



Plant Archives

Journal homepage: <http://www.plantarchives.org>

DOI Url : <https://doi.org/10.51470/PLANTARCHIVES.2026.v26.no.1.339>

MEASURE INSTABILITY AND SUSTAINABILITY ANALYSIS OF PULSE PRODUCTION IN MAJOR STATE IN INDIA

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(Date of Receiving : 27-02-2026; Date of Revision : 05-04-2026; Date of Acceptance : 19-04-2026)

ABSTRACT

Agriculture significantly impacts the Indian economy, with 50% of the population depending on it and contributing 20.2% to GDP in 2020-21. Pulses, essential to Indian agriculture, provide high-quality protein, essential amino acids, fibers, minerals, and vitamins. This study measures instability and analyzes sustainability in pulse production in Karnataka, Madhya Pradesh, Maharashtra, Rajasthan, Uttar Pradesh, and India from 1950 to 2022. Data were collected from www.indiastat.com and Agricultural Statistics at a Glance. Instability was assessed using the Cuddy-Della Valle index, coefficient of variation, and decomposition analysis, while sustainability was evaluated through composite indices incorporating yield trends, resource use efficiency, and environmental factors. Results indicate high instability in pulse production due to climatic variability and market fluctuations, with Maharashtra and Rajasthan showing greater volatility. Sustainability analysis reveals improved practices in Madhya Pradesh and Karnataka, supported by government initiatives, but Uttar Pradesh faces challenges from soil degradation and water scarcity, leading to shifts in crop choices.

Keywords : Instability, Sustainability, Pulse production.

Introduction

Pulses occupy a pivotal position in global and Indian agriculture owing to their immense nutritional, agronomic, and environmental significance. According to FAO (2022), pulses are rich in protein, containing nearly double the protein content of cereals and several times more than tuber crops. When combined with cereals and root crops, pulses and whole grains act as vital plant-based protein sources, significantly improving dietary protein intake (Bouchard *et al.*, 2022). In addition to their high protein value, pulses are low in fat, making them particularly beneficial for aged populations. They are also rich sources of essential vitamins such as thiamine, riboflavin, pyridoxine, folic acid, and vitamins E and K, contributing to overall human health and nutritional security.

Beyond their nutritional importance, pulse crops play a crucial role in enhancing soil health and ensuring sustainability of agricultural systems. Pulses improve soil fertility by fixing atmospheric nitrogen

through symbiotic biological nitrogen fixation in their root nodules, thereby meeting a substantial portion of their nitrogen requirement (Shrestha *et al.*, 2021). Pulse-based cropping systems significantly enhance soil organic carbon (SOC) levels compared to monocropping systems, thereby improving soil structure and nutrient availability (Kumar *et al.*, 2023). Moreover, cereals grown after pulses often yield up to 1.5 tonnes per hectare more, underscoring the agronomic benefits of pulses in crop rotations (Caonet *et al.*, 2016). Thus, pulses contribute not only to food security but also to long-term ecological sustainability.

In recent years, India has witnessed a remarkable resurgence in pulse production, driven by technological advancements and strategic policy interventions. According to the Directorate of Pulses Development (2022), pulse production in India increased from 14.76 million tonnes in 2000–01 to 26.96 million tonnes in 2020–21, nearly doubling over two decades. This growth has largely been supported by an expansion in area under pulses, which rose from 22.39 million

hectares to 29.56 million hectares during the same period. Productivity improvements have also been observed, with yields increasing from 658 kg/ha to 912 kg/ha. Enhanced agronomic practices, introduction of improved pulse varieties, and strong government support programs have been identified as key drivers behind this growth (Choudhary *et al.*, 2022; Jat *et al.*, 2019).

Despite these encouraging developments, pulse production in India remains regionally concentrated. Major pulse-producing states such as Madhya Pradesh, Maharashtra, Karnataka, Uttar Pradesh, Rajasthan, and Gujarat account for a substantial share of national output. For instance, nearly 95 percent of India's lentil production originates from Madhya Pradesh, West Bengal, Bihar, and Jharkhand, while significant proportions of other pulses are produced in a few selected states (ICAR, 2023). Pulses in India are predominantly rainfed crops, requiring minimal irrigation, with major rainfed pulse-growing regions located in Karnataka, Maharashtra, and Madhya Pradesh (Dadhich *et al.*, 2022). However, despite production gains, India continues to import pulses to meet domestic demand. Recognizing this gap, the Government of India has set an ambitious target of achieving self-sufficiency in pulses by 2027 through price incentives, procurement policies, and area expansion strategies (NITI Aayog, 2022).

India is the world's largest producer and consumer of pulses, contributing significantly to global pulse output, which was estimated at around 90 million tonnes in 2017 (Institute of Economic Studies, 2020). However, India has also emerged as a net importer of pulses in recent years, importing nearly one million tonnes annually. To address this challenge, the government has increased the Minimum Support Price (MSP) for major pulse crops such as tur, urad, moong, gram, and masur and strengthened initiatives like the National Food Security Mission (NFSM), which focuses on expanding cultivation area, enhancing productivity, and promoting improved production technologies (Statista, 2023).

While production growth is essential, agricultural instability remains a major concern. Agriculture in India is characterized by significant year-to-year fluctuations in output due to monsoon dependence, price volatility, and technological risks. Such instability affects farmer incomes, discourages investment, and increases vulnerability among small and marginal farmers (Chand and Raju, 2009). Although technological advancements, particularly since the Green Revolution, have contributed to production growth, several studies have highlighted

that the adoption of new technologies has also increased production uncertainty (Rao *et al.*, 1988; Ray, 1983). These fluctuations have serious implications for food prices, consumer welfare, and macroeconomic stability.

In this context, sustainability has emerged as a central concern in agricultural development. Sustainable agriculture aims to balance productivity, economic viability, environmental protection, and social acceptability over the long term. The Food and Agriculture Organization (FAO, 1989) defines sustainable agriculture as a system that enhances environmental quality, ensures food and nutritional security, remains economically viable, and improves the quality of life for farmers and society. The World Bank further emphasizes five pillars of sustainability: productivity, security, protection, viability, and acceptability. Assessing sustainability in pulse production is therefore essential for ensuring long-term food and nutritional security in India (Mishra *et al.*, 2015; Devi *et al.*, 2018; Vishwajith *et al.*, 2019; Sahu *et al.*, 2015).

Accurate forecasting of pulse production plays a vital role in addressing challenges related to food security, price stability, and policy planning. Agriculture is inherently marked by large and unpredictable fluctuations in area, yield, and output. Governments, farmers, and agribusiness stakeholders rely heavily on reliable forecasts to formulate policies related to pricing, procurement, storage, distribution, and market interventions. Time-series forecasting models, particularly the Box-Jenkins Auto-Regressive Integrated Moving Average (ARIMA) model, have been widely used for agricultural forecasting due to their ability to capture stochastic patterns with minimal forecast error (Shukla *et al.*, 2011).

ARIMA models assume that future values of a time series depend on past values and past forecast errors. These models require the time series to be stationary in terms of mean, variance, and autocorrelation. When non-stationarity exists, differencing techniques are employed to stabilize the series. The ARIMA framework, introduced by Box and Jenkins in 1976, has been extensively applied in forecasting agricultural production, offering valuable insights for long-term planning and policy formulation (Wankhade *et al.*, 2010).

Keeping in view the nutritional importance of pulses, their role in soil sustainability, the prevalence of production instability, and the increasing demand for accurate forecasts, it is imperative to analyze historical trends and predict future production patterns

of pulses in India and major producing states. Such analysis will provide critical inputs for policymakers, planners, and stakeholders to design strategies aimed at achieving food security, income stability, and sustainable agricultural development.

Accordingly, the present study is undertaken with the following objectives:

1. To measure the instability in pulse production in the study area;
2. To assess the sustainability of pulse production in the study area.

Materials and Methods

Descriptive Statistics

Descriptive statistics are used to present numerical data logically and intelligibly. In a research study, we may employ a range of metrics or only one to evaluate a significant number of people. Descriptive statistics help us make sense of massive amounts of data. Each descriptive statistic distils a significant quantity of information into a brief description. Descriptive statistics are classified into three types: measures of central tendency (CT), measures of dispersion, and measures of association ship. Because of their obvious advantages over a number of other measures, the arithmetic mean, standard deviation/error, skewness, kurtosis correlation, regression, and other metrics are often used to characterise the given data. Descriptive statistics provide simple summaries of the data and metrics. The series is anticipated for the coming years based on descriptive statistics in order to take suitable measures. Maximum, minimum, mean, median, skewness, kurtosis, and other descriptive statistics studies were utilised to explain the pattern of the series and establish a consensus under consideration.

Results and Discussion

Measure the instability of pulse production

Then, we measure the instability of pulse production over the period and over the state presented in table 1. 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 Supriya *et al.*, 2023 thus the R^2 used in Cuddy and Della model and the present study modified Cuddy and Della. During the analysis of instability, the detrend coefficient of variation is measured in three periods: period 1 from 1950 to 1985, period 2 from 1986 to 2022, and period 3 from 1950 to 2022.

In which from table 1 clearly depicted that the coefficient variance around trend (CV_t) increased marginally, from 20.44 (period 1) to 20.09 (period 2) in Karnataka, from 13.95 (period 1) to 26.03 (period 2) in Madhya Pradesh, from 17.77 (period 1) to 28.69 (period 2) in Maharashtra, from 30.85 (period 1) to 36.88 (period 2) in Rajasthan, from 15.74 (period 1) to 42.81 (period 2) in Uttar Pradesh and from 11.81 (period 1) to 15.95 (period 2) in India. However, the instability in Madhya Pradesh, Maharashtra, and Uttar Pradesh depicted a drastic change from period 1 to period 2. Thus it can be inferred as the introduction of new technologies has increased the insecurity of pulse 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 1: Instability of total pulse production in major states in India

States or Country	Statistics	Period 1	Period 2	Period 3
Karnataka	R^2	0.48	0.82	0.72
	CV	28.31	47.42	64.56
	CV_t	20.44	20.09	34.05
Madhya Pradesh	R^2	0.64	0.61	0.68
	CV	23.23	41.93	55.02
	CV_t	13.95	26.03	30.88
Maharashtra	R^2	0.04	0.51	0.64
	CV	18.16	40.97	58.64
	CV_t	17.77	28.69	35.11
Rajasthan	R^2	0.40	0.47	0.43
	CV	39.70	50.68	53.99
	CV_t	30.85	36.88	40.68
Uttar Pradesh	R^2	0.29	0.01	0.12
	CV	18.72	42.81	32.41
	CV_t	15.74	42.81	30.43
India	R^2	0.13	0.71	0.60
	CV	12.68	29.87	32.24
	CV_t	11.81	15.95	20.37

Sustainability analysis

Sustainability in production of pulse in different states along with whole India has been measured with the help of sustainability indices as described in material and method section and has been presented in table 2. It is clearly visible that India shows highest sustainability in production of pulse as per indices given by SI-1 (Singh *et al.*, 1990), SI-2 (Sahu *et al.*, 2005) and SI-3 (Pal and Sahu, 2007). For production of pulse, Maharashtra showed low sustainability in all the

three above mentioned measures.

Thus, from the study of sustainability, two salient points emerge out a) the sustainability measure used are not uniform in identifying the nature of sustainability, there is need for in-depth study on measures of sustainability, at least under the present

frame work; b) lower sustainability values always does not mean detrimental for the development. What we need moderate sustainability with increasing trend. Combining the results of instability and sustainability, one can find a clear picture about the scenario of pulse production in major states of India.

Table 2: Sustainability pulse production measurement

Sustainability Index	Karnataka	Madhya Pradesh	Maharashtra	Rajasthan	Uttar Pradesh	India
SI1	0.1281	0.1625	0.1269	0.1708	0.2244	0.3344
SI2	1.7660	1.7686	2.2595	1.6947	2.0124	1.0265
SI3	0.0001	0.0001	0.0001	0.0000	0.0000	0.0001

Modelling and Forecasting of pulse production

Before employing model, it is essential to ensure that time series data are stationary and meaning its statistical properties do not depend on the specific time point. Stationarity can be associated with a white noise series with a constant mean (μ) and constant variance (σ). Therefore, in this study, the first step involved conducting the augmented Dickey–Fuller (ADF) test on the pulse production time series data in India and different major producing state. The results of the ADF test indicated that almost all series were non-stationary ($p > 0.05$), implying the need for further processing. To address this, first differencing was applied to the

original data, which successfully transformed all the series into stationary ones, with constant mean and variance, as evidenced in Table 3. Subsequently, different models ranging from (0, 1, 0) to (1, 1, 5) were considered suitable for modeling and forecasting the behavior of pulse production. However, to ensure the adequacy of the selected models, a diagnostic check was performed on the residuals using the ACF and PACF graphs, as depicted in Fig.1 to 6. This step aimed to verify the model's appropriateness and identify any remaining patterns or autocorrelations in the residuals.

Table 3: Augmented Dickey Fuller Test

Particulars		Karnataka	Madhya Pradesh	Maharashtra	Rajasthan	Uttar Pradesh	India
t-ratio (p-value)	At level	0.252 (0.801)	0.017 (0.985)	-0.736 (0.465)	-0.727 (0.470)	-1.964 (0.303)	3.049 (1.000)
	At first difference	2.272 (0.026)	1.237 (0.022)	-2.044 (0.047)	3.126 (0.024)	-3.150 (0.023)	2.990 (0.004)

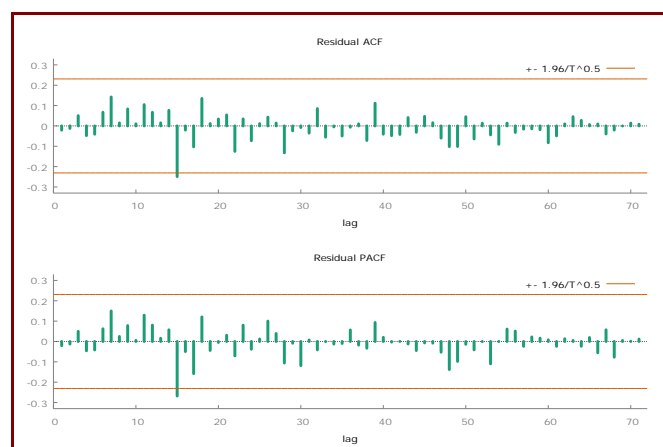


Fig. 1 : ACF and PACF graph of residuals for the best fitted model of pulse production in Karnataka (ARIMA 1,1,5)

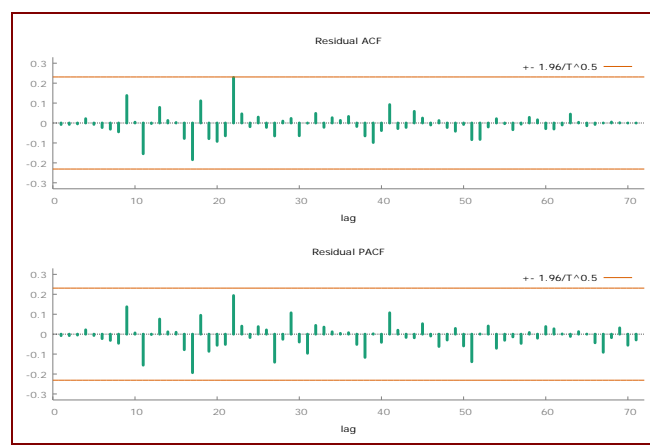


Fig. 2 : ACF and PACF graph of residuals for the best fitted model of pulse production in Madhya Pradesh (ARIMA 1,1,5)

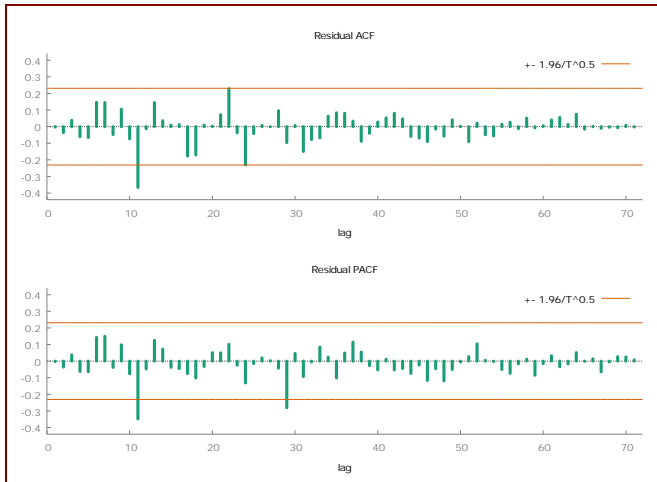


Fig. 3 : ACF and PACF graph of residuals for the best fitted model of pulse production in Maharashtra (ARIMA 1,1,5)

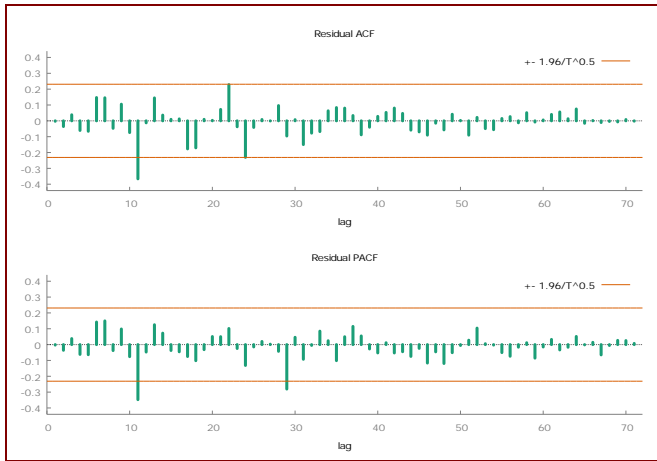


Fig. 4 : ACF and PACF graph of residuals for the best fitted model of pulse production in Rajasthan (ARIMAX 1,1,5)

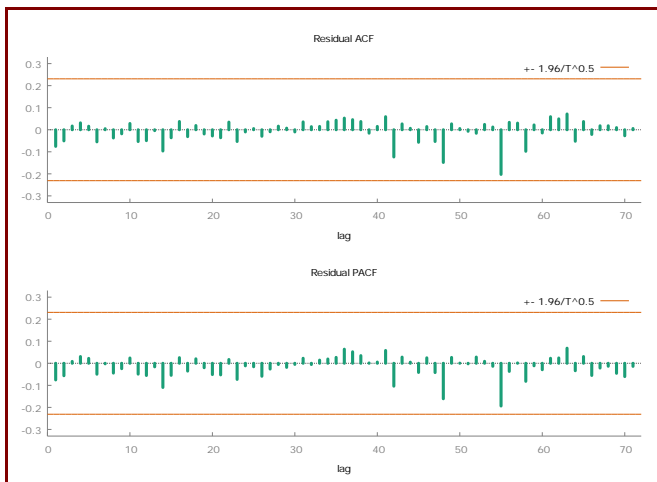


Fig. 5 : ACF and PACF graph of residuals for the best fitted model of pulse production in Uttar Pradesh (ARIMA 1,1,5)

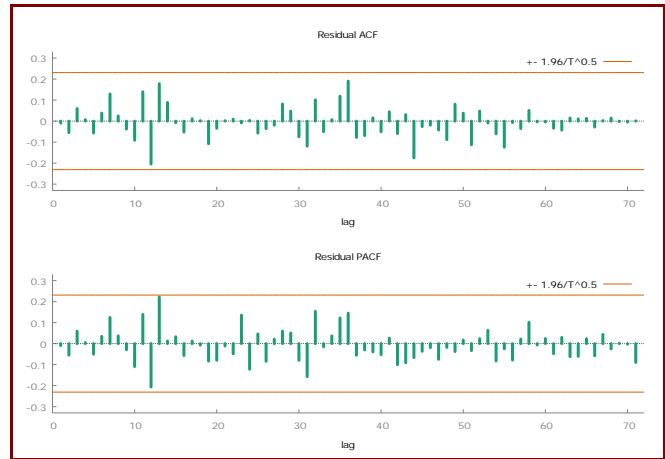


Fig. 6 : ACF and PACF graph of residuals for the best fitted model of pulse production in India (ARIMAX 1,1,3)

After that we employed ARIMA and ARIMAX to model and forecast pulse production time series data in India. The best model is then determined by having the lowest RMSE, MAPE, MAE, AIC and highest value of R^2 values for five states and India. After models have been fitted for each of the series, the results are then compared. In which found that the ARIMA (1,1,5) model was the best at making forecasts in Karnataka, Madhya Pradesh, Maharashtra and Uttar Pradesh but in Rajasthan and India ARIMAX (1,1,3) were the best model for forecasting as shown in Table 4. Following that, we confirm the estimated value of pulse production from 2017 to 2022.

Table 4 : Model fitting for pulses production in major states in India

State or Country	Model	R^2	RMSE	MAPE	MAE	AIC
Karnataka	ARIMA (1,1,5)	0.906	149.010	16.678	110.140	941.628
	ARIMAX (1,1,1)	0.900	154.83	17.341	113.35	946.775
Madhya Pradesh	ARIMA (1,1,5)	0.838	644.890	17.303	413.460	1152.341
	ARIMAX (1,1,2)	0.833	652.360	16.782	409.300	1155.801
Maharashtra	ARIMA (1,1,5)	0.836	384.780	19.723	285.310	1081.538
	ARIMAX (1,1,1)	0.723	501.790	21.360	337.310	1116.567
Rajasthan	ARIMA (1,1,5)	0.516	584.220	36.528	438.590	1138.513
	ARIMAX (1,1,3)	0.535	572.280	36.698	437.84	1141.917
Uttar Pradesh	ARIMA (1,1,5)	0.191	774.070	18.351	453.940	1182.087
	ARIMAX (1,1,2)	0.151	775.350	14.535	367.670	1184.651
India	ARIMA (1,1,4)	0.892	1438.700	8.485	1098.900	1275.383
	ARIMAX (1,1,3)	0.895	1419.600	8.442	1083.600	1272.408

Note: Bold values indicate the criteria for best model selection

Conclusion

Statistical study on agricultural commodities is very essential in decision making portfolio such as govt.-non govt. policies, food security scenario, economic development management etc. The present research study implemented the forecasting nature of production of pulse in Karnataka, Madhya Pradesh, Maharashtra, Rajasthan, Uttar Pradesh and India by using different parametric models and time series models to get the best pattern from available data, which may play an important role for future forecast. Before analysis, thorough review of work is done to frame the model of analysis befitting to the objectives of the study.

Based on the objective, uni-variate time series information is used for the data series under consideration. All the data series are described with the visualization of *per se* performance. Measure of central value and scatterness of data are used to describe the series. Skewness and kurtosis are also estimated to check the nature of the curve of the distribution. Rajasthan has the highest production variation registered 1772 % followed by Maharashtra, Madhya Pradesh, Karnataka and Uttar Pradesh. India has total pulse production has increased by nearly 231 percent since 1950.

After knowing the nature of the data series, trend analysis implemented to estimate the trending behaviour of the series. Quadratic trend model were found suitable model for the data series of production in Karnataka, Madhya Pradesh, Maharashtra Rajasthan and India while in Uttar Pradesh exponential trend was found suitable for the pulse production.

Instability analysis also introduced for the presence of inherent trend component in this time series data. Coefficient of variation around trend (CV_t) was used for instability analysis. In this study the nonlinearity in trend models and the coefficient of determination obtained from such best fitted models are used in getting the CV_t values for different series. It called as modified Cuddy and Della measures. For this instability analysis the whole study period was divided in two equal periods; (i) 1st period 1950 to 1985, (ii) 2nd period 1986 to 2022. Based on this, CV_t performed well over CV in the instability analysis. Then employed the sustainability index to estimate biophysical, social, and economic characteristics of pulse produce to maintain the production sustainability in order to guarantee food and nutritional security.

After the evaluation of trend of each series, the main objective is to evaluate the forecasting nature of the series by using the Box- Jenkins and ARIMAX

methodology. Autoregressive Integrated Moving Average (ARIMA) model is used to develop a model and based on the performance of the model, forecast the series for the year to come. Before applying the ARIMA and ARIMAX model, the data series was divided into training and testing set for model selection and model validation purpose respectively. Goodness of fit; such as maximum R^2 , minimum value of RMSE, MAPE, MAE and AIC were used to select the best model.

It was found that ARIMA (1,1,5) and ARIMAX (1,1,3) selected as best fitted model on production of pulse in India respectively. ARIMA (1,1,5) elected as best fitted model on production of pulse in Karnataka, Madhya Pradesh, Maharashtra, Uttar Pradesh while ARIMAX (1,1,3) best fitted model on production of pulse in Rajasthan and India respectively. The autocorrelation of residual also examined through the autocorrelation function (ACF) and partial autocorrelation function (PACF) plot. From the plot one can examined that the selected model was fitted well as the spick are followed in between the confidence interval for all the series. After finding the model prediction was done up to 2030 for the data series. Based on the prediction, it can be estimated that Karnataka will be produce 2045.65 thousand tonnes, Madhya Pradesh will produce 7206.19 thousand tonnes, Maharashtra will produce 4418.64 thousand tonnes, Rajasthan will produce 3404.44 thousand tonnes, Uttar Pradesh will produce 3272.42 thousand tonnes, and India will produce 32788.50 thousand tonnes in the year 2030.

Forecasting value it can be said that production in most of the selected state and India would improve in future and the forecasted values are likely to help the policy maker in existing battle against food and nutritional security.

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