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MODELING AND FORECASTING OF LENTIL PRODUCTION IN INDIA AND ITS INSTABILITY

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ABSTRACT

India is a major producer of pulses around the world, which constitute an essential component of vegetarians' protein-rich diets in India. The present study attempts to apply the autoregressive integrated moving average (ARIMA) and Holt linear trend model approach to investigate lentil production trends in Bihar, Madhya Pradesh, Uttar Pradesh, West Bengal, and India. Yearly data were collected from Agriculture Statistics at a glance, 1970 to 2019 were used for forecasting up to 2029. In comparison, the ARIMA model is the best for prediction based on the maximum value of R^2 and lowest value of MAPE, MPE, RMSE, and MAE. The results showed that ARIMA (1,1,5) model for Bihar, ARIMA(0,1,4) model for Madhya Pradesh, ARIMA (0,1,5) for Uttar Pradesh, ARIMA (0,1,4) for West Bengal, and ARIMA (0,1,2) for India was found suitable to forecast the future of lentil with an 80% and 95% accuracy level and according to the analysis of instability, the instability is increasing in all three states and India, but the instability was decreasing in Uttar Pradesh. While in the decomposition analysis the area effect was an essential factor for the change in lentil production in Bihar, Madhya Pradesh, West Bengal, and India, but in Uttar Pradesh the yield effect was responsible during the overall periods. Besides this research will be essential to determining the future gap between pulse production and demand.

Keywords: ARIMA, Decomposition, Forecasting, Holt's linear trend, Instability and lentil production.

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INTRODUCTION

India, with a large population of poor and malnourished people, has long encouraged a cereal-based diet based on subsidized staples like rice and wheat. Dietary habits, on the other hand, are changing today. Policymakers, researchers, and health advocates are exploring strategies to combat malnutrition, not only hunger, in the country. Pulses (the dried, edible seeds of legumes) are becoming more popular as the focus shifts from calorie consumption to nutrients. Hunger can be classified into three types: calorie insufficiency, protein deficiency, and micronutrient deficiency (Yashpal *et al.,* 2022).

Pulses are one of the most significant food crops in the world and India, where they contribute the most to financial gains. Chickpeas, pigeon peas, moong beans, black beans, lentils, peas, and a variety of other beans are among the major pulses farmed (Mishra *et al.,* 2021a). Most countries' pulses are produced in India, which produces for 25% of global output. Additionally, it consumes the most pulses, accounting for 27% of global consumption. In 2018, total pulse production was 92.28 million tonnes (FAO, 2018), with dry beans accounting for 32.98 percent, chickpeas for 18.63 percent, peas for 13.53 percent, cowpeas for 7.83 percent, lentils for 6.86 percent, and pigeon peas for 6.45 percent. (Srivastava *et al.,*2010).

Although India is the world's leading pulses producer (23020 tonnes in 2019), local production is insufficient to meet domestic demand, and the country must import pulses of 3 to 5 million tonnes of annually (15 percent of global imports), making it the leading importer of pulse globally (Suresh and Reddy, 2016). After, arhar and gram, lentil is the third most important pulse crop.

Lentils are thought to be one of the first crops to be domesticated and cultivated in human history. The significance of this crop is still seen as similar among the world's vegetarian population. In 2014, global lentil production reached over 5.0 million tonnes. After chickpea, lentil is India's second most popular rabi pulse. In India, according to the government of India 90% of the total lentil production in 2017-18 are from Madhya Pradesh (45.09 percent), Uttar Pradesh (29.69 percent), Bihar (9.47 percent), and West Bengal (6.59 percent) (FAO, 2017).Until recently, India was the world's greatest producer of lentils, but Canada has taken over the lead and moved India to second place. It has been claimed that there is potential for growing lentil area during the rabi season, as the crop has a lower cost per hectare and a greater net return than competitive crops such as gram and mustard when water is scarce and resources are few. Furthermore, the lentil-based cropping system is lucrative and has a very high yield, making it suited for largely untapped rice-fallows in water-stressed areas. (Ahmad *et al.,*2018).

Lentil is a vital human meal that is mainly taken as dried seeds and contains protein, carbohydrates, vitamins, minerals, and other nutrients. Lentil is a great feed for cattle, according to nutritional studies. Livestock can be fed husks, dried leaves, stems, fruit walls, and bran. Lentil residue is made up of around 10.2% moisture, 1.8% fat, 4.4% protein, 50% carbohydrate, 21.4% fiber, and 12.2% ash (bran).

The present investigation used Holt's linear trend and ARIMA models to anticipate lentil production in Bihar, Madhya Pradesh, Uttar Pradesh, West Bengal, and India over 10 years period from 2020 to 2029. This would allow for the forecasting of lentil pulse production from 2019 onwards. Such an endeavor would enable policymakers to anticipate future grain storage, import, and export requirements for lentil pulses, allowing them to take necessary measures in this area. As a result, the forecasts will aid in the conservation of many of our country's valuable resources, which would otherwise be wasted (Rahman *et al.,*2013).

Many studies have attempted to apply the ARIMA and Holt's linear trend model for forecasting for example, studies were supported by,Mishra*et al.,* (2015) and Patowary *et al.,* (2017).Pirzado *et al.,* (2021) were used sophisticated statistical approaches to forecast wheat production in Pakistan's Sindh province. Devi*et al.,* (2021) created a model to anticipate wheat production in Haryana using the Box–Jenkins ARIMA model and artificial neural network (ANN) approach. ARIMA (4,1,4) was the best-fitted model over the ARIMAX and GARCH models in Vishwajith *et al*., (2019) estimating of moong production. Contrary to it, Ray and Bhattacharyya (2020) found that ARIMAX (1,1,1) is better suited than the ARIMA model for pulse output. The three aspects such as data trends in a certain location, the quantity of output, and pulse yield in India were researched by Savadatti (2017) who applied the ARIMA type and observed stagnancy in the area while increasing pulse yield and production. Many other reviews have employed the ARIMA model for forecasting, viz., cotton yield and production (Ali *et al.,*2015) in Pakistan, the different crops of forecasting of area, production, and productivity (Balanagammal *et al.,*2000), sugarcane yield (Mishra *et al.,* 2021b) in India. Yonar *et al.,*(2021), used ARIMA and Holt's Linear Trend Model to forecast wheat production in the South Asian region. Mishra *et al.,* (2021c) used ARIMA, GARCH, and Holt's linear trend model to forecast milk output in SAARC countries and other countries. Vishwajith *et al.,*2018 were unable to prove that GARCH or ARIMA were superior in data modelling for arhar production in India.

MATERIALS AND METHODS

The methodologies of the research problem are discussed below-

Source of data: The data gathered is entirely secondary. The data on lentil production from 1970 to 2019 was collected from Agricultural Statistics at a Glance.

Descriptive Statistics: Descriptive statistics provide numerical data in a logical and understandable format. We may employ a variety of measures or just one measure to assess a large number of people in a research project. Descriptive statistics help in the interpretation of large quantities of data. Each descriptive statistic reduces a large amount of information into a small amount of text. To describe the pattern of the series in Bihar, Uttar Pradesh, Madhya Pradesh, West Bengal, and India, researchers used maximum, minimum, mean, skewness, and kurtosis analyses.

Instability and It's Measure: Srivastava *et al.,* (2022 a) and the index developed by Cuddy and Della (1978) were used to measure the production's level of instability.

$CV_t = (CV) \times \sqrt{1 - R^2}$

$C.V. = \frac{\sigma}{\bar{X}} \times 100$

Where, σ= Standard Deviation

$\bar{X} = Mean$

R^2 = coefficient of determination of the variable's linear trend model.

CV_t = CV around trend

Decomposition analysis: Minhas (1964) used the Decomposition analysis model, which is shown below, to determine the proportional contribution of area and productivity to the overall production of the lentil crop.

$P_o = A_o \times Y_o$ and

$P_n = A_n \times Y_n$ -- (1)

Area, production, and yield in the base year are A_o, P_o, and Y_o, respectively, whereas A_n, P_n, and Y_n are the values of the relevant variable in the nth-year item.

Where,

A_o and A_n = Area Y_o and

Y_n = yield in the base year and nth year respectively.

$P_n - P_o = \Delta P$ $A_n - A_o = \Delta A$ $Y_n - Y_o = \Delta Y$--- (2)

For equations (1) and (2) we can write

$P_o + \Delta P = (A_o + \Delta A)(Y_o + \Delta Y)$

Hence,

$$P = \frac{A_0 \Delta Y}{\Delta P} \times 100 + \frac{Y_0 \Delta A}{\Delta P} \times 100 + \frac{\Delta Y \Delta A}{\Delta P} \times 100$$

Production = Yield effect + area effect + interaction effect (Srivastava *et al.,*2022 b)

As a result, the overall change in production can be broken down into yield effect, area effect, and interaction effect due to yield and area changes.

Modelling and Forecasting: The data in this study pertains to lentil production in four key producing states as well as India from 1970 to 2019, with ARIMA and Holt's linear trend model being utilized to model and anticipate lentil production. Because they are simple to apply and give accurate projections, these models are the two most often used methods for modelling and anticipating. The data sets were split into two parts: 80 percent for model creation and 20 percent for model validation, respectively. The data were modelled, validated, and forecasted using Gretl software and MS Excel.

(ARIMA) Auto-Regressive integrated moving average model: Box and Jenkins (1976) proposed the (ARIMA) model, widely known in the literature as the Box Jenkins approach. The ARIMA model combines an autoregressive (AR) and a moving average (MA) model (ARMA). The ARIMA model is employed with non-stationary data, whereas the other models function well with stationary data (Tekindal *et al.,* 2020). ARIMA (p, d, q) model is made by subtracting the data differences from the *d* degree for the stabilization process, followed by the addition of the ARMA (p, q) model. In the ARIMA (p, d, q) model, p indicates the AR model's degree, q represents the MA model's degree, and d specifies the quantity of differences that must be considered in order to stabilize the data (Yonar *et al.,*2020). The equation for the ARIMA(*p*, *d*, *q*) model is as follows:

$Y_t = \phi_1 Y_{t-1} + \phi 2 Y_{t-2} + \cdots + \phi p Y_{t-p} + \alpha_1 - \theta_1 \alpha_{t-1} - \alpha_2 - \theta_2 \alpha_{t-2} - \cdots - \alpha_q - \theta_q \alpha_{t-q}$,

where, $\phi_p$denotes the parameter values relating to the AR operator,

$\alpha_q$denoteserror term coefficient,

$\theta_q$denote the parameter values relating to the MA operator and,

Ytrepresents the data with d*th* differences of the actual data (Brockwell *et al.,*2016; Gujarati *et al.,*2012;Kumari et.al.,2022). The steps listed below can be used to fit time-series data to an ARIMA model (Ahmadzai and Eliw, 2019;Kumari and Kumar, 2021)

Identification Stage: Identified seasonality in the series, confirmed that the variables were stationary, and used the Augmented Dickey-Fuller test, the auto-correlation function (ACF), and the partial auto-correlation function (PACF) of the series to determine the autoregressive or moving average.

Estimation Stage: Discovery coefficients that best fit the selected ARIMA model through the use of computer algorithms.

Diagnostic Stage: The residuals should be autonomous of one another and persistent in mean and variance over-time, and this may be verified by determining whether the projected model fulfills the requirements of a stationary uni-variate process. If the assessment is insufficient, we must go back to the initial stage and attempt to develop a more precise model.

Forecasting Stage: We can utilize the chosen ARIMA model to forecast whether it meets the requirements of a stationary uni-variate process.

Holt's linear trend method: The exponentially weighted moving average is a smoothing random variability average that has the following benefits: (1) The weight of earlier data is reducing, which is highly significant; (2) fairly easy to evaluate; and (3) at most importance for the data set, minimal data are required. Holt (1957) used Holt's three equations for level, trend, and forecast (Mishra *et al.,*2021 b and c)

Level Equation:$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1})$

Trend Equation:$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$

Forecast Equation:$Y_{t+1} = L_t + (h)T_t$

Where, $L_t$stands for an estimate of the series' level at time t,

T_t stands for an estimate of its trend at time t,f

α is the Smoothing parameter for level, ranging from 0 to 1 and,

β is the smoothing parameter for trend, ranging from0 to 1

Augmented Dickey-Fuller Test:

A sort of statistical assessment called a unit root test contains the Augmented Dickey-Fuller test. When employing time series models, a unit root, a property of some random walks (such as stochastic process) in probability theory and statistics, may interfere with the statistical inference process. The unit root is non-stationary but it is not always trend-driven, to put it simply. The following presumptions are used when conducting an ADF test (Karakaya and Jain, 2022)

Null Hypothesis (H_O)-Non-stationary series or series with a unit root.

Alternate Hypothesis(H_A)-Series either had no unit root or is stationary.

If the null hypothesis cannot be demonstrated, this test may reveal that the series is not stationary.

Conditions to Reject Null Hypothesis(H_O).if the time series does not have a unit root and the p-value is less than 0.05, this indicates that the time series is stationary. It doesn't have an ever-changing structure.

RESULTS AND DISCUSSION

Descriptive statistics of lentil production: Table 1 shows descriptive information for the nation's total lentil output from 1950 to 2019 for Bihar, Madhya Pradesh, Uttar Pradesh, West Bengal, and India. Between 1950 and 2019, the total amount of lentils produced in India ranged from 301.00 to 1636.70. As a result, total lentil production in India has increased by nearly 443 percent since 1950. Furthermore, production climbed by 252 percent, 839 percent, 494 percent, and 531 percent in Bihar, Madhya Pradesh, Uttar Pradesh, and West Bengal, respectively. As a result, India's average total lentil production is 784.63. Uttar Pradesh has the highest average lentil production (324.60), while West Bengal has the lowest at 55.33. When looking at the standard deviations of lentil output, India has the largest standard deviation at 289.82.

The positively skewed and platykurtic form of the data for Bihar and India show that there was a minor shift in the area in favor of lentil output during the early era, and that it stayed nearly unchanged during the research period (Vishwajith*et al.,*2018). The data for Madhya Pradesh and West Bengal is leptokurtic and positively skewed, indicating a relatively minor change in the area during the early era. The platykurtic and negatively skewed structure of the data in Uttar Pradesh implies a marginal shift in the area during the late period, and it stayed nearly equivalent throughout the study. The measure of central tendency, namely, mean > median > mode (positive skewness) and mean< median< mode (negative skewness) confirms the criterion, implying that the data are asymmetric in nature.

Table 1: Descriptive statistics of lentil production data

STATE OR COUNTRY	MAXIMUM	MINIMUM	MEAN	STANDARD DEVIATION	SKEWNESS	KURTOSIS
BIHAR	214.69	61.00	131.51	35.30	0.12	-0.36
MADHYA PRADESH	680.50	72.40	212.59	112.11	1.83	5.08
UTTAR PRADESH	505.00	85.00	324.60	139.03	-0.44	-1.19
WEST BENGAL	160.50	25.40	55.33	29.02	2.42	6.22
INDIA	1636.70	301.00	784.63	289.82	0.25	-0.02

Measure the instability of lentil production: Then, we measure the instability of lentil production over the period and over the state presented in table 2. In this analysis, we had to integrate nonlinearity into the trend model, and the coefficient of determination obtained from such a best-fitting model was used to calculate the CV_t value for various sequences, which we call modified Cuddy and Della used by Srivastava *et al.,*2022a, thus the R^2 used in Cuddy and Della model and the present study modified Cuddy and Della. During the analysis of instability, the de-trend coefficient of variation is measured in three periods: period 1 from 1970 to 1986, period 2 from 1987 to 2003, and period 3 from 2004 to 2019.

In which from table2 clearly depicted that the coefficient variance around trend (CV_t) increased marginally, from 13.300 (period 1) to 20.335 (period 3) in Bihar, from14.844 (period 1) to 28.950 (period 3) in Madhya Pradesh, from 27.067 (period 1) to 31.558 (period 3) in West Bengal, and from 12.872 (period 1) to 12.874 (period 3) in India. However, the instability in Uttar Pradesh fell from 23.774 (period 1) to 20.613 (period 3), showing that the maximum instability was seen in Period 3 from 2004 to 2019, whereas the highest instability was seen in Period I in Uttar Pradesh. Thus it can be inferred as the introduction of new technologies has increased the insecurity of lentil production. It increases the risk of farm production and impacts farmer income and the decision to invest in high-paying technology in farming. It also has an impact on price stability and the vulnerability of the low-income household sector. Instability increases agricultural production risk, affecting farmer income and the decision to employ high-paying technology. (Chand and Raju, 2009).

Table 2: Instability of total lentil production

STATE OR COUNTRY	STATISTICS	PERIOD 1	PERIOD 2	PERIOD 3	OVERALL
	R^2	0.612	0.124	0.0417	0.492
BIHAR	CV	21.353	14.561	20.773	26.837
	CV_t	13.300	13.624	20.335	19.116
	R^2	0.003	0.565	0.3810	0.674
MADHYA PRADESH	CV	14.866	20.146	36.797	52.736
	CV_t	14.844	13.281	28.950	30.096
	R^2	0.743	0.501	0.036	0.622
UTTAR PRADESH	CV	46.959	15.511	21.003	42.831
	CV_t	23.774	10.953	20.613	26.321
	R^2	0.214	0.007	0.716	0.161
WEST BENGAL	CV	30.536	30.623	59.269	52.459
	CV_t	27.067	30.511	31.558	48.039
	R^2	0.671	0.617	0.471	0.871
INDIA	CV	22.456	14.465	17.705	36.936
	CV_t	12.872	8.949	12.874	13.221

Decomposition analysis: Afterward, we performed an analysis effort to determine how productivity and area have affected the production (decomposition) of lentils. As described in the methodology section, the study period was split into three sub-periods: Period I (1970–1986), Period II (1987–2003), and Period III (2004–2019).

According to Table 3, the area impact was the main cause of change in lentil production during Period II and the overall Period in Bihar, Period II and the overall Period in Madhya Pradesh and West Bengal, and Period II and the overall Period in India. While the yield impact was a contributing factor to changes in lentil production throughout Period I in Bihar, Period I and Period II in Madhya Pradesh, Period I and Overall Period in Uttar Pradesh, Period III in West Bengal, and India Period I, it was also a factor during Period I in Bihar. The highest yield effect was observed during period III in Bihar and Uttar Pradesh and period I in West Bengal i.e., 3131.52, 2431.37 and 3631.5 with negative area effect and interaction 364.39, 475.63 and 327.00, while in Madhya Pradesh during period II i.e., 904.08 with 61.66 area effect and in interaction 34.19 and while in India Period II i.e., with 1872.54 are effect and 640.58 interaction.

While during period I and period II in Bihar, Madhya Pradesh, Uttar Pradesh and India the yield effects were (679.92 and 79.14 per cent, 582.14 and 904.08 percent, 808.95 and 669.20 percent and 582.48 and 598.71 percent) respectively with area effect (264.63 and 905.15 per cent, 375.92 and 61.66 percent, 68.06 and 483.64, and 289.61 percent and 1872.54 percent respectively) and interaction effect (55.17 and 15.61 per cent, 42.56 and 34.19, 123.00 and 237.60, and 127.90 and 640.58 respectively).

During the overall period, the area effect, yield effect, and interaction effect were 714.67, 198.16, and 48.15 percent in Bihar, 561.48, 207.35, and 226.03 percent in Madhya Pradesh, 178.18, 506.87, and 316.12 percent in Uttar Pradesh, 386.96, 317.58, and 305.90 percent in West Bengal, and 371.56, 354.53, and 282.81 percent in India. Thus, in Bihar, Madhya Pradesh, Uttar Pradesh, and India, the period I, period II, and overall period were driving forces in the differential production of lentil, whereas in West Bengal, the period III and overall area effect were driving forces.

Modelling and Forecasting: First prerequisite for using ARIMA is that the series must be stationary, which implies that the properties of the series do not depend on the moment at which it is conceived. A stationary series can also be well-conceived as a white noise series. Therefore, the present work is initiated with a stationary checks of India and different states of lentil production time series data using the Augmented Dickey-Fuller test. Almost all series are non-staitionary ($p > 0.05$).Thus, first differencing with original data made all the series stationary: constant mean (μ) and constant variance (σ) as depicted in table 4.Then, it was discovered that from (0, 1, 0) ARIMA model to (1, 1, 5) models are suitable for modelling and forecasting lentil production behaviour. However, use the ACF and PACF graphs in Figure 1 to perform a diagnostic check on the residuals.

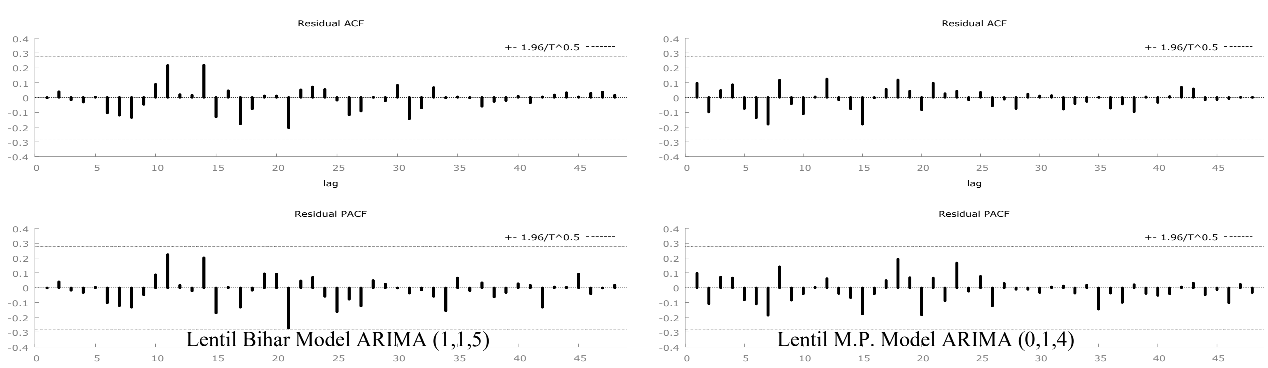
Table 3:Per cent contribution of area, yield and their interaction for change in production of Lentil.

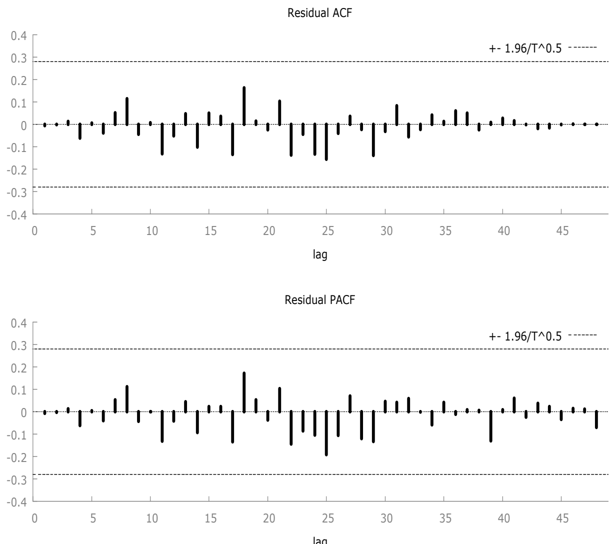
S.No.	PERIOD	AREA EFFECT	YIELD EFFECT	INTERACTION
		BIHAR		
1	PERIOD I	264.63	679.92	55.17
2	PERIOD II	905.15	79.14	15.61
3	PERIOD III	-2309.13	3131.52	364.39
4	OVERALL	714.67	198.16	48.15
		MADHYA PRADESH		
1	PERIOD I	375.92	582.14	42.56
2	PERIOD II	61.66	904.08	34.19
3	PERIOD III	2319.86	-793.31	-541.62
4	OVERALL	561.48	207.35	226.03
		UTTAR PRADESH		
1	PERIOD I	68.06	808.95	123
2	PERIOD II	483.64	669.2	237.6
3	PERIOD III	-1911.89	2431.37	475.63
4	OVERALL	178.18	506.87	316.12
		WEST BENGAL		
1	PERIOD I	-2958.57	3631.5	327
2	PERIOD II	197.35	829.84	-27.42
3	PERIOD III	177	529.55	303.19
4	OVERALL	386.96	317.58	305.9
		INDIA		
1	PERIOD I	289.61	582.48	127.9
2	PERIOD II	1872.54	598.71	640.98
3	PERIOD III	1736.2	-527.06	-171.02
4	OVERALL	371.56	354.53	282.81

Table 4. Augmented Dickey fuller Test.

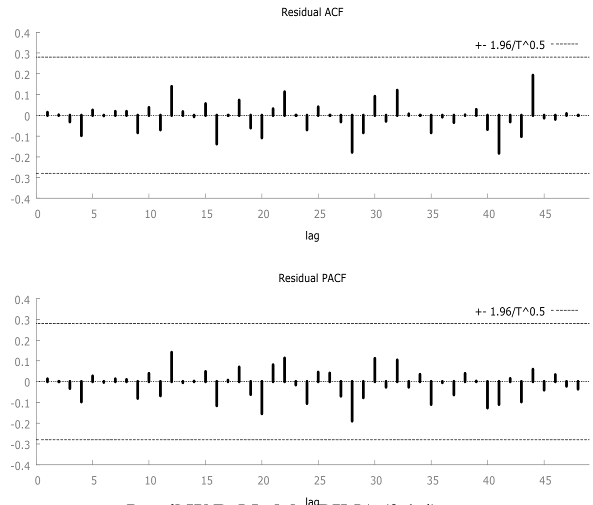
Particulars		Bihar	Madhya Pradesh	Uttar Pradesh	West Bengal	India
t-ratio (p-Value)	At level	-0.1086 (0.6464)	-1.660 (0.4515)	-1.84469 (0.591)	-0.7538 (0.9933)	-1.290 (0.6365)
	At first difference	-3.407 (0.0014)	-1.793 (0.0397)	-2.455 (0.0417)	-1.908 (0.0028)	-2.089 (0.0042)

Figure 1: ACF and PACF graphs of residuals for the best-fitted models of lentil production in different state and countries

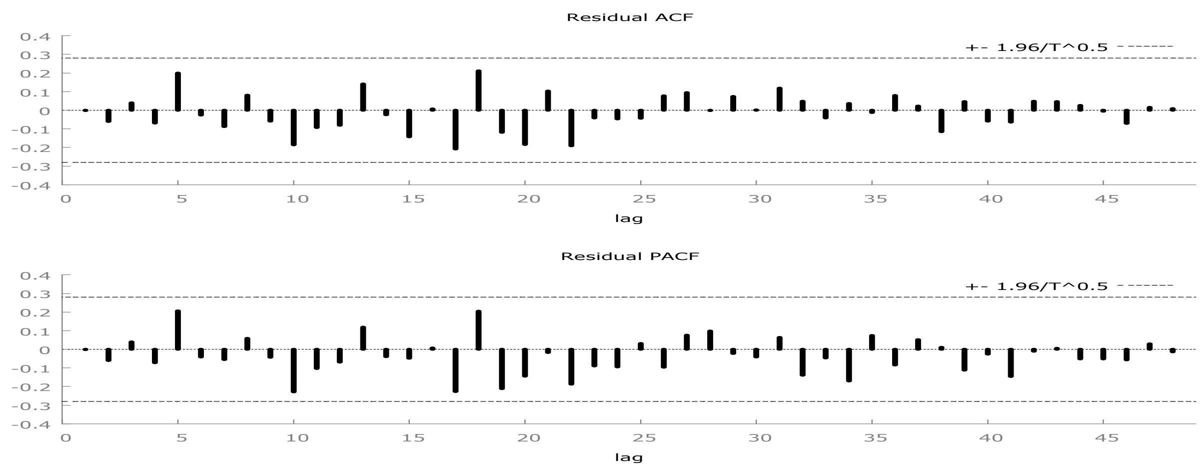




Lentil U.P. Model ARIMA (0,1,5)



Lentil W.B. Model ARIMA (0,1,4)



Lentil India Model ARIMA (0,1,2))

After that we employed ARIMA and Holt's linear trend approaches to model and forecast lentil production time series data in India. The best model is then determined by having the lowest RMSE, MAE, MPE, MAPE, and highest value of R^2 values for four states and India. After models have been fitted for each of the series, the results are then compared. In which we find that the ARIMA model is the best at making forecasts in both India and all four states as shown in Table 5. Following that, we confirm the estimated value of lentil production from 2016 to 2019, which is displayed in Table 6.

Then, using the ARIMA model, we create a point forecast with a forecast interval of 80% and 90%. Tables 7, to 11 show the forecast and forecast intervals obtained by the specified model, ranging from 80% to 95%. In this table, Lo80 and Hi80 represent the lower and upper bounds of the predictive interval for significance levels less than 0.20, respectively, while Lo95 and Hi95 represent the lower and upper bounds for significance levels less than 0.05, respectively.

On the basis of the forecast, lentil production in Bihar, Madhya Pradesh, Uttar Pradesh, West Bengal, and India is predicted to increase in the next years. In 2029, lentil production is expected to reach 185.68 thousand tonnes in Bihar (Table 7), Madhya Pradesh 427.50 thousand tonnes (Table 8), Uttar Pradesh 498.71 thousand tonnes (Table 9), West Bengal 241.80 thousand tonnes (Table 10) and India 1422.51 thousand tonnes (Table 11). Figure 2 shows the forecast visuals, which support the above observations. The main factors sustaining this trend will be agricultural finance, price support programmes, better management practises, research personnel, etc, for long-term production.

Table 5: Model fitting for lentil production

STATE OR COUNTRY	MODEL	R^2	RMSE	MAPE	MAE	MPE
BIHAR	ARIMA(1,1,5)	**0.670**	**20.159**	**11.799**	15.469	**-0.889**
	Holt's (α=0.915, β=0.001)	0.528	102.431	15.557	**14.486**	-0.200
MADHYA PRADESH	ARIMA(0,1,4)	**0.762**	**55.332**	**17.585**	37.791	**-7.880**
	Holt's (α=0.276, β=0.258)	0.643	72.789	17.586	**10.294**	-0.096
UTTAR PRADESH	ARIMA(0,1,5)	**0.848**	53.785	**14.427**	40.606	**-2.120**
	Holt's (α=873, β=0.073)	0.807	**13.370**	16.472	**1.892**	-0.01
WEST BENGAL	ARIMA(0,1,4)	**0.712**	**15.540**	**20.859**	10.995	**-6.477**
	Holt's (α=0.823, β=0.130)	0.605	19.950	21.217	**2.822**	-0.100
INDIA	ARIMA(0,1,2)	**0.873**	**101.98**	**9.762**	72.381	600.281
	Holt's (α=0.462, β=0.246)	0.823	223.148	12.733	**31.558**	**-0.080**

Table 6: Validation of Predicted Value of Lentil Production

YEAR	OBSERVED	PREDICTED (ARIMA)	PREDICTED (Holt's)
		BIHAR	
2016	149.60	152.62	133.5
2017	139.80	145.06	138.8
2018	140.40	142.99	130.2
2019	120.60	130.35	130.1
		MADHYA PRADESH	
2016	449.80	433.30	380.7
2017	680.50	580.98	425.8
2018	330.50	340.50	540.4
2019	320.60	330.50	511.7
		UTTAR PRADESH	
2016	369.8	375.28	229.7
2017	500.5	490.35	350.9
2018	490.1	480.52	490.1
2019	450.1	444.98	498.6
		WEST BENGAL	
2016	79.6	90.522	90.1
2017	149.8	139.32	85.0
2018	150.1	140.707	148.9
2019	160.5	164.615	160.5
		INDIA	
2016	1214.9	1225.65	1037.9
2017	1636.7	1580.84	1143.4
2018	1223.1	1280.41	1451.5
2019	1180.0	1190.56	1399.7

Table 7: Lentil Production Forecasting For Bihar

YEAR	FORECASTING	LO80	HI80	LO95	HI95
2020	148.55	122.72	174.39	109.04	188.06
2021	154.16	126.01	182.30	111.11	197.20
2022	170.04	40.23	199.86	124.45	215.64
2023	163.17	132.84	193.49	116.78	209.55
2024	182.83	150.57	215.09	133.49	232.17
2025	177.72	145.21	210.24	128.00	227.45
2026	181.72	149.17	214.27	131.94	231.50
2027	182.37	149.82	214.92	132.59	232.15
2028	184.25	151.70	216.80	134.46	234.03
2029	185.68	153.12	218.23	135.89	235.46

Table 8:Lentil Production Forecasting For Madhya Pradesh

YEAR	FORECASTING	LO80	HI80	LO95	HI95
2020	517.20	447.70	586.60	411.00	623.40
2021	302.00	231.50	372.60	194.20	409.90
2022	322.30	251.30	393.40	213.70	431.00
2023	390.30	304.50	476.20	259.00	521.70
2024	396.50	310.60	482.40	265.20	527.90
2025	402.70	316.80	488.60	271.40	534.10
2026	408.90	323.00	494.80	277.50	540.20
2027	415.10	329.20	501.00	283.70	546.40
2028	421.30	335.40	507.10	289.90	552.60
2029	427.50	341.60	513.30	296.10	558.80

Table 9: Lentil Production Forecasting For Uttar Pradesh

YEAR	FORECASTING	LO80	HI80	LO95	HI95
2020	425.04	356.24	493.84	319.81	530.26
2021	421.76	331.12	512.41	283.14	560.39
2022	446.42	343.46	549.38	288.95	603.88
2023	455.98	346.01	565.95	287.79	624.17
2024	464.40	352.98	575.83	293.99	634.81
2025	471.26	353.24	589.29	290.75	651.77
2026	478.13	353.84	602.41	288.05	668.20
2027	484.99	354.75	615.22	285.80	684.17
2028	491.85	355.92	627.78	283.97	699.73
2029	498.71	357.32	640.10	282.47	714.95

Table 10: Lentil Production Forecasting For West Bengal

YEAR	FORECASTING	LO80	HI80	LO95	HI95
2020	178.67	159.35	198.00	149.14	208.23
2021	207.46	184.33	230.59	172.09	242.83
2022	216.42	187.83	245.00	172.70	260.14
2023	218.72	182.82	254.62	163.81	273.62
2024	222.57	176.43	268.70	152.01	293.12
2025	226.41	171.94	380.89	143.10	309.73
2026	230.26	168.56	291.96	135.90	324.62
2027	234.07	165.94	302.27	129.86	338.36
2028	237.96	163.89	312.02	124.68	351.23
2029	241.80	162.27	321.33	120.17	363.44

Table 11:Lentil Production Forecasting For India

YEAR	FORECASTING	LO80	HI80	LO95	HI95
2020	1240.29	1111.71	1368.87	1043.64	1436.94
2021	1270.33	1136.91	1403.74	1066.29	1474.37
2022	1292.00	1158.22	1425.78	1087.40	1496.59
2023	1311.35	1177.55	1445.16	1106.72	1515.99
2024	1330.07	1196.26	1463.87	1125.43	1534.71
2025	1348.60	1214.80	1482.41	1143.96	1553.24
2026	1367.09	1233.28	1500.90	1162.45	1571.73
2027	1385.87	1251.76	1519.37	1180.93	1590.21
2028	1404.04	1270.23	1537.84	1199.40	1608.68
2029	1422.51	1288.70	1556.31	1217.87	1627.15

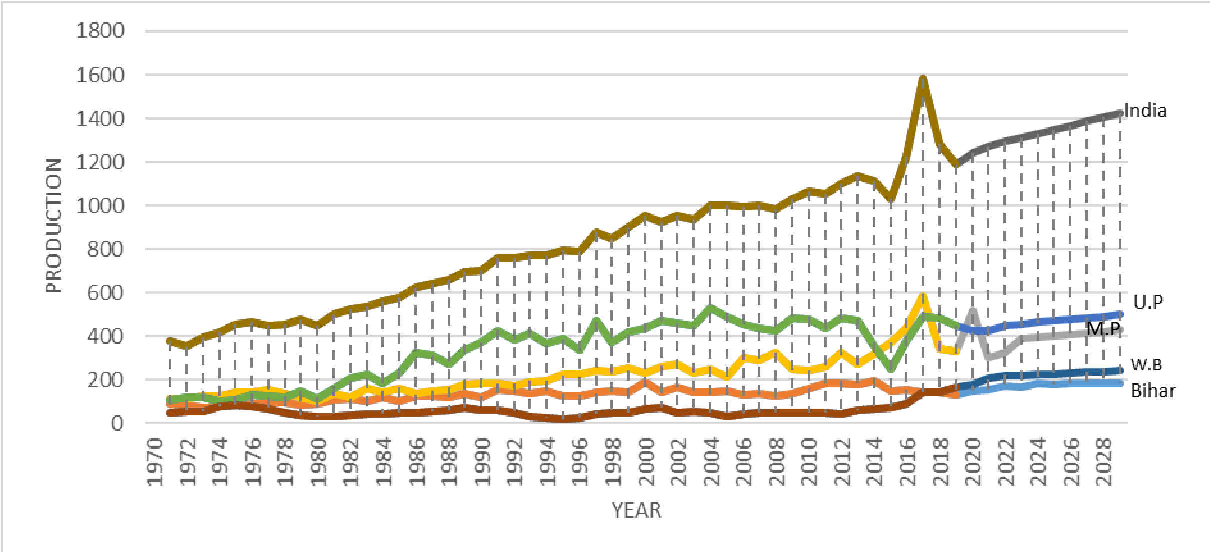


Figure 2: Point forecasts and 80% and 95% prediction intervals obtained using selected best models of different state and countries.

Conclusion: The above discussion highlight the fact that ARIMA model is the best for forecasting lentil production in Bihar (ARIMA 1,1,5), Madhya Pradesh (ARIMA 0,1,4), Uttar Pradesh (ARIMA 0,1,5), West Bengal (ARIMA 0,1,4), and India (ARIMA 0,1,2). The findings of employing the best models to anticipate lentil output from 2020 to 2029 reveal that production will increase in all four states and India. The results of this study prove beyond a shadow of a doubt that India will have the highest anticipated value in 2029. However, after 2019, there would be a fall in Madhya Pradesh and Uttar Pradesh, but after 2021, it will begin to increase slowly.

According to the study, instability is increasing in all three states and India, but Uttar Pradesh shows the instability is decreased. Instability raises the risk of agricultural production, which has an impact on farmer income and the decision to use high-paying technologies. And according to the decomposition analysis the area effect was an essential factor behind the changes in lentil output in Bihar, Madhya Pradesh, West Bengal and India, but in Uttar Pradesh the yield effect was responsible during the overall periods. The most significance factors in maintaining this trend will be finance for agriculture, price support programmes, better management techniques, research staff, and other factors affecting long-term output. This kind of project aids in the long-term planning and implementation of policies for a certain crop. The cultivation of this crop would increase the income of the farmers, while also assisting in bridging the demand and supply at the state and national levels.

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