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Time Series Modelling and Forecasting of Pulses Productivity in Tamil Nadu, India

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Abstract

Pulses are staple protein-rich food for Indian vegetarians, and India is one of the largest producers in the world. Pulse production is influenced by a variety of elements such as rainfall, fertilizer, crop area as well as productivity. Analysis of production behavior, modeling and forecasting of productivity taking all these factors in to consideration play vital roles in human nutritional security. The present investigation is an attempt to predict and forecast the productivity of total pulses in Tamil Nadu using time series data. The present study was carried out to efficiently forecast the productivity of black gram, chickpea, green gram, horse gram, red gram, and total pulses in Tamil Nadu. Yearly data were used for the period from 1970 to 2020. based onthe results of model adequacy criteria, the most suitable ARIMA (autoregressive integrated moving average) model and Holt's Linear Trend model are chosen to capture the pulse productivity. Results revealed that Holt's linear trend model fits best for black gram, chickpea, green gram, and red gram. ARIMA (0,1,1) fits best for horse gram and ARIMA (3,1,0) fits best for the total pulses productivity. The forecasted value of pulses using the best-fitted model shows that there is a steady increase in the productivity of pulses. The productivity of total pulse increases in 2021,2022,2023 but slightly decreases in 2024 and again increases in 2025. This study will play an important role in determining the gap between the productivity of and demand for pulses in the future.

Keywords: *ARIMA, Holt's Linear Trend Model, Forecasting, Pulse's productivity, Tamil Nadu*

Introduction

Pulses are one of the important segments of the human diet in the Indian subcontinent along with cereals and oilseeds. The split grains of pulses, called dal are an excellent source of high-quality protein, essential amino and fatty acids, fibers, minerals, and vitamins [23]. Pulses are an important component to sustain agriculture production as the pulse crops possess wide adaptability to fit into various cropping systems, improve the soil fertility being leguminous in nature and physical health of soil while making the soil more porous due to the tap root system [5].

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India is the largest producer and consumer of pulses in the world contributing around 25-28 percent of the total global production. Globally 90 percent of the red gram, 75 percent of chickpea, and 37 percent of the lentil area is contributed by India [18]. Pulses are the basic ingredient in the diets of a vast majority of the Indian population, as they provide a perfect mix of the vegetarian protein component of high biological value when supplemented with cereals [3]. The country grows a variety of pulse crops such as chickpea, red gram, green gram, black gram, dry peas, lentils, etc. under a wide range of agro-climatic conditions [20].

Pulses are also excellent feed and fodder for livestock. Endowed with the unique ability of biological nitrogen fixation, carbon sequestration, soil amelioration, low water requirement (250 to 300 mm), and capacity to withstand the harsh climate, pulses have remained an integral component of sustainable crop production systems, especially in the dry areas [22]. Every class of Indian society invariably includes pulses in their daily diet and traditionally it is consumed with cereals, which are relatively rich in fsulfur-containing amino acids. A good quality protein is obtained in dishes prepared using pulses with cereals. The human body utilizes between 32 and 78% of protein from pulses ingested. [11] stated that pulses represent the most important food grain to prepare staple food extensively to cover basic protein and energy needs throughout the history of humanity. Further, in India, the government sector provides all assistance to promote pulse production besides offering minimum support price (MSP) for food grains produced by farmers.

Despite the imports, in 2019, the consumption of pulses in India amounted to 48 g per capita per day, slightly less than the50 g per capita per day recommendation of the Indian Medical Research Council. One of the major hurdles in meeting self-sufficiency in pulses is policies that promote staple crop production, such as subsidies for fertilizers and credit and irrigation facilities that discourage the production of pulses and other legumes [10].

In Tamil Nadu, pulses are grown mostly under rain-fed conditions. Besides other external factors, erratic rainfall has a serious impact on the productivity of pulses [17]. There is already a demand and supply gap for pulses in the country, and the uncertainty caused by vagaries in rainfall further widens the gap. Therefore, forecasting production, productivity, and prices areimportant for effective planning and decision-making related to the production of pulses. The time-series approach of forecasting is the most reliable one. based on the past pattern in data, a very common method applied for forecasting a time series [16] is the autoregressive integrated moving average (ARIMA) method. [19] applied the ARIMA model for projection purposes and observed stagnancy in the area of pulse production but a rise in pulse production and productivity. Many other studies have used the ARIMA model for forecasting; for example, for forecasting sugarcane production [13] and sugarcane and cotton crop production and yield [4] in Pakistan. In Tamil Nadu, ARIMA models were used for area, production, and production forecasting for various crops [6] and sugarcane yield [21]. Holt's Linear Trend method and Holt-Winters method are both long-term forecasting techniques. This paper compared the performance ofARIMA and Holt's Linear Trend model for forecasting of pulse productivity of Tamil Nadu.

Materials and Methods

In the present investigation, the majority of the information on the time series data of black gram, chickpea, green gram, horse gram, red gram, and total pulse productivity of Tamil Nadu the period of 1970 to 2020 (India stat, 2022).To set the model structure, 80% of the total data is selected for training, and to approve the model, the remaining 20% is chosen for the test.

Time series modeling

Time series analysis is performed for the data containing a sequence of observations that are taken at equal successive points of time interval [12]. With help of past observation, time series analysis can predict the future scenario of the current study. There are different techniques in time series analysis that are used based on the nature of the study and the nature of the data [14]. In this study, two different methods are employed and the best model fitted for each data is selected based on the error measures. For a good estimation of time series analysis, a minimum of 50 observations is required for the study.

Auto-Regressive Integrated Moving Average (ARIMA) model

In 1976, [7] came out with a new univariate time series model called Auto-Regressive Integrated Moving Average (ARIMA) model. It is also called Box and Jenkins model. ARIMA model is a classical linear time series technique developed by combining two components such as Auto-Regressive (AR) and Moving Average (MA) along with Integration (I). In ARIMA (p, d, q) equation, indicates the degree of the AR component, indicates the degree of the MA component and d indicates the number of differences (I)required to make the data stationary. ARIMA model with (p, q) indicates that data is already in stationary form and requires no differencing. ARIMA (p, d, q) shows that the data is nonstationary and differenced d times [15]. The method consists of the following steps.

Step 1: Identification – Initially the data is checked for stationarity. Stationarity is the form where the mean and variance of data are constant over time. If the data is -non-stationary then appropriate differencing is done to convert the data into [8]. The augmented dickey fuller test is performed to test the stationarity of study data. Autocorrelation function plots and partial autocorrelation function plots were also used to check the stationarity of the data visually. From plots and tests, the values of p, d, and q can be obtained. The lags in the PACF plot give the value of the AR(p) component and the lags in the ACF plot give the value of the MA(q) component. The value of d is based on the number of differentiations done on data.

Step 2: Estimation – The next step is to estimate the parameter of AR and MA components by appropriate estimation methods.

Step 3: Diagnostic checking – Different combinations of p, d, and q values are checked for the process and the appropriate ARIMA model is fitted based on the values model selection criteria. Probabilistic model selection criteria like the Akaike information criterion (AIC) and Schwartz-Bayesian criterion (BIC) are used to select the best model [12]. The lower the value of AIC and BIC, the model is best fitted. Finally, the residual of the selected model is checked for white noise using the Box-pierce test. If the residuals are white noise, then the fitted model is used for forecasting. If the condition is not satisfied then, the process goes back to fitting another best model [2]. This is an iterative process, which is repeated until the condition is satisfied. Forecasting by ARIMA is done only if the condition is satisfied.

$$AIC = - 2LL + 2k$$
$$BIC = k\ln(n) - 2\ln$$

Here, k indicates the number of estimated parameters in the model and L stands for the maximum value of the likelihood function for the model, n denotes sample sizes.

Holt's linear trend model

Holt's linear trend method is a conventional method of estimating the level and trend in the data. This method is also referred to as the double exponential smoothening method and was introduced by Charles holt [1]. This method is the extension of simple exponential smoothening which deals with level and trend components in the data [24]. The equation is given by

$$u_i = \alpha y_i + (1-\alpha)(u_{i-1} + v_{i-1})$$
$$v_i = \beta (u_i - u_{i-1}) + (1-\beta)v_{i-1}$$
$$\hat{y}_{i+1} = u_i + v_i$$

Where α is used as a level smoothing constant. There is a second constant, β being added in this method which acts as a trend smoothing constant. u_i is the trend smoothed constant process value for period i and v_i is the smooth trend value for period i.

Validation of models and forecasting

A comparative study is carried out between the models using error prediction criteria like Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Both models were fitted for the data and the model containing a low error score is considered to be the best model for the respective data [9]. Forecasting is done for each data based on the selected best model.

$$RMSE = \sqrt{\frac{\Sigma_{i=1}^{n} |y_i - \hat{y}_i|^2}{n}}$$

$$MAE = \frac{\Sigma_{i=1}^{n} |y_i - \hat{y}_i|}{n}$$

Softwares like SAS, MATLAB, EViews, and R program were good in and analyzing the time series data. This present study makes use of the R program for fitting ARIMA and Hot's linear trend model for selected data.

Results and Discussion

Summary statistics are calculated for the productivity data concerning black gram, chickpea, green gram, horse gram, red gram, and total pulse of Tamil Nadu for 51 years (Table 1). It revealed the maximum, minimum, range, mean, standard deviation, kurtosis, and skewness value of different pulse crops. The average productivity of the total pulse of Tamil Nadu is 431.65 over the last 51 years. The table also shows that the productivity of red gram (678.65) is higher and it was followed by chickpea (654.06). Green gram has observed the lowest productivity (386.04) in the last 51 years.

Table 1. Descriptive statistics of pulses productivity in Tamil Nadu

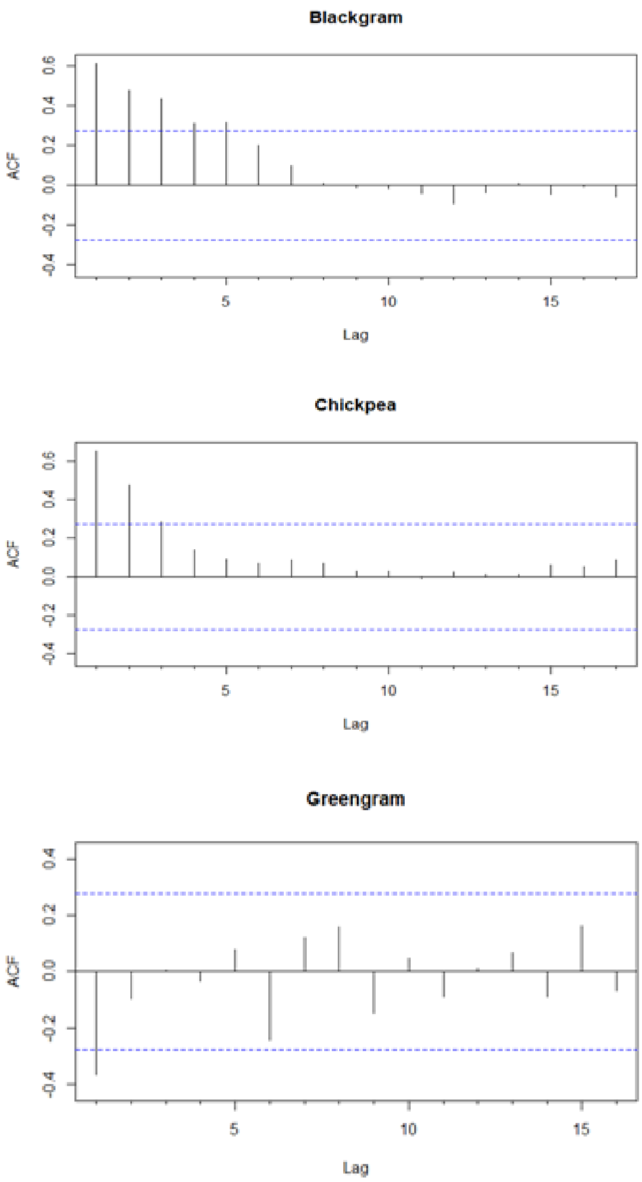
Statistics	Black gram	Chickpea	Green gram	Horse gram	Red gram	Total Pulses
Minimum	209	375	182	225	367	205
Maximum	960	932	787	784	1284	930
Range	751	557	605	559	917	725
Mean	445.92	654.06	386.04	422.31	678.65	431.65
Standard Deviation	169.88	96.11	119.22	158.36	218.78	156.32
Kurtosis	1.12	4.46	3.27	0.02	1.41	1.79
Skewness	1.22	1.29	1.34	0.70	1.25	1.34

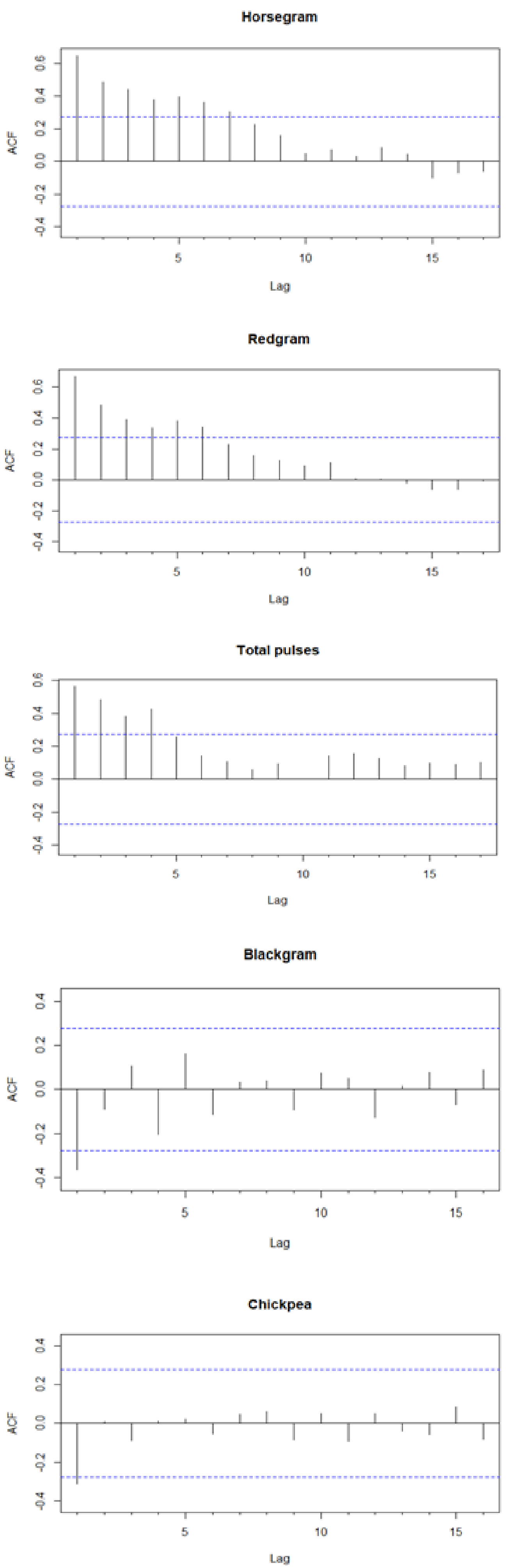
Pearson correlation coefficient is calculated among the pulls data (Table 2). The results noticed that correlation between the productivity of horse gram and red gram is high (0.815) followed by black gram-green gram (0.767), chickpea-red gram (0.747), black gram-horse gram(0.740), black gram- (0.735). green gram –chickpea was found to have a low correlation (0.242). No negative correlation is observed in the pulse data. Total pulse productivity is found to have a high correlation with black gram followed by the , horse gram, green gram, and chickpea.

Table.2. Correlation between different pulse productivity in Tamil Nadu

	Red gram	Chick-pea	Horse gram	Green gram	Black gram	Total Pulses
Red gram	1.000					
Chick-pea	0.747	1.000				
Horse gram	0.815	0.716	1.000			
Green gram	0.545	0.242	0.615	1.000		
Black gram	0.735	0.556	0.740	0.767	1.000	
Total Pulse	0.699	0.576	0.697	0.681	0.779	1.000

Time series data of five pulse crops (black gram, chickpea, green gram, horse gram, red gram) and total pulse productivity of Tamil Nadu is zand analyzed from the period of 1970-2020. Two different time series models ARIMA and Holt's linear trend models were applied to each pulse crop in this study and the best model is selected based on model adequacy criteria. Initially, the data is checked for stationarity using Augmented Dickey-Fuller (ADF) test. The ADF test having a p-value greater than 0.05 indicate the presence of non-stationary in the data. If the data is non-stationary, then appropriate differencing is done to convert them into stationary data [8]. This can also be graphically confirmed by ACF and PACF plots. As the result of this test, it is found that data taken for the study were non-stationary and are differenced one time to convert them into stationary data. This process is presented in fig 1 where the ACF chart of data is presented before and after differences. Even though the ACF plot of green gram seems stationary before differencing, they had shown non-stationary by ADF test. So, they have also differenced one time before they are subjected to modeling [12].





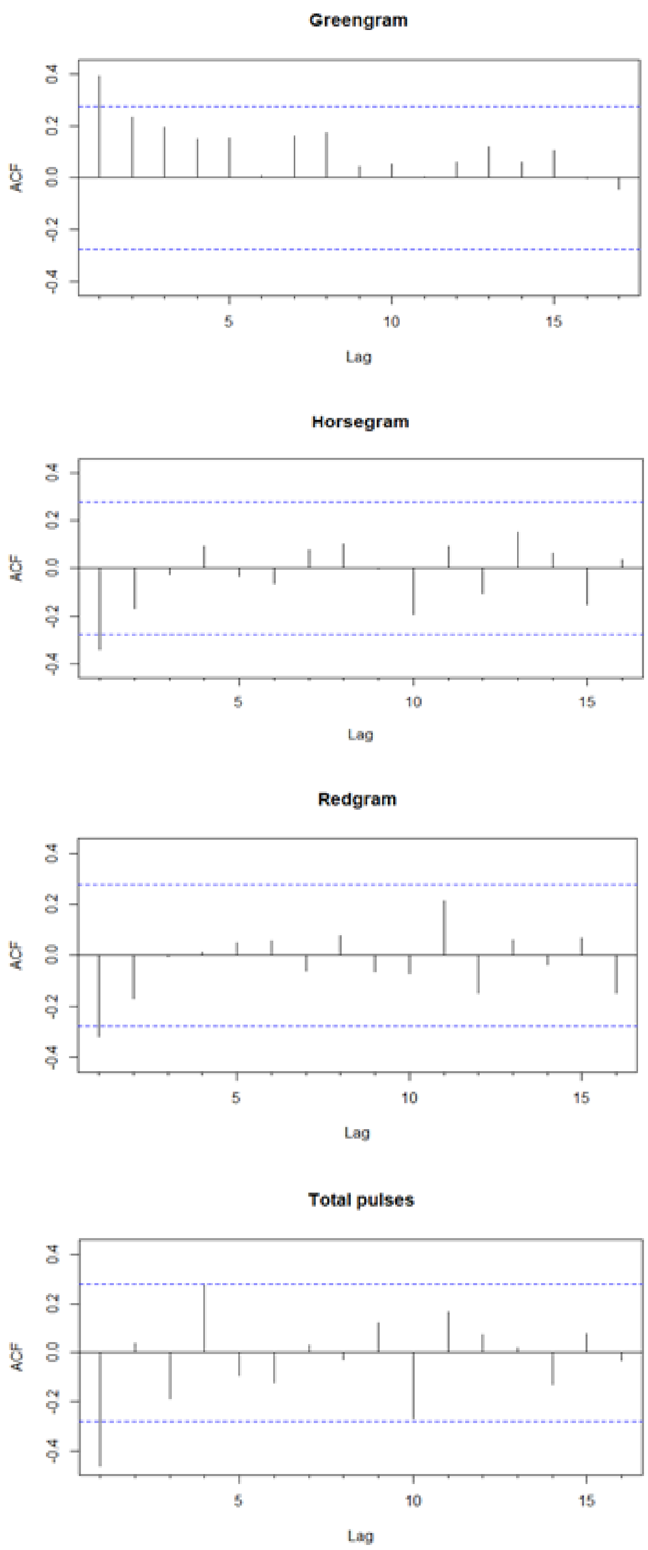


Fig.1. Auto Correlation Function (ACF) plot of the data before and after differences in pulses productivity of Tamil Nadu using ARIMA models

Once all the pulse data was converted to stationarity, they have first modeled using the ARIMA method. The results showed that all the crops (black gram, chickpea, green gram, horse gram, red gram)exhibit the same ARIMA model (0,1,1), and total pulses data of Tamil Nadu exhibit ARIMA model (3,1,0). All the pulses (black gram, chickpea, green gram, horse gram, red gram)have zero AR component and one MA component. Several ARIMA models were fitted for each data and the best model is selected based on the selection criteria like AIC and BIC. The ARIMA model (0,1,1) was selected as the best-fitted model for all the pulse crops as they have low AIC and BIC values. Once the best-fitted ARIMA model is fitted, the residuals are checked for white noise [2]. Box Pierce test was tested for residuals for each model and the white noise is confirmed if the p-value is greater than 0.05. Table 3 shows the values of the ARIMA model component, the standard error of the fitted model, log-likelihood along with the AIC and BIC values. The p-values and X-squared values of the box pierce test were presented in table3 for each data.

Holt's linear trend model is chosen to fit the data as that study data (yearly) is prone to level, trend factor and mostly free from a seasonal component. HLT model is fitted for the given pulse data and the best model for each data is sorted using AIC and BIC values [1]. Results of the HLT model, containing smoothening parameters like alpha, beta values, and initial state values (Table 3). Box pierce test was also used to check the residuals of fitted models.

Table 3. ARIMA and Holt's linear trend model for pulses productivity in Tamil Nadu

	ARIMA model						Box Pierce test	
Black gram	**Model**	**MA1**	**Std. error**	**Log-likelihood**	**AIC**	**BIC**	**X-squared**	**p-value**
	ARIMA (0,1,1)	-0.5297	0.1366	-312.26	628.53	632.35	0.0086096	0.9261
	Holt's linear trend model						**Box Pierce test**	
	Smoothening parameters		**Initial states**		**AIC**	**BIC**	**X-squared**	**p-value**
	alpha	**beta**	**l**	**b**				
	0.3946	$1e^{-04}$	282.6571	9.6246	699.8736	709.532	0.29223	0.5888

	ARIMA model						Box Pierce test	
Chick pea	**Model**	**MA1**	**Std. error**	**Log- likelihood**	**AIC**	**BIC**	**X-squared**	**p-value**
	ARIMA (0,1,1)	-0.3429	0.1388	-279.37	562.74	566.56	0.023298	0.8787
	Holt's linear trend model						**Box Pierce test**	
	Smoothening parameters		**Initial states**		**AIC**	**BIC**	**X-squared**	**p-value**
	alpha	**beta**	**l**	**b**				
	0.606	$1e^{-04}$	566.7646	7.1025	632.9670	642.6261	0.021062	0.8846

	ARIMA model						Box Pierce test	
Green gram	**Model**	**MA1**	**Std. error**	**Log- likelihood**	**AIC**	**BIC**	**X-squared**	**p-value**
	ARIMA (0,1,1)	-0.7940	0.1226	-306.26	616.52	620.34	0.99425	0.3187
	Holt's linear trend model						**Box Pierce test**	
	Smoothening parameters		**Initial states**		**AIC**	**BIC**	**X-squared**	**p-value**
	alpha	**beta**	**l**	**b**				
	$1e^{-04}$	$1e^{-04}$	276.5274	4.2072	680.9897	682.3230	1.9947	0.1579

	ARIMA model						Box Pierce test	
Horse gram	**Model**	**MA1**	**Std. error**	**Log-likelihood**	**AIC**	**BIC**	**X-squared**	**p-value**
	ARIMA (0,1,1)	-0.7507	0.1166	-301.86	609.73	615.47	0.5325	0.4656
	Holt's linear trend model						**Box Pierce test**	
	Smoothening parameters		**Initial states**		**AIC**	**BIC**	**X-squared**	**p-value**
	alpha	**beta**	**l**	**b**				
	0.2345	$1e^{-04}$	226.7808	9.7008	679.9618	689.6210	0.69973	0.4029

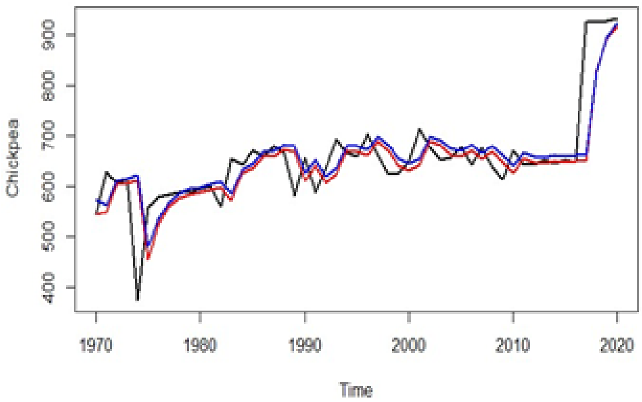
	ARIMA model						Box Pierce test	
Red gram	**Model**	**MA1**	**Std. error**	**Log-likelihood**	**AIC**	**BIC**	**X-squared**	**p-value**
	ARIMA (0,1,1)	-0.6164	0.1233	-315.12	636.23	641.97	0.33544	0.5625
	Holt's linear trend model						**Box Pierce test**	
	Smoothening parameters		**Initial states**		**AIC**	**BIC**	**X-squared**	**p-value**
	alpha	**beta**	**l**	**b**			1.4223	
	0.0801	0.0801	434.4553	10.2336	702.7247	712.3838		0.233

	ARIMA model							Box Pierce test	
	Model	**AR1**	**AR2**	**AR3**	**Log-likeli-hood**	**AIC**	**BIC**	**X-squared**	**p-value**
Total pulse	ARIMA (3,1,0)	-0.6121 (0.1323)	-0.3804 (0.1470)	-0.3227 (0.1293)	-308.43	624.85	632.5	0.030829	0.8606
	Holt's linear trend model							**Box Pierce test**	
	Smoothening parameters		**Initial states**		**AIC**		**BIC**	**X-squared**	**p-value**
	alpha		**beta**	**l**	**b**				
	1e^{-04}		1e^{-04}	235.103	7.5316	688.6949	698.3540	1.7415	0.1869

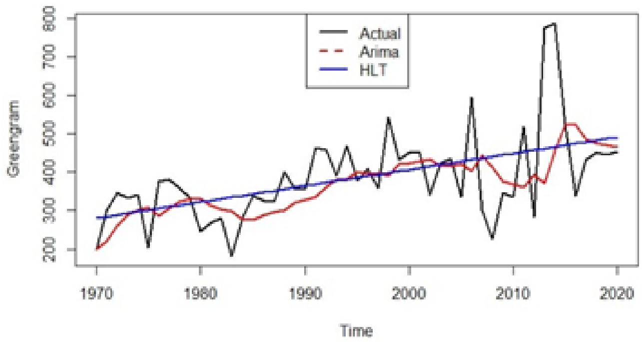
Error measures like root mean square error and mean absolute error were calculated for the fitted models. The suitable method for respective data is found by comparing the error measure results [9]. Method which has low error values are considered to be the best model. The results shows that Holt's linear trend model was the best-fitted model for pulse crops like black gram, chickpea, green gram, and red gram where ARIMA model is the best-fitted model for horse gram and total pulse data (Table 4). Fig. 2 shows the plots containing fitted values of ARIMA and Holt's linear trend model along actual values.

Table 4. Best-fitted model for pulses productivity in Tamil Nadu

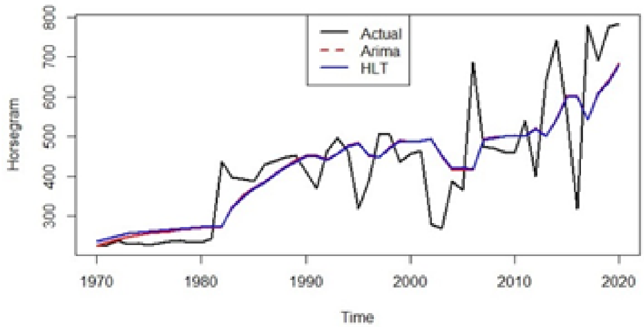
	RMSE		MAE	
	ARIMA	HLT	ARIMA	HLT
Black gram	123.12	**121.21**	86.01	**85.68**
Chickpea	63.90	**62.90**	38.00	**37.90**
Green gram	108.46	**100.73**	74.61	**73.78**
Horse gram	**99.50**	99.72	**69.64**	71.30
Red gram	130.1527	**124.6495**	106.0096	**99.75024**
Total Pulses	**108.63**	113.66	**66.76**	69.73



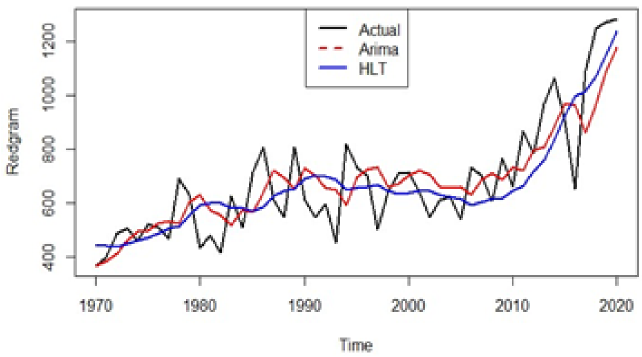
Chick pea



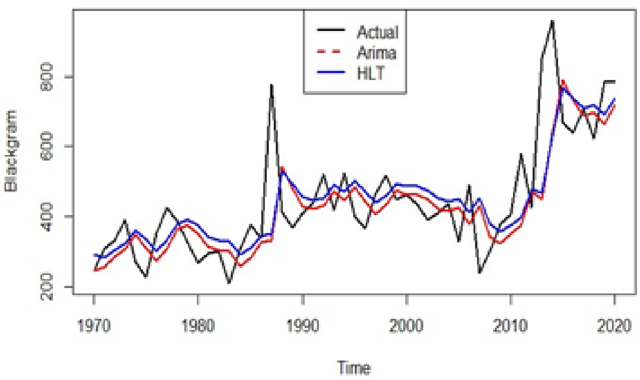
Green gram



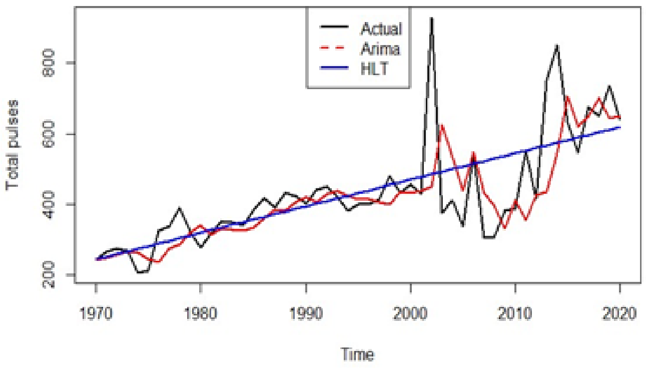
Horse gram



Red gram



Black gram



Total gram

Fig.2. Actual vs Fitted plot by ARIMA and Holt's linear trend model

Table. 5. Forecasting the productivity (Kg/ha) of different pulses in Tamil Nadu

Year	black gram	Chick-pea	Green gram	Horse gram	Red gram	Total Pulses
	Forecast values					
2021	766.08	935.08	495.35	719.88	1320.31	673.38
2022	775.70	942.18	499.56	729.97	1399.31	660.78
2023	785.32	949.28	503.76	740.06	1478.31	686.40
2024	794.94	956.39	507.97	750.15	1557.31	664.41
2025	804.56	963.49	512.18	760.24	1636.31	672.19

To assess future quantity based on recent information, the application mainly uses time series in forecasting models (Das *et al.*, 2019). The present investigation aimed to establish the importance of ARIMA models and Holts's linear trend models. It has attempted to make short-term predictions for pulse productivity (Kg/ha) in Tamil Nadu (Table 5). The crops are forecasted based on the model which fits best for the respective crop. Blackgram, chickpea, green gram, and red gram was forecasted using Holts's linear trend model whereas horse gram and total pulse productivity were forecasted using the ARIMA model.

Conclusion

The study attempts to forecast the productivity of pulse crops and total pulse using the time series models like ARIMA and Holt's linear trend. The results revealed that holt's linear trend model fits best for the pulses like black gram, chickpea, green gram, and red gram. ARIMA (0,1,1) fits best for horse gram and ARIMA (3,1,0) fits best for the total pulse productivity. The forecasted value of pulses using the best-fitted model reveals that there is a steady increase in the productivity of pulses in recent years. The productivity of total pulse increases in 2021, 2022, 2023 but slightly decreases in 2024 and again increases in 2025. This slight variation may be due to external factors like climate. A clear idea for understanding and developing the tactic for further improvement in pulse productivity can be obtained from the above critical findings. Agriculture funding, price support programs, improved management practices, research employees, and other variables that will contribute to long-term output will be the most important factors in maintaining this trend. It also aids the policymakers in understanding the future insight of pulse demand and supply.

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