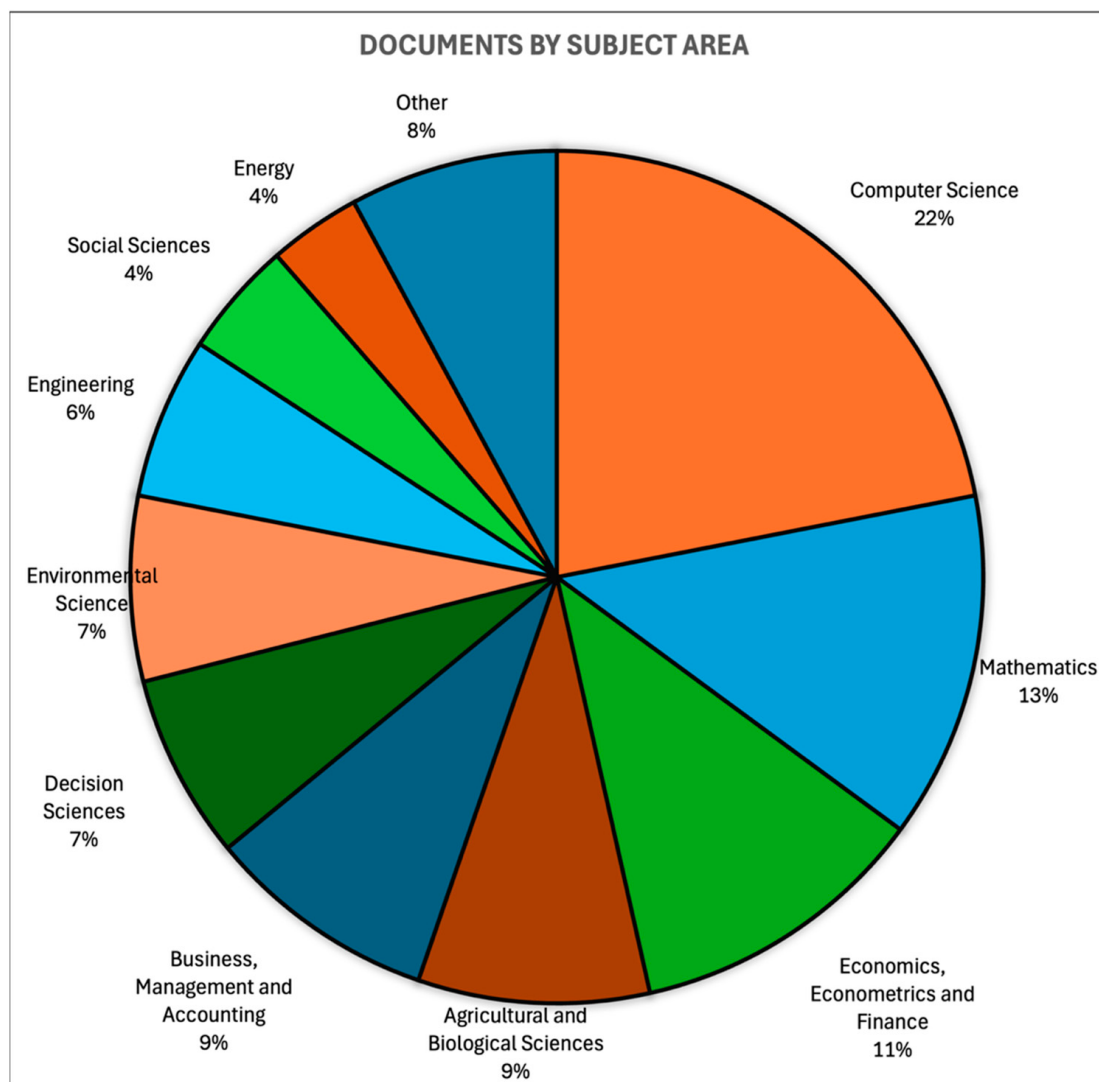


Figure 6. Percentage of papers published by subject area.

Table 3. Overview of machine learning techniques in wheat, rice, and corn price prediction.

Refs.	Year	Commodity Name	Dataset	Technique	Findings	Limitation
[18]	2011	Eggs, Meat, Milk, Oilseeds, Rice, Sugar, Wheat	Global macroeconomic and food price data	PCA	Oil prices indirectly affect food prices via the food production index (corr.: 0.87 with GDP, 0.36 with CPI).	Historical macroeconomic relationships may not account for future structural changes
[19]	2022	Rice	Monthly average prices from 1995 to 2014, Commission for Food Security (Dakar retail level)	Model-based recursive partitioning trees	Local prices are affected by world prices, more so by increases than by declines; 11.80% of positive deviations and 39.50% of negative deviations are eliminated after one month	Focused only on the ordinary broken rice segment
[20]	2024	Corn, Soybean	Futures and cash daily price data for corn and soybean (1991–2006)	Semiparametric Regression	Confidence bands for yield and price forecasts	The accuracy of the forecasted cash price depends largely on the current futures price
[21]	2016	Corn	Spot Price (South Africa), Grain Storage Spot Price, US Corn Trade, Demand and Supply (South Africa), Production and Consumption (USA), Interest Rate and Currency Exchange, Crude Oil Prices	BPNN	MAPE of 1.31% (in-sample) and 2.26% (out-sample) for 1-month prediction. Outperformed expert traders in real-time prediction	Decreased prediction accuracy over longer periods
[22]	2024	Rice	Weekly rice prices and weather data (2017–2022) from seven cities in Java	ARIMAX-GARCH, SVR	SVR outperformed in most cities and for premium quality; ARIMAX-GARCH stable for mid/low rice	Weather-only exogenous variable; city-specific results; moderate generalizability
[23]	2024	Wheat	Global wheat prices, macroeconomic indicators	ARIMA, SARIMA, ARIMAX, SARIMAX, LSTM, CNN, Regression	ARIMAX and SARIMA performed best; LSTM and CNN overfit training data	Limited generalizability of DL models; high error in testing phase
[24]	2021	Wheat	Daily wheat futures from NCDEX (May 2009–August 2014)	ARMA (1,1), ARMA (1,2), Economic Variable Model, ANN	Random walk model outperforms all	Compared neural network not fine-tuned

Machine learning models have been tailored to forecast both yields and prices for crop-specific forecasting. Kantanantha et al. [20] developed a semiparametric regression model to forecast yield and a futures-based model for price forecasting, emphasizing within- and between-year relationships and incorporating futures prices with basis adjustment to

forecast cash prices. Ayankoya et al. [21] developed a Backpropagation Neural Network (BPNN) model using Big Data to forecast corn prices in South Africa. Their approach achieved high accuracy for 1-month predictions both for in-sample and out-sample predictions. Additionally, their model outperformed eight volunteer expert commodities traders in real-time prediction.

3.3. Ensemble Learning Techniques

The application of ensemble learning techniques to agricultural commodity price prediction has been effective and has also shown potential for both short- and long-term forecasting (Table 4). Zelingher and Makowski [25] analyzed 60 years of deflated price data for corn, soybean, and cocoa, finding that TBATS outperformed short-term forecasts, while Gradient Boosting Machines (GBM) excelled at long-term projections. Similarly, in a different study, Zelingher and Makowski [26] emphasized the dominance of Northern America's corn production in influencing global prices and highlighted the superior performance of Random Forest (RF) and GBM for long-term predictions, while TBATS remained effective for horizons of 2–5 months.

Table 4. Overview of ensemble learning techniques in wheat, rice, and corn price prediction.

Refs.	Year	Commodity Name	Dataset	Technique	Findings	Limitation
[25]	2024	Corn, Soybean, Cocoa	The World Bank's commodity market database, global monthly price data (1960–2020)	TBATS, GBM, CART, LM, RF	Corn (Short-term, TBATS): RA: 80%, Corn (Long-term, GBM): RA: 60%	Asymmetrical price responses to production changes reduce predictability consistency
[26]	2022	Corn	FAOSTAT corn yield/production (1961–2019), World Bank corn price	CART, RF, GBM, MLR, VAR, TBATS	RF and GBM outperform linear models for long-term forecasts, TBATS for short-term (2–5 months)	Difficulty in capturing complex inter-regional production dependencies
[27]	2023	Rice	Average Rice Price dataset at the Indonesian Wholesale Trade Level (2010–2022)	RF	MAPE reduced from 0.0093573 to 0.0089389	The model's performance was only compared with datasets from UCI
[28]	2021	Corn, Sugar	Daily prices (2003–2019) CEPEA database	ARIMA, SARIMA, SVR, AdaBoost, LSTM, Ensemble models	Best performing models: SVR, followed by SVR/LSTM Ensemble models	Models did not capture significant volatility and non-stationary data trends in the datasets
[29]	2024	Corn	Planting land area, crop price, crop yield, rainfall, import and export volumes, import and export values, and price in a total of 53 variables (2002–2023)	RT, SVR, Ensemble Bagging, RF	Bag-SVR: $R^2 = 0.961$, MAE = 0.234, RMSE = 0.315; SVR: $R^2 = 0.959$	Focus on a specific commodity and region limits broader application

Table 4. Cont.

Refs.	Year	Commodity Name	Dataset	Technique	Findings	Limitation
[30]	2022	Rice	2004–2013 weather (BARC) and food prices (OCHA), Bangladesh	MLR, AdaBoost, Gradient Boosting, Bagging, Random Forest	RFR had $R^2 = 0.864$; windspeeds found to be most correlated to price; ensemble methods outperformed MLR	Dataset limited to 2004–2013; only one country analyzed
[31]	2021	Corn	Futures corn prices (2015–2019), CBOT; daily temperature and precipitation, Refinitiv; supply and demand data, USDA	ML-KNN outperforms ML-RF	MAE 0.0372, RMSE 0.0512, MAPE 0.6908	More complex algorithms might improve the model
[32]	2022	Soybean, Corn	CBOT daily corn and soybean prices (1974–2017)	ABC, SSA, EMD, LSTM, ARIMA, SVR	Error reduction (MAPE): 53.3%, Improvement (Dstat): 32.4%. ABC-based semi-heterogeneous forecast combination outperformed all other methods in both precision accuracy and direction accuracy	High complexity due to combining multiple models and techniques

Ensemble learning methods have also been further explored to increase the accuracy of price prediction in other studies. Dewi et al. [27] used Random Forest with hyperparameter tuning to forecast Indonesian rice prices, with MAPE reduced from 0.0093573 to 0.0089389 and R^2 increased from 0.9916805 to 0.9921578. Silva et al. [28] showed that combining support vector regression (SVR) with LSTM or AdaBoost provided better prediction performance for corn and sugar prices in Brazil in comparison with traditional econometric models, and the SVR model outperformed all. Mao and Soonthornphisaj [29] reported that the Bagging–SVR model had the highest accuracy in predicting corn prices in Thailand, with an R^2 of 0.961, an MAE of 0.234, and an RMSE of 0.315, which entails the merit of feature importance in promoting forecasting performance. Imran et al. [30] used ensemble regressors with meteorological data, applying feature engineering and Bayesian optimization for hyperparameter tuning; they found that Random Forest Regressor was the best-performing model, achieving an R^2 of 0.864, an EV of 0.865, and the lowest MAE, MSE, and MSLE among the ensemble approaches. Oktoviany et al. [31] developed a hybrid ML-based model combining K-means clustering and classification (KNN, RF) to predict corn futures price states based on weather and macroeconomic factors, improving forecasting accuracy over benchmark models. Wang et al. [32] proposed an ABC-based (Artificial Bee Colony Algorithm) ensemble strategy combining denoising techniques (SSA, EMD, VMD) with models like ARIMA, SVR, LSTM, RNN, and GRU. The semi-heterogeneous ABC ensemble achieved MAPE reductions of 53.3% (corn) and 50% (soybeans).

3.4. Deep Learning

Deep learning techniques have been extensively applied to forecast agricultural commodity prices, leveraging advanced architectures for improved accuracy, as shown in Table 5. Several studies have integrated neural networks with decomposition and hy-

bridization techniques to enhance prediction capabilities. For instance, Wang and Li [33] combined Singular Spectrum Analysis (SSA) with neural networks to forecast commodity futures prices, excelling in trend prediction but facing computational challenges. Similarly, Choudhary et al. [34] employed a VMD–TDNN hybrid model, which showed superior performance in both level and directional predictions, while Zhang and Tang [35] proposed a VMD–SGMD–LSTM model that achieved robust results despite increased computational demands. Halim et al. [36] utilized multivariate standard LSTM with attention mechanisms for Indonesian commodity prices, achieving better results than univariate LSTM, Bi-LSTM, Conv LSTM, and Conv Bi-LSTM.

Table 5. Overview of deep learning techniques in wheat, rice, and corn price prediction.

Refs.	Year	Commodity Name	Dataset	Technique	Findings	Limitation
[33]	2018	Corn, Gold, Crude Oil	Corn, Gold, Crude oil futures prices (1983–2016) CBOT, COMEX, EIA	SSA, BPNN, RBFNN, WNN	SSA–NN models outperform baseline NN models	High computational complexity
[34]	2023	Corn, Palm Oil, Soybean Oil	Monthly international price for Corn, Palm Oil, Soybean Oil (1960–2021); World Bank Commodity Market	VMD–TDNN, EMD–TDNN, EEMD–TDNN, CEEMDAN–TDNN	Directional prediction accuracy: 90% (Corn), MAPE 0.0345, RMSE 9.49, DSTAT 90.90	Lack of formal methodology to determine the number (n) of extracted modes by VMD
[35]	2024	Strong Wheat, Corn, Sugar	Weekly futures prices (2005–2023) from China’s agricultural futures market	VMD–SGMD–LSTM	Outperformed benchmark models in 1-step-, 2-step-, and 4-step-ahead forecasting scenarios Lowest for 1-step with MAE 11.13, MAPE 0.43	Other price influencing factors could be considered
[36]	2022	Rice, Chicken Meat, Eggs, Onions, Garlic, Large Red Chilies, Curly Red Chilies, Red Chilies, Green Chilies, Cooking Oil, Sugar	Prices of 11 commodities (2017–2021) (Indonesian Ministry of Finance and Bank Indonesia)	LSTM	Standard LSTM outperformed Bi-LSTM, Conv LSTM, and Conv Bi-LSTM; Multivariate LSTM outperformed univariate Lowest MAE: 255.998	Focused only on a specific set of food commodities
[37]	2022	Corn, Soybean, PVC, Egg, Rebar	Daily trading data from the CSI 300 index; futures prices of corn, soybean, polyvinyl chloride (PVC), egg, and rebar; Baidu and Google dual-platform search data (2016–2021)	GWO–CNN–LSTM	Significant improvement in price prediction accuracy. MAE 15.2499, RMSE 18.8905, MAPE 0.0079	Focus on a limited set of commodities may not represent the entire futures market

Table 5. Cont.

Refs.	Year	Commodity Name	Dataset	Technique	Findings	Limitation
[38]	2024	Soybean, Corn, Wheat	Monthly prices from China, regional market level (2014–2022)	LSTM	LSTM outperformed SVR and BP-NN; Corn: MAE 84.82, RMSE 102.32, MAPE 3.08%; Wheat: MAE 222.66, MESE 269.26, MAPE 7.09%	Evaluation limited to a single region and fixed sliding window configuration
[39]	2023	Soybean Meal, Wheat	Soybean meal and wheat future prices CBOT (1980–2021)	PSO, CS	Improved forecast performance through combination methods; MAPE wheat (0.7144%)	Focused on specific commodities without broader market consideration
[40]	2024	Wheat, Corn, Soybean	Related agricultural products (10 features), Energy and metals (25 features), Economy (3 features), Wheat futures (4 features)	Bi-DConvLSTM-Attention	RMSE = 5.61, MAE = 3.63, MAPE = 0.55, R2 = 0.9984	Generalization was not addressed
[41]	2022	Corn	Corn daily average futures prices and spot prices (2011–2021), national average price data of corn, early rice, and middle-late rice; soybean futures price; Dalian Commodity Exchange and Zhengzhou Commodity Exchange	AttLSTM–ARIMA–BP	MAPE: 0.0043, MAE: 1.51, RMSE: 1.642	Sensitivity to extreme price fluctuations caused by unforeseen economic factors
[42]	2022	Rice	Monthly Thai Rice FOB Price (1987–2017)	Hybrid with K-means Clustering, HANTS, and MLPNN	Hybrid model outperformed ARIMA, EMD–ARIMA, ANFIS, and persistence models; RMSE = 14.37, MAPE = 4.09% (yearly).	Limited focus on the impact of external factors on forecasting accuracy

Table 5. Cont.

Refs.	Year	Commodity Name	Dataset	Technique	Findings	Limitation
[43]	2024	Corn	Weekly corn future prices (2019–2023). Corn-related opinions, news, policy analysis, and other textual information are collected from the “China Grain” website (2019–2023)	CEEMDAN–CNN–JADE–TFT	The model outperformed JADE-BPNN, JADE-GRU, JADE-RNN, and JADE-LSTM’ MAPE 0.67%, MAE 17.89, RMSE 26.37	Single, narrow-focused media source
[44]	2024	Corn	Chinese corn futures data + causal variables (COFCO Technology stock prices, US and Chinese soybeans futures prices, US and Chinese corn futures prices, China-US exchange rate) (2005–2023)	SCINet, LSTM, GRU, TCN	SCINet outperformed baseline DL models (TCN, GRU, LSTM) for both single- and multi-step price forecasting. For one-step prediction combining Chinese soybean futures: MAE 15.791, MAPE 0.570, RMSE 21.181. Adding key influencing factors further improved performance.	Not delving deeply into nonmarket factors and other potential influencing market factors
[45]	2024	Onion, Potato, Rice, Wheat	1.6 million news articles and daily prices (2006–2020)	REN	RMSE: 135.62 (rice), 55.96 (wheat); RMSE reduction: 13% (rice), 5% (wheat)	Relies on accurate event extraction for prediction reliability
[46]	2021	Corn	Daily corn cash prices and corn futures prices (2006–2011); GeoGrain	ANN (NAR)	RMSE reduced from 0.00057 to 0.00047	Dependence on cubic spline interpolation for missing data approximation
[47]	2022	Coffee, Corn, Cotton, Oats, Soybean, Soybean Oil, Sugar, Wheat	Daily price for coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat, covering periods of 49, 63, 50, 52, 54, 62, 60, and 63 years, all up to 2021; Macrotrends	ANN (NAR)	The overall RRMSEs based on chosen settings for coffee, corn, cotton, oats, soybeans, soybean oil, sugar, and wheat are 2.47%, 1.84%, 1.71%, 2.08%, 1.70%, 1.81%, 3.19%, and 2.12%, respectively; they all outperformed the ARIMA benchmark model	The advantage of the neural network model over no-change models was small

Table 5. Cont.

Refs.	Year	Commodity Name	Dataset	Technique	Findings	Limitation
[48]	2024	Hard Red Winter Wheat	Wheat futures price data and aerial imagery that shows cloud cover, sun elevation, and azimuth over the planted areas for wheat (1984–2023)	CNN, SVM, MLP	Average trained PNL: 2.1%, Average test PNL: 1.01%; the proposed model outperformed the SVM and MLP comparison models	The model's performance may degrade as data become more accessible or the strategy becomes crowded
[49]	2023	Oat, Corn, Soybean, Wheat	17 variables out of three categories: weather, macroeconomics and the prices of the four crops; USDA (SWE), NOAA (Weather), USDA (Snow Data) (1990–2021)	ARIMA, CNN, LSTM, LSTM–CNN	LSTM–CNN had the lowest MSE for Wheat for 5 weeks (0.0090), 10 weeks (0.0086), and 15 weeks (0.0088), but not for 20 weeks, outperforming ARIMA, CNN, and LSTM	Model performance deteriorated for 20-week predictions
[50]	2024	Corn	Corn price for US, South Africa (1931 onward), Malawi (1996 onward); corn yield for US, South Africa, and Malawi (1961–2022); corn mask data; remote sensing data (1982–2018); satellite-derived gross primary production	EOFs, AEs, VAEs, GLM, NN	Non-masked β -VAEs excelled in the US, non-masked AEs in South Africa and Malawi (BSS 0.68, MCC 0.9, AUC 0.93).	Regional variability in dimension-reduction strategy effectiveness limits universal applicability
[51]	2024	Corn	Corn-related: 12 different indicators, namely the previous closing price, previous settlement price, opening price, highest price, lowest price, closing price, settlement price, price change ratio 1, price change ratio 2, trading volume, trading value, and open interest (2013–2022); Dalian Commodity Exchange	Bezier Curve, LSTM, ARIMA, VMD–LSTM, SVR	Bezier curve-based LSTM model outperformed traditional LSTM, ARIMA, VMD–LSTM, and SVR models in predictive accuracy; MAPE 0.80%, RMSE 30.42, Dstat 0.606	High computational complexity due to multiple indicators

Table 5. Cont.

Refs.	Year	Commodity Name	Dataset	Technique	Findings	Limitation
[52]	2021	Corn, Palm Oil	Monthly price of Corn and Palm oil (1980–2020); World Bank Commodity Price Data	DLSTM, TDNN, ARIMA	DLSTM reduced RMSE, MAPE, and MAD by 72% compared to ARIMA and 47% compared to TDNN; for corn: RMSE 0.031, MAPE 7.337%, MAD 0.026	Limited focus on model adaptability to other commodities or time frames.
[53]	2024	Corn	Daily corn futures prices (2000–2020), Barchart	LSTM, VAR, ARIMA	LSTMs outperform traditional models for longer horizon forecasts (7-day forecast horizon MAE 2.75)	LSTMs failed to capture seasonality and trends
[54]	2023	Wheat, Rice	Soil test reports, crop yield data, stock information	RANC algorithm, SVM, ANN, RNN, RBM	Crop recommendation accuracy exceeded 90%; price prediction component integrated into decision system	Specific accuracy for price forecasting not reported; challenges with real-time data integration
[55]	2023	Wheat, Millet, Sorghum, Corn, Rice	Historical price data (2005–2022)	Hybrid SARIMA–LSTM, SVR, XGBoost, ARIMA, LSTM, SARIMA	MAPE: Wheat 5.37, Corn 7.80, Rice 6.87	High model complexity may hinder scalability
[56]	2017	Wheat, Corn, Soybean	Daily Wheat, Corn, Soybean futures prices. (2010–2016); Chicago Board of Trade	PSO–BPNN with Decomposition Methods	VMD–PSO–BPNN had the best accuracy; for wheat: MAPE = 0.55%, MAE = 2.68, RMSE = 3.41, for corn: MAPE = 0.57%, MAE = 2.12, RMSE = 2.82	Focus only on one-step-ahead forecasting
[57]	2023	Wheat	Wheat price, freight volume, turnover, express delivery, consumer price index, money supply, and other related factors (2012–2021); Bureau of Statistics of China	BP–LSTM, LSTM, BP	BP–LSTM model outperformed others (MSE = 0.00026); captured complex price dynamics using external factors like freight volume, CPI, etc.	Limited dataset (10 years); the theoretical depth of DL approach is still under development
[23]	2024	Wheat	Global wheat prices, macroeconomic indicators	ARIMA, SARIMA, ARIMAX, SARIMAX, LSTM, CNN, Regression	ARIMAX and SARIMA performed best; LSTM and CNN overfit training data	Limited generalizability of DL models; high error in testing phase
[58]	2024	Corn	Corn prices and statistical variables, Weibo text data. (2007–2021)	ChineseBERT, Text CNN, Ensemble Empirical Mode Decomposition, SHapley Additive exPlanations, INBEATs, XGBoost, LSTM	Strong predictive ability for 30-day horizon (MAPE 2.72, MAE 63.66) and 60-day horizon (MAPE of 3.42 and MAE of 78.80), outperforming comparative models	No comparison experiments with other model decomposition methods have been conducted

Hybrid models incorporating optimization algorithms and external data sources have also shown promise. Liang and Jia [37] developed a GWO–CNN–LSTM model using the Baidu Index and Google Trends data, enhancing predictions with real-time insights, though limited in commodity diversity. Wang et al. [38] applied an LSTM model to forecast prices of soybean, corn, and wheat in China. The model was trained using historical prices and optimized using time-based sliding windows. In comparative evaluations, LSTM achieved the lowest prediction errors across all three crops, outperforming traditional methods such as SVR and BP neural networks. Zeng et al. [39] introduced a decomposition–reconstruction–ensemble framework with PSO and CS algorithms, improving forecast accuracy, relying on specific datasets. Yun et al. [40] proposed the Bi-DSCnvLSTM–Attention model, which integrated BiLSTM and DSCnvLSTM with an attention mechanism, demonstrating significant accuracy improvements, but with limited discussion on generalization. Guo et al. [41] incorporated spatial-temporal factors into an AttLSTM–ARIMA–BP model for corn price prediction in Sichuan Province, showcasing its efficacy in regional applications. Menhaj and Kavoosi-Kalashami [42] proposed a hybrid model using K-means clustering, HANTS, and MLPNN for Thai rice price forecasting. Their model achieved superior accuracy (RMSE = 14.37, MAPE = 4.09%) compared to four benchmark methods, namely ARIMA, EMD–ARIMA, ANFIS, and persistence models.

Explainable and event-driven models have also gained traction. Wu et al. [43] introduced the CEEMDAN–CNN–JADE–TFT (temporal fusion transformer) model for corn futures, achieving high accuracy and interpretability. Wang et al. [44] applied SCINet to predict Chinese corn futures prices, which outperformed LSTM, GRU, and TCN—even more so when enhanced with causally related economic indicators like soybean prices and exchange rates. Chakraborty et al. [45] developed a neural network model integrating real-world events from news articles with historical data to forecast prices for multiple commodities, achieving superior accuracy and outperforming all other linear and nonlinear models, but it relied on event extraction precision. Xu and Zhang [46] enhanced short-term forecasts by incorporating futures prices into neural network models for daily corn cash prices and found that the NAR (nonlinear autoregressive) univariate model led to lower RMSEs benchmarked against a naïve (no-change) model and a linear autoregressive (LAR) model, and the bivariate NAR model further improved results. In a different study, Xu and Zhang [47] demonstrated the effectiveness of NN models over ARIMA benchmark models for capturing long-term trends.

Advanced architectures and innovative data inputs have further improved prediction accuracy. Thaker et al. [48] utilized CNNs with aerial imagery for wheat futures, highlighting the potential of visual data; their model produced greater PNL than the SVM and MLP (multilayer perceptron) comparison models. Wang et al. [49] combined LSTM and CNN to outperform other models in forecasting weekly grain prices, incorporating weather and macroeconomic factors to boost performance, with the inclusion of the snow factor for the first time in commodity price forecasting. Teste et al. [50] leveraged Autoencoders and Variational Autoencoders with satellite-derived GPP data for corn yield and price predictions, though regional variability posed challenges. Zhao et al. [51] proposed a Bezier curve-enhanced LSTM model for predicting corn futures prices. The hybrid model outperformed traditional LSTM, ARIMA, VMD–LSTM (variational mode decomposition), and SVR, achieving the lowest RMSE (30.42), MAPE (0.80%), and Dstat (0.606).

A Deep LSTM model was developed by Jaiswal et al. [52] to forecast international monthly corn and palm oil prices. The model outperformed ARIMA and TDNN models, having the lowest RMSE, MAPE, and MAD and the best directional accuracy. In another study, Brignoli et al. [53] compared LSTM–RNNs to classical econometric time series models for forecasting corn futures prices. LSTM consistently outperformed traditional models,

particularly at longer horizons, but it required careful preprocessing to capture seasonality and trends. Daniel et al. [54] proposed the “RANC Crop Recommendation Tool,” a crop recommendation and price forecasting model using DNNs, achieving over 90% accuracy, and it achieved better results than NN and Naïve Bayes comparison models, but specific metrics for price forecasting were not detailed separately. Patil et al. [55] proposed a hybrid SARIMA–LSTM (HySALS) model to forecast the global prices of five key commodities. The approach achieved MAPEs of 5.37 for wheat, 7.80 for corn, and 6.87 for rice on test data, showing strong predictive performance. A study by Wang et al. [56] proposed four hybrid models (BPNN optimized by the particle swarm optimization (PSO) algorithm and four decomposition methods: empirical mode decomposition (EMD), wavelet packet transform (WPT), intrinsic time-scale decomposition (ITD), and variational mode decomposition (VMD)) to forecast futures prices of wheat, corn, and soybean. VMD–PSO–BPNN yielded the lowest MAPE across all commodities, confirming superior accuracy. Jiang et al. [57] proposed a BP–LSTM hybrid model for short-term wheat price forecasting in China. The model incorporated multiple external factors and achieved high accuracy, with the lowest MSE (0.00026) compared to LSTM-only and BP-only approaches. Wang et al. [58] proposed a deep learning model combining ChineseBERT, text CNNs, and ensemble empirical mode decomposition to predict corn futures prices using Weibo sentiment analysis, achieving high accuracy for 30- and 60-day horizons.

Collectively, these studies underline the versatility and potential of deep learning in agricultural commodity price forecasting.

3.5. Time Series Models

Time series models have been extensively applied to predict commodity prices in agriculture, with various approaches demonstrating unique strengths and limitations, as shown in Table 6. Kohzadi et al. [59] compared feedforward neural networks with ARIMA models for price forecasting, highlighting the neural networks’ superior ability to reduce errors and capture trends, albeit with the need for careful hyperparameter tuning. Similarly, Sharma and Burark [60] identified ARIMA (1, 1, 1) as the most effective model for corn price prediction over ANN and ESM (exponential smoothing models) in Rajasthan markets, though its reliance on historical data posed challenges in adapting to sudden market shifts.

Table 6. Overview of time series model techniques in wheat, rice, and corn price prediction.

Refs.	Year	Commodity Name	Dataset	Technique	Findings	Limitation
[59]	1996	Live Cattle, Wheat	Monthly prices (1950–1990)	ARIMA, FFNN	Neural networks achieved 27% and 56% lower MSE compared to ARIMA; MSE 0.087, AME 0.154, MAPE 4.235	Requires careful hyperparameter tuning
[60]	2016	Corn	Monthly prices of corn in Rajasthan markets (2002–2013)	ARIMA, ANN, ESM	ARIMA (1,1,1) achieved lowest AIC (1677.17), SBC (1685.86), MAD (71.04), MSE (11,477.78), and MAPE (5.64), outperforming other models	Limited adaptability to sudden market fluctuations

Table 6. Cont.

Refs.	Year	Commodity Name	Dataset	Technique	Findings	Limitation
[61]	2018	Rice, Wheat, Corn	Monthly prices from January 1990 to September 2015	ARIMA, ANN, SVR, MARS, ARIMA-ANN, ARIMA-SVR, ARIMA-MARS	MAE, RMSE, MAPE: Rice: 10.365%/12.037%/2.650% Wheat: 9.779%/11.371%/4.347% Corn: 6.495%/9.102%/3.785%	Relies on the accuracy of autoregressive variable selection for effective predictions
[62]	2007	Wheat	Wheat monthly spot price (1996–2005)	ARIMA, ANN, Combined model	In error metrics, the combined model had the lowest MAE 7.662, MSE 143.045, and MAPE 0.545%. In MMRR (mean monthly return rate) and Dstat, ANN has the highest: 0.9627/91.667.	Conflicting results under different evaluation criteria
[22]	2024	Rice	Weekly rice prices and precipitation weather data (2017–2022) from seven cities in Java	ARIMAX-GARCH, SVR	SVR outperformed in most cities and for premium quality; ARIMAX-GARCH stable for mid/low rice. Average MAPE 3.04%, average RMSE 335.01, average MAE 291.19	Weather-only exogenous variable; city-specific results; moderate generalizability
[23]	2024	Wheat	Global prices of wheat, barley, olive oil, palm oil, sunflower oil, rice, and sugar; 134 monthly macroeconomic time-series data, including those that are related to output and income, labor market, consumption and orders, orders and inventories, money and credit, interest rates and exchange rates, prices, and stock market (1990–2024)	ARIMA, SARIMA, ARIMAX, SARIMAX, LSTM, CNN, LR	The linear regression model outperformed all others in testing; MAE 32.23 and RMSE 38.97	Did not take environmental variables into account
[63]	2022	Corn, Crude Oil, Gold	Daily spot market prices of Corn, Crude Oil, and Gold (2016–2021); Bloomberg commodities index	EMD-BPNN, EMD-ARIMA, VMD-BPNN, VMD-ARIMA, BPNN, ARIMA	VMD-ARIMA model for corn achieved MAE = 0.3566, RMSE = 0.5886, MAPE = 0.0954	EMD did not improve the predictive ability of the BPNN model

Table 6. Cont.

Refs.	Year	Commodity Name	Dataset	Technique	Findings	Limitation
[64]	2022	Wheat	Wheat daily US prices (2009–2018), weather details	ARIMA, SARIMA, BPN, LSTM	ARIMA and SARIMA performed well for short-term predictions (Daily MSE 0.0003), BPN outperformed them in weekly and monthly MSE (0.0005, 0.0004)	ARIMA and SARIMA models were less effective for long-term price forecasting
[65]	2023	Yellow Corn	Weekly wholesale price index of yellow corn in China (2010–2020)	Nonlinear Auto-Regressive Neural Network, RW, AR-GARCH, SVR, RT, LSTM	RMSE: 1.05% (training), 1.08% (validation), 1.03% (testing)	Lack of combination (hybrid/ensemble) models for comparison
[24]	2021	Wheat	Daily wheat futures prices, Gram futures prices, real rate of interest, futures prices of wheat in the US, other related economic variables. NCDEX (2009–2014)	ARMA (1,1), ARMA (1,2), Economic Variable Model, ANN, RW	Random walk model outperformed all (RMSE 0.6948, MAE 0.4627)	Compared neural network not fine-tuned
[66]	2011	Crude Oil, Corn, Wheat	Crude oil futures, Corn and Wheat futures (1998–2009); CBOT	Stochastic volatility models, Bayesian Markov chain Monte Carlo	Evidence of volatility spillover post-2006 from oil to corn and wheat; speculation and scalping increase volatility	Focused on volatility transmission rather than direct price prediction (which is only a limitation regarding the scope of this SLR)
[67]	2021	Wheat, Soybean, Corn	Monthly data from January 1980 to December 2016	AR, VAR, VEC, ARCH, GARCH	Predictive models revealed systematic information from market fundamentals, macroeconomic developments, and financial factors. VEC and s-VAR models performed best; REER was most predictive; macroeconomic variables improved long-term commodity price forecasts.	Complexity in model specification and implementation

Hybrid models combining ARIMA with computational intelligence techniques have demonstrated enhanced forecasting accuracy. Shao and Dai [61] integrated ARIMA with ANN, SVR, and MARS to predict prices of rice, wheat, and corn, showing that these hybrid models outperformed standalone approaches. Similarly, Zou et al. [62] explored a linear combination model of ARIMA, ANN, and a combined model for wheat prices in China, where ANN excelled in capturing turning points and delivering high mean monthly

returns, while in error measures, the combined model performed better, thus creating some ambiguity. Sentosa et al. [22] compared ARIMAX–GARCH and SVR models for rice price forecasting across seven Indonesian cities, finding SVR to be superior in most cases, particularly for premium rice, while ARIMAX–GARCH performed better for lower-grade variants. Yadav [23] compared ARIMA, SARIMA, ARIMAX, SARIMAX, LSTM, CNN, and LR (linear regression) models for global wheat price forecasting and found that LR had an MAE of 32.23 and an RMSE of 38.97.

Decomposition techniques combined with ARIMA have further improved price forecasting in agriculture. Antwi et al. [63] employed EMD and VMD in combination with ARIMA and BPNN to forecast prices of corn, crude oil, and gold, finding that the VMD–ARIMA model achieved the smallest predictive errors for corn. However, EMD’s contribution to the predictive ability of the BPNN model was limited. Similarly, Preetha et al. [64] found that while the ARIMA and SARIMA models were effective for short-term wheat price forecasts, neural network models like BPN and LSTM performed better for long-term predictions, especially with weather data.

Advanced neural network models and sentiment analysis have emerged as promising tools for time series forecasting. Xu and Zhang [65] utilized a nonlinear auto-regressive neural network to forecast yellow corn prices in China, delivering stable and accurate results, outperforming all comparison models (RW, AR-GARCH, SVR, RT, LSTM). Kumar [24], in their study, compared the ARMA, ANN, and RW models for forecasting Indian wheat futures. The random walk model delivered the lowest RMSE and MAE. Du et al. [66] used stochastic volatility models and Bayesian MCMC to assess oil price volatility and its spillover effects on corn and wheat futures. Results showed significant post-2006 volatility transmission from oil to corn and wheat due to ethanol-driven interdependence.

Crespo Cuaresma et al. [67] used a comprehensive econometric framework involving AR, VAR, VEC, ARCH, and GARCH models to forecast wheat, soybean, and corn prices. Their results highlight the predictive value of macroeconomic variables—particularly real exchange rates (REER)—and the effectiveness of VEC models.

The previous section highlighted how the techniques have been applied in practice, their effectiveness in different forecasting scenarios, and the advancements made in integrating multiple methods to enhance prediction accuracy. Table 7 presents a unified comparison of selected forecasting models applied to wheat, corn, and rice price prediction. The studies included in this table were selected based on the availability of clearly reported performance metrics (e.g., MAPE, RMSE, R^2 , or techniques comparison) and their focus on directly comparing models using quantitative evaluation.

Table 7. Unified performance comparison table.

Refs.	Year	Commodity	Model Type	Technique	Evaluation Metric	Performance
[68]	2021	Rice, Corn, Soybean	ML	SVM	RRMSE	7.45 (avg)
[21]	2016	Corn	ML	BPNN	MAPE	1.31% (in), 2.26% (out)
[27]	2023	Rice	EL	Random Forest	MAPE	0.0093573
[29]	2024	Corn	EL	Bagging SVR	R^2 /MAE/RMSE	0.961/0.234/0.315
[30]	2022	Rice	EL	Random Forest	R^2	0.864
[31]	2021	CORN	EL	ML–KNN	MAE/RMSE/MAPE	0.0372/0.0512/ 0.6908
[34]	2023	Corn, Palm Oil, Soybean Oil	DL Hybrid	VMD–TDNN	MAPE/RMSE/DSTAT	0.0345/9.49/90.90

Table 7. Cont.

Refs.	Year	Commodity	Model Type	Technique	Evaluation Metric	Performance
[37]	2022	Corn, Soybean, PVC, Egg, Rebar	DL Hybrid	GWO–CNN–LSTM	MAE/RMSE/MAPE	15.2499/18.8905/0.0079
[38]	2024	Soybean, Corn, Wheat	DL	LSTM	MAE/RMSE/MAPE	Corn: 84.82/102.32/3.08% Weat: 222.66/269.26/7.09%
[39]	2023	Soybean Meal, Wheat	DL Hybrid	Full-PSO–CS	MAPE	0.7144%
[40]	2024	Wheat, Corn, Soybean	DL	Bi-DSCovLSTM–Attention	RMSE/MAE/MAPE/R ²	5.61/3.63/0.55/0.9984
[41]	2022	Corn	DL + TS	AttLSTM–ARIMA–BP	MAPE/MAE/RMSE	0.0043/1.51/1.642
[42]	2022	Rice	DL Hybrid	K-means + MLPNN	RMSE/MAPE	14.37/4.09%
[43]	2024	Corn	DL Hybrid	CEEMDAN–CNN–JADE–TFT	MAPE/MAE/RMSE	0.67%/17.89/26.37
[44]	2024	Corn	DL Hybrid	SCINet	MAE/MAPE/RMSE	15.791/0.570/21.181
[45]	2024	Onion, Potato, Rice, Wheat	DL Hybrid	REN	RMSE	Onion: 155.56, Potato: 86.08, Rice: 135.62, Wheat: 55.96
[46]	2021	Corn	DL	ANN (NAR)	RMSE	0.00047
[47]	2022	Coffee, Corn, Cotton, Oats, Soybean, Soybean Oil, Sugar, Wheat	DL	ANN (NAR)	RMSE	Coffee: 2.47%, Corn: 1.84%, Cotton: 1.71%, Oats: 2.08%, Soybean: 1.70%, Soybean Oil: 1.81%, Sugar: 3.19%, Wheat: 2.12%
[48]	2024	Hard Red Winter Wheat	DL Hybrid	CNN	PNL	1.01%
[49]	2023	Oat, Corn, Soybean, Wheat	DL Hybrid	LSTM–CNN	MSE	Wheat for 5 weeks: 0.0090, 10 weeks: 0.0086, 15 weeks: 0.0088
[50]	2024	Corn	DL Hybrid	AEs, VAEs	BSS/MCC/AUC	Malawi 0.68/0.9/0.93
[51]	2024	Corn	DL Hybrid	Bezier LSTM	RMSE/MAPE	30.42/0.80%
[52]	2021	Corn, Palm Oil	DL	DLSTM	RMSE/MAPE/MAD	For Corn: 0.031/7.337%/0.026
[53]	2024	Corn	DL Hybrid	LSTM–RNN	MAE	(Seven-day forecast horizon) 2.75
[55]	2023	Wheat, Millet, Sorghum, Corn, Rice	DL + TS	SARIMA–LSTM	MAPE	Wheat 5.37, Corn 7.80, Rice 6.87

Table 7. Cont.

Refs.	Year	Commodity	Model Type	Technique	Evaluation Metric	Performance
[56]	2017	Wheat, Corn, Soybean	DL Hybrid	VMD–PSO–BPNN	MAPE/MAE/RMSE	Wheat 0.55%/2.68/3.41 Corn 0.57%/2.12/2.82
[57]	2023	Wheat	DL	BP–LSTM	MSE	0.00026
[59]	1996	Live Cattle, Wheat	ML, TS	ARIMA, FFNN	MSE/AME/MAPE	Wheat: 0.087/0.154/4.235
[60]	2016	Corn	TS, ML	ARIMA (1,1,1)	AIC/SBC/MAD/MSE/MAPE	1677.17/1685.86/71.04/11,477.78/5.64
[61]	2018	Rice, Wheat, Corn	TS, ML	ARIMA–ANN ARIMA–SVR ARIMA–MARS	MAE/RMSE/MAPE	Rice: 10.365%/12.037%/2.650% Wheat: 9.779%/11.371%/4.347% Corn: 6.495%/9.102%/3.785%
[62]	2007	Wheat	TS, ML	ARIMA, ANN, Combined mod-el	MAE/MSE/MAPE/MMRR/Dstat	Combined model had the lowest MAE (7.662), MSE (143.045), MAPE (0.545%); in MMRR and Dstat, ANN had the highest: 0.9627/91.667
[22]	2024	Rice	TS, ML	ARIMAX–GARCH, SVR	Average MAPE/average RMSE/average MAE	3.04%/335.01/291.19
[23]	2024	Wheat	TS/DL	ARIMAX, SARIMA, LSTM, CNN, LR	MAE/RMSE	32.23/38.97
[63]	2022	Corn, Crude Oil, Gold	DL + TS	VMD-ARIMA	MAE/RMSE/MAPE	0.3566/0.5886/0.0954
[64]	2022	Wheat	DL + TS	ARIMA, SARIMA, BPN, LSTM	MSE	ARIMA, SARIMA daily MSE: 0.0003; BPN weekly and monthly MSE: 0.0005, 0.0004
[58]	2024	Corn	DL Hybrid	INBEATSx, XGBoost, LSTM	MAPE/MAE	30-day horizon (MAPE of 2.72, MAE of 63.66) and 60-day horizon (MAPE of 3.42 and MAE of 78.80),
[65]	2023	Corn	DL, TS	Nonlinear Auto-Regressive Neural Network, RW, AR–GARCH, SVR, RT, LSTM	RMSE	1.05% (training), 1.08% (validation), 1.03% (testing)
[24]	2021	Wheat	TS, ML	ARMA, ANN, RW	RMSE/MAE	0.6948/0.4627
[67]	2021	Wheat, Soybean, Corn	TS	VEC, s-VAR	MAE/MSE	7.331/128.674

MAPE (Mean Absolute Percentage Error) is the average of the absolute percentage differences between actual and predicted values; it is useful for comparing forecast accuracy across datasets. MAE (mean absolute error) is the average of the absolute differences between actual and predicted values, a straightforward measure of average prediction error. RMSE (root mean squared error) is the square root of the average of squared prediction errors; it gives a greater weight to larger errors. R^2 (coefficient of determination) is a statistical measure indicating how well predictions approximate actual outcomes; values closer to 1 indicate better model performance. MAD (mean absolute deviation) is the average of the absolute deviations between actual and predicted values; it is like MAE but sometimes used in different contexts.

While additional studies were reviewed, some did not provide consistent, comparable performance data, or they focused on qualitative aspects, specific components of hybrid frameworks, or regional insights without clear model benchmarking. Therefore, to maintain clarity and comparability, only representative studies with well-documented metrics and outcomes are included in this summary.

4. Discussion

This section focuses on the methods employed for predicting the prices of wheat, corn, and rice, their evolution, and the challenges in their use. It details multiple methods, including statistical models, machine learning algorithms, and hybrid techniques, that predict price trends for the selected agricultural commodities and how they impact the results. The evolution of these techniques is presented in the context of obtaining higher accuracies and adaptability and improvement in the limitations of data availability, computational complexity, and model interpretability. The shape of these challenges still constrains the development of more robust reliable forecasting models.

Descriptive synthesis was employed. Data were organized into structured tables and visual taxonomies. No meta-analysis was conducted. No heterogeneity or sensitivity analyses were performed. This review is limited by the absence of formal quality assessment and a lack of meta-analysis. Despite this, it highlights key gaps in commodity price forecasting and suggests future work on the explainability and transferability of models. Practical implications include better-informed policymaking and farm-level decision support.

4.1. Common Techniques

The analysis of approaches for agricultural commodity price prediction reveals the increasingly sophisticated nature of the field in terms of the use of advanced computational techniques. Figures 7 and 8 present the frequency of the techniques and methods used in the price prediction of the selected agricultural commodities. Multi-class classification is usually handled using machine learning techniques, as they are convenient and can work with various datasets. Since feature selection techniques such as Support Vector Machines, Decision Trees, and Random Forests excel at capturing nonlinear relationships as well as performing robust predictions, these methods can be very useful [26,29,31]. Ensemble learning combines various models to strengthen their individual algorithms' faults to improve predictive accuracy. Techniques such as GBM and Boosting can work on complex datasets and adjust prediction horizons [26].

Deep learning methods have become increasingly popular due to their efficiency in learning complex patterns in extensive and unstructured data. These architectures include Long Short-Term Memory (LSTM) networks [53], CNNs, and hybrid models, which are suited to long-term forecasting and temporal dependencies [48]. These models often outperform traditional methods in accuracy but have greater complexity and computational

demands. Time series models, including some of their hybrids (ARIMA), remain important for forecasting because of their interpretability and their effectiveness in trend analysis [60].

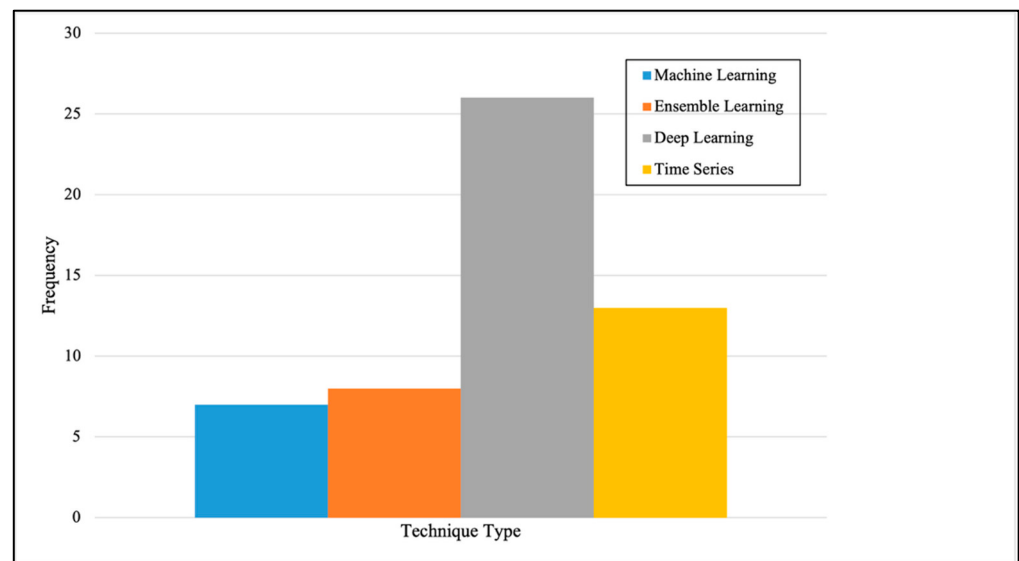


Figure 7. Frequency of techniques used.

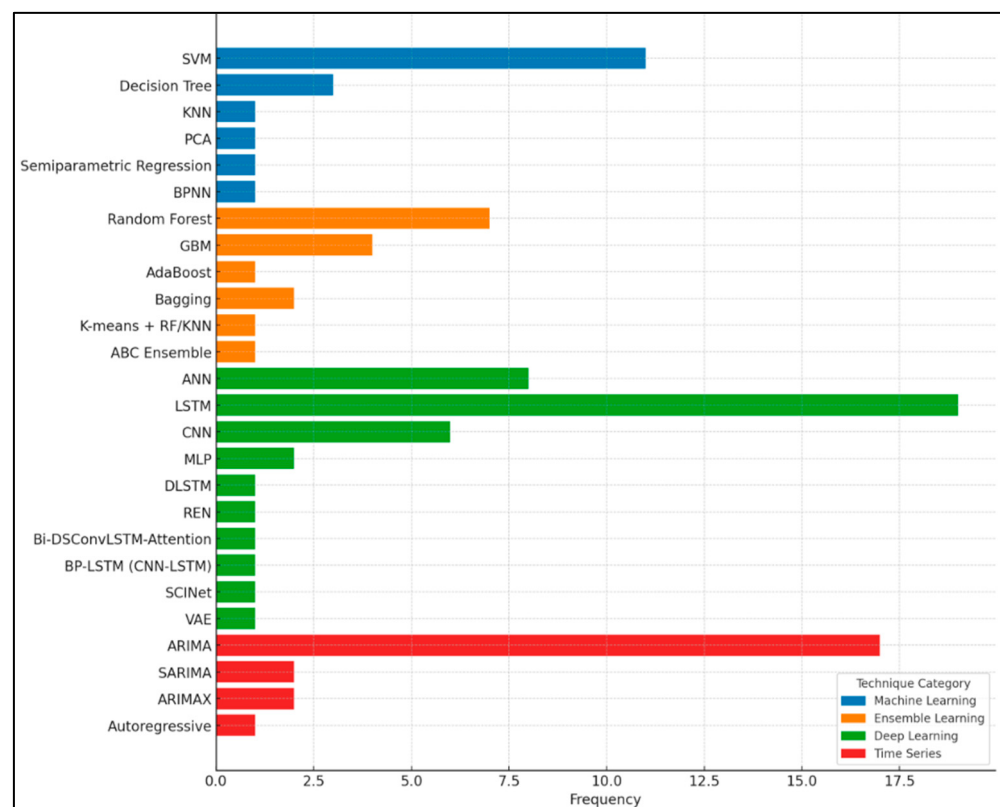


Figure 8. Common models used in commodity price prediction.

Support Vector Machines (SVMs) are popular machine learning approaches because they work well when dealing with high-dimensional data and nonlinear relationships [68]. Decision Trees are often used for predictive modeling because they are simple and easy to interpret [25]. Random Forest is a dominant technique for ensemble learning. It reduces overfitting and improves predictive accuracy through the aggregation of multiple decision trees [29]. GBM is popular for its efficiency and has strong performance in structured

datasets [26]. Featuring the ability to model sequential data and the ability to capture temporal dependencies, LSTM networks are widely used with deep learning methods for time-series forecasting [53]. Other architectures, including Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs), complete the toolkit for complicated patterns and large datasets [43]. Traditional time series methods such as ARIMA provide solid trend analysis and interpretability, and more modern approaches like Autoregressive methods are flexible in working with seasonality and irregularities [64].

4.2. The Studied Commodities

Among the commonly studied commodities—wheat, corn, and rice—the largest occurrence frequency is observed for corn, as depicted in Figure 9, which is often analyzed due to its importance as a staple crop and its wide use in the food, feed, and biofuel industries [31]. Its price is susceptible to many factors, including weather conditions, the amount produced in a specified period, and large economies. Wheat is also a global staple crop, and its price fluctuations can have wide-ranging economic and food security implications [69]. To enhance prediction accuracy, researchers often study its relationship with external factors, such as global oil prices and market volatility. Rice is a staple for more than half of the world’s population, and price prediction studies have focused on it due to its critical role in food security. Price dynamics are often related to domestic and international production, exchange rates, and price interventions [18].

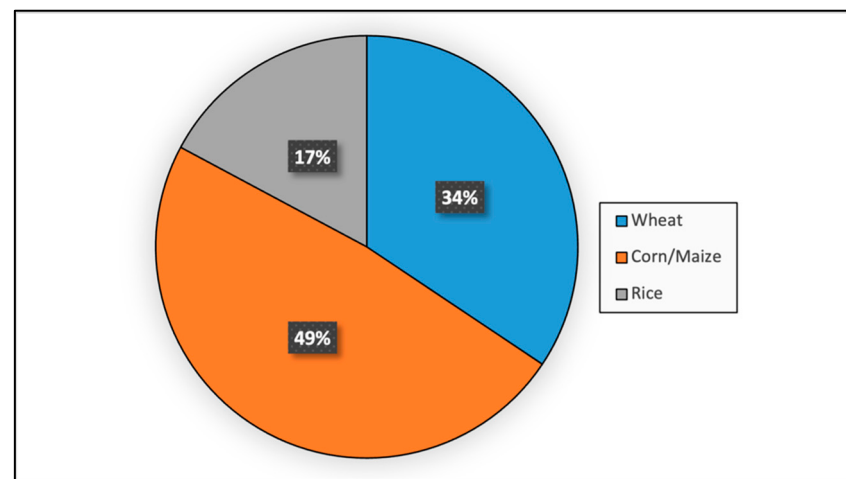


Figure 9. Percentage of each studied crop in the literature.

4.3. Evolution of Techniques

Techniques that evolved in the agricultural commodity price prediction problem follow a progressive change from simple and conventional to more sophisticated and integrated methods. Traditional statistical models like ARIMA and foundational ML tools such as PLS regression and neural networks have been used in earlier studies to identify linear and nonlinear relationships in the data, but they continue to be extensively used for their interpretability, simplicity, and performance. In time, ensemble learning models that utilized the combined strengths of multiple algorithms such as Random Forest and XGBoost increased predictive accuracy [29]. These models perform better than previous approaches, especially in cases of complex data sets with many interacting features. Deep learning techniques have provided robust techniques for handling temporal dependencies and complex patterns inherent to agricultural data. Methods like LSTM and hybrid models like SARIMA–LSTM [55,70] have been used to model sequential data. Frameworks that combine time series methods with deep learning, such as AttLSTM–ARIMA–BP [41], merge domain-specific insights with computational advances. The growing use of large datasets,

advances in computational power, and the need for improved predictions to tackle market volatility and global food security are driving the evolution of forecasting.

The adoption of techniques for agricultural commodity price forecasting has progressed over time in distinct phases (Figure 10). Early research (prior to 2017) relied on traditional methods such as ARIMA and foundational ML models, valued for their simplicity and interpretability. From 2017–2018, deep learning approaches began to appear, although their use was limited. There was no noticeable increase in novel techniques during 2019–2020. However, starting in 2021, there was a substantial surge in the application of deep learning and time series methods, particularly LSTM-based architectures and hybrid models. Ensemble learning also gained traction in this period. In 2023–2024, deep learning and time series remained dominant, with ensemble and standard machine learning techniques also contributing to the methodological landscape.

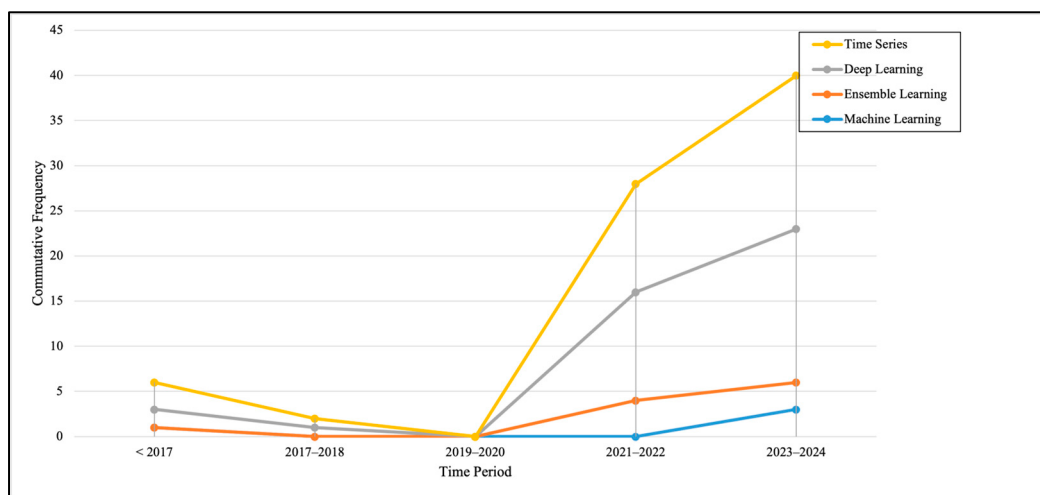


Figure 10. Evolution of agriculture commodity price prediction techniques.

4.4. Challenges and Limitations

4.4.1. Data Availability

One of the primary challenges observed in agricultural commodity price forecasting is the reliance on limited or region-specific datasets, which can block the generalizability of the models [71]. Models trained from datasets belonging to certain countries or markets perform poorly when applied to others with different economic conditions. This limitation can lower the credibility of forecasting models, particularly for long-term predictions. Additionally, incomplete and low-quality data, such as missing export/import statistics or meteorological conditions, reduce the effectiveness of models.

4.4.2. Model Complexity and Computational Challenges

Many of the forecasting models employed in agricultural price prediction are computationally intensive, especially when multiple techniques are combined or when deep learning architectures are used [72]. Thus, even though LSTM, CNN, and many other hybrid techniques tend to provide better efficiency than traditional techniques most of the time, they can be quite computationally heavy. This malleability is typical for longer training times, scaling resource consumption, and issues of scaling, particularly in real-time applications or large volumes of data. Furthermore, using more models or techniques simultaneously, for example, the complicated system that integrates ARIMA and deep learning methods, may do a better job when it is used to make predictions, but they come with high model complexity that might be hard to address and control. For instance, models developed to integrate different algorithms such as LSTM–CNN registered great

performance; nevertheless, they demand massive computer processing and could hardly be implemented at an extremely large scale.

4.4.3. Model Interpretability

The reviewed studies are also faced with another challenge: interpretability is missing from many advanced forecasting models, e.g., LSTM and CNN [73]. While these models may be precise, they lack interpretability; in other words, it is very difficult to say how exactly the model comes to a particular prediction, which is a significant requirement for agricultural markets. In this case, a lack of clear and coherent explanations of model results poses a problem to the use of such models in practice. In addition, many models show inconsistent performance depending on the forecast horizon and market condition, and this makes it hard to deploy them. For instance, deep learning methods can make good long-term predictions but may perform as well in short-term predictions or on datasets containing significant price fluctuations supported by extreme economic factors that may be beyond humans' control to forecast. This places further refinement and optimization required to enhance the robustness and reliability of forecasting models to more general scenarios and datasets.

4.4.4. Interaction of Limitations

The limitations discussed—data availability, model complexity, and interpretability—often interact in ways that compound the overall challenge. For example, limited and region-specific datasets reduce the volume and variety of input features available for training, which in turn pressures researchers to use more complex models (e.g., deep learning with multiple layers or hybrid structures) to extract patterns. These more complex models tend to require greater computational resources and longer training times, increasing operational costs and making them much more difficult to deploy. Furthermore, such models are often opaque or “black box” in nature, making them uninterpretable, especially when trained on sparse or noisy datasets. This lack of transparency undermines user trust and limits adoption, particularly in high-stakes agricultural policy contexts. Thus, these limitations form a cycle, where attempting to solve one issue may adversely affect others.

In addition to the methodological challenges already addressed, the forecasting of agricultural commodity prices remains difficult due to the broad range and variability of influencing factors. These include oil prices [18], global market linkages [19], and weather-related variables such as rainfall, temperature, humidity, wind speed, and sunshine [30,31,68]. Macroeconomic indicators, as well as domestic and international demand and supply conditions, have also been identified as significant contributors to price fluctuations [21]. The increasing financialization of agricultural markets has introduced further volatility and complexity [43].

These factors, and their interactions, influence both the selection and performance of forecasting models. As highlighted by Zelingher and Makowski [25], no single model can be expected to perform best across all contexts. Model effectiveness varies depending on the specific crop, forecasting horizon, data availability, and preprocessing strategies [27,29]. A notable limitation across the reviewed studies is the absence of standardized datasets and consistent evaluation metrics, which prevents direct comparison of model performance [53].

Several additional considerations, such as the selection of time lags, the configuration of model parameters (e.g., learning rate, window length), and the choice of input features, were also shown to significantly affect forecasting results [33,35,36]. Furthermore, the integration of external data—such as sentiment indicators, macroeconomic variables, and open-source weather data—has shown potential to improve predictive performance [26,41,42], though systematic validation remains limited.

Given the volatility of grain commodity prices and their implications for producers, markets, and consumers [41,42], the development of forecasting models that are both accurate and interpretable is essential. Priority should be given to the advancement of explainable AI approaches and hybrid frameworks that support informed decision-making in real-world applications [45,49].

One of the main limitations encountered in this review is the lack of a standardized framework for evaluating and comparing forecasting models under common conditions. A potential direction for future research involves the development of controlled, game-like simulation environments, like those used in supply chain forecasting competitions [74]. Such platforms would allow researchers to test their models using the same datasets and forecasting scenarios, facilitating more realistic, transparent, and reproducible performance comparisons. This approach could complement existing empirical evaluations and contribute to the establishment of benchmarking standards in the field.

5. Conclusions

Agricultural commodity price forecasting techniques, commodities, and associated challenges were systematically reviewed herein to objectively and comprehensively analyze advancements in the field up to 31 December 2024. This provides important insights into the adoption of machine learning (ML), ensemble learning (EL), deep learning (DL), and time series approaches, with new predictive performance contributions. Staple crops like wheat, corn, and rice are commonly forecasted for their contribution to universal food security. This study highlighted persistent challenges, such as the generalization of models being limited to region-specific datasets, computational complexity, and lack of interpretability in advanced models. This review highlights the need to develop more robust and scalable forecasting techniques that leverage multiple data sources, such as weather, economic, and trade data. Moreover, explainable AI (XAI) approaches should be emphasized for more interpretable and trusted complex models for adoption in real-world applications.

The absence of the use of standardized datasets to be used as benchmarks does not allow for cross-comparison of models and cross-study replication. Alongside this deficiency, the use of different/inconsistent evaluation metrics hinders forecasting accuracy assessment and model comparison.

Future work should engage in the development of hybrid models, which will utilize the strength of ML, DL, and time series methods while addressing their weaknesses. Standardizing and placing datasets into open-access repositories alongside the use of common evaluation metrics could improve model generalizability and benchmarking. Region-specific challenges and socioeconomic factors should be incorporated into forecasting models to improve their relevance and impact. Finally, the utilization of abundant and relevant exogenous data (weather, macroeconomic indicators, sentiment markers, etc.) would probably greatly benefit the prediction accuracy of the models. Additionally, future studies should prioritize the development of explainable AI (XAI) frameworks tailored to agricultural forecasting, enabling model transparency and user trust in real-world decision-making contexts. Another important direction is the design of regionally transferable forecasting systems trained on multi-country datasets and evaluated under variable market conditions. These strategies would help overcome current limitations in generalizability and interpretability while supporting broader adoption of advanced models. This study lays a foundation for the development of agricultural price prediction research, innovation, and sustainable agricultural practices.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
ANN	Artificial Neural Network
ARIMA	AutoRegressive Integrated Moving Average
ARIMAX	ARIMA with Exogenous Variables
BP	Backpropagation
BPNN	Backpropagation Neural Network
CBOT	Chicago Board of Trade
CNN	Convolutional Neural Network
CS	Cuckoo Search
DL	Deep Learning
EL	Ensemble Learning
EMD	Empirical Mode Decomposition
EV	Explained Variance
FFNN	Feedforward Neural Network
GDP	Gross Domestic Product
GRU	Gated Recurrent Unit
GWO	Grey Wolf Optimizer
ITD	Intrinsic Time-scale Decomposition
KNN	k-Nearest Neighbors
LSTM	Long Short-Term Memory
MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error
ML	Machine Learning
MLP	Multi-Layer Perceptron
MSE	Mean Squared Error
MSLE	Mean Squared Logarithmic Error
NN	Neural Network
PLS	Partial Least Squares
PCA	Principal Component Analysis
PSO	Particle Swarm Optimization
R ²	Coefficient of Determination
RF	Random Forest
RFR	Random Forest Regressor
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
SARIMA	Seasonal ARIMA

SARIMAX	Seasonal ARIMA with Exogenous Variables
SCINet	Series-wise Convolutional Interaction Network
SLR	Systematic Literature Review
SSA	Singular Spectrum Analysis
SVR	Support Vector Regression
SVM	Support Vector Machine
TDNN	Time-Delay Neural Network
VMD	Variational Mode Decomposition
XGBoost	Extreme Gradient Boosting

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