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Commodity Price Forecasting: A Systematic Review

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Abstract

Commodity price forecasting has become increasingly important because commodity markets play a central role in economic activity, including trade, industrial planning, and investment decisions. Despite this importance, forecasting commodity prices remains challenging because prices are highly volatile and are influenced by the complex interaction of many factors, such as demand and supply conditions, macroeconomic shifts, geopolitical issues, and environmental factors. The literature offers a wide range of approaches to commodity price forecasting, from classical time series models to machine learning, deep learning, and hybrid methods. This study conducts a systematic review of the literature to identify the leading commodity price forecasting models and to map the field's main trends. It covers key commodity categories such as crude oil, natural gas, various metals, agricultural commodities, and lumber. As a contribution, this review also proposes a taxonomy that organizes the main approaches used in the field. This review provides a clear picture of current directions in the field and offers guidance for future work in commodity price forecasting.

Keywords
Commodity price forecasting, systematic literature review, machine learning, deep learning, hybrid models.

1. Introduction
Commodity markets play an important role in the global economy, as they support international trade, industrial production, and overall economic stability. However, their prices are difficult to predict because they are affected by many connected factors, such as supply and demand, geopolitical events, climate-related disruptions, and changes in the global energy system. Between 2020 and 2023, global commodity prices changed significantly and became highly volatile. According to the World Bank Commodity Markets Outlook, this situation was mainly linked to the effects of the COVID-19 pandemic, supply chain disruptions, and geopolitical tensions, especially the Russia–Ukraine conflict and growing trade rivalries (World Bank 2023; Mitsas et al. 2022). These events increased short-term price fluctuations and also created deeper changes in the market, making traditional forecasting methods less reliable. The main commodity groups include crude oil, natural gas, metals, agricultural products, and lumber. Their prices are often connected because they are influenced by similar demand conditions, energy costs, and broader economic cycles. Crude oil, for example, accounts for more than 52% of the World Bank's commodity price index, and its 11% increase

in the third quarter of 2023 highlights its economic significance (World Bank 2023). Similarly, natural gas prices in Europe stayed much higher than their 2015–2019 average. Metal prices were affected by lower demand from China's real estate sector, even though they still have strong long-term potential because of the energy transition. Agricultural commodities also remained sensitive to climate and trade-related shocks, while lumber prices continued to be strongly influenced by interest rates and construction demand (World Bank 2023; Johnston et al. 2024). The complexity and volatility of these markets have motivated a growing body of forecasting research. This paper reviews this research area through a systematic literature review. It aims to identify the main forecasting methods, describe the major publication trends, and highlight the gaps that still exist in the literature on commodity price forecasting.

2. Related Works

Raw material price forecasting has received increasing attention because it is important for industrial planning and financial decision-making. Since commodity prices are often volatile and non-linear, researchers have studied different forecasting approaches to better understand and predict their movements.

Early works relied on classical statistical models such as ARIMA, SARIMA, and GARCH, which proved effective for capturing linear trends and seasonal patterns in prices of commodities like crude oil, natural gas, and agricultural products (Albuquerquemello et al. 2018; Aamir et al. 2018; Mitra and Paul 2017). However, their limited ability to model complex non-linear dynamics motivated the adoption of machine learning techniques. Methods such as Support Vector Regression, Random Forest, and XGBoost have since been widely applied across multiple commodity markets, often demonstrating superior generalization over statistical baselines (Wang and Zhang 2025; Boussatta et al. 2025; Zhang et al. 2020; He et al. 2021).

More recently, deep learning architectures, particularly LSTM, GRU, and their bidirectional variants have become dominant in the literature due to their capacity to capture long-range temporal dependencies in price series (Kharisudin and Oktaviani 2025; Wang and Fang 2025; Aidoni et al. 2025; Lopes et al. 2021). A notable trend involves hybrid models that combine signal decomposition techniques such as EMD, CEEMDAN, or VMD with deep learning predictors, allowing the model to separately handle trend, seasonal, and residual components before forecasting (Lin et al. 2025; Alnssyan et al. 2024; Li et al. 2019; Aamir et al. 2018).

In this paper, we build on these findings and provide a systematic review of forecasting methods used for raw material price prediction. We discuss their main strengths, limitations, and evaluation metrics in a structured and comparative way.

3. Methodology

The scarcity of reviews specifically dedicated to commodity price forecasting models, together with the rapid advance-ment of machine learning and deep learning for financial time series, is the main motivation for this work. To ensure reproducibility and high-quality outcomes, we followed the principles of systematic review methodology (Zonta et al. 2020). We first formulated research questions, derived search strings to query selected scientific databases, and applied inclusion and exclusion criteria to isolate the most relevant papers. Beyond this systematic search, we also manually added a few recent and significant contributions to commodity price prediction that were not captured by the initial queries.

3.1 Research Questions

The purpose of this study is to systematically examine the literature on commodity price forecasting, identify the main themes, and organize the findings into a clear taxonomy. For this purpose, a main research question was developed to guide the review and to help summarize the most important studies, forecasting methods, and challenges in this field. The main research question is stated as follows:

- What are the main forecasting models used to predict commodity prices?

To address the main research question, the study was structured around two sub-questions (SQ), formulated as follows:

- **SQ 1:** What are the main means of dissemination of research related to commodity price forecasting?
- **SQ 2:** What are the most frequently used forecasting models for commodity price prediction?

3.2 Research Strategy

Three databases were used in this study: Scopus, Web of Science, and Google Scholar. Based on the research questions and an initial screening of the literature, the keywords were grouped into three main categories: commodity-related terms, forecasting-related terms, and methodological terms. Other possible terms were also added to make the search broader and to reduce the chance of missing relevant studies.

These keywords were combined using Boolean operators such as AND and OR, as well as the truncation symbol (*) to include different word forms. The search strategy was adapted to each database. In Scopus and Web of Science, the terms were combined into one structured search string. Proximity operators were also used: W/2 in Scopus and NEAR/2 in Web of Science. These operators helped ensure that commodity-related terms appeared close to words such as “price” or “future”, which made the search more precise without changing its meaning. The full search strings used for these two databases are shown in Table 1. For Google Scholar, the search was divided into several shorter queries instead of using one complex search string. This is because Google Scholar does not always support advanced operators and complex Boolean expressions in a consistent way. This approach made the search easier to manage, reduced ambiguity, and helped retrieve more relevant studies.

Table 1. Search strings used in Scopus and Web of Science

Database	Search string
Scopus	(("commodity price*" OR "raw material*" OR "metal*" OR "oil*" OR "natural gas" OR "gold*" OR "copper*" OR "silver*" OR "aluminum*" OR "precious metals" OR "crude oil*" OR "steel*" OR "lumber*" OR "wood*" OR "timber*") W/2 (price* OR future*)) AND (forecast* OR predict*) AND ("machine learning" OR "deep learning" OR "artificial intelligence" OR "time series" OR "hybrid" OR "statistical" OR "econometric") AND ("method*" OR "model*" OR "structure*" OR "architecture*" OR "technique*")
Web of Science	(("commodity price*" OR "raw material*" OR "metal*" OR "oil*" OR "natural gas" OR "gold*" OR "copper*" OR "silver*" OR "aluminum*" OR "precious metals" OR "crude oil*" OR "steel*" OR "lumber*" OR "wood*" OR "timber*") NEAR/2 (price* OR future*)) AND (forecast* OR predict*) AND ("machine learning" OR "deep learning" OR "artificial intelligence" OR "time series" OR "hybrid" OR "statistical" OR "econometric") AND ("method*" OR "model*" OR "structure*" OR "architecture*" OR "technique*")

3.3 Article Selection

To identify the primary studies, the search queries were applied to the selected databases on 1st December 2025, returning 2,989 publications from Scopus, 2,305 from Web of Science, and approximately 19,800 from Google Scholar. The overall identification, screening, eligibility, and inclusion procedure was guided by the PRISMA 2020 statement for systematic reviews (Page et al. 2021). After filtering according to the inclusion and exclusion criteria in Table 2, 178 papers were selected from Scopus, 124 from Web of Science, and 63 from Google Scholar. The selected records were exported to Rayyan, a free application designed to support systematic reviews during title and abstract screening (Ouzzani et al. 2016), where records were merged and duplicates removed, yielding 248 unique records. A final screening based on criterion 7 resulted in 68 articles being selected for in-depth analysis. Figure 1 summarizes the PRISMA-adapted selection process, and Table 3 presents the selected studies. In addition to the systematic search, five articles were added through a complementary manual search step to improve recall of emerging topics not fully captured by the automated queries. These articles, focused on sentiment analysis and foundation models, were included because their recent and significant contributions were underrepresented in the initial results due to novel terminology. For transparency, they are listed separately in Table 4.

Table 2. Selection Criteria of Research Papers

Identifier	Criteria
Criteria 1	The title must contain terms related to the selected raw materials and to forecasting, prediction, or equivalent concepts.
Criteria 2	Publication year between 2015 and 2025.
Criteria 3	The paper must belong to one of the following fields: Computer Science, Engineering, Mathematics, Economics, Econometrics and Finance, Energy, or Environmental Science.
Criteria 4	The document type must be either an article or a conference paper while all other publication types (books, technical reports, dissertations, and theses) are excluded.
Criteria 5	The source type must be either a journal or conference
proceedings. Criteria 6	Language: English.
Criteria 7	The title, abstract, and full text must be screened to exclude papers not relevant to this study.

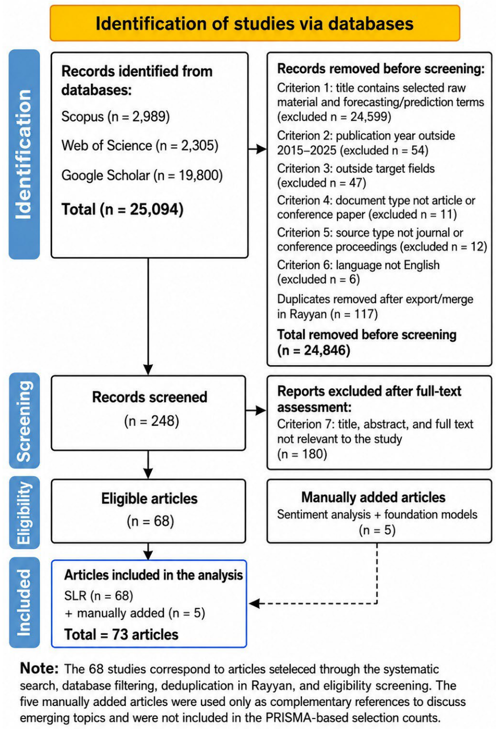

Figure 1. PRISMA 2020 - adapted study selection process

4. Discussion and Results

a) What are the main means of dissemination of research related to commodity price forecasting?

A synthesis of the selected studies reveals several important patterns in the commodity price forecasting literature. In terms of publication type, journal articles clearly dominate the field, representing 92.6% of the selected studies, whereas conference papers account for only 7.4% (Figure 3). This result suggests that most contributions in this area are disseminated through established journal outlets rather than conference proceedings. Regarding the geographic focus of the reported studies, Asia appears as the most represented region, accounting for 51.5% of the selected papers (Figure 2). America follows with 30.9%, while Europe represents 8.8%. The Middle East accounts for 4.4% of the studies, whereas Africa, South America, and Australia each represent 1.5%. Overall, the geographic distribution highlights a strong concentration of research in Asia and America.

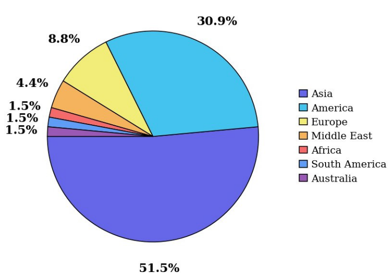

Figure 2. Geographic region of the reported studies

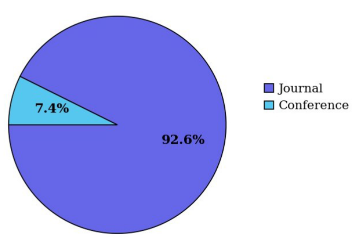

Figure 3. Distribution of publica-tions by type

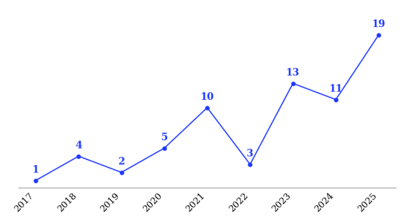

Figure 4. Distribution of publica-tions by year

Overall, the results show a growing interest in commodity price forecasting, with publications increasing after 2021 and reaching a peak of 19 studies in 2025 (Figure 4); the literature is mainly concentrated among major publishers, especially Elsevier, Springer, MDPI, and IEEE (Figure 5); and most studies focus on metals, crude oil, and natural gas, while lumber remains underexplored with only 2 publications (Figure 6).

Table 3. Selected Articles

Article	Type	Publisher	Name
Mitra et al. (2017)	Journal	IOS Press	Model Assisted Statistics and
Applications Xiong et al. (2018)		Journal	Elsevier Neurocomputing
Aamir et al. (2018)	Journal	Universiti Teknologi Malaysia	Jurnal Teknologi
Albuquerquemello et al. (2018)	Journal	Elsevier	Energy
Wang et al. (2018)	Journal	Elsevier	Applied Energy
Su et al. (2019)	Journal	MDPI	Energies
Li et al. (2019)	Journal	Elsevier	Physica A
Livieris et al. (2020)	Conference	Springer	Artificial Intelligence Applications and Innovations (AIAI
2020) Zhang et al. (2020)	Journal	IEEE	IEEE Access
Lin et al. (2020)	Journal	Elsevier	Physica A: Statistical Mechanics and its
Applications Wang et al. (2020)		Journal	Elsevier Journal of Petroleum Science
and Engineering			
Hu et al. (2020)	Journal	Elsevier	Physica A: Statistical Mechanics and its
Applications Parida et al. (2021)		Journal	Springer Evolutionary Intelligence
Lopes et al. (2021)	Journal	MDPI	Forests
He et al. (2021)	Journal	Forest Products Society	Forest Products Journal
Wang et al. (2021)	Journal	Wiley	Computational Intelligence and Neuroscience
Mohtasham Khani et al. (2021)	Journal	Springer	SN Computer Science
Zhang et al. (2021a)	Journal	Elsevier	Resources Policy
Zhang et al. (2021b)	Journal	Elsevier	Resources Policy
Khoshalan et al. (2021)	Journal	Elsevier	Resources Policy
Paul et al. (2021)	Journal	Springer	Soft Computing
Wang et al. (2021)	Journal	Elsevier	Energy
Zhan et al. (2022)	Journal	Wiley	Mathematical Problems in Engineering
Wang (2022)	Journal	Springer	Applied Intelligence
Lin et al. (2022)	Journal	Elsevier	Resources Policy
Wang et al. (2023)	Journal	MDPI	Processes
Huang et al. (2023)	Journal	Taylor & Francis	Cybernetics and
Systems Palazzi et al. (2023)	Journal	SciELO	Production
Das et al. (2023)	Journal	Society of Statistics, Computer and Applications (SSCA)	Statistics and Applications
García-Gonzalo et al. (2023)	Journal	Oxford University Press	Logic Journal of the
IGPL Xu et al. (2023)	Journal	Elsevier	Resources Policy
Mohanty et al. (2023)	Journal	Springer	Neural Computing and Applications
He et al. (2023)	Journal	Elsevier	Resources Policy
Zheng et al. (2023)	Journal	Elsevier	Journal of Environmental Management
Zhang et al. (2023)	Journal	University Computing Centre SRCE	Tehnički vjesnik
Guo et al. (2023)	Journal	Elsevier	Energy Economics
Guan et al. (2023)	Journal	Elsevier	Energy Economics
Maryati et al. (2023)	Journal	Bright publisher	Journal of Applied Data
Sciences Lu et al. (2024)	Journal	Springer	Computational Economics
Wang et al. (2024)	Journal	IEEE	IEEE Access
Cao et al. (2024)	Conference	ACM	the 2024 Guangdong-Hong Kong-Macao Greater Bay Area International Conference on Digital Economy and Artificial Intelligence
Purohit et al. (2024)	Journal	Elsevier	Information Sciences
García-Gonzalo et al. (2024)	Journal	MDPI	Mathematics
Varshini et al. (2024)	Journal	Elsevier	Resources Policy
Avinash et al. (2024)	Journal	Elsevier	Applied Soft Computing
Sari et al. (2024)	Journal	Springer	Neural Computing and Applications
Gandhi et al. (2024)	Journal	EconJournals	International Journal of Energy Economics and
Policy Li et al. (2024)	Journal	Elsevier	Expert Systems with Applications
Alnssyan et al. (2024)	Journal	Pakistan Statistical Society	Pakistan Journal of
Statistics Alcalde et al. (2025)		Journal	Oxford University
Press	Logic Journal of the IGPL		
Aidoni et al. (2025)	Conference	Sciendo	the 19th International Conference on Business
Excellence Boussatta et al. (2025)		Journal	WILEY Applied Computational Intelligence
and Soft Computing			
Masud et al. (2025)	Conference	IEEE	IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI)
Iftikhar et al. (2025)	Journal	IEEE	IEEE Access
Yaswanth et al. (2025)	Journal	Springer	Asia-Pacific Financial Markets
Wang et al. (2025)	Journal	IEEE	IEEE Access
Celik et al. (2025)	Journal	Elsevier	Borsa Istanbul Review
Du et al. (2025)	Journal	Elsevier	Petroleum Science
Yu et al. (2025)	Journal	MDPI	Sustainability
Lin et al. (2025)	Journal	MDPI	Energies
Zhao et al. (2025)	Journal	MDPI	Mathematics
Wang et al. (2025)	Journal	Elsevier	Expert Systems With Applications
Purohit et al. (2025)	Journal	Springer	Neural Computing and Applications
Guo et al. (2025)	Conference	ACM	the 2025 4th International Conference on Cyber Security, Artificial Intelligence and the Digital Economy
Wang et al. (2025)	Journal	Elsevier	Energy
Lin et al. (2025)	Journal	Elsevier	Energy

Kharisudin et al. (2025)	Journal	Lublin University of Technology Publishing House	Informatyka Automatyka Pomiary w Gospodarce i Ochronie Środowiska
Zhang et al. (2025)	Journal	Springer	Journal of Big Data

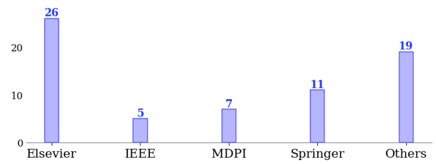

Figure 5. Distribution of publications by publisher

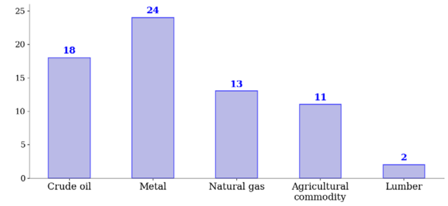

Figure 6. Distribution of Publications by Commodity Type

Table 4. Manually Added Articles

Article	Type	Publisher	Name
Wang et al. (2024)	Journal	Wiley	Journal of Forecasting
He et al. (2024)	Journal	Elsevier	Procedia Computer Science
Li et al. (2025)	Journal	Springer	Journal of King Saud University - Computer and Information Sciences
Ehsan et al. (2025)	Journal	VFAST	VFAST Transactions on Software Engineering
Ouyang et al. (2025)	Conference	IEEE	2025 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET)

b) What are the most frequently used forecasting models for commodity price prediction?

Commodity price forecasting covers a wide range of markets, including crude oil, metals (gold, copper, silver, steel), natural gas, agricultural commodities, and lumber; Table 5 classifies the reviewed studies by commodity. Each category tends to rely on different input variables: crude oil studies often incorporate macroeconomic and geopolitical indicators, while agricultural studies lean more on weather and seasonal data (Mitra and Paul 2017; Zhang et al. 2020; Mohanty et al. 2023; Sari et al. 2024). Metal markets are typically modelled using price history and global demand proxies (Zhang et al. 2021; Khoshalan et al. 2021; Varshini et al. 2024), and natural gas forecasting relies on storage levels and temperature variables (Su et al. 2019; Wang et al. 2021; Du et al. 2025). Historical price series remain a common foundation across all categories, often complemented by decomposed sub-series (Aamir et al. 2018; Purohit and Panigrahi 2025).

Table 5. Classification by commodity

Commodity	Authors associated
Crude oil	Aamir et al. (2018), Albuquerquemello et al. (2018), Wang et al. (2018), Lin et al. (2020), Wang et al. (2021), Xu et al. (2023), Guo et al. (2023), Guan et al. (2023), Purohit et al. (2024), Li et al. (2024), Alnssyan et al. (2024), Boussatta et al. (2025), Iftikhar et al. (2025), Yaswanth et al. (2025), Lin et al. (2025), Wang et al. (2025), Purohit et al. (2025), Wang et al. (2025)
Metal	Li et al. (2019), Hu et al. (2020), Mohtasham Khani et al. (2021), Zhang et al. (2021), Zhang et al. (2021), Khoshalan et al. (2021), Wang (2022), Lin et al. (2022), Wang et al. (2023), Huang et al. (2023), García-Gonzalo et al. (2023), He et al. (2023), Zhang et al. (2023), Maryati et al. (2023), Wang et al. (2024), Cao et al. (2024), García-Gonzalo et al. (2024), Varshini et al. (2024), Alcalde et al. (2025), Masud et al. (2025), Zhao et al. (2025), Guo et al. (2025), Kharisudin et al. (2025), Zhang et al. (2025)
Natural gas	Su et al. (2019), Livieris et al. (2020), Wang et al. (2020), Wang et al. (2021), Zhan et al. (2022), Zheng et al. (2023), Lu et al. (2024), Gandhi et al. (2024), Aidoni et al. (2025), Wang et al. (2025), Du et al. (2025), Yu et al. (2025), Lin et al. (2025)
Agricultural commodity	Mitra et al. (2017), Xiong et al. (2018), Zhang et al. (2020), Parida et al. (2021), Paul et al. (2021), Palazzi et al. (2023), Das et al. (2023), Mohanty et al. (2023), Avinash et al. (2024), Sari et al. (2024), Celik et al. (2025)
Lumber	Lopes et al. (2021), He et al. (2021)

On the methodological side, ARIMA remains a widely used reference model across crude oil (Aamir et al. 2018; Xu et al. 2023), agricultural commodities (Mitra and Paul 2017; Palazzi et al. 2023), gold (Maryati et al. 2023; Masud et al. 2025), and other categories. It mostly serves as a benchmark, though in some cases it is embedded as a linear component within hybrid models (Aamir et al. 2018; Alnssyan et al. 2024).

Machine learning methods are broadly applied. SVR appears across copper (Zhang et al. 2021; García-Gonzalo et al. 2023), crude oil (Xu et al. 2023; Guo et al. 2023), agricultural products (Paul and Garai 2021; Celik and Celik 2025) and gold (García-Gonzalo et al. 2024), owing to its ability to handle non-linear patterns without overfitting. Random Forest and XGBoost are also frequent across most commodity categories (Das et al. 2023; Sari et al. 2024; Lin et al. 2025; Wang and Fang 2025), with XGBoost increasingly used in recent work.

Since around 2020, deep learning has become increasingly prominent. LSTM networks are the most used architecture (Wang et al. 2018; Guan and Gong 2023; Purohit and Panigrahi 2024; Zhao et al. 2025), owing to their capacity to learn from long sequences, followed by GRU networks (Li et al. 2019; Huang et al. 2023; Lu et al. 2024).

CNNs typically serve as feature extractors within hybrid systems (Wang et al. 2018; Wang et al. 2024), while

Transformer-based architectures have gained ground, particularly in natural gas and gold forecasting (Wang et al. 2025; Zhao et al. 2025).

Hybrid models are among the most common forecasting systems in the literature. They usually decompose the price series into sub-components using methods such as EMD, CEEMDAN, VMD or Wavelet Decomposition, model each component separately, and combine the forecasts; this structure has been applied across virtually all commodity categories. The overall methodological distribution of the reviewed studies is presented in Table 6, which classifies the literature by forecasting approach.

Finally, a growing strand of research incorporates textual and sentiment data, mainly for crude oil and agricultural markets (He et al. 2024; Li et al. 2025; Wang et al. 2024), using news and social media inputs processed through lexicon-based methods, classical classifiers, or NLP models such as BERT and FinBERT, and recently large language models such as Llama-2 and GPT-4 (He et al. 2024; Ouyang et al. 2025). This emerging direction suggests a gradual shift toward richer information sources beyond historical prices.

Table 6. Classification by forecasting approach

Category	Articles
Time series analysis	Albuquerquemello et al. (2018), Zhang et al. (2023), Maryati et al. (2023), Wang et al. (2025)
Machine learning	Su et al. (2019), Livieris et al. (2020), Zhang et al. (2020), Parida et al. (2021), Lopes et al. (2021), He et al. (2021), Mohtasham Khani et al. (2021), Zhang et al. (2021), Zhang et al. (2021), Khoshalan et al. (2021), Wang et al. (2023), García-Gonzalo et al. (2023), Xu et al. (2023), Mohanty et al. (2023), Zheng et al. (2023), Guo et al. (2023), García-Gonzalo et al. (2024), Varshini et al. (2024), Sari et al. (2024), Alcalde et al. (2025), Boussatta et al. (2025), Masud et al. (2025), Yaswanth et al. (2025), Du et al. (2025), Kharisudin et al. (2025), Aidoni et al. (2025)
Hybrid	Mitra et al. (2017), Xiong et al. (2018), Aamir et al. (2018), Wang et al. (2018), Li et al. (2019), Lin et al. (2020), Wang et al. (2020), Hu et al. (2020), Wang et al. (2021), Paul et al. (2021), Wang et al. (2021), Zhan et al. (2022), Wang (2022), Lin et al. (2022), Huang et al. (2023), Palazzi et al. (2023), Das et al. (2023), He et al. (2023), Guan et al. (2023), Lu et al. (2024), Wang et al. (2024), Cao et al. (2024), Purohit et al. (2024), Avinash et al. (2024), Gandhi et al. (2024), Li et al. (2024), Alnssyan et al. (2024), Iftikhar et al. (2025), Wang et al. (2025), Celik et al. (2025), Yu et al. (2025), Lin et al. (2025), Zhao et al. (2025), Wang et al. (2025), Purohit et al. (2025), Guo et al. (2025), Lin et al. (2025), Zhang et al. (2025)

Quantitative performance comparison across model families

After identifying the most frequently used forecasting approaches, we further examined how these model families compare in terms of reported predictive performance. This quantitative comparison was conducted using the perfor-mance indicators available in the reviewed studies, including MAPE, SMAPE, MAE, RMSE, MSE, R^2, and directional accuracy. Since the corpus covers different commodities, price scales, currencies, and forecasting horizons, scale-dependent metrics such as RMSE, MAE, and MSE were interpreted mainly within individual studies, while scale-free or bounded indicators such as MAPE, SMAPE, R^2, and directional accuracy were considered more appropriate for cross-family comparison.

The reviewed evidence reveals a consistent quantitative tendency. Statistical and econometric models show the widest dispersion of errors, with best-model MAPE ranging from roughly 2–3% in carefully specified cases, such as the steel combinatorial model (Zhang et al. 2025) and the oil price forecasting model (Albuquerquemello et al. 2018), up to about 7% for gold (Maryati et al. 2023). These models are also frequently outperformed by neural networks within the same study (Xu et al. 2023). Machine-learning models generally improve predictive accuracy, with occasional cases of very high explanatory power, such as an R^2 of about 0.98 for copper price forecasting (Khoshalan et al. 2021), as well as clear within-study gains over competing learners (García-Gonzalo et al. 2024; Zhang et al. 2021; Mohanty et al. 2023). However, these peak performances appear to be commodity-specific rather than systematic.

Standalone deep-learning models provide more consistent results across studies, with best-model MAPE often around 3–4% and R^2 values close to 0.89 (Livieris et al. 2020; Lopes et al. 2021; Wang et al. 2024; Aidoni et al. 2025). Although individual machine-learning models can match or outperform deep-learning models on specific metrics in particular studies, deep learning appears to be the more stable standalone family across commodities and forecasting horizons. Across nearly all reported indicators, hybrid and decomposition–ensemble models achieve the strongest results, with MAPE frequently below 3%, R^2 often above 0.95 and reaching up to 0.999 (Wang et al. 2023; Wang et al. 2025; Zhao et al. 2025), SMAPE reduced to a very low level through secondary decomposition and error correction (Zhang et al. 2025), directional accuracy reaching about 0.89–0.93 (Aamir et al. 2018; Li et al. 2025), and within-study RMSE/MAE reductions of about 20–90% compared with non-decomposed baselines (He and Huang, 2023; Wang et al. 2025).

These results suggest that hybrid models generally achieve lower errors and higher explanatory power than single-family approaches, while deep learning emerges as the strongest standalone family. At the same time, no single model dominates across all commodities, forecasting horizons, and evaluation metrics. Therefore, these findings should be interpreted as indicative quantitative tendencies rather than as a definitive universal ranking (Figure 7).

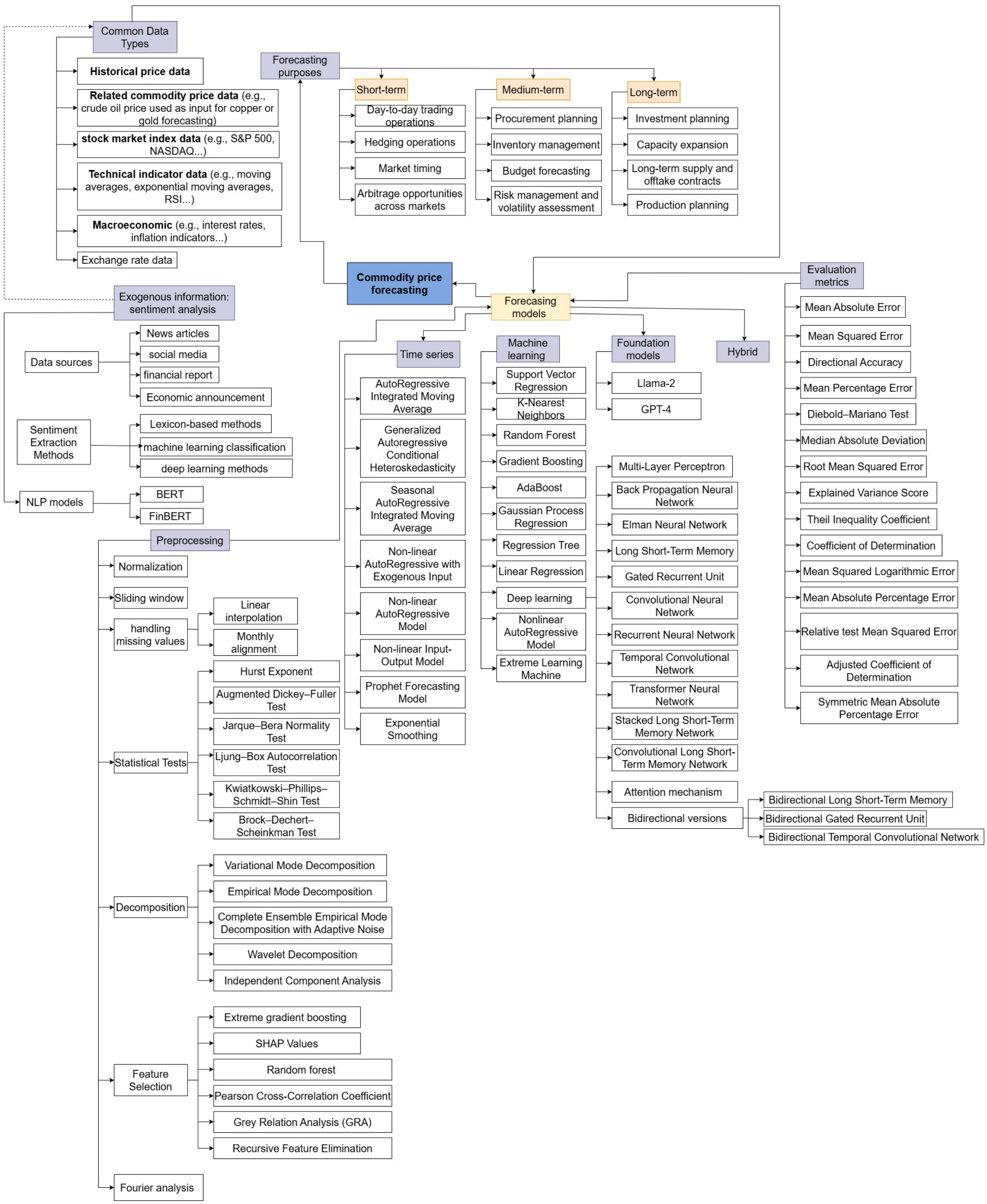

Figure 7. Taxonomy

5. Conclusion
This paper presented a structured review of commodity price forecasting studies across major commodity categories, including crude oil, metals, natural gas, agricultural commodities, and lumber. The review shows that the literature is unevenly distributed across these markets, with crude oil, metals, and natural gas attracting most of the research attention, while lumber remains only marginally studied.

A major finding of the review is the clear methodological evolution of the field. Classical statistical models remain important as benchmark tools, but recent studies are increasingly dominated by hybrid forecasting systems that combine decomposition methods with machine learning or deep learning predictors. This shift reflects the complex structure of commodity price series, which often involve nonlinear behavior, multiple temporal scales, and abrupt market shocks. Another contribution of this paper is the taxonomy proposed in Figure 7, which organizes the literature along five dimensions: input data, preprocessing methods, forecasting models, forecasting purposes, and evaluation metrics. Unlike prior reviews that focus on a single commodity or model family, this taxonomy provides a structured overview of the methodological landscape in commodity price forecasting and serves as a reference framework for researchers seeking to navigate the diversity of approaches used in the field.

Despite these advances, several gaps remain. Some commodity categories, particularly lumber, are still underrepre-sented in the literature. Richer exogenous and textual data sources including financial news, social media, and sentiment indicators are not yet broadly integrated, despite showing early promise in recent studies on crude oil and agricultural markets. Additionally, comparisons across studies remain difficult due to differences in datasets, input features, and evaluation settings, which points to a need for greater standardization in the field. Overall, the review shows that com-modity price forecasting research has become more methodologically sophisticated, but that its development remains uneven across commodities and information sources.

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