

Article

Comparison of ARIMA, SutteARIMA, and Holt-Winters, and NNAR Models to Predict Food Grain in India

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Abstract: The agriculture sector plays an essential function within the Indian economic system. Food-grains provide almost all the calories and proteins. This paper aims to compare ARIMA, SutteARIMA, Holt-Winters, and NNAR models to recommend an effective model to predict foodgrains production in India. The execution of the SutteARIMA predictive model used in this analysis was compared with the established ARIMA, Neural Network Auto-Regressive (NNAR), and Holt-Winters models, which have been widely applied for time series prediction. The findings of this study reveal that both the SutteARIMA model and the Holt-Winters model performed well with real-life problems and can effectively and profitably be engaged for food grain forecasting in India. The food grain forecasting approach with the SutteARIMA model indicated superior performance over the ARIMA, Holt-Winters, and NNAR models. Indeed, the actual and predicted values of the SutteARIMA and Holt-Winters forecasting models are quite close to predicting foodgrains production in India. This has been verified by MAPE and MSE values that are relatively low with the SutteARIMA model. Therefore, India's SutteARIMA model was used to predict foodgrains production from 2021 to 2025. The forecasted amount of respective crops are as follows (in lakh tonnes) 1140.14 (wheat), 1232.27 (rice), 466.46 (coarse), 259.95 (pulses), and a total 3069.80 (foodgrains) by 2025.

Keywords: ARIMA; SutteARIMA; NNAR; Holt-Winters; food grain



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1. Overview of the Study

India's agriculture has the potential to increase productivity and overall production [1,2]. The present global governance architecture for nutrition, food, and agriculture is incapable of appropriately addressing the difficulties of ensuring progress toward food security [3]; with disproportionately concentrated malnutrition among poor children in India [4]. India's population is expected to reach 1.7 billion by 2050, roughly equaling China and the United States combined. Can India adequately feed its 1.7 billion people? If food is scarce now [5], what will the circumstances be like in 2050, when India will have an additional 430 million people to feed? [6–8].

Food grain prediction is a significant activity for global decision-making in the agriculture sector. An accurate foodgrains prediction approach will help farmers decide when and how much to cultivate [9]. In this situation, it is even more essential to forecast the quantity of crops produced across India effectively. To accomplish this, multiple forecasting models were used to choose the most appropriate model and anticipate future crop output values. An accurate crop production estimate serves as the cornerstone for its agricultural commodities marketing policy decisions. Crop yield forecasting is essential in farm planning and management, domestic food production, international food trade, habitat preservation, and other fields [10]. As a result, the primary goal of this work is to provide an adequate model

for forecasting food grain production in India. Several models were used for crop yield forecasting: machine learning algorithms and modeling techniques are often undervalued in defining agricultural produce. A land of a growing population undoubtedly requires optimized output from agriculture. Incorporating the latest comprehensive technology in agriculture is the only way to survive. Liakos et al. [11] demonstrated how agri-technology domain and machine learning programs benefit farmers' decisions regarding crop, live-stock, water, and soil management. Veenadhari et al. [12] have attempted to develop a crop advisor to consider the effect of the most influential climate change parameters on crop yields in Madhya Pradesh. Paul and Sinha [13] forecasted wheat yield concerning weather variables in the Kanpur district of Uttar Pradesh using parametric and non-parametric tests. Turmeric yield was similarly forecasted on climate parameters using a data set for 20 years [14]. In another study performed by Kandianan et al. [14], turmeric yield was predicted using a multiple regression model where a significant correlation was found between yield and rainfall, evaporation wind speed, minimum temperature, and humidity. Gandhi and Armstrong [15] in their study examined the correlation between climate factors and rice crop yields for the Kharif season in India using a historical data set of agriculture. Likewise, Woodhouse [16] also found technological options for the productivity revolution in Africa. With technology, environmental impact is also an important dimension to consider. The research study by Chlingaryan et al. [17] talks about precision agriculture and improvement in yield production with proper nitrogen management. The future demands sustainable and optimized crop management while minimizing environmental harm. Machine learning algorithms and remote sensing technologies are of great use in this estimation. According to [18], machine learning is a reliable technology for analyzing crop price prediction considering annual rainfall, WPI to produce a logical conclusion. Random Forest Ensembled (RFE) learning and decision tree regressor were compared, and RFE was found to have a higher accuracy. Data mining techniques helped improve crop yield prediction as reflected by studies conducted by Gandhi and Armstrong [15] and Sujatha and Isakki [19].

The developing model that accurately forecasts growth and output can support policy makers by improving control for accurate production, equating market supply and demand with lower cost. According to Alhnaity et al. [20], development in machine learning, in particular, deep learning, can provide new analytical tools.

India has the most significant number of hungry people in the world, as the research work by Banik [21] demonstrates; it reviews India's success in preventing famine and compares it to the country's inability to provide food security to hundreds of millions of its citizens. A study conducted by Sherman [22] explores how the methods to get the country to "grow more food" as part of the drive towards nationwide self-sufficiency were marked by conflict between the dream of supplying the benefits of development to all Indians and the reality that the resources in independent India were minimal. Hazra and Bohra [23] suggested meeting growing food demand by ensuring sustainable intensification of crops, achieving high yield per unit production, and bringing more cropland area under cultivation. Thus, achieving food security with constrained resources is required. Agricultural policy makers in most countries rely on prediction models to influence food security policies.

The paper by Mittal et al. [24] stresses using modeling results to coordinate environmental and renewable energy source policies to reach the GHG emission lowering target efficiently and cost-effectively. The mitigation price in terms of economic development and social welfare loss can be reduced by improving the penetration of renewable energy. Farmer's income is also considered an essential factor in determining agricultural yield. Farmers who lack access to resources, capital, and information lag in optimizing their produce. So, BIRTHAL et al. [25] suggested diversification by small farmers towards high-value crops such as fruits and vegetables that significantly raise farm income. Choosing and producing a crop is a tedious task as various factors affect agriculture such as soil, temperature, humidity, and rainfall, and these differ across regions. According to Thomas [26], it would

be of incredible help to agricultural farmers to determine on the storage and business side if it was possible to find the best crop before sowing it. Recommending appropriate crops to farmers can significantly increase productivity and reduce loss. Sujatha and Isakki [19] also demonstrate the crop yield estimation by selecting the most excellent crop, thereby improving the value and gain of the farming area using data mining.

Kang et al. [27] present an estimation of maize yield forecast in the U.S. using different machine learning algorithms [random forest, XGBoost, support vector regressor, Lasso, LSTM, and CNN]. Furthermore, the study found that the yield prediction method helps from the advanced algorithm and large composite of details. The XGBoost outperforms other algorithms both in exactness and strength. It also showed that incorporating the best algorithm and inputs enhances the prediction exactness by 5% compared to the baseline model (Lasso). Zheng et al. [28] added that crewless-aerial-vehicle (UAV)-based remote sensing (RS) possesses the significant advantage of collecting images for precision agricultural applications. Data visualization is vital for understanding the general trends of various factors influencing crop yield. The study by Gandhi and Armstrong [15] examined data visualization approaches to find a correlation between rice crop yield and climatic factors. In agriculture, crop yield production is becoming a significantly challenging task. Earlier, yield prediction was performed by considering farmers' experience in particular. However, this demands accuracy and farmers' involvement which is not always feasible. So competitive analysis was performed by Sivanandhini et al. [29] of the crop yield protection model for a district in Tamil Nadu. Then, empirical investigation suggested that SVM (support vector regression) implementation is better than KNN (k-nearest neighbor) decision tree models. The SVM model with two other enhanced variants, F-SVM (fuzzy-support vector regression) and BS-SVR (boosted-support vector regression), was used by Fung et al. [30] to predict the standardized precipitation and transpiration indices and minimize potential drought impact in oil palm plantations at the Langat river basin. F-SVR was found to be best with improved accuracy.

Research Gap

Studies have explained multiple views on the comparative performance of forecasting models. Hence, further investigation is required to help unify a coherent picture of an advanced methodology. This paper, therefore, seeks to compare and clarify different contradictory opinions reported in the literature on the superiority of ARIMA, SutteARIMA, Holt-Winters (H-W), and Neural Network Auto-Regressive (NNAR) models. Moreover, the study has compared ARIMA, SutteARIMA, H-W, and NNAR with their MAPE and MSE values to suggest an appropriate prediction model. The ARIMA method was chosen because it is used in agriculture crop research and foodgrains predictions; for example, ARIMA was used to forecast food crop price [31] and Chinese food grain price [32]; ARIMA along with LSTM-NN models was used to forecast rice cultivation in India [33]. Studies have also predicted the amount of monsoon rainfall in Andhra Pradesh, India by using MANNs (Modular Artificial Neural Network). Subsequently, the crop yield is predicted with rainfall data and the area allotted to that gave crop output by support vector regression. ANN and multiple linear regression were also used by Maya Gopal and Bhargavi [34]. A hybrid relationship of the Multiple Linear Regression-Artificial Neural Network (MLR-ANN) model has been proposed in research work for crop yield forecasts. This hybrid model was compared with Artificial Neural Network (ANN), Multiple Linear Regression (MLR), Support Vector Regression (SVR), k-Nearest Neighbor (KNN), and Random Forest models, and its accuracy outperforms all the other conventional models.

The SutteARIMA model also performed well in several other areas, including COVID-19 and stock prices in Spain [35], to predict COVID-19 in the U.S. [36], and to predict COVID-19 in the World [37]. Moreover, the Holt-Winters method is one of the most widely used predicting algorithms [38]. The method estimated the trend in overall emissions of organic water contaminants in Poland and Romania [39]. In one study, Kahforoushan et al. [40] applied ANN and H-W methods to predict the added value of agriculture

subsections. In addition, Michel and Makowski [41] have compared different forecasting models, including Holt-Winters, to predict wheat yield in France.

2. Model

2.1. ARIMA

The Y_t process is an ARIMA(p, q) or autoregressive-moving average model if it fulfilled as:

$$\phi_p(B)Y_t = \theta_q(B)a_t, a_t \sim WN(0, \sigma^2), \phi_p, \theta_q \in \mathbb{R}, t \in \mathbb{Z}. \quad (1)$$

with $\phi_p(B)$ is AR(p) and $\theta_q(B)$ is MA(q).

The ARIMA model becomes:

$$\phi_p(B)(1 - B)^d Y_t = \theta_q(B)a_t, a_t \sim WN(0, \sigma^2), \phi_p, \theta_q \in \mathbb{R}, t \in \mathbb{Z}.$$

If there is a difference with $\phi_p(B)$ is AR(p), $(1 - B)^d$ is differencing non-seasonal, and $\theta_q(B)$ is MA(q).

2.2. α -Sutte Indicator

This model (α -Sutte indicator) are developed on the technique of forecasting on the previous values of the indicator set [42]. The ideal applies the adapted version of the moving average method of forecasting. α -Sutte indicator is essentially used to identify and forecast trends and fluctuations in a time-series database. It is based on four data sets of the previous period, that is, Y_{t-1} , Y_{t-2} , Y_{t-3} , and Y_{t-4} [42]. The equations of the α -Sutte indicator method are [42]:

$$Y_t = \frac{\gamma \left(\frac{\Delta x}{\frac{\gamma+\delta}{2}} \right) + \beta \left(\frac{\Delta y}{\frac{\beta+\gamma}{2}} \right) + \alpha \left(\frac{\Delta z}{\frac{\alpha+\beta}{2}} \right)}{3} \quad (2)$$

where:

$$\delta = Y_{t-4}$$

$$\gamma = Y_{t-3}$$

$$\beta = Y_{t-2}$$

$$\alpha = Y_{t-1}$$

$$\Delta x = \gamma - \delta = Y_{t-3} - Y_{t-4}$$

$$\Delta y = \beta - \gamma = Y_{t-2} - Y_{t-3}$$

$$\Delta z = \alpha - \beta = Y_{t-1} - Y_{t-2}$$

$$Y_t = \text{data at } t \text{ time}, Y_{t-k} = \text{data at } (t - k) \text{ time}$$

2.3. SutteARIMA

SutteARIMA is a method of forecasting that incorporates ARIMA with the method of α -Sutte Indicator [42]. SutteARIMA using the average of results from ARIMA and α -Sutte indicator.

The ARIMA in Equation (1) can be described as:

$$(1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p) Y_t = (1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q) a_t \quad (3)$$

$$Y_t - \phi_1 B Y_t - \phi_2 B^2 Y_t - \dots - \phi_p B^p Y_t = a_t - \theta_1 B a_t - \theta_2 B^2 a_t - \dots - \theta_q B^q a_t$$

While Equation (3) can be reduced by using the backward shift operator ($B^p Z_t = Z_{t-p}$):

$$Y_t - \phi_1 Y_{t-1} - \phi_2 Y_{t-2} - \dots - \phi_p Y_{t-p} = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \dots - \theta_q a_{t-q}$$

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \dots - \theta_q a_{t-q} \quad (4)$$

If we define:

$$\begin{aligned}\delta &= Y_{t-4} \\ \gamma &= Y_{t-3} \\ \beta &= Y_{t-2} \\ \alpha &= Y_{t-1}\end{aligned}$$

Equation (4):

$$Y_t = \phi_1\alpha + \phi_2\beta + \phi_3\gamma + \phi_4\delta + \dots + \phi_p Y_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \dots - \theta_q a_{t-q} \quad (5)$$

Furthermore, Equation (2) can be simplified as:

$$\begin{aligned}Y_t &= \frac{\gamma\left(\frac{\Delta x}{\gamma+\delta}\right) + \beta\left(\frac{\Delta y}{\beta+\gamma}\right) + \alpha\left(\frac{\Delta z}{\alpha+\beta}\right)}{3} \\ Y_t &= \frac{\frac{\gamma\Delta x}{\gamma+\delta} + \frac{\beta\Delta y}{\beta+\gamma} + \frac{\alpha\Delta z}{\alpha+\beta}}{3} \\ Y_t &= \frac{\gamma\Delta x}{3\gamma+3\delta} + \frac{\beta\Delta y}{3\beta+3\gamma} + \frac{\alpha\Delta z}{3\alpha+3\beta} \\ Y_t &= \frac{2\gamma\Delta x}{3\gamma+3\delta} + \frac{2\beta\Delta y}{3\beta+3\gamma} + \frac{2\alpha\Delta z}{3\alpha+3\beta} \\ Y_t &= \gamma\frac{2\Delta x}{3\gamma+3\delta} + \beta\frac{2\Delta y}{3\beta+3\gamma} + \alpha\frac{2\Delta z}{3\alpha+3\beta}\end{aligned}$$

When Equation (4) is added to Equation (5), we find:

$$\begin{aligned}2Y_t &= \phi_1\alpha + \phi_2\beta + \phi_3\gamma + \phi_4\delta + \dots + \phi_p Y_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \dots - \theta_q a_{t-q} + \\ &\quad \gamma\frac{2\Delta x}{3\gamma+3\delta} + \beta\frac{2\Delta y}{3\beta+3\gamma} + \alpha\frac{2\Delta z}{3\alpha+3\beta} \\ Z_t &= \alpha\left(\frac{\phi_1}{2} + \frac{\Delta z}{3\alpha+3\beta}\right) + \beta\left(\frac{\phi_2}{2} + \frac{\Delta y}{3\beta+3\gamma}\right) + \gamma\left(\frac{\phi_3}{2} + \frac{\Delta x}{3\gamma+3\delta}\right) + \\ &\quad \frac{\phi_4\delta}{2} + \dots + \frac{\phi_p Y_{t-p}}{2} + \frac{a_t}{2} - \frac{\theta_1 a_{t-1}}{2} - \frac{\theta_2 a_{t-2}}{2} - \dots - \frac{\theta_q a_{t-q}}{2}\end{aligned} \quad (6)$$

Therefore, Equation (6) is the formula of SutteARIMA.

2.4. Holt-Winters

Holt-Winters approach was divided into two categories: Additive Holt-Winters (AH-W) and Multiplicative Holt-Winters (MH-W). These parts are explained in following equations:

The component form for the multiplicative method is:

$$A_t = \alpha \frac{y_t}{s_{t-m}} + (1 - \alpha)(A_{t-1} + B_{t-1}), \quad (7)$$

$$B_t = \beta^*(A_t - A_{t-1}) + (1 - \beta^*)B_{t-1}, \quad (8)$$

$$X_t = \gamma \frac{y_t}{(\ell_t)} + (1 - \gamma)X_{t-m}, \quad (9)$$

$$F_{t+m} = (A_t + B_{t+m}) X_{t-s+m}, \quad (10)$$

The component form for the additive method is:

$$A_t = \alpha(y_t - X_{t-m}) + (1 - \alpha)(A_{t-1} + B_{t-1}), \quad (11)$$

$$B_t = \beta^*(A_t - A_{t-1}) + (1 - \beta^*)B_{t-1}, \quad (12)$$

$$X_t = \gamma(y_t - A_{t-1} - B_{t-1}) + (1 - \gamma)X_{t-m}, \quad (13)$$

$$F_{t+m} = (A_t + B_{t+m}) X_{t-s+m}, \quad (14)$$

where: y_t = data on t time, s = the seasonal length in a certain time, and m = the amount of data to be predicated.

2.5. Neural Network Auto-Regressive (NNAR)

The NNAR is the widely used model for time series modeling and forecasting [43]. This model is a three-layer feedforward neural network involving linear combination and activation functions. The relationship between the model output (y_t) and the inputs ($a_{t-1}; \dots; y_{t-p}$) has the following mathematical representation:

$$y_t = w_0 \sum_{i=0}^k w_j \cdot g \left(w_{0j} + \sum_{i=0}^n w_{i,j} \cdot y_{t-1} \right) + \mathcal{E}_t, \quad (15)$$

where, $w_{i,j}$ ($i = 0, 1, 2, \dots, n, j = 1, 2, \dots, h$) and w_j ($j = 0, 1, 2, \dots, h$) are techniques parameters or association weights; n is number of input nodes; and h is number of hidden nodes. A sigmoid function used as the hidden layer transfer function shown in Equation (16). A linear function is the output layer's most widely used activation function.

$$\text{Sig}(x) = \frac{1}{1 + \exp(-x)}, \quad (16)$$

3. Methodology

Agriculture food grain production data from 1950–1951 to 2019–2020 was collected from the open data source of Reserve Bank of India (RBI) in India [44]. Reserve Bank of India collects agriculture food grain data from the Ministry of Agriculture & Farmers Welfare, Government of India. Data for 2019–2020 is based on fourth advance estimates. This data was fragmented into five parts: wheat, rice, coarse, pulses, and total crops. Total crops are the sum of all four crops (wheat, rice, coarse, and pulses). The data was split into two categories: training data and test data. Data from 1951 to 2013 was considered for training on that basis test conducted from 2014 to 2020. Based on the fitted data, this study conducted short-term forecasts for the next five years (2021–2025). Ahmar [45] designed the SutteForecast R package in R software which compares the forecasting outcomes of other forecasting approaches. In diagnosing the predictions, we used the forecasting accuracy estimation MAPE (Mean Absolute Percentage Error) [46].

$$\text{MAPE} = \frac{1}{N} \sum_{t=1}^N \left| \frac{A_t - Y_t}{A_t} \right|, \quad (17)$$

The mean square error is

$$\text{MSE} = \frac{\sum_{t=1}^n (A_t - Y_t)^2}{N}, \quad (18)$$

where, A_t = actual values at data time t , and Y_t = forecast value at data time t .

4. Experimental Results and Discussion

Due to extensive growth of the population, there is a need to make predictions on food-grains. Past studies, which have made predictions on various aspects, employed limited approach/models. The present research study employs SutteForecast R-studio package to analyze models for ARIMA, SutteARIMA, H-W, and NNAR models, which would be quite helpful in making relatively accurate predictions. Hence, the usage of extensive models makes this study unique and valuable. The acquired findings are provided in the sections below. The first step for analysis is plot data. The plot of data can see in Figure 1.

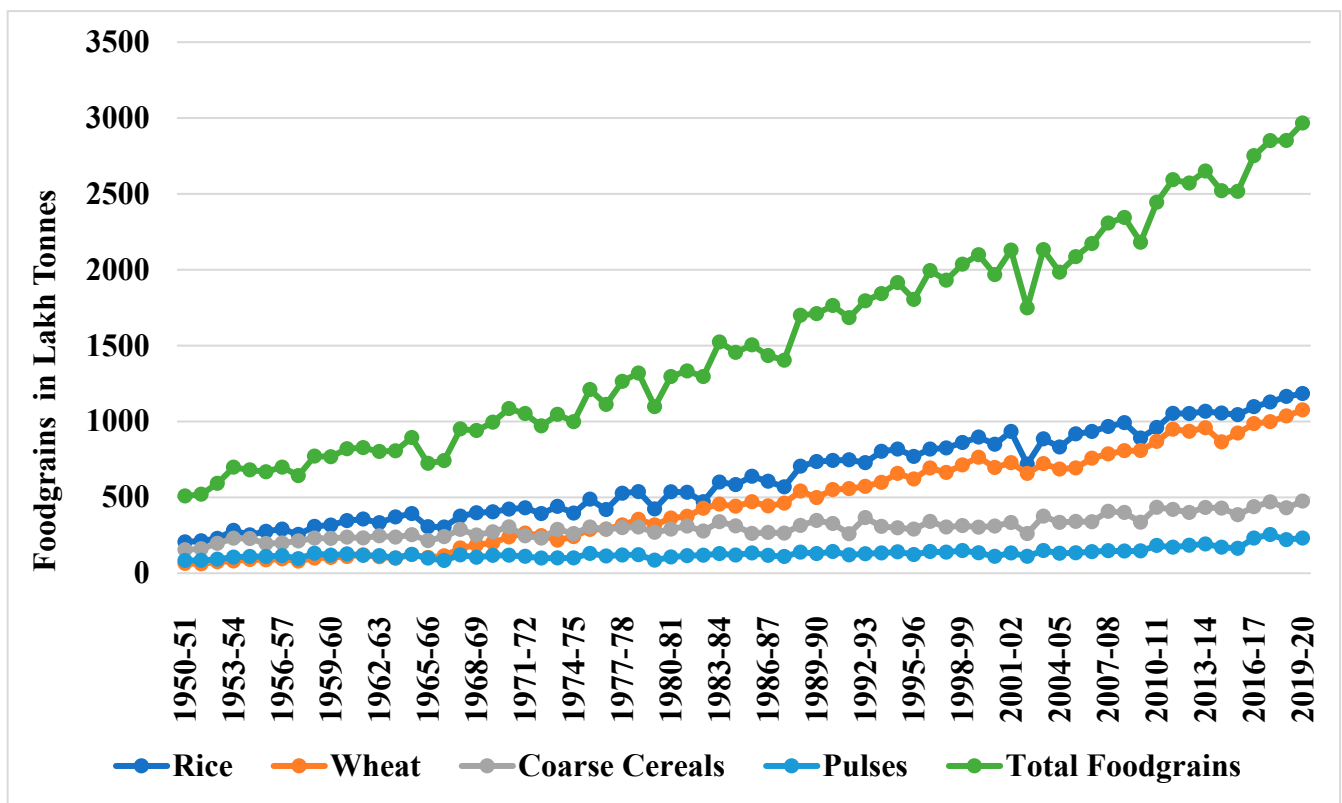


Figure 1. Foodgrains production in India (1950–51 to 2019–20).

From Figure 1, we can see that the data has increased from year to year in both data rice, wheat, coarse cereals, pulses, and total foodgrains.

4.1. Result of ARIMA Model

Although ARIMA has been working as a good model for forecasting [47], the current experiment with the ARIMA model gave relatively poor forecast results, as indicated in Tables 1–5. Therefore, ARIMA has not been considered the best model based on the criteria of MAPE and MSE. As shown in Table 6 the mean absolute percentage error (MAPE) and the mean square error (MSE) values for wheat (MAPE:3.71 and MSE:339.78), rice (MAPE:3.23 and MSE:260.77), coarse (MAPE:7.68 and MSE:201.08), pulses (MAPE:16.06 and MSE:272.83), and total (MAPE:2.83 and MSE:3082.6) with ARIMA is relatively higher as compared to some of the other models.

Table 1. Results of the fitting value of wheat production in India.

Year	Actual	ARIMA (1,1,0) with Drift	APE	SutteARIMA	APE	H-W	APE	NNAR(1,1)	APE
2014	959	960.08	0.11	969.68	1.11	959.96	0.10	934.12	2.59
2015	865	970.15	12.16	980.23	13.32	981.84	13.51	933.36	7.90
2016	923	985.99	6.82	912.37	1.15	1003.73	8.75	932.71	1.05
2017	985	999.61	1.48	960.48	2.49	1025.62	4.12	932.16	5.36
2018	999	1014.08	1.51	1005.33	0.63	1047.50	4.85	931.68	6.73
2019	1036	1028.22	0.75	1036.61	0.06	1069.39	3.22	931.26	10.10
2020	1076	1042.50	3.11	1058.55	1.62	1091.27	1.42	930.91	13.48

Table 2. Results of the fitting value of rice production in India.

Year	Actual	ARIMA (0,1,1) with Drift	APE	SutteARIMA	APE	H-W	APE	NNAR (1,1)	APE
2014	1067	1034.46	3.05	1071.21	0.39	1037.96	2.72	1011.00	5.24
2015	1055	1047.62	0.70	1075.88	1.98	1052.62	0.23	985.60	6.57
2016	1044	1060.78	1.61	1058.25	1.37	1067.28	2.23	968.77	7.20
2017	1097	1073.93	2.10	1057.67	3.59	1081.94	1.37	957.16	12.74
2018	1128	1087.09	3.63	1097.28	2.72	1096.59	2.78	948.92	15.87
2019	1165	1100.25	5.56	1126.59	3.30	1111.25	4.61	942.96	19.05
2020	1184	1113.40	5.96	1159.76	2.05	1125.91	4.91	938.61	20.72

Table 3. Results of the fitting value of coarse production in India.

Year	Actual	ARIMA (0,1,1) with Drift	APE	SutteARIMA	APE	H-W	APE	NNAR (2,2)	APE
2014	433	398.64	7.93	412.19	4.81	416.32	3.85	387.98	10.39
2015	429	402.06	6.28	417.70	2.63	425.78	0.75	383.05	10.70
2016	385	405.48	5.32	419.04	8.84	435.23	13.05	380.02	1.29
2017	438	408.90	6.64	395.07	9.80	444.69	1.53	378.54	13.57
2018	470	412.31	12.27	426.96	9.16	454.15	3.37	377.66	19.64
2019	431	415.73	3.54	450.85	4.61	463.60	7.56	377.19	12.48
2020	475	419.15	11.76	433.78	8.68	473.06	0.41	376.92	20.64

Table 4. Results of the fitting value of pulses production in India.

Year	Actual	ARIMA (0,1,1) with Drift	APE	SutteARIMA	APE	H-W	APE	NNAR (2,2)	APE
2014	193	173.30	10.21	184.90	4.20	174.28	9.70	178.34	7.59
2015	172	174.63	1.53	185.82	8.03	175.71	2.16	178.53	3.80
2016	164	175.95	7.29	174.46	6.38	177.13	8.01	178.34	8.74
2017	231	177.28	23.26	167.75	27.38	178.56	22.70	178.33	22.80
2018	254	178.61	29.68	213.26	16.04	179.99	29.14	178.32	29.80
2019	221	179.93	18.58	232.74	5.31	181.41	17.91	178.32	19.31
2020	232	181.26	21.87	213.09	8.15	182.84	21.19	178.32	23.14

Table 5. Results of the fitting value of total food grain production in India.

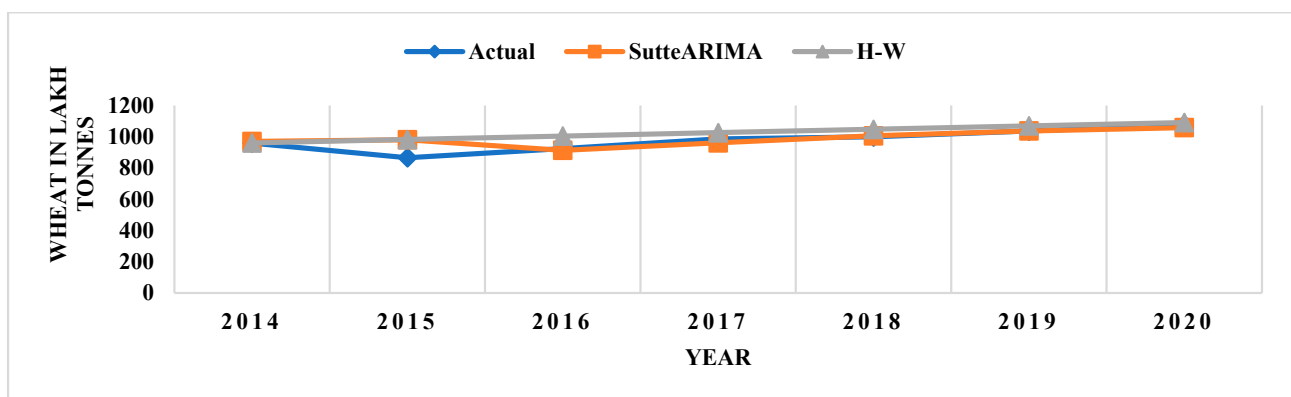
Year	Actual	ARIMA (0,1,1) with Drift	APE	SutteARIMA	APE	H-W	APE	NNAR (1,1)	APE
2014	2650	2536.40	4.29	2621.95	1.06	2550.90	3.74	2534.96	4.34
2015	2520	2568.49	1.92	2644.35	4.93	2591.82	2.85	2506.17	0.55
2016	2516	2600.57	3.36	2548.88	1.31	2632.74	4.64	2482.89	1.32
2017	2751	2632.66	4.30	2565.91	6.73	2673.66	2.81	2463.88	10.44
2018	2850	2664.74	6.50	2727.00	4.32	2714.58	4.75	2448.24	14.10
2019	2852	2696.83	5.44	2830.45	0.76	2755.50	3.38	2435.30	14.61
2020	2966	2728.91	7.99	2848.49	3.96	2796.42	5.72	2424.52	18.26

Table 6. Error values of models for wheat, rice, coarse, pulses, and total foodgrains.

Foodgrains	Forecasting Models	MAPE	MSE
Wheat	ARIMA (1,1,0) with drift	3.71	339.78
	SutteARIMA	2.91	294.93
	Holt-Winters	5.14	520.84
	NNAR (1,1)	6.74	912.86
Rice	ARIMA (0,1,1) with drift	3.23	260.77
	SutteARIMA	2.20	106.32
	Holt-Winters	2.69	180.96
	NNAR (1,1)	12.49	3566.22
Coarse	ARIMA (0,1,1) with drift	7.68	201.08
	SutteARIMA	6.93	153.24
	Holt-Winters	4.36	85.20
	NNAR (2,2)	12.67	586.46
Pulses	ARIMA (0,1,1) with drift	16.06	272.83
	SutteARIMA	10.78	133.09
	Holt-Winters	15.83	260.16
	NNAR (2,2)	16.45	278.95
Total Foodgrains	ARIMA (0,1,1) with drift	4.83	3082.16
	SutteARIMA	3.29	1652.90
	Holt-Winters	3.98	1857.13
	NNAR (2,2)	9.09	14,800.21

4.2. Result of SutteARIMA Model

In this study, the SutteARIMA model has performed as the best forecast model in predicting wheat, rice, coarse, pulses, and total crops, as indicated in Tables 1–5. On the other hand, the forecast error is relatively low and outstanding since the projected values are near to the actual values and move in the direction of the forecasted values in many instances, as demonstrated in Tables 1–5. In addition, MAPE and MSE values with the SutteARIMA model were recorded relatively lower compared to ARIMA, Holt-Winter (except coarse), and NNAR, as given in Table 6. The actual and predicted values are presented in Tables 1–5, comparing all the models mentioned in the study. Hence, this model has been selected as the best model to predict crop production for the next five years (2021–2025). Figures 2–6 provide the graph for the predicted values of crops.

**Figure 2.** Actual wheat versus predicted values using SutteARIMA and H-W.

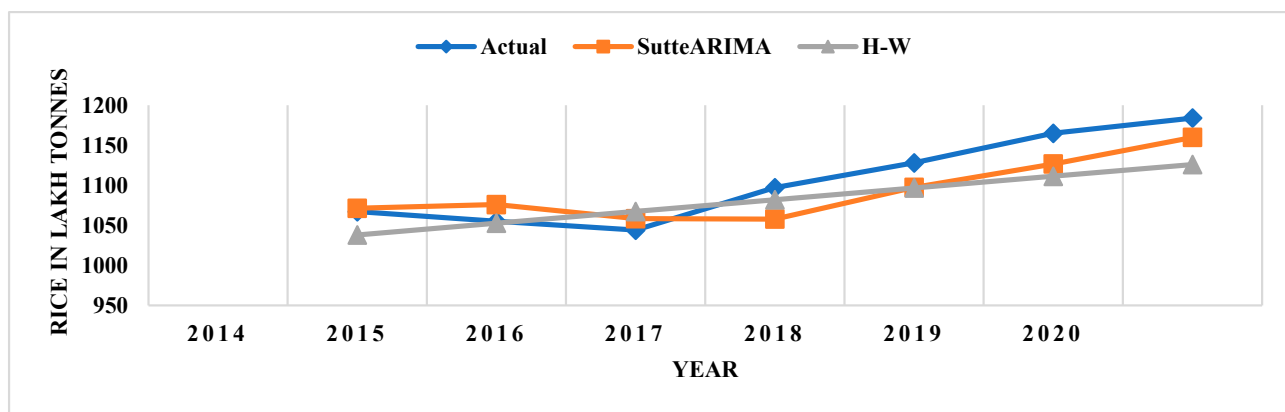


Figure 3. Actual rice versus predicted values using SutteARIMA and H-W.

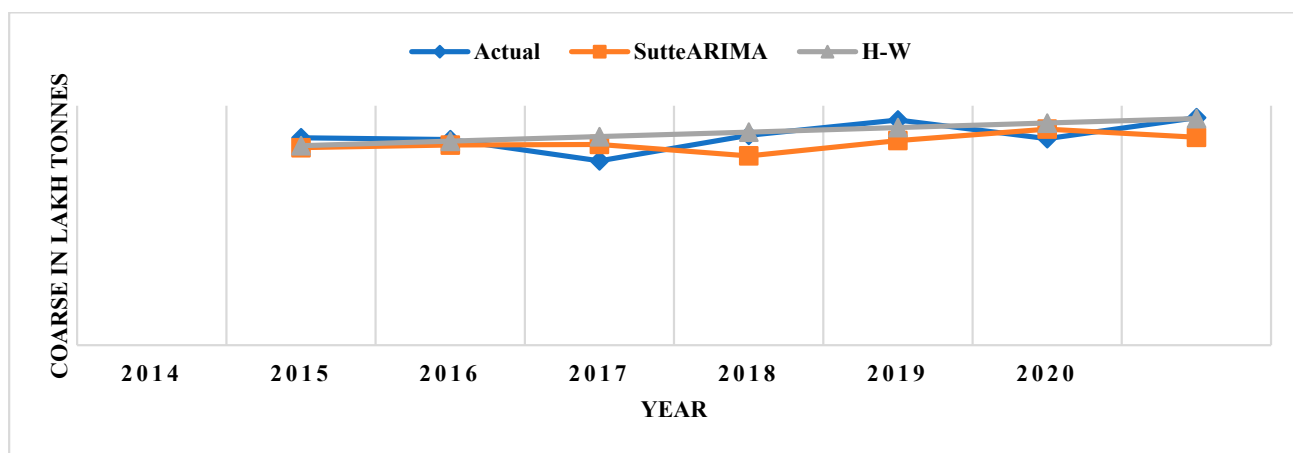


Figure 4. Actual coarse versus predicted values using SutteARIMA and H-W.

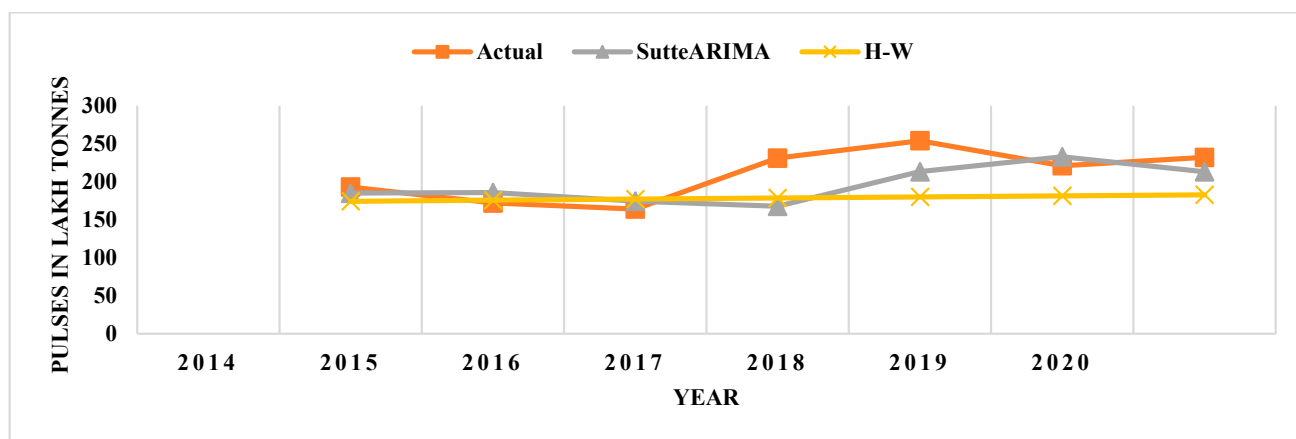


Figure 5. Actual pulses versus predicted values using SutteARIMA and H-W.

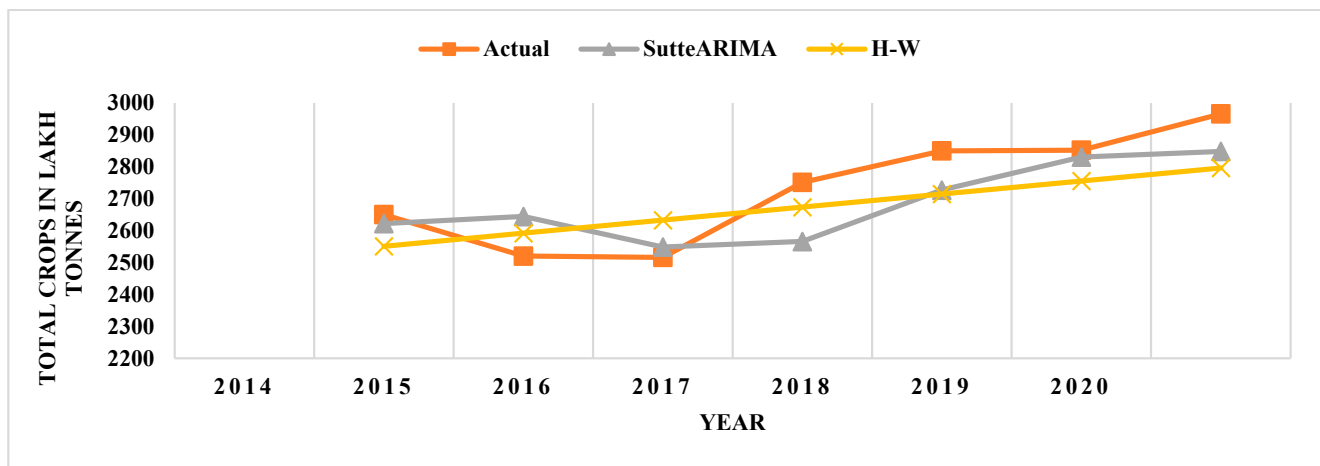


Figure 6. Actual total crops versus predicted values using SutteARIMA and H-W.

4.3. Comparison of SutteARIMA and Holt-Winters (H-W)

From the observed outcomes presented in Tables 1–5 and Figures 2–5, it is observed that the forecasting exactness level of the SutteARIMA model compared with that of the Holt-Winters (H-W) model is not quite significantly different from each other. It can be argued that both models achieved good forecast performance. They were judged on the prediction error (MAPE and MSE) for both models (SutteARIMA and Holt-Winters), which came out pretty low as compared to ARIMA and NNAR models. The SutteARIMA model was also found as the best method in several studies to forecast COVID-19 and the stock price in Spain [35], to predict COVID-19 in the U.S. [36], and to predict COVID-19 in world [37]. The Holt-Winters approach is one of the widely used forecasting techniques [38]. It was used to evaluate the movement in overall emissions of organic water contaminants as well as the exposure of the textile industry to pollution in Eastern Europe [39]. It has ensured the best predicting values for long-term and short-term thermal load forecasting [48]. However, the execution of the SutteARIMA model is better than the Holt-Winter model in terms of forecasting accuracy in test data in the current study. Table 6 shows that the SutteARIMA model is better than the Holt-Winters model for wheat, rice, pulses, and total food grain production, whereas Holt-Winters performed well to predict coarse production with lower MAPE (4.36) and MSE (85.20) values. Statistical tests were carried out, showing no significant difference between the actual and predicted values of the SutteARIMA and Holt-Winters models, as shown in Tables 1–5. Notwithstanding, SutteARIMA is still better. Hence, this study further clarifies the contrary opinions reported in the literature about the superiority of the SutteARIMA model over ARIMA, Holt-Winters, and NNAR models in time series prediction.

4.4. Result of NNAR Model

MAPE and MSE values with the NNAR model were significantly higher compared to ARIMA, SutteARIMA, and H-W. This finding agrees with some research studies; ARIMA was found more accurate in forecasting the horizon-daily values of CO₂ than NNAR [49], in admission the NNAR model is considered inferior to H-W and ARIMA to predict tourist arrival data [50]. However, in several studies, it performed quite well, including unemployment rate prediction in Romania [51] and dengue epidemics [52].

Based on forecasting results, this study concludes that the SutteARIMA model is the most suitable forecasting method to predict foodgrains production in India. The value of MAPE, the least that of MSE value were verified. India's SutteARIMA model was used to predict foodgrains production from 2021–2025. The result of the forecast of SutteARIMA is shown in Table 7. In addition, Table 7, presents the lower and upper value (99%) of forecasting.

Table 7. The SutteARIMA forecast for foodgrains (in lakh tonnes) from 2021 to 2025 in India.

Year	Wheat			Rice			Coarse			Pulses			Total Food Grain		
	F *	U	L	F *	U	L	F *	U	L	F *	U	L	F *	U	L
2021	1072.74	979.80	1165.69	1174.26	1124.20	1174.26	446.74	411.37	482.10	229.08	180.67	277.50	2894.25	2698.61	3089.90
2022	1089.59	973.35	1205.83	1188.76	1118.00	1188.76	451.67	416.30	487.03	236.803	186.89	286.72	2938.14	2674.80	3201.48
2023	1106.44	970.81	1242.08	1203.27	1116.58	1203.27	456.60	421.23	491.96	244.521	193.14	295.91	2982.03	2665.03	3299.03
2024	1123.29	970.66	1275.92	1217.77	1117.64	1217.77	461.53	426.16	496.89	252.239	199.41	305.07	3025.91	2663.01	3388.83
2025	1140.14	972.19	1308.09	1232.27	1120.28	1232.27	466.46	431.09	501.82	259.95	205.72	314.20	3069.80	2666.10	3473.52

* F-Forecasted Value, L-Lower value at 99%, U-Upper Value at 99%.

5. Conclusions

The observed results combined with published food grain data on the performance of different prediction models SutteARIMA, ARIMA, Holt-Winters, and NNAR models were used in this study. The performance of the SutteARIMA predictive model applied in this study was compared with the conventional ARIMA, Holt-Winters, and NNAR models, which were widely used for time series forecasting. Our findings reveal that both the SutteARIMA model and the Holt-Winters model could achieve reliable forecasts when applied to real-life problems. This helps further to effectively and profitably engage food grain forecasting in India. The food grain prediction with the SutteARIMA approach revealed superior performance over ARIMA, Holt-Winters, and NNAR models. Indeed, the actual and predicted values of the SutteARIMA and Holt-Winters predictive model are quite close in predicting food grain production in India. This has been verified by MAPE and MSE values that are relatively low for the SutteARIMA model. India's SutteARIMA model has been used to predict food grain production from 2021 to 2025. The forecasted amount of respective crops in lakh tonnes was predicted to be 1140.14 (wheat), 1232.27 (rice), 466.46 (coarse), 259.95 (pulses), and a total of 3069.80 (foodgrains) by 2025.

6. Policy Implication and Further Suggestion for Research

India enjoys the dubious distinction of being ranked the second most populated country on the planet. Speculations are made that in the near future, India can supposedly overtake China in the number of inhabitants. This presents a precarious condition as the rising population will eventually place demand on foodgrains for human survival, and it would necessarily be the responsibility of the State to provide the same. Hence, to feed the huge population, there has to be a realistic attempt to understand what would be the possible demand placed by the population. Predictions about foodgrains can assist in understanding whether the current rate at which foodgrains are produced would be adequate to meet the increasing demands. Accurate predictions of foodgrains is a herculean task in the Indian context considering the volatile environment and extremely diverse soil quality. The issues of predictions of foodgrains will be resolved if the appropriate method is used. The SutteARIMA model was found to be a suitable method for predictions of foodgrains in India. Moreover, it will assist in providing a baseline from which various policymakers can seek to resolve future predictions of foodgrains while designing the strategy. It is estimated that the world population will grow to 9 billion by the year 2050.

Consequently, there will be enormous challenges at the global level to produce a significant amount of food as compared to the present scenario. In the given scenario, the study would ideally help in accurately anticipating food grain production. This study would essentially assist the policy makers/decision makers in designing special policies in case of a serious mismatch between the demand placed for foodgrains by the ever-increasing population and the predictions about the production of foodgrains. By and large, these policy interventions would yield benefits for future studies and also for the larger society. In the future, research combining this model with other methods, such as the LSTM, RNN, decision tree, and reinforcement learning methods, can lead to better forecasting accuracy. This research work has been conducted for academic and research

only, and the predictions for the future are based on the premise that the existing restrictive circumstances will remain.

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