

ISSN Print: 2664-844X
ISSN Online: 2664-8458
NAAS Rating (2026): 4.97
IJAFS 2026; 8(10): 842-847
www.agriculturaljournals.com
Received: 13-08-2026
Accepted: 25-09-2026
Published: 20-10-2026

Harshitha Nanda
PG Scholar, Department of Agricultural Statistics, KSNUAHS, College of Agriculture, School of Post Graduation Studies, Main Campus, Iruvakki, Shivamogga, Karnataka, India

Mallikarjuna HB
Associate Professor, Department of Agricultural Statistics, College of Agriculture, Navile, Shivamogga, Karnataka, India

Raveesha S
Associate Professor, Department of Agricultural Economics, University of Agricultural Sciences, GKVK, Bangalore, Karnataka, India

Nagaraja MS
Assistant Professor, Department of Agricultural Statistics, College of Agricultural Sciences, Hassan, Karnataka, India

HM Vinaya Kumar
Assistant Professor, Department of Agricultural Extension and Technical Officier, KSNUAHS, College of Agriculture, School of Post Graduation Studies, Main Campus, Iruvakki, Shivamogga, Karnataka, India

Corresponding Author:
Harshitha Nanda
PG Scholar, Department of Agricultural Statistics, KSNUAHS, College of Agriculture, School of Post Graduation Studies, Main Campus, Iruvakki, Shivamogga, Karnataka, India

Identifying suitable models for forecasting production and price of rice and wheat: a *meta*-analysis

Harshitha Nanda[1], Mallikarjuna HB[2], Raveesha S[3], Nagaraja MS[4], HM Vinaya Kumar[5]

DOI: https://www.doi.org/10.33545/2664844X.2026.v8.i10k.2098

Abstract
Rice and wheat are important cereal crops, and accurate forecasting of their production and prices is essential for agricultural planning, resource allocation and policy formulation. However, the suitability of prediction models varies across crops, regions and forecasting tasks. This study used *meta*-analysis to identify suitable prediction models for forecasting production and price of rice and wheat. A systematic literature search following the PRISMA framework identified 105 primary studies published between 1996 and 2026, comprising 229 model-level observations. Coefficients of determination (R^2) were Fisher's z-transformed and pooled using random-effects *meta*-analysis, with subgroup analyses by prediction type, crop, individual model, country and publication period. The overall pooled R^2 was 0.88 (95% CI: 0.82–0.91), with very high heterogeneity (I^2 = 99.97%; $p < 0.001$). Production forecasting represented 71.6 per cent of observations and price forecasting 28.4 per cent; production models gave a pooled R^2 of 0.87 and price models 0.91, while rice and wheat showed comparable values of 0.88 and 0.87. ARIMA recorded the highest pooled effect size for production forecasting of both rice (2.71) and wheat (2.50), whereas Decision Tree recorded the highest for price forecasting of both rice (2.85) and wheat (3.45). Random Forest was a competitive alternative in both tasks. Pooled performance was highest in Bangladesh (R^2 = 0.95) and varied across publication periods. The findings indicate that model suitability is driven by the forecasting task rather than the crop, and that greater model complexity does not guarantee better performance.

Keywords: Meta-analysis, Rice, Wheat, Production forecasting, Price forecasting, ARIMA, Decision Tree

1. Introduction

Rice (*Oryza sativa* L.) and wheat (*Triticum aestivum* L.) are the two most important staple cereal crops, together accounting for more than half of the world's cereal production and playing a central role in food security, particularly in Asia and in India (Anonymous, 2024) [1]. Their production and prices are influenced by climatic conditions, rainfall variability, soil characteristics, irrigation, technology, government policy, input costs, market demand and international trade (Ray *et al.*, 2015) [2], and climate change has further complicated agricultural planning (Anonymous, 2023) [3]. Accurate forecasts of production and market prices help farmers decide cropping patterns, storage and marketing, and help governments plan procurement, buffer stocks, trade policy and price stabilisation (Hyndman *et al.*, 2014) [4].

Agricultural forecasting has traditionally relied on statistical methods such as regression, exponential smoothing and the Auto Regressive Integrated Moving Average (ARIMA) model (Box *et al.*, 1976) [5]. Because agricultural systems often show nonlinear relationships (Zhang, 2003) [6], machine learning (ML) and deep learning (DL) techniques, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), Decision Trees and Long Short-Term Memory (LSTM) networks, as well as hybrid models, have been increasingly applied (Goodfellow *et al.*, 2016) [7]. Reported performance, however, varies with the study area, data characteristics, forecasting horizon, input variables and evaluation metrics (Makridakis *et al.*, 2018) [8], which makes it difficult to identify the most suitable model for rice and wheat production and price forecasting from individual studies alone.

Meta-analysis provides a quantitative framework for combining findings from independent studies, quantifying heterogeneity and comparing performance across diverse conditions (Borenstein *et al.*, 2021) [9]. Therefore, the present study aimed to identify suitable prediction models for forecasting the production and price of rice and wheat by synthesising the published evidence.

26648458, 2026, 8(10), Downloaded from https://www.doi.org/10.33545/2664844X.2026.v8.i10k.2098 by International Journal of Agriculture and Food Science on [20/10/2026]. See the Terms and Conditions (https://www.agriculturaljournals.com) for rules of use; OA articles are governed by the applicable Creative Commons License

2. Materials and methods

2.1. Literature search and study selection

A systematic literature search was conducted following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework (Moher *et al.*, 2009) [10]. Google Scholar, *Scopus*, Web of Science, ScienceDirect and AgEcon Search were searched using combinations of keywords such as *production forecasting*, *price prediction*, *rice*, *wheat*, *ARIMA*, *Artificial Neural Network*, *Support Vector Machine*, *Random Forest*, *LSTM*, *machine learning*, *deep learning*, *hybrid models*, *RMSE*, *MAE*, *MAPE* and R^2, combined using Boolean operators. After removal of duplicates and screening of titles, abstracts and full texts, studies were included when they evaluated one or more statistical, econometric, machine learning, deep learning or hybrid models for forecasting the production or price of rice or wheat and reported quantitative performance metrics with sufficient information (such as sample size) for effect-size estimation. Only original, peer-reviewed research articles in English were considered. Reviews, conference abstracts, editorials, book chapters, duplicate publications and studies without accessible full text or adequate quantitative information were excluded. Of 435 records initially identified, 105 primary studies, published between 1996 and 2026, satisfied the eligibility criteria and were included.

2.2. Data extraction and classification

For each study, the author, year, country, crop (rice or wheat), predicted variable (production or price), prediction model, data period, sample size and performance metrics (R^2, RMSE, MAE, MAPE) were recorded in a *meta*-analysis master sheet. Where a study reported more than one model, crop or variable, each instance was treated as a separate model-level observation, giving 229 observations. Observations were grouped by prediction type (production or price), crop, individual model, country and publication period to enable identification of the most suitable model for each forecasting task.

2.3. Effect size and statistical analysis

Because RMSE and MAE were reported in non-comparable units (for example kg ha^{-1}, tonnes and different price units), the coefficient of determination (R^2), the only metric reported on a common unit-free scale across the majority of studies, was used as the effect size. The reported R^2 was converted to a correlation coefficient and Fisher's z-transformed:

$$r = \sqrt{R^2}\ , \qquad z = \frac{1}{2}\ln\left(\frac{1+r}{1-r}\right), \qquad v = \frac{1}{n-3}$$

where n is the sample size used for model evaluation and v is the sampling variance of z. Studies were weighted by inverse variance ($w_i = 1/v_i$) and the fixed-effect pooled estimate was $\theta = \sum w_i\theta_i / \sum w_i$. Heterogeneity was assessed using Cochran's Q-test, between-study variance (τ^2) and the I^2 statistic:

$$Q = \sum w_i(\theta_i - \theta)^2, \qquad \tau^2 = \frac{Q-(k-1)}{\sum w_i - \frac{\sum w_i^2}{\sum w_i}}, \qquad I^2 = \frac{Q-(k-1)}{Q}\times 100$$

where k is the number of studies (τ^2 was set to zero when $Q < k-1$). Where significant heterogeneity was detected ($p < 0.05$), the random-effects model with weights $w_i' = 1/(v_i + \tau^2)$ was used for interpretation; otherwise the fixed-effect estimate was retained. Pooled estimates were back-transformed to the R^2 scale ($R^2 = \tanh^2 z$) where reported as R^2. Separate pooled estimates with 95% confidence intervals were obtained within each subgroup, and overlapping confidence intervals were taken to indicate performance that was not statistically distinguishable. For the crop × prediction-type subgroups, individual models are compared using their pooled effect sizes (Fisher's z). Funnel plots were examined to assess publication bias and small-study effects (Sterne *et al.*, 2001) [11]. All analyses were performed in R (RStudio) using the *meta* and *metafor* packages, and results were interpreted at the 5 per cent level of significance.

3. Results

3.1 Overall pooled performance

The 105 studies yielded 229 model-level observations, of which 164 (71.6%) pertained to production forecasting and 65 (28.4%) to price forecasting; 127 (55.5%) related to rice and 102 (44.5%) to wheat. The studies originated from 29 countries and were published between 1996 and 2026. The overall pooled random-effects R^2 was 0.88 (95% CI: 0.82–0.91), with extremely high heterogeneity (Q = 382,724, df = 104, $p < 0.001$; $\tau^2 = 1.11$; $I^2 = 99.97\%$), which justified the random-effects model for all pooled estimates.

3.2 Performance by prediction type and crop

Production-forecasting models (k = 84; total n = 2,04,371) had a pooled R^2 of 0.87 (95% CI: 0.83–0.90), while price-forecasting models (k = 21; n = 1,60,116) had a marginally higher pooled R^2 of 0.91 (95% CI: 0.80–0.95) with a much wider interval (Table 1). Rice-based models (k = 61) and wheat-based models (k = 44) performed comparably (R^2 = 0.88 and 0.87, respectively), indicating that neither crop was intrinsically more predictable.

Table 1. Pooled performance by prediction type and crop

Subgroup	k	Total sample size (n)	Random-effects R^2	95% CI
Production	84	2,04,371	0.87	0.83–0.90
Price	21	1,60,116	0.91	0.80–0.95
Rice	61	1,78,438	0.88	0.81–0.92
Wheat	44	96,837	0.87	0.77–0.93

3.3 Suitable models for production forecasting

For rice production, ARIMA recorded the highest pooled effect size (Fisher's z = 2.71, 95% CI: 1.80–3.62), followed by LSTM (1.79), ANN (1.65) and CNN-LSTM (1.64), while Random Forest (1.24) and Linear Regression (1.14) formed a mid-performing group and the VH-polarisation ANN (0.91) and Lasso Regression (0.66) performed lowest (Table 2, Fig. 1a). For wheat production, ARIMA again ranked

2664844X, 2026, 8(10), Downloaded from https://www.doi.org/10.33545/2664844X.2026.v8.i10k.2098 by International Journal of Agriculture and Food Science on [20/10/2026]. See the Terms and Conditions (https://www.agriculturaljournals.com) for rules of use; OA articles are governed by the applicable Creative Commons License

first (2.50, 95% CI: 2.28–2.72), closely followed by Random Forest (2.10), with ANN (1.56), CNN-LSTM (1.41) and LSTM (1.38) forming an intermediate cluster and SVM (1.01) the lowest (Table 2, Fig. 1b). The funnel plot for rice production (k = 52 studies) showed several smaller studies with lower effect sizes trailing to the left of the pooled estimate, suggesting possible small-study effects, whereas that for wheat production (k = 31 studies) was broadly symmetrical.

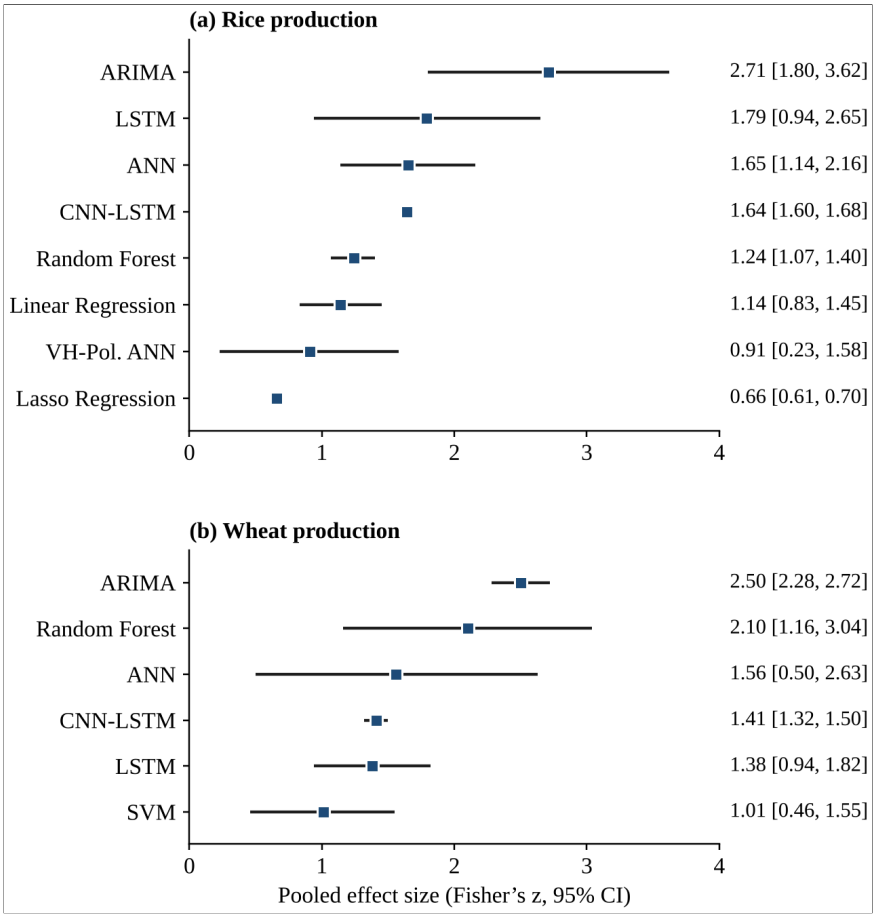


Figure 1. Forest plots of pooled effect sizes of individual models for (a) rice production and (b) wheat production

3.4 Suitable models for price forecasting

For rice price, Decision Tree recorded the highest pooled effect size (2.85, 95% CI: 2.07–3.64), followed by Linear Regression (2.64), Random Forest (2.53), Ridge Regression (2.46) and Lasso Regression (2.26), whereas SVM (1.88), the Fuzzy Cognitive Map (1.78) and ARIMA-SVM (0.42) recorded the lowest values (Table 3, Fig. 2a). For wheat price, Decision Tree again recorded the highest value (3.45, 95% CI: 3.02–3.88), followed by Random Forest (2.79), Lasso (2.42), Ridge (2.42) and SVM (2.32), while Naive Seasonal (1.29) and Gradient Boosting (0.72) performed lowest (Table 3, Fig. 2b). Machine learning and regression-based models clearly outperformed the statistical and hybrid models (Fuzzy Cognitive Map and ARIMA-SVM) for rice price. The rice-price and wheat-price funnel plots (each k = 9 studies) were tightly clustered around the pooled estimates, with a single low-effect-size outlier for wheat price. Many price-model estimates rested on very few studies and should be treated as preliminary.

Table 2. Pooled effect sizes (Fisher's z) of production models (models with $k \geq 2$)

Model	Rice production (95% CI)	Wheat production (95% CI)
ARIMA	2.71 (1.80–3.62)	2.50 (2.28–2.72)
Random Forest	1.24 (1.07–1.40)	2.10 (1.16–3.04)
LSTM	1.79 (0.94–2.65)	1.38 (0.94–1.82)
ANN	1.65 (1.14–2.16)	1.56 (0.50–2.63)
CNN-LSTM	1.64 (1.60–1.68)	1.41 (1.32–1.50)
Support Vector Machine	–	1.01 (0.46–1.55)
Linear Regression	1.14 (0.83–1.45)	–
VH-Polarisation ANN	0.91 (0.23–1.58)	–
Lasso Regression	0.66 (0.61–0.70)	–

(continued on next page)

26648458, 2026, 8(10), Downloaded from https://www.doi.org/10.33545/26648458.2026.v8.i10k.2098 by International Journal of Agriculture and Food Science on [20/10/2026]. See the Terms and Conditions (https://www.agriculturaljournals.com) for rules of use; OA articles are governed by the applicable Creative Commons License

Table 3. Pooled effect sizes (Fisher's z) of price models (models with $k \geq 1$)

Model	Rice price (95% CI)	Wheat price (95% CI)
Decision Tree	2.85 (2.07–3.64)	3.45 (3.02–3.88)
Linear Regression	2.64 (2.60–2.69)	–
Random Forest	2.53 (2.49–2.57)	2.79 (2.38–3.20); 2.03 (0.66–3.40)[a]
Ridge Regression	2.46 (2.41–2.50)	2.42 (2.11–2.73)
Lasso Regression	2.26 (2.21–2.30)	2.42 (2.12–2.72)
Support Vector Machine	1.88 (1.84–1.92)	2.32 (2.04–2.60)
FCM	1.78 (1.62–1.94)	–
Naive Seasonal	–	1.29 (0.97–1.61)
Gradient Boosting	–	0.72 (0.50–0.94)
ARIMA-SVM	0.42 (0.38–0.45)	–

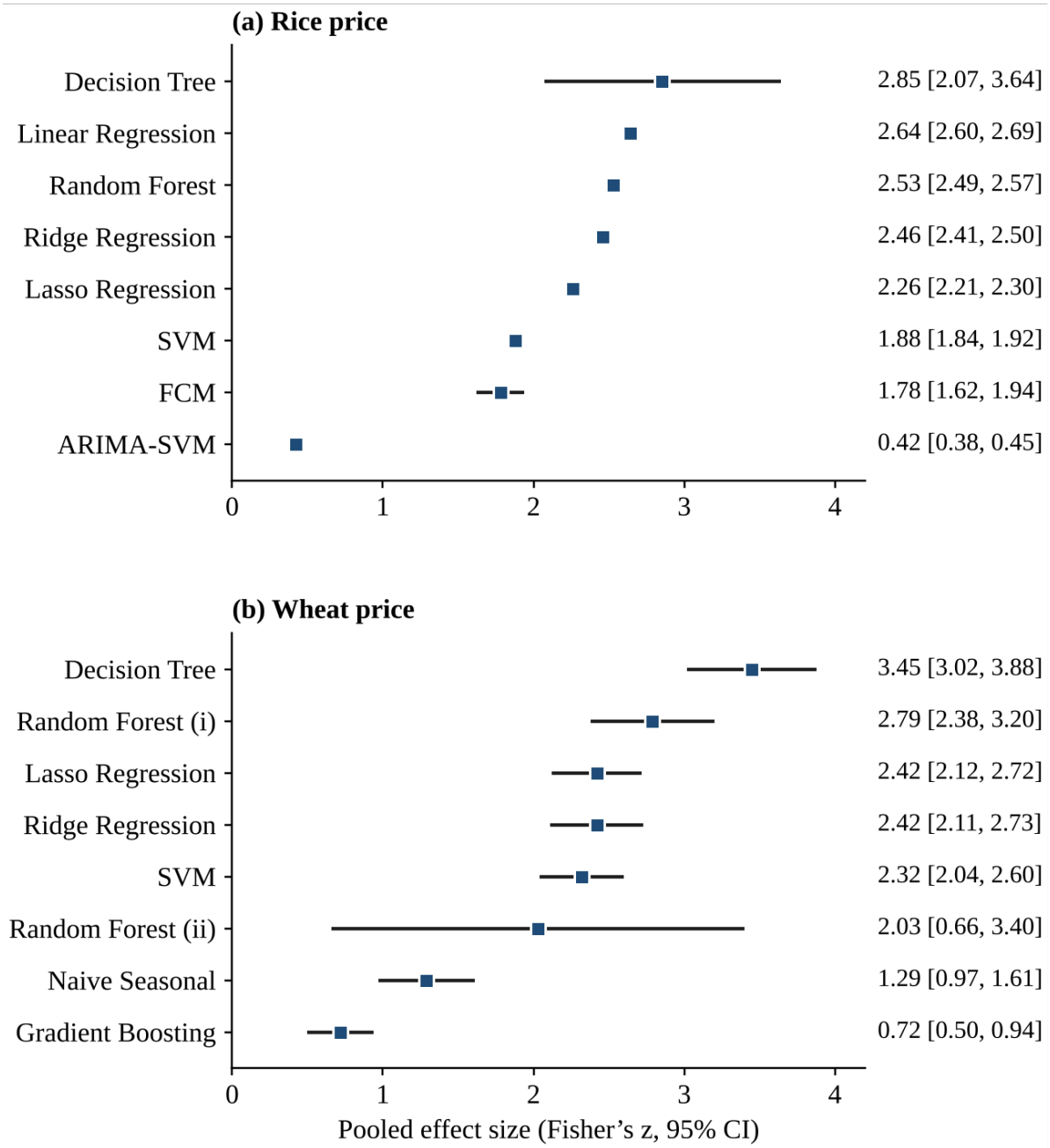


Figure 2. Forest plots of pooled effect sizes of individual models for (a) rice price and (b) wheat price

3.5 Performance by country and publication period

Among countries contributing three or more estimates, Bangladesh recorded the highest pooled R^2 (0.95), followed by the China Taihu Lake Region (0.94), India (0.89), Pakistan (0.78), China (0.77), Indonesia (0.76) and Australia (0.74) (Table 4). Pooled performance was highest in 2011–2018 (R^2 = 0.93), declined in 2019–2022 (0.82) and partly recovered in 2023–2026 (0.87), the period that contributed 60 per cent of all pooled estimates.

2664844X, 2026, 8(10), Downloaded from https://www.doi.org/10.33545/2664844X.2026.v8.i10k.2098 by International Journal of Agriculture and Food Science on [20/10/2026]. See the Terms and Conditions (https://www.agriculturaljournals.com) for rules of use; OA articles are governed by the applicable Creative Commons License

Table 4. Pooled random-effects R^2 by country of study ($k \geq 3$) and publication period

Subgroup	k	R^2	95% CI
Country			
Bangladesh	20	0.95	0.92–0.97
China (Taihu Lake Region)	6	0.94	0.90–0.96
India	20	0.89	0.69–0.96
Pakistan	7	0.78	0.59–0.89
China	32	0.77	0.72–0.82
Indonesia	6	0.76	0.67–0.83
Australia	6	0.74	0.57–0.85
Publication period			
2011–2018	17	0.93	0.88–0.96
2019–2022	25	0.82	0.69–0.90
2023–2026	63	0.87	0.80–0.92

3.6 Synthesis: most suitable models

Integrating the crop- and task-specific analyses (Tables 2 and 3), ARIMA emerged as the most suitable and consistent model for production forecasting of both rice and wheat, combining a high pooled effect size with comparatively narrow confidence intervals. For price forecasting, Decision Tree emerged as the most suitable model for both crops, recording the highest pooled effect size in both crop-specific analyses. Random Forest and ANN were competitive alternatives for production forecasting, while Random Forest and Linear/Ridge/Lasso Regression were competitive alternatives for price forecasting. Deep learning models, despite their popularity, did not outperform the simpler statistical and machine learning models on a pooled basis for either task.

4. Discussion

The overall pooled R^2 of 0.88 indicates that, on average, the reviewed models explained a high proportion of the variance in cereal production and price, but the extreme heterogeneity (I^2 = 99.97%) shows that performance is strongly context-dependent, varying with crop, region, length and frequency of the data series, feature set and modelling choices (Liakos *et al.*, 2018) [12]. The random-effects model was therefore the appropriate and conservative basis for interpretation, and the subgroup estimates are best read as indicative trends rather than precise universal values.

ARIMA was the most suitable model for production forecasting of both rice and wheat. This agrees with the long-established ability of ARIMA to capture trend and autocorrelation in univariate series (Box *et al.*, 1976) [5] and with single-country applications to rice production in Bangladesh (Hamjah, 2014) [13] and Tamil Nadu (Hemavathi *et al.*, 2018) [14], and to wheat production in Pakistan (Saeed *et al.*, 2000) [15] and India (Nath *et al.*, 2019) [16]. Sultana *et al.* (2020) [17] likewise found ARIMA to give lower errors than ANN for rice production in Bangladesh. Hybrid formulations may extend this strength: Alam *et al.* (2018) [18] reported that an ARIMA-ANN hybrid reduced the mean absolute percentage error of long-term rice yield forecasts to 4.65 per cent compared with 17.68 per cent for ARIMA alone. Random Forest, which ranked second for wheat production, and ANN were competitive alternatives, in line with the capacity of machine learning models to capture nonlinear relationships with a wide range of predictors (Breiman, 2001) [19].

For price forecasting the pattern reversed: Decision Tree recorded the highest pooled effect size for both rice and wheat, followed by Random Forest and regularised regression. Production is shaped mainly by gradually evolving biophysical and agronomic factors, whereas prices are additionally influenced by market behaviour, storage, minimum support prices, trade policy and international linkages (Gouel *et al.*, 2016) [20], which produce threshold-driven, nonlinear behaviour that tree-based methods can capture (Breiman, 2001) [19]. Jha *et al.* (2013) [21] similarly found that multi-feature models incorporating weather and market variables outperformed price-only models. Random Forest, an ensemble of trees, ranked second in several subgroups and may offer greater robustness at some cost to the interpretability that makes a single Decision Tree attractive to extension officers and farmer cooperatives. The comparatively higher pooled R^2 of price models should be read cautiously because it rests on only 21 estimates against 84 for production, and Saiyad *et al.* (2026) [22] show that RNN can outperform ARIMA and ANN for weekly wheat prices in Gujarat markets, so local validation remains important.

Deep learning models did not outperform simpler models in the pooled analysis. Deep architectures usually need large, high-frequency datasets, whereas much of the production literature reviewed relied on short annual national or sub-national series. Manogna *et al.* (2025) [23] found that LSTM and GRU substantially outperformed ARIMA for highly volatile, perishable commodities but that simpler models remained competitive for comparatively stable commodities such as paddy and wheat, and Paul *et al.* (2025) [24] observed that cereals show lower price volatility and more linear behaviour than perishables. Meroni *et al.* (2021) [25] similarly noted that machine learning gains over simple benchmarks under small-data conditions are not always practically significant. The dip in pooled R^2 during 2019–2022 coincides with rapid, early adoption of deep learning on modest datasets, with partial recovery in 2023–2026 as hybrid architectures and validation practices matured. Rice and wheat showed near-identical pooled performance (0.88 and 0.87), suggesting that model suitability is driven mainly by the forecasting task rather than the crop, and that methodological lessons can transfer between the two crops.

Country-level differences (Bangladesh 0.95 to Australia 0.74) are consistent with the concentration of ARIMA-based production forecasting in Bangladesh and India, while the wider interval for India reflects its diverse agro-ecological zones, irrigation regimes and markets. Several limitations apply. Only studies reporting R^2 could be pooled, so the synthesis may favour better-documented studies; many individual models, particularly for rice and wheat price, were reported in only one study; and heterogeneity was very high throughout. The subgroup estimates are therefore indicative rather than definitive.

5. Conclusion

This *meta*-analysis of 105 studies (229 model-level observations) identified suitable models for forecasting rice and wheat production and price. The overall pooled random-effects R^2 was 0.88 (95% CI: 0.82–0.91) with extremely high heterogeneity. Production and price models performed comparably (0.87 and 0.91), as did rice and wheat (0.88 and 0.87).

Model suitability depended on the forecasting task rather than the crop: ARIMA was the most suitable model for production forecasting of both rice and wheat, while Decision Tree was the most suitable for price forecasting of both crops, with Random Forest a competitive alternative in each case. Deep learning models did not outperform simpler statistical and machine learning models on a pooled basis. Task-

2664-8458, 2026, 8(10), Downloaded from https://www.doi.org/10.33545/2664844X.2026.v8.i10k.2098 by International Journal of Agriculture and Food Science on [20/10/2026]. See the Terms and Conditions (https://www.agriculturaljournals.com) for rules of use; OA articles are governed by the applicable Creative Commons License

specific model selection, guided by the nature and volume of the available data and validated locally, is recommended; future work should extend the evidence base for price forecasting and for under-represented regions.

References

1. Anonymous. Agricultural Statistics at a Glance 2024. New Delhi, India: Directorate of Economics and Statistics, Ministry of Agriculture and Farmers Welfare, Government of India; 2024.
2. Ray DK, Gerber JS, MacDonald GK, West PC. Climate variation explains a third of global crop yield variability. Nat Commun. 2015;6:5989.
3. Anonymous. Climate Change 2023: Synthesis Report. Geneva, Switzerland: Intergovernmental Panel on Climate Change (IPCC); 2023.
4. Hyndman RJ, Athanasopoulos G. Forecasting: Principles and Practice. Melbourne, Australia: OTexts; 2014.
5. Box GEP, Jenkins GM. Time Series Analysis: Forecasting and Control. San Francisco, CA: Holden-Day; 1976.
6. Zhang GP. Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing. 2003;50:159–175.
7. Goodfellow I, Bengio Y, Courville A. Deep Learning. Cambridge, MA: MIT Press; 2016.
8. Makridakis S, Spiliotis E, Assimakopoulos V. Statistical and machine learning forecasting methods: Concerns and ways forward. PLoS ONE. 2018;13(3):e0194889.
9. Borenstein M, Hedges LV, Higgins JPT, Rothstein HR. Introduction to Meta-Analysis. 2nd ed. Chichester, United Kingdom: John Wiley & Sons; 2021.
10. Moher D, Liberati A, Tetzlaff J, Altman DG. Preferred reporting items for systematic reviews and *meta*-analyses: The PRISMA statement. PLoS Med. 2009;6(7):e1000097.
11. Sterne JAC, Egger M, Smith GD. Investigating and dealing with publication and other biases in *meta*-analysis. BMJ. 2001;323(7304):101–105.
12. Liakos KG, Busato P, Moshou D, Pearson *S*, Bochtis D. Machine learning in agriculture: A review. Sensors. 2018;18(8):2674.
13. Hamjah MA. Rice production forecasting in Bangladesh: An application of Box-Jenkins ARIMA model. Math Theory Model. 2014;4(4):1–11.
14. Hemavathi M, Prabakaran K. ARIMA model for forecasting of area, production and productivity of rice and its growth status in Thanjavur District of Tamil Nadu, India. Int J Curr Microbiol Appl Sci. 2018;7(2):149–156.
15. Saeed N, Saeed A, Zakria M, Bajwa TM. Forecasting of wheat production in Pakistan using ARIMA models. Int J Agric Biol. 2000;2(4):352–353.
16. Nath B, Dhakre DS, Bhattacharya D. Forecasting wheat production in India: An ARIMA modelling approach. J Pharmacogn Phytochem. 2019;8(1):2158–2165.
17. Sultana A, Khanam M. Forecasting rice production of Bangladesh using ARIMA and artificial neural network models. Dhaka Univ J Sci. 2020;68(2):143–147.
18. Alam W, Ray MR, Kumar RR, Sinha KA, Rathod SA, Singh KN. Improved ARIMAX modal based on ANN and SVM approaches for forecasting rice yield using weather variables. Indian J Agric Sci. 2018;88(12):1909–1913.
19. Breiman L. Random forests. Mach Learn. 2001;45(1):5–32.
20. Gouel C, Gautam M, Martin WJ. Managing food price volatility in a large open country: The case of wheat in India. Oxf Econ Pap. 2016;68(3):811–835.
21. Jha GK, Sinha K. Agricultural price forecasting using neural network model: An innovative information delivery system. Agric Econ Res Rev. 2013;26(2):229–239.
22. Saiyad SR, Kalola AD, Baladaniya US. A comparative study of linear and machine learning models for wheat price forecasting in Gujarat, India. J Sci Res Rep. 2026;32(7):784–794.
23. Manogna RL, Dharmaji V, Sarang S. Enhancing agricultural commodity price forecasting with deep learning. Sci Rep. 2025;15(1):20903.
24. Paul RK, Yeasin M, Tamilselvi C, Paul AK, Sharma P, Birthal PS. Can deep learning models enhance the accuracy of agricultural price forecasting? Insights from India. Intell Syst Acc Fin Mgmt. 2025;32(1):e70002.
25. Meroni M, Waldner F, Seguini L, Kerdiles H, Rembold F. Yield forecasting with machine learning and small data: What gains for grains? Agric For Meteorol. 2021;308:108555.

How to cite this article: Nanda H, HB M, Raveesha S, MS N, Kumar HV. Identifying suitable models for forecasting production and price of rice and wheat: a *meta*-analysis. *International Journal of Agriculture and Food Science*. 2026;8(10):842-847. doi: https://www.doi.org/10.33545/2664844X.2026.v8.i10k.2098

2664844X, 2026, 8(10), Downloaded from https://www.doi.org/10.33545/2664844X.2026.v8.i10k.2098 by International Journal of Agriculture and Food Science on [20/10/2026]. See the Terms and Conditions (https://www.agriculturaljournals.com) for rules of use; OA articles are governed by the applicable Creative Commons License