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Forecasting of area and production of sorghum in Maharashtra, India using ARIMA and ANN models

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Abstract
Sorghum, a highly valued crop in India, has been experiencing a decline in production over the past two decades, despite India being the largest producer and consumer of millets. Forecasting expected area under cultivation and production of sorghum in advance can play a pivotal role in reversing this trend. This study made an attempt to find suitable model for sorghum area and production forecasting in Maharashtra, India. From 1966 to 2021, data on sorghum area and production were gathered and forecasted using ARIMA and ANN techniques. ARIMA (0, 1, 1) with drift is fitted best for the sorghum area and ANN (3:2S:1) best-fitted model for sorghum production. The model's accuracy was compared using RMSE, MAE and MAPE measures. The study found the ARIMA model effectively forecasts sorghum areas, while the Time delay neural network model effectively captures heterogeneity and complexity in production data.

Keywords: Sorghum, time series modeling, India, neural networks, forecasting

1. Introduction

Millets have played a vital role in shaping the agricultural landscape, particularly in regions like Asia and Africa. For their resilience to harsh climatic conditions and minimal water requirement, millets are now recognized as vital contributors to sustainable agriculture as well as safer diversification option for the farmers. Their high nutritional value, low environmental impact, and ability to thrive in challenging conditions make them indispensable for ensuring food and nutritional security [1]. Globally, millets are grown over an area of 71.71 million ha, with 90.65 million tons of production. India is the leading producer of millets accounting for 19% of the total global production [2]. Among millets, sorghum (*Sorghum bicolor*), invariably referred to as the "king of millets”, secures a prominent position with 56% of the world’s millet production. Despite being the largest millet producer and consumer, India does not rank among the top five global sorghum producers. In 2021-2022, the global area under sorghum cultivation was 40.44 million ha, producing 60.13 million tons, of which India contributed 4.40 million tons [3, 4].

Sorghum holds immense economic and social value in India as a staple food and fodder crop. Advancements in production technologies have significantly improved yields, with reported increases of up to 58% and net returns growing by 170% [5]. The United States is a giant producer of sorghum, accounting for 13% of total production, followed by Nigeria (11%) and Brazil (8%) [6]. In 2023-2024, India’s total sorghum production stood at 4.03 million tons, with lead by Maharashtra (37%) followed by Karnataka, Tamil Nadu, Rajasthan, and Madhya Pradesh [6].

Despite being one of the major millets, the area under cultivation in India has declined drastically with a reduction of 69.64% in area and 62.42% in production over the last three decades [7]. Despite its advantages, sorghum cultivation has witnessed a steady decline due to a shift toward other high-yield crops. However, the growing awareness of its health benefits and ecological advantages is fostering renewed interest in its production and consumption. Forecasting expected area under cultivation and production in advance can play a pivotal role in reversing this trend. Forecasting enables better resource allocation, optimizes production, and strengthens supply chains, thereby enhancing economic stability and rural livelihoods. To support farmers in making informed decisions and planning effectively during the cropping season, there is a pressing need for suitable statistical and machine learning models to predict sorghum crop production and area under cultivation. It can inform policy-making, facilitate government incentives, and drive campaigns to promote their cultivation, further boosting their social and economic significance. By focusing on millets, India can tackle the twin challenges of climate change and food security, paving the way for a more resilient and sustainable agricultural future. So, considering the importance of the sorghum crop, this article is an attempt to project the production and area under cultivation of sorghum in Maharashtra, India.

2. Review of Literature:

Time series analysis is a robust and reliable technique widely utilized for predicting commodity prices and agricultural yields. The Autoregressive Integrated Moving Average (ARIMA) model, in particular, is well known for its ability to uncover underlying paradigms and trends in temporal data. The most widely used classical linear time series models are linear regression models and ARIMA. Rathod *et al.* (2011) [8] and Naveena *et al.* (2014) [9] used different time series models to forecast coconut production in India. Nireesha *et al.* (2016) [10] forecasted the area, production, and productivity of pearl millet in Andhra Pradesh for the period 1966 to 2012. Goyal (2022) [11] used ARIMA and seasonal ARIMA model to forecast pea prices of the Varanasi market. The advent of machine learning and deep learning techniques has transformed the field, providing sophisticated methods for analyzing and forecasting complex data patterns. For instance, one can refer to Vijay and Mishra (2018a) [12]utilized ARIMA and ANN models to forecast pearl millet production in Karnataka. Jhade *et al.* [13] (2020) forecasted the area and production of wheat crops in India using the ARIMA model. Singh (2021) [14] compared ANN and ARIMA models for price forecasting of edible oils in the Indian market. Manjubala *et al.* (2023) [15] efficiently forecasted weekly prices of garlic and ginger using ARIMA, exponential smoothing, and artificial neural networks.

In case of millet production and price forecasting, similar research has been conducted at the International and national levels. Muhammad *et al.* (2021) [16] suggested that the ARIMA model is better for modeling millet production in Nigeria. Several researchers, including Yadav *et al.* (2023) [17], Sarvanad *et al*. (2022) [18], Prabhu *et al*. (2022) [19], and Gandhi *et al*. (2023) [20], have conducted significant studies on trends and forecasts related to the area and production of millets in various states of the country. Vijay and Mishra (2018b) [21] forecasted the area and production of sorghum in Karnataka using machine learning techniques and found the performance of SVR to be better than ANN for predicting both area and production. Sridhara *et al*. (2020) [22] performed a study using six multivariate weather-based models to forecast sorghum yield in Karnataka, India, and concluded that LASSO and ENET were the best-suited models for weather-based district-level sorghum yield forecasting. Bezabih *et al.* (2023) [23] utilized the ARIMA model to forecast sorghum production in Ethiopia. Prabha Rani *et al.* (2023) [24] analyzed the growth rates of area, production, and yield of sorghum in India, as well as in major sorghum-cultivating states. To assess the state of the relationship among area, production and productivity, several statistical tools were employed. Their findings indicate a potential deficit scenario in the coming years, which raises significant concerns. There has been comparatively less focus on forecasting the area and production of sorghum crops at both national and international levels. Given the importance of sorghum in India, there is a pressing need to analyze its trends and forecast its area and production comprehensively. This study aims to forecast and analyze the area and production of sorghum in Maharashtra and the leading producer of sorghum in India, using statistical and machine learning models such as ARIMA and ANN. Maharashtra, accounting for 37% of India's total sorghum production across both kharif and rabi seasons, has been selected as a focus area. The article integrates a review of literature, methodology for time series models, detailed results, and discussion, followed by references.

3. Methodology

Maharashtra, selected purposively as it is a leading producer [25] and accounts for 49.40 per cent of the total area under cultivation [26].

Yearly data for the period from 1966 to 2021 pertaining to area and production of sorghum in Maharashtra were collected from the Millets Stat website of Indian Institute of Millets Research (ICAR-IIMR), and the Directorate of Economics and Statistics, Government of Maharashtra. Forecasting was attempted using two techniques- Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Network (ANN). The data from 1966 to 2017 have been used for model calibration and validation was carried out on data from 2018 to 2021.

3.1 Autoregressive Integrated Moving Average (ARIMA) model

ARIMA is the classical, univariate statistical model widely used for non-stationary time series analysis [27]. The ARIMA model permits time series to be explained by their lagged values and stochastic error terms. It is indicated by ARIMA (p, d and q) where "p" stands for the auto-regressive process order, "d" is the order of the stationarity and "q" gives the order of the moving average process. A standard ARIMA model equation is presented as

$$\phi(B)(1-B)^d x_t = \theta(B)\varepsilon_t \quad \dots (1)$$

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{q-1} \quad \dots (2)$$

Where,

B is the backshift operator, that is $B\ (X_t = X_{t-1})$, 'p', denotes the number of autoregressive terms, 'q' number of moving average terms.

Building an ARIMA model involves three key stages: identification, estimation, and diagnostic checking. During the identification phase, parameters are selected experimentally, and the differencing parameter (d) is determined to transform a non-stationary time series into a stationary one. Stationarity was confirmed by employing the Augmented Dickey-Fuller (ADF) and Phillips-Perron (P-P) test, which checks for the presence of a unit root.

Once the series is stationary, assessment of autoregressive (AR) or moving average (MA) terms was done with the help of the autocorrelation function (ACF) and partial autocorrelation function (PACF), respectively. During the estimation stage, parameters of the selected ARIMA model are estimated using methods such as iterative least squares or maximum likelihood estimation [28]. The Ljung-Box test was used for diagnostic analysis of the model.

3.2 Time delay Neural Network (TDNN)

The Artificial Neural Network for time series, termed as Time Delay Neural Network (TDNN), is a powerful supervised machine learning tool for modeling data when underlying relationships within data are unknown. Like conventional models, Artificial Neural Networks (ANNs) do not depend on predefined assumptions of linearity, normality and stationarity about the data-generating process. Instead, they are adept at capturing complex nonlinear patterns and intricate relationships within the data by working similarly to the central nervous system of the human brain [15].

TDNN has three key components, *viz*, input layer, hidden layer, and output layer. In univariate analysis, the number of input layers is chosen by using past values of the same variable, with this crucial number often identified through the autocorrelation structure. A single hidden layer is commonly utilized in time series forecasting. Selecting the output layer is straightforward, as it typically requires just one output. The TDNN can be stated as

$$x_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j \left(\beta_{0j} + \sum_{i=1}^{p} \beta_{ij}\, x_{t-p}\right) + \varepsilon_t \quad \dots (3)$$

Where, α_j (j = 0,1,2,…,q) and β_{ij} (i= 0,1,2,…, p, j= 0,1,2,...,q) stands for connection weights or the model parameters, p is the number of input nodes and q is the number of hidden nodes. The weighted total of all inputs and bias terms, whose value is always 1, is sent to each node in the hidden layer. Each hidden node modifies this weighted sum of input variables using the activation function, which is the nonlinear relationship between a network's inputs and outputs. Sigmoid functions are commonly employed as activation functions for hidden layer transfer functions.

$$g(y) = \frac{1}{1+\exp(-x)} \quad \dots (4)$$

The output node receives the weighted sum of the output from each hidden node, just like the input node, and converts the weighted total into an output using its activation function.

$$x_t = f\left(x_{t-1}, x_{t-2}, \dots, x_{t-p}, w\right) + \varepsilon_t \quad \dots (5)$$

Where, 'f' act as a function of the network structure and 'w' is a vector of network parameters. The behavior of this structure is comparable to that of a nonlinear autoregressive model. Learning by doing is one of the adaptive features of neural networks. The study's data was split into two sets for this reason: a training set and a test set. While the test set is used to assess sample performance, the training set is used to build the network and estimate parameters.

3.3 Model accuracy measures

To compare the forecasting effectiveness of ARIMA and TDNN for sorghum area and production forecasting, Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) are computed by the following equations,

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(x_t - \hat{x}_t)} \quad \dots (6)$$

$$\text{MAE} = \frac{1}{N}\sum_{t=1}^{N}|x_t - \hat{x}_t| \quad \dots (7)$$

$$\text{MAPE} = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{x_t - \hat{x}_t}{x_t}\right| \quad \dots (8)$$

4. Results and Discussion

Descriptive statistics provide the insights from the nature variable and the same for the area and production of sorghum have been reported in Table 1. Over the study period area under sorghum ranged from 2.23 million ha to 6.82 million ha, with an average of 5.14 million ha, whereas production ranged from 1.19 million tons to 6.68 million tons with a mean of 3.27 million tons. Higher variability was observed in production than in the area with a magnitude of the coefficient of variation of 37.69. It was observed that the area as well as production continuously declined during the study period (Figure 1). The area under cultivation was found to be negatively skewed and platykurtic, whereas production was found to be positively skewed and platykurtic

Table 1: Descriptive statistics of the area and production of the sorghum series of Maharashtra

Measures	Area	Production
Count	56	56
Mean	5140.90	3720.47
Median	5528.80	3711.90
Standard Deviation	1411.08	1402.34
Kurtosis	-0.6517	-0.5201
Skewness	-0.7757	0.1136
Minimum	2231.30	1197
Maximum	6825	6687.60
Coefficient of Variation (C.V.)	27.44	37.69

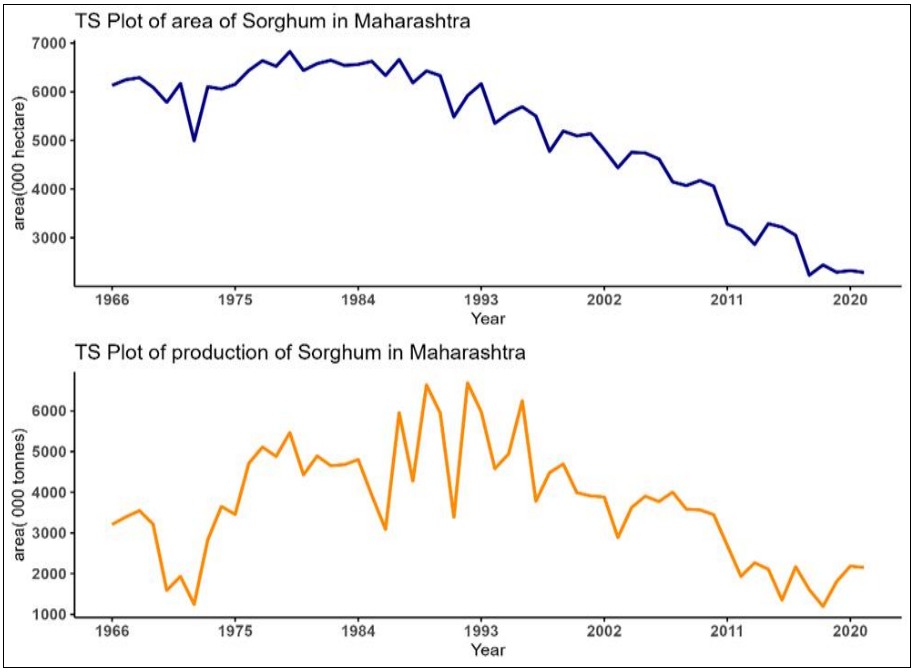

Fig 1: Time plot for area and production of sorghum in Maharashtra from 1966-2021

4.1 Fitting of ARIMA model for area and production of Sorghum:

The necessary assumption for fitting a time series model like ARIMA is to confirm stationarity of time series under consideration. The visualization of area and production of sorghum (Figure1) has shown the declining trend over time, which confirms the non-stationarity. To validate this non-stationary nature scientifically, ADF and PP unit root test were performed (Table 2). The insignificant results of both tests confirmed the non-stationary nature at the level, but found stationary at first difference. The differenced series were considered for further analysis. The ACF and PACF plots of the differenced series of area and production have been visualized in Figure 2 and 3, respectively and on the basis of this, order for p and q were identified.

Table 2: The Specification of unit root test of area and production time series

		Level			1st Difference		
	Unit root test	**Statistics**	**p- value (<0.05)**	**lag**	**Statistics**	**p- value (<0.05)**	**lag**
Area	Augmented Dicky Fuller (ADF) test	-1.21	0.8928	3	-4.87	0.01	3
	Philips -Perron(P-P)	-6.35	0.7391	3	-68.26	0.01	3
Production	Augmented Dicky Fuller (ADF) test	-1.8286	0.6437	3	-3.97	0.01	3
	Philips -Perron(P-P)	-16.62	0.1151	3	-71.53	0.01	3

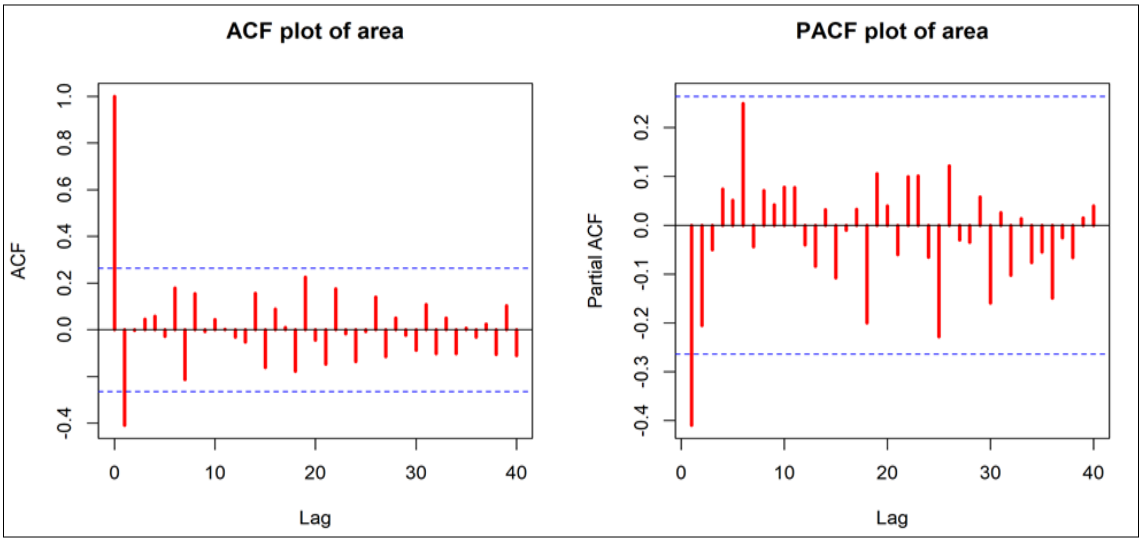

Fig 2: ACF and PACF plot of 1st difference series of area

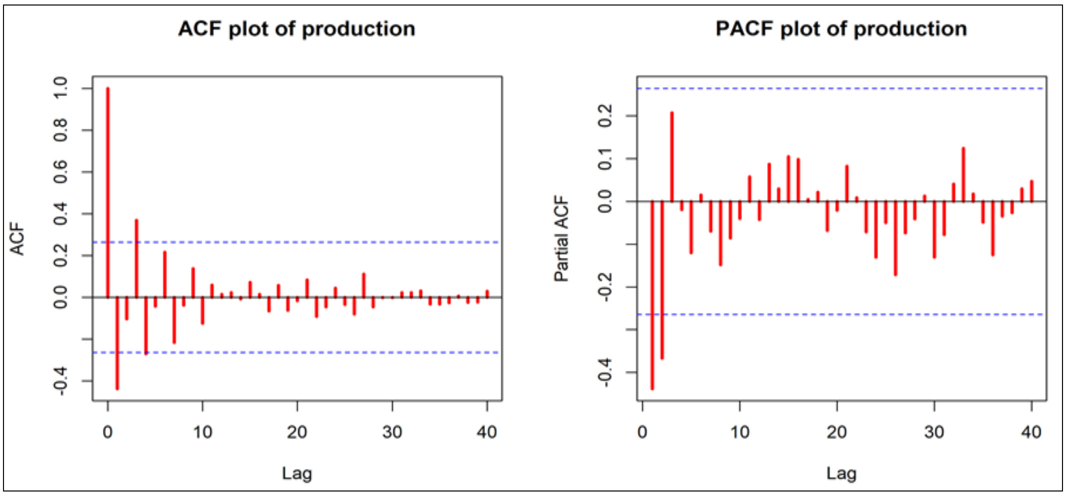

Fig 3: ACF and PACF plot of 1st difference series of production

We perform model building process on training dataset comprising of 52 observations, as mentioned in methodology. Eight tentative model have been checked for different p and q value. The results of the candidate ARIMA models for area and production are given in Table 3. The best fit model was selected for both area and production data based on the minimum AIC value. For area series ARIMA (0, 1, 1) with drift model is selected with AIC- 751.53 and BIC-757.33 value. Parameters of selected best fit model of area were estimated through maximum likelihood method and mentioned in panel A of Table 4. ARIMA (2, 1, 0) was found to be best with AIC-847.31 and BIC- 854.77 for sorghum production series. Parameters for ARIMA (2, 1, and 0) were also estimated through maximum likelihood and depicted in Panel B of Table 4. Best fitted models are now tested for prediction using test datasets comprising of 4 observations each of area and production, respectively.

Table 3: The specification of candidate ARIMA models for area and production

Sr. No.	Sorghum Area Series			Sorghum Production Series	
	ARIMA		**AIC**	**ARIMA**	**AIC**
1	(2,1,2)	With drift	754.37	(0,1,0)	863.33
2	(0,1,0)	With drift	759.89	(1,1,0)	854.12
3	(1,1,0)	With drift	753.14	(0,1,1)	851.08
4	(0,1,1)	With drift	751.53	(0,1,2)	850.01
6	(1,1,1)	With drift	753.18	(1,1,2)	853.70
7	(0,1,2)	With drift	752.89	(2,1,0)	847.31
8	(1,1,2)	With drift	752.41	(2,1,1)	849.49

Table 4: Parameter estimation of ARIMA models

Panel (A): Sorghum Area Series				
Fitted Model: ARIMA (0,1,1) with drift log-likelihood: -372.77				
	Estimate	Std error	Z value	Pr(|z|)
MA (1)	-0.4473	0.1081	-4.1350	0.0003***
drift	-71.54	28.396	-2.5195	0.0117*
Panel (B): Sorghum Production Series				
Fitted Model: **ARIMA (2,1,0)** log-likelihood: -420.66				
AR (1)	-0.5978	0.1296	-4.6119	0.00003***
AR (2)	-0.3508	0.1282	-2.7349	0.0062**

Significance codes: 0 '***', 0.001, '**' 0.01, '*' 0.05, '.' 0.1, ' '

Accuracy of prediction for both models on test dataset was calculated by RMSE, MAE and MAPE measures which are reported in Table 5. For area series RMSE value of test set was found to be 77.13 which is much lower that training set RMSE value-357.20. Similarly for production dataset RMSE value on testing data was 396.16 which was less than training set RMSE value- 911.25. Other accuracy measures like MAE and MAPE also found less in testing set than training set. This confirmed the accuracy of forecasting of fitted ARIMA (0, 1, 1) and ARIMA (2, 1, 0) models.

To check the adequacy of selected forecasting models diagnostic test was performed on the residuals of the area and production. Results of the diagnostic test are represented in Table 6. Figure 5represents the graph of residual series, ACF plot and histogram of residuals. Non-significant chi-square statistics of Box-Ljung test in Table 5 for autocorrelation on residuals followed by a graphical representation of a non-significant ACF residual plot in Figure 5 confirmed that fitted ARIMA models are adequate for forecasting area and production of sorghum.

Table 5: The specification of accuracy of prediction of training and testing datasets of area and production

	AIC	**BIC**	**RMSE**	**MAE**	**MAPE**
Area dataset: ARIMA (0,1,1) with drift					
Training set	751.53	757.33	357.20	277.79	5.8733
Test set	---	---	77.13	57.90	2.4825
Production dataset: ARIMA (2,1,0)					
Training set	847.31	854.77	911.25	694.06	21.53
Test set	---	---	396.16	346.95	20.33

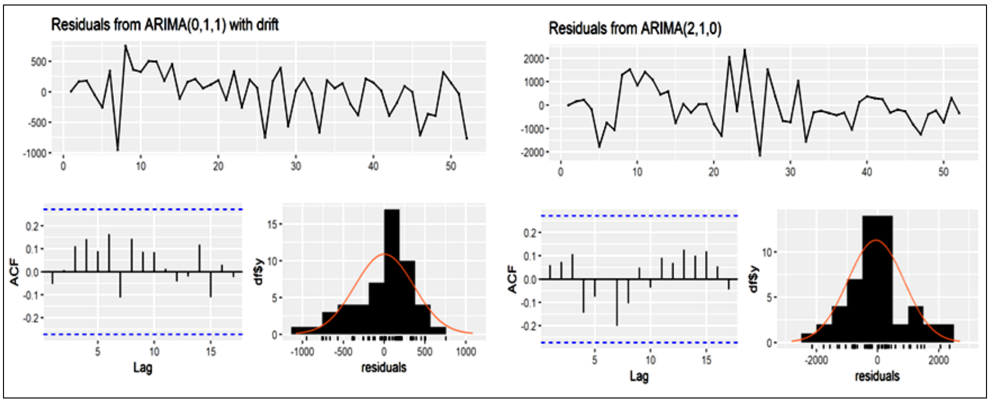

Fig 4: Residuals correlogram and histogram for ARIMA (0, 1, 1) model for area and residuals correlogram and histogram for ARIMA (2, 1, 0) model for production of Sorghum

Table 6: Diagnostic test for ARIMA model of area and production series of Sorghum

Box-Ljung test			
Series	**Chi-square statistics**	**df**	**p-palue**
Area	0.8649	3	0.8339
Production	0.1998	3	0.6549

5. Fitting of TDNN model for area and production of Sorghum:

A time delay neural network was fitted to the area and production time series data of sorghum. As mentioned in the TDNN procedure above data series were divided into training and testing datasets. Modeling building on training dataset was done by using the Levenberg-Marquardt (LM) back propagation algorithm based on repetitive iteration. For model building, ninety percent observations of both time series was used and model validation was carried out with remaining observations. Several models were tried with different pairs of input and hidden nodes before deciding the final skeleton of the model (Table 7). On the basis of lowest RMSE on training and testing datasets, final TDNN model has been selected with two tapped delay and two hidden nodes (2:2S:1) for area forecasting. Selected TDNN model for production forecasting is comprises of three tapped delay and two hidden nodes (3:2S:1) (Table 7). Forecasting performance of different models was compared with help of RMSE, MAE and MAPE values which are measures the difference between test and forecast values of testing datasets for area and production. Forecasting performance of TDNN is given in Table 8.

Table 7: Forecasting performance of TDNN model for Sorghum area and production time series

Model	Parameter	RMSE (Sorghum area)		RMSE (Sorghum production)	
		Training set	**Testing set**	**Training set**	**Testing set**
2:2S:1L	9	**331.33**	**179.00**	783.21	443.36
2:4S:1L	17	330.62	2699.00	570.00	507.16
2:6S:1L	33	251.43	1214.98	421.21	592.75
3:1S:1L	6	381.01	417.38	892.69	472.70
3:2S:1L	11	311.57	434.23	663.79	340.05
3:4S:1L	27	197.60	1344.43	407.36	457.48

Comparison of forecasting performance of ARIMA and TDNN model under consideration

Table 8 compares the forecasting performance of a few chosen ARIMA and TDNN models for area and production. The area data of the sorghum ARIMA model forecast is close to actual test values. ARIMA model shows the lowest RMSE, MAE and MAPE value than TDNN for area data. In production data of sorghum, the TDNN model was found to be better in forecasting close to the actual values of the test dataset. It measures smallest RMSE, MAE and MAPE values on testing data of production. Empirical results on the sorghum area dataset reveal the forecasting efficiency of the ARIMA model. Similarly, forecast value of TDNN model along with self-explanatory statistical measures shows that it outperformed the ARIMA model in the sorghum production forecast.

Table 8: Comparison of forecasting performance of ARIMA and ANN for area and Sorghum time series in testing dataset

Year	Actual values	Forecast Area		Actual values	Forecast production	
		ARIMA	**TDNN**		**ARIMA**	**TDNN**
2018	2440	2500.37	2513.93	1197	1656.64	2090.92
2019	2290.58	2428.82	2525.85	1807.51	1824.55	1986.36
2020	2325	2357.28	2471.88	2186	1706.64	2035.33
2021	2285	2285.73	2426.90	2150	1718.22	2018.88
Criteria	RMSE	77.13	143.60		396.06	375.21
	MAE	57.90	131.24		346.95	288.39
	MAPE	2.48	5.67		20.33	20.29

6. Conclusion

Sorghum is prominent millet and an essential crop for human consumption. It serves as primary food and fodder crop with enormous economic and social importance in India. The declining area and production of sorghum is matter of concern seeing its life saving role in food security and supporting the livelihoods of millions. Therefore, the research was conducted to model the sorghum area and production in state of Maharashtra India. Study utilized the available secondary data for 56 years from 1966 to 2021 published by "Millets stats India and Government of Maharashtra. The classical ARIMA model as well as machine learning TDNN model served a useful tool for forecasting magnitude of any variable. In present study ARIMA (0, 1, 1) with drift is fitted best for sorghum area and ANN (3:2S:1) best-fitted model for sorghum production. The results of the study revealed that ARIMA model shows significant performance in forecasting area of sorghum. However, the heterogeneity and complexity in production data are captured superbly by the Time delay neural network model. This forecast assists administrations, academicians, and policy formulators in executing enlightened determinations concerning repository, commercialization, and regulatory interventions.

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