Forecasting Area, Yield And Production of Groundnut Crop In Ceded Region Using–R

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ABSTRACT: *Groundnut is an important crop in India. Groundnut is king of oilseeds . Groundnut is also called wonder nut as well as poor men's cashew nut too. This study focuses on forecasting the cultivated area yield and production of groundnut in Ceded region using Auto Regressive Integrated Moving Average(ARIMA) using R-software. Time series data covering the period of 2003-2018 was used of Ceded districts (Rayalaseema) of Andhrapradesh was used for the study. The study is to identify the best ARIMA model, which is for fitting and forecasting of Groundnut Area, Yield, Production in Ceded region respectively. Conclusions are drawn and found the forecasting for the future. The R-Software is used to analyse and graphical representation of the results.*

Keywords: *ARIMA, Forecasting, Auto Correlation Function, Akaike Information Criterion, R-software.*

I. INTRODUCTION

Groundnut is one of the major oilseed crops of India and also, an important agricultural export commodity, a leguminous crop too. All India groundnut acreage was 38,90,000 hectares. Five states, Gujarat(14,67,600 ha; 37.7%), Andhrapradesh (6,60,000 ha; 17%), Rajasthan(5,49,052 ha; 14.1%), Karnataka(3,82,940 ha; 9.8%), Maharashtra(1,95,594 ha; 5%) jointly accounted for 83.7%of the National acreage. India ranks first in groundnut acreage with about 80.85 lakh metric tonnes (in shell groundnuts), second in production. Gujarat is the largest producer of Groundnut. Groundnut requires an average daily temperature to grow is 30°C and growth ceases at 15°C. For rapid emergence, soil temperature above 21°C is needed. The optimum temperature for most rapid germination and seedling development is about 30° C.

Groundnut is grown throughout the tropics and its cultivation is extended to the subtropical countries lying between 45° North and 35° South and up to an altitude of 1,000 meters. The crop can be grown successfully in places receiving a minimum rainfall of 500 mm and a maximum rainfall of 1250 mm. The rainfall should be distributed well during the flowering and pegging of the crop. The total amount of rainfall required for presuming operations (preparatory) is 100 mm, for sowing it is 150 mm and for flowering and pod development an evenly distributed rainfall of 400-500 mm is required, Madhusudana *, B et al*(2013)[1].

Crop area estimation and forecasting of crop yield are an essential procedure in supporting policy decision regarding land use allocation, food security and environmental issues. Statistical techniques able to provide crop forecast with reasonable precessions well in advanced. Various approaches have been used for forecasting such agricultural systems. Concentration have been given on the uni-variate time series Auto Regressive Integrated Moving Average (ARIMA) MODELS, which are primarily due to World of Box and Jenkins(1970). Among the stochastic time series models ARIMA types are powerful and popular as they can successfully describe the observed data and can make forecast with minimum forecast error. These types of models are very difficult to identify and estimate. Muhammad et al(1992) conducted an empirical study of modelling and forecasting time series data of rice production in Pakistan [2]. Similar studies have been done by Rachana et al. (2010) for forecasting pigeon pea production in India by using ARIMA Modelling [3], N.M.F. Rahman et al. (2010)for forecasting of Boro rice production in Bangladesh [4], Najeeb Iqbal et al. (2005) for forecasting wheat area and production in Pakistan [5], M.K Debnath et al. (2013)for forecasting Area, production, and Yield of Cotton in India using ARIMA Model [6], M. Hemavathi et al.(2018) ARIMA Model for Forecasting of Area, Production and productivity of Rice and Its Growth Status in Thanjavur District of TamilNadu, India[7], P.K. Sahu et al.(2015) for modelling and forecasting of area, production, yield and total seeds of Rice and Wheat in SAARC Countries and the World towards Food Security[8], Mohammed Amir Hamjah et al.(2014) for Rice Production Forecasting in Bangladesh: An Application of Box-Jenkins ARIMA Model[9], Muhammad Iqbal Ch et al.(2016) for forecasting of wheat production: A comparative study of Pakistan and India [10], Niaz Md. Farhat Rahman et al.(2013)**,** Modeling for Growth and Forecasting of pulse production in Bangladesh [11], Vishwajith K..P et al.(2014), Timeseries Modeling and forecasting of pulses production in India[12], Ashwin Darekar et al.(2017), Forecasting oilseeds prices in India: Case of Groundnut [13] , Bhola Nath et al.(2018) DS , Forecasting Wheat production in India: An ARIMA modelling approach [14] , Pant, D.C. and Pradeep Pal, et al.(2004*)*, Comparative Economics of Agro-processing units for Groundnut in Southern Rajasthan [15], Ap Patel, G.N., and N.L. Agarwal et al. (1993*)*, Price Behaviour of Groundnut in Gujarat [16], also use the ARIMA Model . The study is to identify the best ARIMA model, which is for fitting and forecasting of Groundnut Area, Yield, Production in Ceded region respectively. Conclusions are drawn and found the forecasting for the future. The R-Software is used to analyse and graphical representation of the results.

. **R- software**: The R- language is widely used among statistician and data miners for developing statistical software and data analysis. Although R has a command line interface, there are several graphical user interfaces, such as R studio, an integrated development environment. R is a programming language and environment commonly used in statistical computing, data analytics and scientific research. It is one of the most popular languages used by statisticians, data analysts, researchers and marketers to retrieve, clean, analyze, visualize and present data.

II. MATERIALS AND METHODS

(i)Data collection: The study has utilized secondary source of data. The time series data on yearly kharif and Rabi seasons totals area, yield and production of groundnut crop from 2003-2004 to 2017-2018 of 15 years data required for the study was collected from the DIRECTORATE OF ECONOMICS AND STATISTICS, HYDERABAD . The 15 years of data of groundnut crop producing in Ceded region viz., Anantapuramu, Kurnool, cuddapah, chittoor districts of Andhra Pradesh. Ceded is also known as Rayalaseema (Rocky region).

Fig: 1 Area, Yield, and Production of Groundnut crop in Ceded region of Andhra Pradesh.

(ii)Auto Regressive Integrated Moving Average (ARIMA) model (Box-Jenkins model):

One of the most popular and frequently used stochastic time series models is the Auto Regressive Integrated Moving Average (ARIMA) model was introduced by Box and Jenkins. The basic assumption made to implement this model is that considered time series is linear and follows a particular known statistical distribution, such as the Normal Distribution. ARIMA model has subclasses of other models, such as Auto Regressive (AR), Moving Average (MA) and Auto Regressive Moving Average(ARMA) models. For seasonal time series forecasting , Box and Jenkins had proposed a quite successful variation of ARIMA model, viz. the Seasonal ARIMA (SARIMA). The popularity of the ARIMA model is mainly is due to its flexibility to represent several varieties of time series with simplicity as well as the associated Box-Jenkins methodology for the optimal model building process. The term ARIMA stands for "Auto-Regressive Integrated Moving Average." Lags of the differenced series appearing in the forecasting equation are called "auto-regressive" terms, lags of the forecast errors are called "moving average" terms, and a time series which needs to be differenced to be made stationary is said to be an "integrated" version of a stationary series. Random-walk and random-trend models, autoregressive models, and exponential smoothing models (i.e., exponential weighted moving averages) are all special cases of ARIMA models. A non seasonal ARIMA model is classified as an "ARIMA (p, d, q)" model, where p is the number of autoregressive terms, d is the number of non seasonal differences, and q is the number of lagged forecast errors in the prediction equation. The Box-Jenkins methodology seeks to transform any time series data to be stationary; and then apply the stationary process for forecasting by using past uni-variate time series process for future forecast with a host of selection and diagnostic tools.

i. Model Identification : This stage involves the specification of the correct order of ARIMA model by determining the appropriate order of the AR, MA and the integrated parts or the differencing order. The major tools in the identification process are the (sample) autocorrelation function and partial autocorrelation function. The identification approach is basically designed for both stationary and non-stationary processes. Spikes represent in the line at various lags in the plot with length equal to magnitude of autocorrelations and these spikes distinguish the identification of a stationary and non stationary process. The main objective in fitting ARIMA model is to identify the stochastic process of the time series and its stationarity counterpart. The main objective in fitting ARIMA models is to identify the stochastic process of the time series and predict the future values accurately. Ansari and Ahmad [17] worked with application of ARIMA modelling and co-integration analysis on time series of tea price. Different stages in forecasting model are given below. Identification: A good starting point for time series analysis is a graphical plot of the data . It helps to identify the presence of trends. Before estimating the parameters p and q of the model, the data are not examined to decide about the model which best explains the data. This is done by examining the sample ACF, and PACF. Both ACF and PACF are used as the aid in the identification of appropriate models. There are several ways of determining the order type of process, but still there was no exact procedure for identifying the model.

ii. Estimating the parameters: After tentatively identifying the suitable model is not “estimating a second time series”, it is filtering it. The function accuracy gives multiple measures of accuracy of the model fit, ME(mean error), RMSE(root mean squared error), MAE(mean absolute error), MPE(mean percentage error), MAPE(mean absolute percentage error), MASE(mean absolute scaled error) , And ACF (auto correlation function) It is up to you to decide, based on the accuracy measures, whether you consider this a good fit or not. For example, mean percentage error of nearly -70% does not look good to me in general, but that may depend on what your series are and how much predictability you may realistically expect. It is often a good idea to plot the original series and the fitted values, and also model residuals. You may occasionally learn more from the plot than from the few summarizing measures such as the ones given by the accuracy` function. Depending on the ACF and PACF of these sequence plots a model is run with appropriate software (R-Software). The best fitting model must also have few parameters as much as possible alongside best statistics of the model according to the information selection criteria.

iii. Diagnostic Checking: After having estimated the parameters of a tentatively identify ARIMA model, it is necessary to do diagnostic checking to verify that the model is adequate. Examining ACF And PACF considered random when all their ACF and PACF considered random when all their ACF were within the limits. Model checking in time series can be done by looking at the residuals. Traditionally the residuals given by Residuals = observed values – fitted values. These results should be normally distributed with zero mean, uncorrelated, and should have minimum variance or dispersion, if indeed a model fits the well. That is model validation usually consist of plotting residuals overtime to verify the validation.

iv. Forecasting: After satisfying about the adequacy of the fitted model, it can be used for forecasting future values. This was done with the help of R- Software.

III. RESULTS AND DISCUSSION

Analysis of Time series data regarding agricultural oriented groundnut crop area, yield and production using R-software tabulated along with necessary graphical presentations mentioned below, Groundnut is an important protein supplement for cattle and poultry rations. It is also consumed as confectionery product. The cake can be used for manufacturing artificial fibre. The haulms are fed to live stock . Groundnut shell is used as fuel for manufacturing coarse boards. Cork substitutes. Groundnut is also valued as a rotation crop. Being a legume with root nodules, it can synthesize with atmospheric nitrogen and thereby improve soil fertility.

Table 1

AREA, YIELD AND PRODUCTION OF GROUNDNUT CROP IN CEDED REGION

S.NO	YEAR	Area (in 000'ha.)	Yield (in Kg/ha.)	Prod. (in 000'tones)
1	2003-2004	1164	2664	603
2	2004-2005	1511	3455	1267
3	2005-2006	1554	2800	924
4	2006-2007	1041	2522	366
5	2007-2008	1474	6278	2076
6	2008-2009	1447	1978	471
7	2009-2010	991	2588	493
8	2010-2011	136	3466	962
9	2011-2012	1058	2681	444
10	2012-2013	1089	2899	635
11	2013-2014	1111	3933	739
12	2014-2015	832	2774	391
13	2015-2016	732	4785	694
14	2016-2017	968	3112	485
15	2017-2018	697	6243	942
	TOTAL	15805	52178	11492

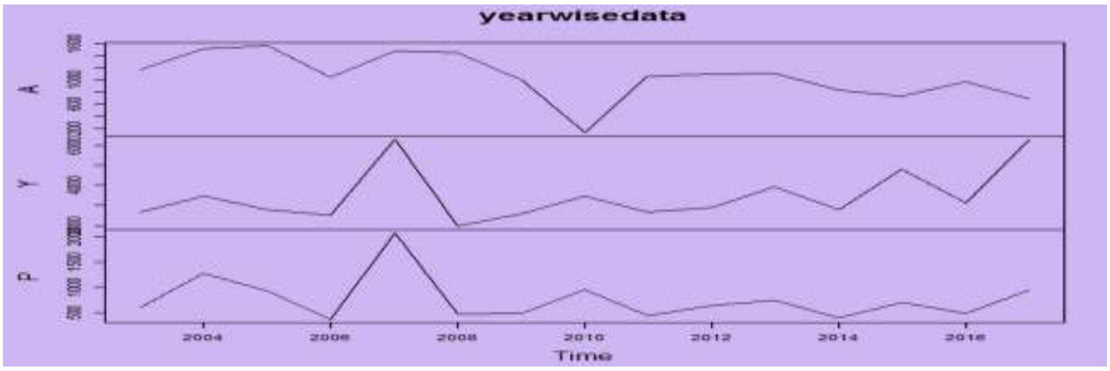


Fig : 2 AREA, YIELD AND PRODUCTION OF GROUNDNUT CROP IN CEDED REGION.

Table 2

Area, Yield and Production ACF and PACF(CEDED REGION)

Lag	ACF(area)	PACF(area)	ACF(YIELD)	PACF(YIELD)	ACF(PROD.)	PACF(PROD)
0	1.000	0	1.000	0	1.000	0
1	0.299	0.299	-0.306	-0.306	-0.348	-0.348
2	-0.030	-0.131	0.119	0.028	-0.037	-0.180
3	0.006	0.062	0.081	0.138	0.449	0.437
4	0.205	0.202	-0.123	-0.073	-0. 318	-0.025
5	-0.057	-0.217	-0.041	-0.135	0.023	-0.104
6	-0.201	-0.100	0.033	-0.008	0.046	-0.240
7	0.016	0.140	-0.152	-0.115	-0.204	-0.137
8	-0.051	-0.221	0.115	0.046	0.027	-0.054
9	-0.130	-0.002	-0.228	-0.206	-0.161	-0.191
10	-0.209	-0.104	0.284	0.208	0.054	0.047
11	-0.108	-0.145	-0.077	0.061	-0.033	-0.014
12	-0.130	-0.048	-0.112	-0.181	-0.037	0.079
13	-0.089	0.001	0.010	-0.185	-0.049	-0.118
14	-0.020	-0.030	-0.094	-0.113	-0.010	-0.060

ACF, PACF plots are analysed to check stationarity of data upto15 (0 to 14) lags as shown below:

Fig:3 Area- ACF(CEDED REGION)

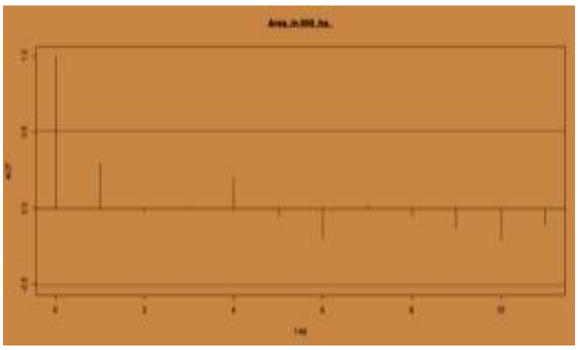


Fig: 4 AREA- PACF(CEDED REGION)

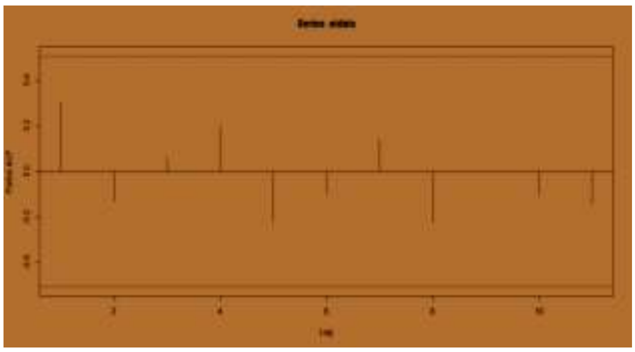


Fig:5 Yield- ACF(CEDED REGION)

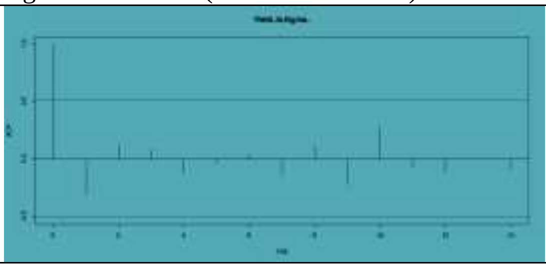


Fig: 6 YIELD - PACF(CEDED REGION)

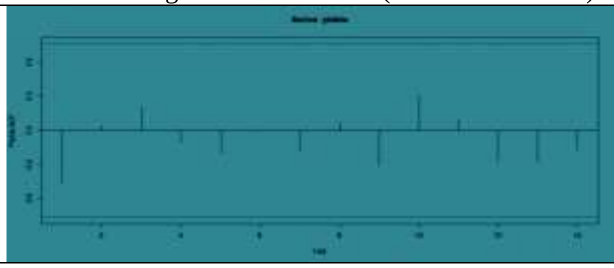


Fig : 7 Production -ACF(CEDED REGION)

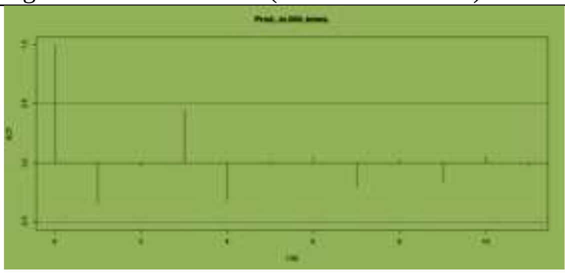


Fig:8 PRODUCTION- PACF(CEDED REGION)

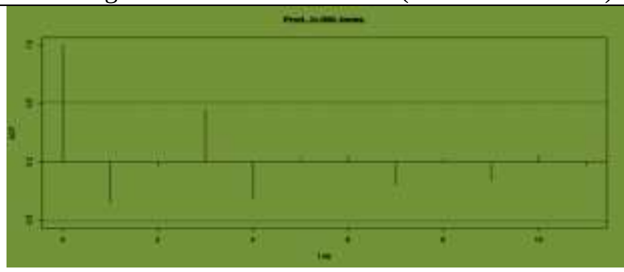


Table :3

Identification of ARIMA(p,d,q) MODEL for AREA(CEDED REGION)

Model	ARIMA	Coefficients	SE	Intercept	$\sigma^{\wedge 2}$	Log likelihood	AIC
(1,0,1)	AR1	0.0498	0.5624	1046.008	115069	-108.74	225.49
	MA1	0.2924	0.5138	117.233			
(1,1,1)	AR1	0.1970	0.3672		134509	-102.82	211.65
	MA1	-0.7633	0.2536				
(2,1,1)	AR1	0.0369	0.3832		124849	-102.36	212
	AR2	-0.3039	0.2835				
	MA1	-0.5565	0.3623				
(0,1,1)	MA1	-0.6696	0.2105		137404	-102.98	209.95
(1,2,1)	AR1	-0.2117	0.2744		183257		
	MA1	-1.000	0.2106				
(1,1,0)	AR1	-0.2581	0.2570		171256	-104.26	212.51
(2,1,2)	AR1	0.1838	0.6701		123904	-102.32	214.63
	AR2	-0.3665	0.3227				
	MA1	-0.7131	0.7253				
	MA2	0.1540	0.5125				
(2,0,2)	AR1	-0.4117	0.4538	1047.8754	84268	-107.74	227.48
	AR2	-0.7303	0.3632				
	MA1	0.8504	0.5816				
	MA2	0.9998	0.4785	99.7099			
(1,1,2)	AR1	-0.1588	0.7451		131574	-102.68	213.35
	MA1	-0.3572	0.6960				
	MA2	-0.2946	0.4351				
(1,2,0)	AR1	-0.4470	0.2389		378348	-102.04	208.08
(0,2,1)	MA1	-1.000	0.2025		197349	-99.02	202.04

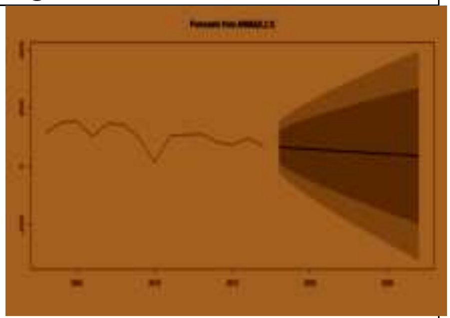
Table 4

AREA, YIELD, AND PRODUCTTION POINT FORECAST

Area Point Forecast of Groundnut (CEDED REGION)

Year	Area Point forecast	Lo 80	Hi 80	Lo95	Hi 95
2018	663.6431	74.34483	1252.941	-237.6108	1564.897
2019	630.2862	-230.43900	1491.011	-686.0794	1946.652
2020	596.9294	-489.68298	1683.542	-1064.9008	2258.760
2021	563.5725	-727.51535	1854.660	-1410.9760	2538.121
2022	530.2156	-952.81919	2013.250	-1737.8904	2798.322
2023	496.8587	-1169.92849	2163.646	-2052.2723	3045.990
2024	463.5018	-1381.29353	2308.297	-2357.8692	3284.873
2025	430.1449	-1588.43457	2448.724	-2657.0060	3517.296
2026	396.7881	-1792.35779	2585.934	-2951.2216	3744.798
2027	363.4312	-1993.76182	2720.624	-3241.5844	3968.447

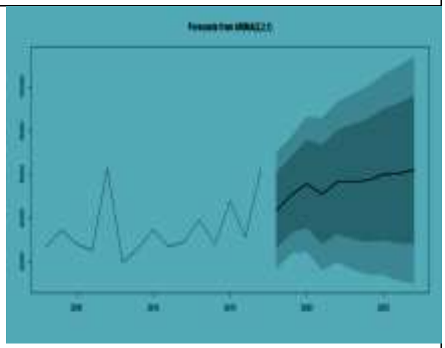
Fig: 9 Area forecast



Yield Point Forecast(CEDED REGION)

Year	Yield point forecast	Lo 80	Hi 80	Lo95	Hi 95
2018	4338.339	2588.741	6087.937	1662.5598	1662.5598
2019	5078.286	3321.278	6835.294	2391.1738	7765.398
2020	5563.951	3536.040	7591.862	2462.5287	8665.374
2021	5098.539	2814.759	7382.319	1605.7985	8591.279
2022	5657.126	3256.581	8057.670	1985.8098	9328.442
2023	5666.277	3015.238	8317.315	1611.8634	9720.690
2024	5738.279	2906.801	8569.757	1407.9071	10068.650
2025	5998.293	2982.656	9013.931	1386.2738	10610.313
2026	6050.198	2823.687	9276.709	1115.6751	10984.720
2027	6216.148	2804.532	9627.765	998.5315	11433.765

Fig:10 Yield forecast



Production Point Forecast(CEDED REGION)

Year	Production Point forecas	Lo 80	Hi 80	Lo95	Hi 95
2018	670.0918	-116.26186	1456.446	-532.5324	1872.716
2019	818.4277	-56.75061	1693.606	-520.0420	2156.898
2020	724.4765	-376.64553	1825.599	-959.5443	2408.497
2021	770.2133	-461.00217	2001.429	-1112.7683	2653.195
2022	735.4144	-663.80745	2134.636	-1404.5108	2875.340
2023	747.0475	-792.33296	2286.428	-1607.2318	3101.327
2024	731.9108	-957.86174	2421.683	-1852.3733	3316.195
2025	732.2079	1098.65717	2563.073	-2067.8586	3532.274
2026	723.6068	-1250.72629	2697.940	-2295.8751	3743.089
2027	720.1359	1394.13130	2834.403	-2513.3568	3953.629

Fig:11 Production forecast

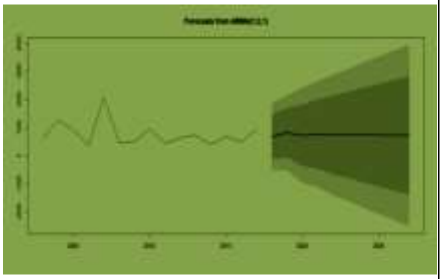


Table: 5

Residuals & Predictive values of Area, Yield and Productions(CEDED REGION)

year	A residuals	Y residuals	P residuals	A predective	Y predictive	P predective
2003	0.5205565	1.191376	0.2696697	1164.5206	266.1914	603.2697
2004	-0.7857512	-1.805380	0.6757360	1510.2142	3453.1946	1267.6757
2005	*-214.9619841*	-533.095212	-463.3631946	1339.0380	2266.9048	460.6368
2006	-578.0808788	-397.622113	-754.3694676	462.9191	2124.3779	-388.3695
2007	410.4950817	2709.383368	1316.2430014	1884.4951	8987.3834	3392.2430
2008	-93.4683524	-1638.368125	-797.0453050	1353.5316	339.6319	-326.0453
2009	-467.9382883	-2070.179756	-883.6285771	523.0617	517.8202	-390.6286
2010	-764.8823535	-450.995919	540.5922361	-628.8824	3015.0041	1502.5922
2011	999.8238396	370.213894	-217.0168277	2057.8238	3051.2139	226.9832
2012	41.7188844	-116.687055	-57.7366664	1130.7189	2783.3129	577.2633
2013	28.7763566	859.505100	252.7839521	1139.7764	4792.5051	991.7840
2014	-260.9630661	-144.666116	-250.2469229	571.0369	2629.3339	140.7531
2015	-66.8461418	1241.299335	145.7239208	665.1539	6026.2993	839.7239
2016	261.3288712	-442.772159	2.3333701	1229.3289	2669.2278	487.3334
2017	-246.6139287	2196.844463	358.7155252	450.3861	8439.8445	1300.7155

Fig:12. Area-Residuals

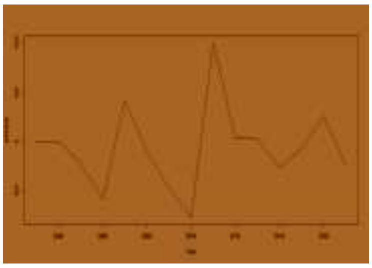


Fig:13:Yield-Residuals

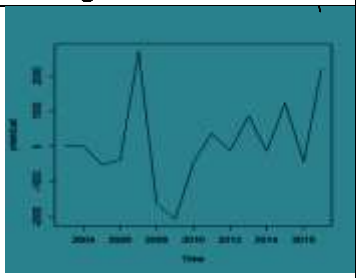


Fig:14Prod.-Residuals

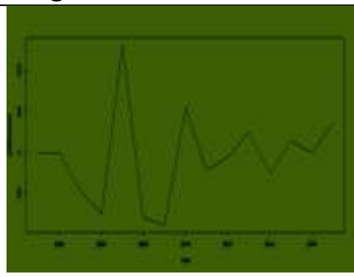


Table: 6

Area, yield , and Production predictive (CEDED REGION)

year	Area predective	Yield predictive	Production predective
2018	663.64312	4338.339	670.0918
2019	630.28624	5078.286	818.4277
2020	596.92936	5563.951	724.4765
2021	563.57247	5098.539	770.2133
2022	530.21559	5657.126	735.4144
2023	496.85871	5666.277	747.0475
2024	463.50183	5738.279	731.9108
2025	430.14495	5998.293	732.2079
2026	396.78807	6050.198	723.6068
2027	363.43118	6216.148	720.1359
2028	330.07430	6367.048	713.7073
2029	296.71742	6480.838	708.9839
2030	263.36054	6636.899	703.2773
2031	230.00366	6769.308	698.1376
2032	196.64678	6905.240	692.6710
2033	163.28990	7048.485	687.3929
2034	129.93301	7183.148	682.0062
2035	96.57613	7322.712	676.6820
2036	63.21925	7461.466	671.3218
2037	29.86237	7598.782	665.9824

Table:7

Time series data values of Area, Yield and Production(CEDED REGION)

Year	TIME SERIES A-DATA	TIME SERIES Y-DATA	TIME SERIES P-DATA
2003	1164	2665.1914	603.2697
2004	1511	3453.1946	1267.6757
2005	1554	2266.9048	460.6368
2006	1041	2124.3779	-388.3695
2007	1474	8987.3834	3392.2430
2008	1447	339.6319	-326.0453
2009	991	517.8202	-390.6286
2010	136	3015.0041	1502.5922
2011	1058	3051.2139	226.9832
2009	991	517.8202	-390.6286
2010	136	3015.0041	1502.5922
2011	1058	3051.2139	226.9832
2012	1089	27832.3129	577.2633
2013	1111	4792.5051	991.7840
2014	832	2629.3339	140.7531
2015	732	6026.2993	839.7239
2016	968	2669.2278	487.3334
2017	697	8439.8445	1300.7155

Fig: 15 **Time series data values of Area, Yield and Production(CEDED REGION)**

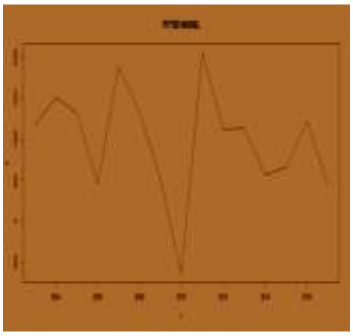
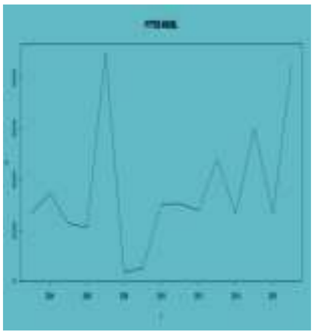
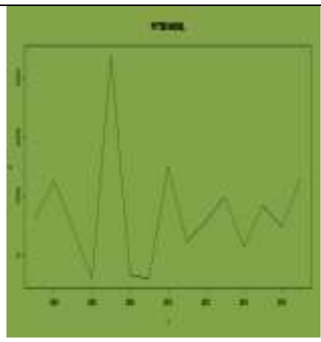




Table: 8

Area, yield and Production Training Set error measure(CEDED REGION)

	ARIMA	Trainng set error measures						
		ME	RMSE	MAE	MPE	MAPE	MASE	ACF
AREA	(1 , 2, 1)	-63.45848	413.5649	295.8136	-40.37166	61.14672	0.913206	-0.2363987
YIELD	(0, 2, 1)	105.483	1222.83	878.3086	-60277613	24.9433	0.5778618	-0.13744871
PRODUCTION	(2, 2, 1)	-53.73797	550.8458	402.7163	-34.2153	62.67673	0.7516369	-0.388102

IV. CONCLUSIONS

AREA OF GROUNDNUT CROP CONCLUSION

Table: 9
Identification of ARIMA(p,d,q) MODEL for AREA

Model	Area ARIMA	Coefficients	SE	Intercept	σ^2	Log likelyhood	AIC
(1,0,1)	AR1	0.0498	0.5624	1046.008	115069	-108.74	225.49
	MA1	0.2924	0.5138	117.233			
(1,1,1)	AR1	0.1970	0.3672		134509	-102.82	211.65
	MA1	-0.7633	0.2536				
(2,1,1)	AR1	0.0369	0.3832		124849	-102.36	212
	AR2	-0.3039	0.2835				
	MA1	-0.5565	0.3623				
(0,1,1)	MA1	-0.6696	0.2105		137404	-102.98	209.95
(1,2,1)	AR1	-0.2117	0.2744		183257		
	MA1	-1.000	0.2106				
(1,1,0)	AR1	-0.2581	0.2570		171256	-104.26	212.51
(2,1,2)	AR1	0.1838	0.6701		123904	-102.32	214.63
	AR2	-0.3665	0.3227				
	MA1	-0.7131	0.7253				
	MA2	0.1540	0.5125				
(2,0,2)	AR1	-0.4117	0.4538	1047.8754	84268	-107.74	227.48
	AR2	-0.7303	0.3632				
	MA1	0.8504	0.5816				
	MA2	0.9998	0.4785	99.7099			
(1,1,2)	AR1	-0.1588	0.7451		131574	-102.68	213.35
	MA1	-0.3572	0.6960				
	MA2	-0.2946	0.4351				
(1,2,0)	AR1	-0.4470	0.2389		378348	-102.04	208.08
(0,2,1)	MA1	-1.000	0.2025		197349	-99.02	202.04

In the present study, the ARIMA (1,2,1) was the best fitted model through the minimum value of AIC, then used for prediction up to 10 years of the area of groundnut in ceded districts using 15 years time series data i.e. from 2003-2004 to2017-2018. ARIMA(1,2,1) was used because the reason of its capability to make prediction using time series data with any kind of patterns and with auto correlated successive values of the time series. The study was also validated and statistically tested that the successive residuals in the fitted ARIMA (1, 2,1) were not correlated, and the residuals appear to be normally distributed with the mean zero and constant variance. Hence, it can be a satisfactory predictive model for the groundnut area in ceded districts in Andhra Pradesh for the period of 2018 to 2027. The ARIMA (1,2,1) model projected an increment in the area for the duration of 2018 to 2027. The prediction of 2027 is resulted approximately **363.4312**'000 ha . Like any other predictive models for forecasting , ARIMA model has also limitations on accuracy of the predictions yet it is widely used for forecasting the future values for time series.

YIELD OF GROUNDNUT CROP CONCLUSION

Table 10

Identification of ARIMA(p,d,q) MODEL for YIELD

Model	YIELD ARIMA	Coefficients	SE	Intercept	σ^2	loglikely-hood	AIC
(1,2,2)	AR1	-0.4498	0.3036		1951664	-114.66	237.32
	MA1	-1.4436	0.3670				
	MA2	0.5442	0.3058				
(1,1,1)	AR1	-0.4554	0.2952		1643425	-120.76	247.53
	MA1	-0.6894	0.3398				
(2,1,1)	AR1	-0.7406	0.5426		1631640	-120.63	249.25
	AR2	-0.2889	0.4637				
	MA1	-0.3637	0.6551				
(2,2,1)	AR	-0.9559	0.2468		1725361	-114.44	236.89
	AR2	-0.4515	0.2410				
	MA1	-1.0000	.7099				
(1,1,2)	AR1	-0.3016	0.5638		1648515	-120.7	249.41
	MA1	-0.8152	0.4808				
	MA2	0.2104	0.6083				
(1,0,0)	AR1	-0.4288	0.2773	3437.8939 217.0428	1374004	-127.38	260.77
(0,0,1)	MA1	-0.4099	0.3307	3423.1423 195.9421	1403675	-127.54	261.07
(1,0,1)	AR1	-0.4054	0.5620	3437.076	1373603	-127.38	262.77
	MA1	-0.0303	0.6045	215.595			
(2,1,2)	AR1	-0.7411	1.1040		1631640	-120.63	251.25
	AR2	-0.2890	0.5541				
	MA1	-	1.0861				

		0.3632					
	MA2	-0.0004	0.9182				
(2,1,0)	AR1	-0.9828	0.2389		1691634	-120.8	247.59
	AR2	-0.4665	0.2322				
(1,2,0)	AR1	-0.7233	0.1845		5998920	-120.26	244.53
(0,1,2)	MA1	-1.000	0.2115		4129228	-118.78	241.57
(1,2,1)	AR1	-0.6431	0.2120		2334899	-115.81	237.63
	MA1	-1.0000	0.2605				
(2,2,2)	AR1	-0.8072	0.4743		1817940	-114.37	238.73
	AR2	-0.3552	0.3826				
	MA1	-1.1280	0.6188				
	MA2	0.2195	0.5262				

In the present study, the ARIMA (0, 2 ,1) was the best fitted model through the minimum value of AIC, then used for prediction up to 10 years of the yield of groundnut in ceded districts using 15 years time series data i.e. from 2003-2004 to 2017-2018. ARIMA (0, 2 ,1) was used because the reason of its capability to make prediction using time series data with any kind of patterns and with auto correlated successive values of the time series. The study was also validated and statistically tested that the successive residuals in the fitted ARIMA (0,2 ,1) were not correlated, and the residuals appear to be normally distributed with the mean zero and constant variance. Hence, it can be a satisfactory predictive model for the groundnut yield in ceded districts in Andhra Pradesh for the period of 2018 to 2027. The ARIMA (0,2,1) model projected an increment in the yield for the duration of 2018 to 2027. The prediction of 2027 is resulted approximately **6216.148** 'kg/ ha .

Like any other predictive models for forecasting, ARIMA model has also limitations on accuracy of the predictions yet it is widely used for forecasting the future values for time series.

PRODUCTION OF GROUNDNUT CROP CONCLUSION

Table 11
Identification of ARIMA(p,d,q) MODEL for PRODUCTION

Model	PROD. ARIMA	Coefficients	SE	Intercept	$\sigma^{\wedge 2}$	Log likelihood	AIC
(1,0,1)	AR1	-0.2205	0.4445	765.2733	159820	-111.21	230.42
	MA1	-0.1346	0.4025	74.9200			
(1,1,2)	AR1	-0.1931	0.3703		166244	-104.9	217.8
	MA1	-1.0998	0.3260				
	MA2	0.4766	03460				
(2,0,2)	AR1	-0.6029	0.3932	765.8953	118707	-109.65	231.3
	AR2	-0.7986	0.2813				
	MA1	0.2050	0.4081				
	MA2	0.8082	0.5450	75.2015			
(2,1,2)	AR1	-1.0477	0.3782		138381	-103.72	217.43
	AR2	-0.6420	0.2091				
	MA1	-0.1285	0.4993				
	MA2	-0.154	0.448				
(2,1,1)	AR1	-0.9458	0.2739		139690	-103.77	215.54
	AR2	-0.6215	0.2299				
	MA1	-0.2511	0.4060				
(0,0,1)	MA1	-0.2998	0.2018	764.5576	162254	-111.31	228.62
				75.0250			
(1,0,0)	AR1	-0.3329	0.2349	765.9133	161114	-111.27	228.53

				79.0824			
(1,1,1)	**AR1**	**-0.4192**	**0.2658**		**186617**	**-105.62**	**217.23**
	MA1	**-0.7552**	**0.2130**				
(2,0,1)	**AR1**	**-0.9846**	**0.3561**	**768.9649**	**140292**	**-110.37**	**230.74**
	AR2	**-0.4429**	**0.2146**				
	MA1	**0.6430**	**0.3488**	**67.3961**			

In the present study, the ARIMA (2,2,1) was the best fitted model through the minimum value of AIC, then used for prediction up to 10 years of the production of groundnut in ceded districts using 15 years time series data i.e. from 2003-2004 to 2017-2018. ARIMA (2,2,1) was used because the reason of its capability to make prediction using time series data with any kind of patterns and with auto correlated successive values of the time series. The study was also validated and statistically tested that the successive residuals in the fitted ARIMA (2,2,1) were not correlated, and the residuals appear to be normally distributed with the mean zero and constant variance. Hence, it can be a satisfactory predictive model for the groundnut yield in ceded districts in Andhra Pradesh for the period of 2018 to 2027. The ARIMA (2, 2, 1) model projected an increment in the production for the duration of 2018 to 2027. The prediction of 2027 is resulted approximately **720.1359** '000 tonnes. Like any other predictive models for forecasting, ARIMA model has also limitations on accuracy of the predictions yet it is widely used for forecasting the future values for time series.

The empirical **Forecasting *Area, Yield, and Production of Groundnut Crop in Ceded Region Using R- software*** findings of study could help to forecast any such commodities. The researchers and policy makers will thus get access for making further extensive research work. We firmly believe that this research has shed some important light on the subject area encompassing time series forecasts of selected agricultural crops in Ceded Region. These empirical findings can be an important source of information to many researchers and policy formulators as far as agricultural crops in Rayalaseema (Ceded region) are concerned.

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