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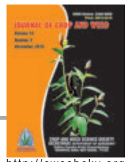

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Forecasting cash crop production with statistical and neural network model

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ABSTRACT

Countries can use forecasts to establish data-driven strategies and make educated commercial decisions. In order to minimize rural poverty and unemployment in developing nations, the development of cash crops is a crucial component of agricultural diversification projects. A comparison of the ARIMA, ETS, and NNAR models for forecasting area, production, and productivity of wheat, paddy, maize, jowar and cotton crops is presented in this study. We have used data from 1980 to 2010 to estimate using models (training) and 2011 to 2020 to test the model's validity (testing). On the basis of goodness of fit, the models were contrasted using training and validation data sets (RMSE, MAE and MASE). Forecast values for the years up to 2027 were derived by choosing the best model. Wheat, paddy, and cotton production are predicted to rise, but jowar and maize production are predicted to fall. The outcomes of the current forecast may enable policymakers to create future strategies that are more aggressive in terms of food security and sustainability, as well as better in terms of Indian cash crop production.

Keywords : Cash crop, ARIMA model, ETS model, NNAR model, forecasting

INTRODUCTION

India is a niche for both food crops and cash crops. The former is important for boosting human health while the latter is important for boosting the country's economy. The chief food crops grown in the country include wheat, paddy, maize, jowar etc. while cotton is the most important cash crop grown in the country. India is the second largest producer of wheat and paddy, seventh largest producer of maize while the topmost producer of cotton in the world. Wheat, paddy, maize and jowar belong to the poaceae family, mainly grown as cereals around the world (Yaseen *et al*., 2019). Chiefly, wheat, paddy and maize and to some extent jowar serve as staple food for people around the world who draw about fifty per cent of total daily calorie intake from the consumption of the cereals (Sarwar *et al*., 2013). India being a nutritionally impoverished nation focused on achieving food and nutritional security and the foremost strategy for bringing about food security was to enhance the production of cereals (Acharya, 2009). Government also focuses on maintaining buffer stocks of paddy and wheat for improving food security in India (Kumar *et al*., 2012). Irrespective of the cropping system followed, cotton accounts for about 48 per cent of total gross returns in crop rotation (Forster *et al*., 2013). Despite being a major commercial crop in India, cotton faces many problems particularly pest damage (Gandhi and Namboodiri, 2009). Commercial growing of Bt cotton has resulted in even greater economic benefits to the farmers when compared to traditional cotton varieties as they are pest resistant (Bennett *et al*., 2006). Adoption of Bt cotton has caused an increase of 24 per cent in yield per acre thereby, giving about 50 per cent gain in profits among the smallholders (Kathage and Qaim, 2012). Despite of the cereals and pulses, it is necessary to study about the cash crop to estimate future of yield, area under cultivation and production.

Time series analysis is the only way to estimate the forecasting nature of any phenomenon. Many researchers tried to estimate the prediction of major agricultural crop by using statistical and machine learning models. Prabakaran *et al*. (2013) forecasted the cultivated areas and production of wheat in using both ARIMA (1,1,1) and ARIMA (1,1,0) models. Sharma *et al*. (2018) forecasted the maize production for the years 2017 to 2022 and found ARIMA (2,1,0) as the most suitable model. Choudhury *et al.* (2017) made an attempt to forecast total area, irrigated area, production and productivity of rice, wheat and maize in India by employing Box-Jenkins ARIMA modelling method. Debnath *et al*. (2013) studied forecasting of the cultivated area, yield and production of cotton in area and found ARIMA (0,1,0), ARIMA (1,1,4) and ARIMA

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(0,1,1) as best fitted models for forecasting cotton area, production and yield in India, respectively. Poyyamozhi and Mohideen (2017) forecasted the cotton area and production in India using ARIMA (0,1,0) model. Saha *et al*. (2021) used tuned-support vector regression model to forecast the cotton production in India.Pandey *et al*. (2008) carried out a comparison between neural-network and fuzzy time series models for forecasting wheat production. Rana (2020) used fuzzy sets models for forecasting agricultural crop yield and concluded that soft computing techniques of forecasting are more comfortable in comparison to statistical models. Athiyarath *et al*. (2020) compared various forecasting algorithmic approaches and explored the usefulness and limitations of each of them.

As a result, it is critical to concentrate on cash crop production in order to forecast future behavior. In the present study comparative analysis was conducted between ARIMA, ETS and NNAR models for forecasting area, production and productivity of wheat, paddy, maize, jowar and cotton crops.

MATERIALS AND METHODS

Data description

The cash crop data i.e. wheat, maize, paddy, jowar and cotton were considered for this study. The area, production and productivity data were collected from Agriculture at a glance, Govt. of India from the study period 1980 to 2020. These data series were evaluated to meet this study objectives.

Applied methodology

Autoregressive integrated moving average (ARIMA) model

Autoregressive integrated moving average (ARIMA) model is the robustly used time series model for univariate data. The model also named as Box-Jenkins methodology (Box and Jenkins, 1976). The model consisted of Autoregressive (AR) model (*p* order), integrated or differencing the series (*d* order) and moving average (MA) model (*q* order).

AR model is the linear function of lagged value of the variable, which can be denoted as

$$x_t = a + \sum_{i=1}^{p} b_i x_{t-i} + \varepsilon_t \quad \text{.......................................} (1)$$

where, a is intercept, b_i is autoregressive parameter, $\varepsilon_t \sim iidN(0,1)$

Integration or differencing is generally used for making the series stationary and it can be defined as

$$\hat{x}_t = x_t - x_{t-1} \quad \text{..} (2)$$

MA model is the function of random error and lagged value of the variable, which can be written as

$$x_t = u + \varepsilon_t + \sum_{i=1}^{q} \phi_i \varepsilon_{t-i} \quad \text{.....................................} (3)$$

where, $u = E(x_t)$, ϕ_t is the parameter of moving average, $\varepsilon_t \sim iidN(0,1)$

To develop an ARIMA (*p,d,q*) model and estimate forecast from the model, we should follow four steps; identification, estimation, diagnostic checking and prediction or forecast. In identification, it is required to find the appropriate order of *p, d, q*. Partial autocorrection function (PACF) and Autocorrelation function (ACF) are used to estimate the appropriate order of *p* and *q* respectively. To estimate the differencing order (*d*), it should be necessary to test the stationarity of the series by using either Augmented Dickey-Fuller (Dickey and Fuller, 1979) test or Phillips–Perron (Phillips and Perron, 1988) test. After the model order has been established, the parameter approximation procedure is computed using maximum likelihood methods. Model selection techniques including the root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and mean absolute squared error (MASE) are used to select the best model both training and testing set. In the last stage, the chosen model's validity (training set) and forecast (testing set) are evaluated using the in-sample forecast and out-of-sample forecast (Ray *et al*., 2016).

ETS Model (Exponential Smoothing)

ETS builds time series from three elements: E(Error), T(Trend), and S. (Seasonal). Error phrase refers to an unpredictable component of a time series and trend term refers to the long-term movement of a time series. Since we have annual data, we ignore (S) in our data. (Yonar *et al*., 2022).

To build the model, we have additive model $Y_t = T + E$, or multiplicative model like $Y_t = T. E$.

The individual component of the model is described below:

E [*A, M*]

T [*N, A M, AD, MD*]

S [*N, A, M*]

Where : N : none ; A : additive ; M: multiplicative; AD : additive dampened ; MD: multiplicative dampened.

The Table 1 describes the model that we are working on (Yonar *et al*., 2022):

Where parameters: α : smoothing factor for the level, β : smoothing factor for the trend, ϕ : damping coefficient. And initial states: l : initial level components, b : initial growth components, which is

Table 1: Probabilities of the model shape in state space

Trend	Additive Error Models	Trend	Multiplicative Error Models
N	$y_t = l_{t-1} + \varepsilon_t$ $l_t = l_{t-1} + \alpha\varepsilon_t$	**N**	$y_t = l_{t-1}(1 + \varepsilon_t)$ $l_t = l_{t-1}(1 + \alpha\varepsilon_t)$
A	$y_t = l_{t-1} + b_{t-1} + \varepsilon_t$ $l_t = l_{t-1} + b_{t-1} + \alpha\varepsilon_t$ $b_t = b_{t-1} + \beta\varepsilon_t$	**M**	$y_t = (l_{t-1} + b_{t-1})(1 + \varepsilon_t)$ $l_t = (l_{t-1} + b_{t-1})(1 + \alpha\varepsilon_t)$ $b_t = b_{t-1} + \beta(l_{t-1} + b_{t-1})\varepsilon_t$
AD	$y_t = l_{t-1} + \phi b_{t-q} + \beta\varepsilon_t$ $l_t = l_{t-1} + \phi b_{t-1} + \alpha\varepsilon_t$ $b_t = \phi b_{t-1} + \beta\varepsilon_t$	**MD**	$y_t = (l_{t-1} + \phi b_{t-1})(1 + \varepsilon_t)$ $l_t = (l_{t-1} + \phi b_{t-1})(1 + \alpha\varepsilon_t)$ $b_t = \phi b_{t-1} + \beta(l_{t-1} + \phi b_{t-1})\varepsilon_t$

estimated as part of the optimization problem. RMSE, MSE, MAPE and MASE were also used to select the best model of both training and testing set.

NNAR model

Time series data that had been advanced in time were fed into the neural network of the NNAR. Acyclic links connect a three-tiered network. The following is the NNAR equation (Perone, 2021)

$$x_t = \omega_0 + \sum_{j=1}^{Q} \omega_g \, g\left(\omega_{oj} + \sum_{i=1}^{p} \omega_{i,j} x_{t-1}\right) + e_t$$

where x and $(x_{t-i}, ... x_{t-p})$ are the output and the input, $\omega_{i,j} (i = 0,1,2,...,P, j = 1,2,...,Q)$ and $\omega_j (j = 0,1,2,...,Q)$ are model parameters, which are known as connection weights; the number of input nodes is represented by P while the number of hidden nodes is indicated by Q.

RESULTS AND DISCUSSION

In Table 1, some descriptive statistics via area, production, and productivity for wheat, maize, paddy, jowar, and cotton are given. It can be seen from Table 1 that wheat has the highest mean for the area, production, and productivity. Paddy has the second-highest average in terms of area and production, while jowar in terms of productivity. Those with the lowest means are cotton in terms of area and productivity and jowar in terms of production. According to the coefficient of variation values, we can say that the biggest change is in jowar for the area, cotton for production and productivity. It also appears that the least change is in cotton for the area, paddy for production and paddy for productivity. The difference between maximum and minimum, with positive skewness except for paddy area and paddy production, indicates that area, production and productivity increased in a stable fashion from 1980 to 2020. Moreover, we can say that the outliers are insignificant according to the calculated kurtosis values.

ARIMA, ETS and NNAR models were used to model these data. We used the data during the period 1980-2010 to estimate using models (training) and 2011-2020 to verify the validity of the model (testing). The best models selected according to the AIC were given in Table 2. Values for the best models according to the RMSE, MAE, MAPE and MASE criteria were shown in bold. For example, ARIMA (0,1,0) for wheat area, ETS(M,A,N) for wheat production, and ARIMA(0,1,1) for wheat productivity were determined as the best models.

According to the obtained best models in Table 2, forecasts with 95% forecasting intervals for the area, production and productivity up to 2027 were obtained as shown in Table 3. A decrease was expected until 2027 for all areas except the wheat area. In terms of production, an increase is expected for wheat, paddy and cotton and a decrease is expected for jowar and maize. An increase was expected until 2027 for all productivities except jowar productivity. Also, forecasts for area, production, and productivity in wheat, maize, paddy, jowar and cotton were presented in Fig. 1. From the figure, one can evaluate the forecasted line obtained in between the confidence interval which confirmed that the models were fitted as best.

CONCLUSION

The development of cash crops became a crucial factor in determining the anticipated behaviour that can

Table 1: Descriptive statistics

	Mean	Std.Dev	Coefficient of Variation %	Maximum	Minimum	Skewness	Kurtosis
Wheat area	4233,0927	876,7525	20,7119	6551,0000	3085,2000	0,9869	-0,0680
Wheat production	7956,0647	4642,5928	58,3529	19607,1430	2154,6000	1,1563	0,1124
Wheat productivity	1760,3623	627,8464	35,6657	2993,0000	698,3664	0,7353	-0,4104
Maize area	912,1537	153,9032	16,8725	1404,0000	750,8000	2,0199	2,9386
Maize production	1459,0503	867,7987	59,4770	4131,4350	540,6000	1,8780	2,7285
Maize productivity	1518,6148	567,6364	37,3786	3260,8011	720,0320	1,2159	1,1568
Paddy area	3504,8634	1676,1597	47,8238	5479,8000	1445,7000	-0,0529	-1,9760
Paddy production	3647,0133	1692,8480	46,4174	6463,0000	982,1000	-0,1280	-1,3404
Paddy productivity	1100,1450	415,8686	37,8012	2370,1131	382,6754	1,1456	0,9578
Jowar area	689,9878	389,3747	56,4321	1748,0000	75,0000	0,8497	0,4954
Jowar production	668,0645	334,5087	50,0713	1737,0000	164,1750	1,5241	2,2714
Jowar productivity	1071,7299	463,4235	43,2407	2189,0000	458,6000	0,8728	-0,2342
Cotton area	566,5268	55,8057	9,8505	706,0000	468,1000	0,1760	-0,7451
Cotton production	798,9072	673,4935	84,3019	2329,0000	210,2000	1,0456	-0,5430
Cotton productivity	232,2858	185,1954	79,7274	644,8371	65,6392	1,0602	-0,5143

Table 2: The results of ARIMA, ETS, and NNAR models

		Training				Testing			
	Model	RMSE	MAE	MAPE	MASE	RMSE	MAE	MAPE	MASE
Wheat area	ARIMA(0,1,0)	379,5604	274,2769	7,364827	0,968093	**1384,799**	**1247,92**	**21,62079**	**4,404683**
	ETS(M,N,N)	354,2717	262,351	6,96234	0,925999	1582,209	1463,906	25,57991	5,167031
	NNAR(1,1)	323,3194	253,3351	6,636239	0,894177	1711,351	1558,656	27,10381	5,501464
Wheat production	ARIMA(0,1,1)	1027,781	741,8601	13,18447	0,811237	7251,904	6592,437	40,68672	7,208946
	ETS(M,A,N)	1043,237	754,1429	14,06316	0,824669	**6734,963**	**6134,401**	**37,9754**	**6,708076**
	NNAR(2,2)	727,7063	593,8806	9,851169	0,649419	8568,433	7879,644	49,08513	8,616529
Wheat productivity	ARIMA(0,1,1)	136,8467	106,4245	7,277053	0,754259	**707,2843**	**660,3936**	**23,62057**	**4,680388**
	ETS(M,Ad,N)	129,1687	103,3937	7,161839	0,732779	870,9071	805,0294	28,57825	5,705461
	NNAR(2,2)	96,32762	77,19185	4,982064	0,547079	1046,241	980,271	35,06983	6,947446
Maize area	ARIMA(0,1,0)	25,25794	18,37583	2,139325	0,969019	339,6707	262,52	20,87687	13,84356
	ETS(M,N,N)	24,59746	18,4384	2,153518	0,972319	336,9318	259,6733	20,6241	13,69344
	NNAR(1,1)	19,8169	15,31474	1,767546	0,807598	**311,5553**	**236,2558**	**18,64308**	**12,45856**
Maize production	ARIMA(0,1,1)	264,4186	211,8531	19,60294	0,879302	1815,811	1437,109	46,66069	5,964759
	ETS(M,N,N)	265,9885	217,9946	20,40157	0,904792	1824,499	1445,923	46,99844	6,001341
	NNAR(1,1)	244,0362	187,129	17,28134	0,776684	**1735,617**	**1351,945**	**43,17606**	**5,611285**

Contd.

Contd. Table 2

		Training				Testing			
	Model	**RMSE**	**MAE**	**MAPE**	**MASE**	**RMSE**	**MAE**	**MAPE**	
Maize productivity	ARIMA(0,1,1)	285,4501	226,6749	18,21859	0,872021	**1095,388**	**909,6294**	**36,50261**	**3,499356**
	ETS(M,N,N)	286,4121	231,6561	18,80366	0,891184	1099,957	914,0467	36,68928	3,516349
	NNAR(1,1)	260,9924	212,7156	17,04712	0,81832	1099,501	913,0623	36,62346	3,512562
Paddy area	ARIMA(0,1,0)	660,4382	181,7281	9,259005	0,968562	600,7407	552,85	26,61703	2,946543
	ETS(M,N,N)	661,1318	184,5591	9,255579	0,983651	597,786	549,638	26,45399	2,929424
	NNAR(1,1)	633,4959	278,5341	10,42036	1,484512	**428,8607**	**365,2672**	**17,17048**	**1,946777**
Paddy production	ARIMA(1,1,0)	1163,714	714,5373	32,55789	0,856143	2298,522	2089,35	56,74309	2,503415
	ETS(M,N,N)	1223,385	756,9725	38,08443	0,906988	2288,424	2080,485	56,53278	2,492793
	NNAR(2,2)	771,9893	544,865	20,48723	0,652846	**2133,303**	**1924,605**	**51,87202**	**2,30602**
Paddy productivity	ARIMA(0,0,0)	182,8185	141,9739	18,70256	0,750802	859,8194	787,1229	44,04794	4,16255
	ETS(A,N,N)	178,1207	134,6719	17,28021	0,712187	875,2175	803,9147	45,08249	4,25135
	NNAR(2,2)	100,8956	80,31196	9,062854	0,424715	771,1691	**691,8444**	**38,27142**	**3,658688**
Jowar area	ARIMA(0,1,0)	108,4006	71,3251	8,403403	0,800177	69,88313	50,58033	26,0882	0,567447
	ETS(A,N,N)	116,5072	86,27721	10,43186	0,967921	225,3409	199,3936	134,2726	2,236942
	NNAR(1,1)	93,39619	63,9759	8,229583	0,717728	370,6555	346,1055	216,9763	3,882863
Jowar production	ARIMA(0,1,0)	232,8806	159,9625	20,5814	0,968081	214,3606	164,7192	69,68045	0,996868
	ETS(M,N,N)	222,0502	159,5227	21,42791	0,965419	218,2994	166,0347	70,64065	1,00483
	NNAR(1,1)	193,3347	132,3443	18,11375	0,800938	250,6718	194,7111	81,16116	1,178377
Jowar productivity	ARIMA(0,1,1)	165,7253	127,6268	16,14312	0,885475	**624,5261**	**565,4549**	**30,46473**	**3,923129**
	ETS(A,N,N)	165,6933	129,1085	16,31135	0,895755	627,9131	569,1936	30,68099	3,949068
	NNAR(1,1)	173,8464	145,8279	18,54726	1,011755	920,0864	853,8844	46,59607	5,924254
Cotton area	ARIMA(1,0,0)	28,52093	22,01113	4,062841	0,946987	54,49602	46,05253	7,515085	1,981322
	ETS(A,N,N)	29,41009	22,49433	4,14753	0,967775	53,00099	40,78028	6,882229	1,754494
	NNAR(2,2)	19,68379	15,21322	2,789164	0,65452	**51,92041**	**39,858**	**6,63427**	**1,714814**
Cotton production	ARIMA(0,1,0)	86,74003	64,89503	17,80238	0,96786	1081,558	1057,269	54,65721	15,76837
	ETS(A,N,N)	85,79257	64,59009	17,52283	0,963312	1081,418	1057,127	54,64966	15,76625
	NNAR(1,1)	80,3611	59,43367	16,40349	0,886408	**1053,168**	**1027,954**	**53,09484**	**15,33115**
Cotton productivity	ARIMA(0,1,1)	23,84628	16,34139	14,58273	0,835375	278,7006	270,0928	49,24582	13,8072
	ETS(M,A,N)	25,06029	18,76907	15,647	0,959479	292,9298	284,9496	52,0539	14,56668
	NNAR(1,1)	292,9298	284,9496	52,0539	14,56668	**257,2793**	**247,0793**	**44,90529**	**12,63074**

Table 3 : Forecasting quantities using the best models with forecasting interval 95%

	2020-2021	2021-2022	2022-2023	2023-2024	2024-2025	2025-2026	2026-2027
Wheat area	6551 (5733,7369)	6551 (5394,7708)	6551 (5134,7968)	6551 (4915,8187)	6551 (4722,8380)	6551 (4547,8555)	6551 (4387,8715)
Wheat production	18996 (12475,25517)	19328 (11482,27174)	19660 (10635,28685)	19992 (9881,30103)	20324 (9192,31456)	20656 (8550,32761)	20988 (7945,34030)
Wheat productivity	3057 (2739,3375)	3089 (2718,3460)	3134 (2689,3579)	3198 (2637,3758)	3242 (2626,3858)	3299 (2610,3989)	3358 (2596,4120)
Maize area	1466 (1395,1539)	1050 (958,1155)	761 (678,869)	664 (342,751)	896 (767,969)	858 (787,938)	851 (781,934)
Maize production	4043 (3483,4591)	4040 (3467,4525)	4040 (3468,4552)	4040 (3458,4634)	4040 (3472,4558)	4040 (3433,4582)	4040 (3422,4620)
Maize productivity	3024 (2428,3620)	3079 (2352,3807)	3135 (2296,3973)	3190 (2253,4126)	3245 (2220,4270)	3300 (2193,4406)	3355 (2173,4537)
Paddy area	1939 (868,3026)	1884 (733,3758)	1847 (681,4363)	1824 (667,4807)	1810 (821,5123)	1802 (678,5354)	1797 (769,5357)
Paddy production	5145 (3703,6581)	5250 (2386,6443)	5277 (2197,6477)	5284 (1963,6390)	5285 (1979,6402)	5286 (1771,6397)	5286 (1622,6420)
Paddy productivity	1999 (1756,2277)	2759 (1990,2942)	2054 (1759,2375)	2883 (1896,3320)	2079 (1800,2480)	2831 (1897,3478)	2090 (1790,2672)
Jowar area	67 (-134,268)	26 (-259,311)	-15 (-364,334)	-56 (-458,346)	-97 (-547,353)	-138 (-631,355)	-179 (-711,353)
Jowar production	157 (-247,562)	122 (-352,596)	86 (-448,621)	51 (-538,640)	15 (-624,655)	-20 (-705,665)	-56 (-784,673)
Jowar productivity	1785 (1348,2221)	1785 (1289,2280)	1785 (1237,2332)	1785 (1190,2380)	1785 (1146,2424)	1785 (1104,2465)	1785 (1065,2504)
Cotton area	632 (586,681)	624 (518,673)	621 (494,672)	621 (484,669)	621 (480,669)	621 (480,668)	621 (476,662)
Cotton production	1896 (1491,2298)	1903 (1536,2312)	1903 (1497,2293)	1903 (1496,2305)	1903 (1479,2299)	1903 (1478,2307)	1903 (1506,2311)
Cotton productivity	541 (432,648)	542 (433,647)	542 (429,646)	542 (431,651)	542 (430,646)	542 (435,648)	542 (440,650)

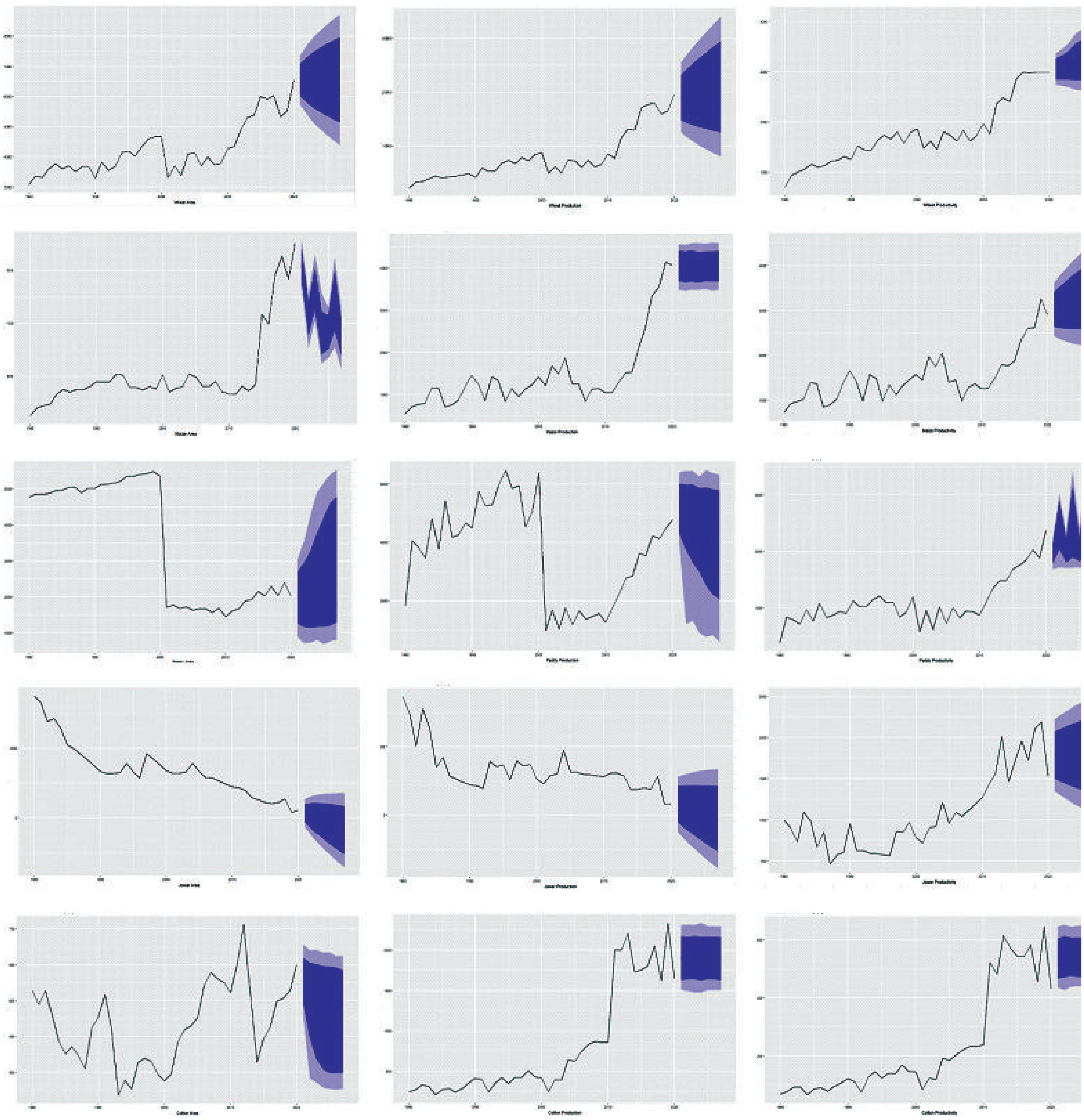

Fig. 1 : Forecasts to 2027

benefit the Indian economy. On the other side, the results of this study showed that, depending on the data availability, time series analysis with a conventional statistical model can be used to determine the forecasting nature of numerous significant commodities. We employed the ARIMA, ETS and NNAR models in accordance with the goal and compared the results using the goodness of fit (RMSE, MSE, MAPE) on the area, production and productivity data series (wheat, paddy, maize, jowar and cotton). Production of wheat, paddy, and cotton is expected to increase, but production of jowar and maize is expected to decline. This information is useful for the effective planning of reforms relating to the people of India's nutritional security.

REFERENCES

Acharya, S.S. 2009. Food security and Indian agriculture: policies, production, performance and marketing environment. *Agric. Econ. Res. Rev.*, **22**(1): 1-19.

Athiyarath, S., Paul, M. and Krishnaswamy, S. 2020. A comparative study and analysis of time series forecasting techniques. *SN Comp.r Sci.*, 1 doi:https://doi.org/10.1007/s42979-020-00180-5

Bennett, R., Kambhapati, U., Morse, S. and Ismael, Y. 2006. Farm-level economic performance of genetically modified cotton in Maharashtra, India. *Appl. Econ. Perspec. Policy,* **28**(1): 59-71.

Box, G.E. and Jenkins, G. M. 1976. Time Series Analysis: Forecasting and Control. Vol. 2nd Edition. John Wiley & Sons, Holden-Day, San Francisco, USA.

Choudhury, N., Saurav, S., Kumar, R.R. and Budhlakoti, N. 2017. Modelling and forecasting of total area, irrigated area, production and productivity of important cereal crops in India towards food security. *Int. J. Curr. Microbiol. Appl. Sci.*, **6**(10): 2591-2600.

Debnath, M.K., Bera, K., Mishra, P. 2013. Forecasting area, production and yield of cotton in India using ARIMA model. *J. Space Sci. Technol*., **2**(1): 16-20.

Dickey, D.A. and Fuller, W.A. 1979. Distribution of the estimators for autoregressive time series with a unit root. *J. Amer. Stat. Asso*.,**74**:427-431.

Forster, D., Andres, C., Verma, R., Zundel, C., Messmer, M.M. and Mader, P. 2013. Yield and economic performance of organic and conventional cotton-based farming systems- results from a field trial in India. *PloS ONE*, **8**(12): e81039.

Gandhi, V.P. and Namboodiri, N.V. 2009. The adoption and economics of Bt cotton in India: preliminary results from a study. IIIMA institutional repository, WP;2006-09-04.

Kathage, J. and Qaim, M. 2012. Economic impacts and impact dynamics of Bt (*Bacillus thuringiensis*) cotton in India. Doi: https://doi.org/10.1073/pnas.1203647109

Kumar, A., Bantilan, M.C.S., Kumar, P., Kumar, S. and Jee, S. 2012. Food security in India: Trends, patterns and determinants. *Indian J. Agric. Econ*., **67**(3): 445-463.

Pandey, A.K., Sinha, A.K. and Srivastava, V.K. 2008. A comparative study of neural-network and fuzzy time series forecasting techniques- case study: wheat production forecasting. *Int. J. Comp. Sci. Network Sec.,* **8**(9): 382-387.

Perone, G. 2021. Comparison of ARIMA, ETS, NNAR, TBATS and hybrid models to forecast the second wave of COVID-19 hospitalizations in Italy. *Eur. J. Health Econ*., **2**3(6):917-940.

Phillips P.C. and Perron, P. 1988. Testing for a unit root in time series regression. *Biometrika,* **75**:335-346.

Poyyamozhi, S. and Mohideen, A.K. 2017. Forecasting of cotton production in India using ARIMA model. *Asia Pacific J. Res*., **1**(48): 70-74.

Prabakaran, K., Sivapragasam, C., Jeevapriya, C. and Narmatha, A. 2013. Forecasting cultivated areas and production of wheat in India using ARIMA model. *Golden Res. Thoughts*, **3**(3): 1-7.

Rana, A.K. 2020. Comparative study on fuzzy models for crop production forecasting. *Math. Stat.,* **8**(4): 451-457.

Ray, S., Bhattacharyya, B. and Pal, S. 2016. Statistical modeling and forecasting of food grain in effects on public distribution system: an application of ARIMA Model. *Indian J. Econ. Dev*., **12**:739-744.

Saha, A., Singh, K.N., Ray, M., Rathod, S. and Choudhury, S. 2021. Modelling and forecasting cotton production using tuned-support vector regression. *Curr. Sci*., **121**(8): 1090-1098.

Sarwar, M.H., Sarwar, F.M., Sarwar, M., Qadri, N.A. and Moghal, S. 2013. The importance of cereals (Poaceae: Gramineae) nutrition in human health: A review. *J. Cereals Oilseeds*, **4**(3): 32-35.

Sharma, P.K., Dwivedi, S., Ali, L. and Arora, R.K. 2018. Forecasting maize production in India using ARIMA model. *Agro Economist- Int. J,* **5**(1):01-06.

Yaseen, M., Kausar, T., Praween, B., Shah, S.J., Jan, Y., Shekhawat, S.S., Malik, M. and Azad, Z.R.A.A. 2019. Insect Pest Infestation During Storage of Cereal Grains, Pulses and Oilseeds. In: Malik, A., Erginkaya, H. (eds) Health and safety aspects of food processing technologies. Springer, Cham.

Yonar, H., Yonar, A., Mishra, P., Abotaleb, M., Alkhatib, A., Makarovskikh, T. and Cam, M. 2022. Modeling and forecasting of milk production in different breeds in Turkey. *Indian J.Animal Sci.*, **92**(1):105-111.