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Modelling and Forecasting of Mung Production in India

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Authors' contributions

This work was carried out in collaboration among all authors. Authors KPV and PKS designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors PM, MD, Suman, AD, BSD, RBS and CF managed the analyses of the study. Authors RBS and CF managed the literature searches. All authors read and approved the final manuscript.

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ABSTRACT

A large proportion of the Indian population is vegetarian and pulses are important sources of protein in the daily diet .In this paper an attempt has been made to summarize the overall nature of area, production and productivity of mung in India. By and large there has been considerable expansion in area, production and productivity of mung in all the states under study including whole India during the study period. Among the states under study, the maximum annual growth in area (9.75%) and production (14.55%) of mung was observed in Rajasthan. Bihar stands first in productivity of mung among the states under study. Rajasthan, Karnataka and Andhra Pradesh

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have fails to reach national average per hectare production of 367.37 kg/ha. In this paper an attempt has been made to summarize these measures along with some new measures with an objective to study the yield sustainability of particular crop over the growing regions and compare across the states/regions. Sustainability in yield of mung in different states along with whole India has been measured with the help of existing and proposed measures of sustainability indices. Whole India is showing higher sustainability in yield of mung as per the two existing and proposed methods. According to all the indices including developed two methods Rajasthan is having comparatively lower sustainability to produce mung among the states under study. Results of existing measures and proposed measure are almost in conformity with each other. From the forecasted value, it can be said that, mung productivity of India would increase to 408.84 kg/ha in 2022 as compared to 2012. In Mung, area, production and productivity Rajasthan would be leading state of India in 2022.This projection would be helpful for policy implication and planning.

Keywords: Productivity; ARIMAx; GARCH; sustainability; forecasting.

1. INTRODUCTION

Agriculture plays an important role in Indian economy, 58% of Indian population depend upon the agriculture and allied sector [1]. About 17.80% (2013-14) Gross Domestic Product (GDP) of Indian economy is contributed by agriculture. In addition to cereals and oilseeds, pulses are one of the important contributors to Indian agriculture. Pulses are popularly known as poor man's meat. Pulses mainly constituted of chickpea, arhar, mung bean, urad bean and lentil etc. Mung is fairly important as a pulse crop in India as it contributes 13.30 percent in area and 9.80 percent in production of total pulses at the country level during 2010-11. It is mainly cultivated as *kharif* season crop in Andhra Pradesh, Gujarat, Karnataka, Madhya Pradesh, Maharashtra, Orissa, Tamil Nadu and Uttar Pradesh. But, in states of Andhra Pradesh, Bihar, Orissa, Tamil Nadu and Uttar Pradesh, it is also grown in *rabi* season as a second crop after paddy. The area under spring mung bean has been increased in 2001-02 to 2007-08 [2]. It is also grown as a summer crop in states of Punjab and Haryana. Summer crop is generally sown in March and is harvested in June before the monsoon sets in, thus making the land available for the next paddy crop. [3] made an attempt to compare the ARIMA and GARCH models by using MAPE and MAE for modeling and forecasting of area, production and yield of total pulses in major states of India. In the study they reported that both ARIMA and GARCH models can be used for modeling pulses production in India and superiority of either ARIMA or GARCH could not be establishing emphatically in modeling data of pulses. [4] studied the ARIMA and GARCH models for forecasting the Arhar production and productivity in India. [5] studied the sustainability of gram in India using different measure.

2. MATERIALS AND METHODS

Based on their relative contributions to Indian Mung basket during 2011, five major states viz. Rajasthan, Maharashtra, Karnataka, Andhra Pradesh and Bihar, along with whole India are considered for the present study. Data related to area, production and yield of mung in five major states along with climatic factors and major fertilizer consumption were obtained from Directorate of Economics and Statistics, India water portal and various issues of fertilizer statistics. To develop models and subsequently to use the best fitted models to forecast the series for the years to come, data for the whole period excepting last three years are used for model building, while data for last three years are used for model validation purpose.

Descriptive statistics are useful to describe patterns and general trends in a data set. It includes numerical and graphic procedure to summarize a set of data in a clear and understandable way. To examine the nature of each series these have been subjected to different descriptive measures. Statistical measures used to describe the above series are minimum, maximum, average, skewness, kurtosis and simple growth rate.

Time series data are often vulnerable to the presence of outlier. The study starts with examination for the existence of outlier. For our study, we employed Grubb’s test. Grubb’s test is the one of the most popular ways to define outlier, also called as the ESD method (extreme studentized deviate). Grubbs' test is defined for the following hypothesis:

H_0 : There are no outliers in the data set.

H_A : There is at least one outlier in the data set

For a two-sided Grubb's test, the test statistic is defined as:

$$G = \frac{\max\limits_{i=1,\ldots n} \left| y_i - \bar{y} \right|}{s}$$

with $\bar{y}$ and s denoting the sample mean and standard deviation, respectively, calculated including the suspected outlier. The critical value of the Grubb's test is calculated as

$$C = \frac{(n-1)}{\sqrt{n}} \sqrt{\frac{t^2_{(\alpha/2,n-2)}}{n-2+t^2_{(\alpha/2,n-2)}}}$$

where $t_{(\alpha/2,n-2)}$ denotes the critical value of the t-distribution with (n-2) degrees of freedom and a significance level of $\alpha/2$. If $G > C$, then the suspected measurement is confirmed as an outlier.

Once outlier is detected, one may choose to exclude/replace the value from the analysis or one can go for transformation of data or may choose to keep the outlier. In our study, if only one outlier was detected, it was replaced by the median, which is often referred to as robust (i.e. small variability) in the presence of a small number of outliers and of course it is the preferred measure of central tendency for skewed distributions.

2.1 Sustainability Index

1. [6] proposed a sustainability index defined as:

$$SI = \frac{\bar{y} - s}{y_{\max}}$$

Where $\bar{y}$, s, $y_{\max}$ are the average, standard deviation and maximum yield respective of particular crop/ cropping sequence or treatment over a period of time.

This is a good measure of sustainability using both the measures of central tendency as well as measures of dispersion. According to measure, higher the value of the index, higher is the sustainability status. The problem with this index is that, the index doesn't have a definite range. Moreover, in some situations, the index may have negative value.

2. [7] proposed sustainability index based on average performance and the highest ever performance during the period of investigation with the help of the following formula:

$$SI = \frac{Y_{\max} - \bar{Y}}{\bar{Y}}.$$

In this measure sustainability has been visualized as the minimum deviation of the average performance over highest ever achieved value during the period of investigation. As such, lower the value of the index higher is the sustainability. Thus from sustainability point of view, a sustainability index value closer to zero is the most desirable value. In an attempt [8] proposed the following measures of sustainability which do not require any assumption like the above measures 2-5 which are based on regression technique.

2.2 Proposed Method-1 (SI-1)

For any comparison across the treatments, it is essential to have a common estimate of error for sustainability. If individual estimates of treatments are derived for measuring sustainability, they do not provide a tool for comparison between treatments. To full the aspiration of achieving the maximum yield, it is always preferable to compare the yield of treatments with the maximum attained yield (Y_{jmax}) across the treatments for the j^{th} years. Hence an attempt has been made to compare the mean yield with the maximum yield for estimation of sustainability using robust error term. The developed sustainability index is a function of the estimate of error derived from a regression of yield through maximum yield among the treatments for j^{th} time period. In this method, the original values are transformed first using the mean of i^{th} treatment and standard error of regression coefficient of the equation $y_{ij} = a + b_i y_{j\max}$ where y_{jmax} is the overall maximum yield for the j^{th} time period. Then the coefficient of variation of these transformed series is obtained. According to this proposed measure $1/CV(y'_{ij})$ is the sustainability index. Higher the value of index, higher is the sustainability.

$$SI = \frac{1}{CV(y'_{ij})}$$

where,

$$y'_{ij} = \frac{y_{ij} - S.E(b_i)}{\bar{y}_i} \text{ and } y_{ij} = a + b_i y_{j\max}$$

Depending on the significance of the effect of maximum yield among the treatments for jth year on ith treatment yield, the error determined would represents estimate of the true deviation than the simple standard deviation. Hence use of de-trended error of maximum yield effect would provide a better estimate of sustainability index of a treatment than using simple standard deviation. Thus, it is one step advance measure than the index given by [6] and [9].

2.3 Proposed Method-2 (SI-2)

In this method we have combined the index given by [9] and [8] as follows: According index given by ICARDA (1994), $y_{ij} = a + b_i\bar{y}_j$,where $\bar{y}_j$ is the mean of all the treatments in the jth year and b_i is the regression coefficient for ith treatment, y_{ij} is the value of yield with respect to ith treatment and jth year and SI is $|1/b_i|$. Whereas in index of [8] as already discussed earlier i.e., $SI = \frac{s_i}{\bar{y}_i}\frac{1}{s_{i\max}}$.

We have used standard error of estimate from the regression equation $y_{ij} = a + b_i\bar{y}_j$ in the index given Pal and Sahu instead of using simple standard deviation. Advantage of using standard error in place of standard deviation is already been discussed. The proposed index is given below

$$S.I = \frac{SE(b_i)}{\bar{y}_i} \cdot \frac{1}{SE(b_{i\max})}$$

where, $y_{ij} = a + b_i\bar{y}_j$

According to this proposed index, lower the value of the index, higher is the sustainability status of the treatment.

ARIMA models [10] stands for Autoregressive Integrated Moving Average models. An ARIMA model is in-fact a combination of AR, MA models with integration.

Autoregressive model (AR): The notation AR (*p*) refers to the autoregressive model of order *p*. The AR (*p*) model is written

$$X_t = c + \sum_{i=1}^{P} \alpha_i X_{t-i} + \mu_t$$

where $\alpha_1, \alpha_2 .... \alpha_p$ are the parameters of the model, *c* is a constant and μ_t is white noise i.e. $\mu_t \sim WN(0,\sigma^2)$. Sometimes the constant term is omitted for simplicity.

Moving Average model (MA): The notation MA (*q*) refers to the moving average model of order *q*: $X_t = \mu + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t$

where the θ_1, ..., θ_q are the parameters of the model, μ is the expectation of X_t (often assumed to equal 0), and the ε_t is the error term.

ARMA model: A time series $\{X_t\}$ is an ARMA (p, q) if $\{X_t\}$ is stationary and if for every t, $X_t - \phi_1 X_{t-1} - .... - \phi_p X_{t-p} = Z_t + \theta_1 Z_{t-1} + ... + \theta_q Z_{t-q}$ where, $\{Z_t\}$~WN(0,σ^2) and the polynomials $(1 - \phi_1 Z - .... - \phi_p Z^p)$ and $(1 + \theta_1 Z + ... + \theta_q Z^q)$ have no common factors.

ARIMA model: A time series $\{X_t\}$ is an ARIMA (p,d,q) if $Y_t=(1-B)^d X_t$ is a causal ARMA(p,q) process. This means $\{X_t\}$satisfies $\phi^*(B)X_t \equiv \phi(B)(1-B)^d X_t = \theta(B)Z_t$, where, $\{Zt\}\sim WN(0,\sigma^2)$; $\phi_{(z)}$ and $\theta_{(z)}$ are polynomials of degree p and q respectively and $\phi_{(z)} \neq 0$ for $|Z| \leq 1$. The polynomial $\phi^*(Z)$ has a zero of order d at z = 1. The process $\{X_t\}$ is stationary if and only if d = 0 and in that case it reduces to ARMA (p,q) process.

The stationarity requirement ensures that one can obtain useful estimates of the mean, variance and ACF from a sample. If a process has a mean that is changing in each time period, one could not obtain useful estimates since only one observation available per time period. This necessitates testing any observed series of data for stationarity. First the given data series are tested for stationarity through ADF and KPSS test. If the data are non-stationary, first order differencing was made to make data stationary. Given a set of time series data, one can calculate the mean, variance, autocorrelation function (ACF), and partial autocorrelation function (PACF) of the time series. The calculation enables one to look at the estimated ACF and PACF which gives an idea about the correlation between observations, indicating the sub-group of models to be entertained. This process is done by looking at the cut-offs in the ACF and PACF. At the identification stage, one would try to match the estimated ACF and PACF with the theoretical ACF and PACF as a guide for tentative model selection, but the final decision is made once the model is estimated and diagnosed.

GARCH (p,q**) Model:** GARCH stands for Generalized Autoregressive Conditional Heteroscedasticity.

Generalized: It is developed by [11] as a generalization of Engle's original ARCH volatility modelling technique.

Autoregressive: It describes a feedback mechanism that incorporates past observations into the present.

Conditional: It implies a dependence on the observations of the immediate past.

Heteroscedasticity: Loosely speaking, we can think of heteroscedasticity as time-varying variance.

GARCH is a mechanism that includes past variances in the explanation of future variances. More specifically, GARCH is a time series technique that allows users to model and forecast the conditional variance of the errors. It is used to take into account excess kurtosis and volatility clustering. To formally define GARCH, let $\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_T$ be the time series observations denoting the errors and let F_t be the set of ε_t up to time T, including ε_t for $t \leq 0$. As defined by [11], "the process ε_t is a Generalized Autoregressive Conditional Heteroscedastic model of order p and q, denoted by GARCH(p, q), if ε_t given an information set F_t has a mean of zero and conditional variance h_t given as

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 h_{t-1} + \ldots + \beta_p h_{t-p}$$

$$= \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}$$

Here the conditional variance h_t is the main component of a GARCH model and is expressed as a function of three terms namely: α_0, $\sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$ and $\sum_{j=1}^{p} \beta_j h_{t-j}$ are a constant, ARCH and GARCH term respectively.

We define ε_{t-i}^2, as the past i period's squared residual from the mean equation while the h_{t-j} is the past j period's forecast variance. The order of the GARCH term and ARCH term are denoted by p and q respectively. The unknown parameters which needs to be estimated are α_0, α_i and β_j, where i = 1, . . . , q and j = 1, . . . , p. To guarantee that the conditional variance $h_t > 0$, it needs to satisfy the following conditions: $\alpha_0 > 0$, $\alpha_i \geq 0$, and $\beta_j \geq 0$.

ARCH (q): The ARCH model is a special case of a GARCH specification in which, there is no GARCH terms in the conditional variance equation. Thus ARCH(q)=GARCH(0, q). The process ε_t is an Autoregressive Conditional Heteroscedastic process of order q or ARCH(q), if h_t is given by

$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$, where $q > 0$ and $\alpha_0 > 0$, and $\alpha_i \geq 0$ for i = 1, . . . , q. Again, the conditions $\alpha_0 > 0$ and $\alpha i \geq 0$ are needed to guarantee that the conditional variance $h_t > 0$. To carry out the process of parameter estimation, consider the simplest model which is the GARCH (0,1) model, where h_t is given by $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2$.

The parameters α_0 and α_1 can be approximated by maximum likelihood estimation or MLE. The likelihood L of a sample of n observations $x_1, x_2, \ldots, x_n$, is the joint probability function $p(x_1, x_2, \ldots, x_n)$ when $x_1, x_2, \ldots, x_n$ are discrete random variables. If $x_1, x_2, \ldots, x_n$ are continuous random variables, then the likelihood L of a sample of n observations, $x_1, x_2, \ldots, x_n$, is the joint density function $f(x_1, x_2, \ldots, x_n)$. Let L be the likelihood of a sample, where L is a function of the parameters $\theta_1, \theta_2, \ldots, \theta_k$. Then the maximum likelihood estimators of $\theta_1, \theta_2, \ldots, \theta_k$ are the values of $\theta_1, \theta_2, \ldots, \theta_k$ that maximize L. Let θ be an element of Ω. If Ω is an open interval, and if

L(θ) is differentiable and assumes a maximum on θ, then MLE will be a solution of the equation $\frac{\partial L(\theta)}{\partial \theta} = 0$.

GARCH (1,1): The most widely used GARCH (p,q) model for GARCH (1,1) takes the form of $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$, where α_0 is Constant term; $\alpha_1 \varepsilon_{t-1}^2$ is ARCH term reflects the volatility from the previous period, measured as the lag of the squared residual from the mean equation and $\beta_1 h_{t-1}$ is the GARCH term, it is the last periods forecast variance

The (1, 1) in GARCH (1, 1) refers to the presence of a first-order GARCH term (the first term in parentheses) and a first-order ARCH term (the second term in parentheses). We can interpret the period's variance as the weighted average of a long term average (the constant), the forecasted variance from last period (the GARCH term), and information about the volatility observed in the previous period.

2.4 ARIMAx Methodology

ARIMAx model is a generalization of ARIMA model and is capable of incorporating an external input variable (X). Given a (k+1)- time-series process $\{(y_t, x_t)\}$, where y_t and k components of x_t are real valued random variables, ARIMAx model assumes the form

$$y_t\left(1-\sum_{s=1}^{p}\alpha_s L^s\right) = \mu + \sum_{s=1}^{q}\beta_s' L^s x_t + \left(1+\sum_{s=1}^{p}\gamma_s L^s\right)e_t$$

Where L is the usual lag operator $(L^s y_t = y_{t-s}, L^s x_t = x_{t-s}, \text{etc.})$, $\mu \in R, \alpha_s \in R, \beta_s \in R^k$ and $\gamma_s \in R$ are parameters, e_t's errors, and p, q and r are natural numbers specified in advance. The first step in building an ARIMAx model consists of identifying a suitable ARIMA model for the endogenous variable. The ARIMAx model concept requires testing for stationarity of exogenous variable before modelling.

Among the competitive ARIMA, GARCH and ARIMAx models, the best fitted models are selected based on the maximum R^2, minimum value Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC), Mean Error (ME), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Percentage Error (MPE) and Mean Absolute Percentage Error (MAPE). In all three type of model, which has fulfilled most of the above criteria is selected. Best fitted models are again put under diagnostic checks through Ljung-Box- test, ACF and PACF graphs of the residuals. Only those models showing white noise are retained. Among these best fitted ARIMA, GARCH and ARIMAx models, one best model has been selected based on same model selection criteria mentioned above and forecast has been made upto 2022.

where $X, \bar{X}, \hat{X}$ are the value of the ith observation, mean and estimated value of the ith observation of the variable X and *k* is the number of parameters in the statistical model, and *L* is the maximized value of the likelihood function for the estimated model. Statistical analysis done using R and SAS softwares.

$$AIC = 2k - 2\ln(L)$$

$$BIC = -2*\ln(L) + k*\ln(n)$$

$$ME = \frac{1}{n}\sum_{i=1}^{n}\left(X_i - \hat{X}_i\right)$$

$$MPE = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{X_i - \hat{X}_i}{X_i}\right)*100$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|X_i - \hat{X}_i\right|$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{X_i - \hat{X}_i}{X_i}\right|*100$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_i - \hat{X}_i)^2}{n}}$$

$$R^2 = \frac{\sum_{i=1}^{n}\left(\hat{X}_i - \bar{X}\right)^2}{\sum_{i=1}^{n}\left(X_i - \bar{X}\right)^2}$$

3. RESULTS AND DISCUSSION

3.1 Per se Performance of Mung in India

Mung is the 3rd most important pulse crop grown in India. Table 1, gives the production performance of mung in India. From the table, one can find that in India, since 1970 the area under mung is varied form 1837.00 thousand hectares in 1971 to 3726.70 thousand hectare in 2007, thereby registering the growth rate of 1.52 percent per year. Average area under mung being 2913.24 thousand hectare coupled with a leptokurtic and negative skewed nature reveals that the maximum shift in area has taken place during recent year under consideration, may be due to area substitution within pulses during 1990-2012. There was a marginal shift in area under gram and pigeon pea towards mung (Srivastav *et al.*, 2010 and Rimal *et al.*, 2015). State wise figures indicate that, on an average major five states under study contributes almost 2/3rd of area sown under mung during the study period. Rajasthan reported the maximum growth rate of 9.74 percent per annum among the states under study. From a mere of 170.70 thousand hectare of area it has reached to 1272.23 thousand hectare in 2011. Positive kurtosis along with right skewed nature of Rajasthan area under mung indicates that maximum shift in area has taken place at the early stage under study and remained almost same in latter half. In Maharashtra, area under mung varied from 296.00 thousand hectare to 798.00 thousand hectare thereby registering a very minute growth rate of 0.01 percent per year during the study. Both the negative value of skewness and kurtosis indicates that a steady change in mung area has taken place during the latter half of period under study. In case of Andhra Pradesh, area under mung shows negative growth rate of 1.03 percent per annum may due to shift in cultivation of mung to other competitive high yielding crops. Leptokurtic nature coupled with negative skewed value indicates that maximum shift in mung area of Andhra Pradesh has taken place during recent year under study. Karnataka and Bihar with an average area of 247.19 and 168.72 thousand hectare reported a growth rate of 6.34 percent and 1.20 percent per annum respectively. Platykurtic nature followed by positive skewness in case area under mung in Karnataka indicates marginal shift in area has taken place during early period under study and remained almost same during latter half. Area under mung in case of Bihar has positive kurtosis and left skewed nature reveals that there is sweeping change in area during recent years under study.

The effect of expansion of area is clearly visible in the production scenario of mung. For whole India, with a mere 524.00 thousand tonnes in 1972 it has reached to 1800.22 thousand tonnes in 2010, registering a growth rate of 3.17 percent per annum. The average mung production being 1084.47 thousand tonnes coupled with platykurtic and right sided skew nature clearly indicates that there has been steady changes in mung production during early period under study and remained almost same thereafter. State wise figures indicates that, there is a drastic improvement in Rajasthan mung production, with a just 10.50 thousand tonnes of production it has reached to 652.53 thousand tonnes there by registering a growth rate of 14.55 percent per year. This could be possible mainly because of increase in area by 9.74 percent per year. Positive value of kurtosis combined with positive skewness reveals that maximum changes in mung production has taken place during early period and remained almost same in latter half. Although with average production of 231.25 thousand tonnes, Maharashtra stands first in mung production among the states under study; maximum production figure and growth rate was noticed in Rajasthan during the study. The Maharashtra registered an annual growth rate of 3.89 percent per year mainly because of improvement in per hectare production (3.86 % per year). A noticeable improvement of mung production can be seen in case of Karnataka, with a only 10.00 thousand tonnes of production it has reached to 202.20 thousand tonnes thereby registering the annual growth rate of 6.77 percent. Positive nature of kurtosis and skewness reveals that improvement has taken place during early period under study. Comparatively minimum growth rate was reported in case of Andhra Pradesh. On an average Bihar has supplied 85.84 thousand tonnes of mung to Indian mung basket. Bihar is the only state showing negative skewness coupled with negative kurtosis which clearly reveals that there has been marginal shift in production in recent year under study.

Table 1. *Per se* performance of mung production in major states of India

	Area ('000ha)					
	Rajasthan	**Maharashtra**	**Andhra Pradesh**	**Karnataka**	**Bihar**	**India**
Minimum	170.70	296.00	283.00	71.00	12.00	1837.00
Maximum	1272.23	798.00	681.00	530.00	231.70	3726.70
Mean	469.00	593.33	480.70	247.19	168.72	2913.24
SE	43.26	19.46	11.39	19.26	5.98	65.50
CV (%)	59.77	21.26	15.36	50.49	22.96	14.57
Kurtosis	0.54	-0.65	2.06	-0.51	5.50	0.33
Skewness	1.17	-0.20	-0.42	0.59	-1.83	-0.62
SGR%	9.74	0.01	-1.03	6.34	1.20	1.52
CGR%	4.00	0.70	-0.70	4.00	1.70	1.00
Production ('000t)						
Minimum	10.50	55.00	62.00	10.00	5.00	524.00
Maximum	652.53	459.60	312.00	202.20	132.20	1800.23
Mean	136.89	231.25	171.66	65.30	85.84	1084.48
SE	24.78	16.44	8.05	6.28	4.76	46.23
CV (%)	117.33	46.09	30.41	62.37	35.91	27.62
Kurtosis	4.01	-0.79	0.62	3.23	-0.23	-0.11
Skewness	2.11	0.41	0.39	1.65	-0.74	0.32
SGR%	14.55	3.89	0.21	6.77	3.77	3.18
CGR%	5.10	2.60	0.30	2.60	3.30	1.40
Yield (Kg/ha)						
Minimum	47.66	160.35	139.78	68.30	232.00	225.50
Maximum	621.43	670.25	572.44	566.86	680.44	513.15
Mean	246.67	375.54	357.46	277.49	494.95	367.37
SE	23.15	19.46	14.48	17.16	16.43	9.62
CV (%)	60.83	33.58	26.26	40.08	21.51	16.96
Kurtosis	0.04	-0.42	-0.33	0.02	-0.49	0.03
Skewness	0.69	0.53	-0.05	0.49	-0.45	0.19
SGR%	0.95	3.86	2.17	0.12	1.71	1.01
CGR%	1.00	1.80	1.10	-1.40	1.60	0.40

For whole India, increased production of mung would not have been possible without a substantial increase in per hectare yield of the crop. The per hectare yield of mung has almost doubled during the study period, starting with only 225.50 kg/ha it has reached to 513.15 kg/ha during the year 2010 thereby registering a growth rate of 1.01 percent per year. State wise figures shows, among the state under study maximum growth in per hectare production of mung has taken place in Maharashtra (3.86% per year) followed by Andhra Pradesh (2.17% per year). Bihar has the maximum potential of producing the mung. Although growth rate of area under mung is negative in Andhra Pradesh, production has achieved positive growth rate mainly because of improvement in per hectare production of mung at the rate of 2.17 percent per annum. Comparatively minimum growth rate was observed in case of Rajasthan (0.95% per year) and Karnataka (0.11% per year). Surprisingly, Rajasthan and Karnataka had higher shares in area but due to dismal performance in the yield, their proportion in production is very less compared to other states. In spite of all these improvements within states, Rajasthan, Karnataka and Andhra Pradesh with a average production of 246.67 kg/ha, 277.49 kg/ha and 357.46 kg/ha respectively has fails to reach national average per hectare production of 367.37 kg/ha indicating the dependency of major states on area for production. As now a day's area is one of the most limiting factors of production and due to ever increasing population and urbanization, expansion in area would not be possible. Hence utmost care should be taken to improve the per hectare production of mung.

3.2 Test of Outliers and Randomness for Area, Production and Productivity of Mung

Having an idea about area, production and productivity scenario of mung in major growing states as well as for whole India, it is now our objective is to study the pattern of growth of all these parameters. Before getting the trends in all the series, it is better to have idea about each and every series, whether the series exhibit any trend or followed a randomness nature. Before performing the test of randomness the series under consideration are subjected to test of outlier as described in materials and methods section. The results of both the test of randomness and that of outlier are presented in Table 2. Analysis of different data series for presence of outlier is rejected in most of the cases, except in case of area under mung in Bihar and production of mung in case Rajasthan and Karnataka. No outlier was noticed in productivity data series. The outlier in case of area under mung in Bihar was noticed in 1971-72 which has no match with data series; hence it has been treated as typological error and replaced by median of the series. The outlier in case of mung production in Rajasthan was detected in 2003-04, 2007-8, 2010-11 and 2011-12 may be due increase in area under mung as a result of favorable pre-sowing rainfall. In case of mung production of Karnataka, outlier was noticed in 1991-92, as it has no match with the minute change in area or the growth in productivity it can be treated as typological error and suitable measure has taken before further analysis.

From the test of randomness, one can see that except area and productivity of mung in case of Bihar, all other data series are random in nature. In spite of having clear cut trends in area and productivity of mung in Bihar, production series fails to have clear cut trend which may be due to lack of modern technology to sustain mung production, so as to reap the benefit of both increased area and yield. By considering the overall results of test of randomness, there is no clear cut policy for maintain the mung production sustainably in India or if policy exist, it has failed to reach the farmer. One cannot ignore the minor variation in production scenario between the two consecutive years due to factors beyond the control of human. Hence appropriate policy should be made to avoid these fluctuations and to sustain the mung production.

Table 2. Test of outliers and randomness for area, production and productivity of mung

	Rajasthan	Maharashtra	Andhra Pradesh	Karnataka	Bihar	India
Area						
No. of Obs.	42	42	42	42	42	42
P	26	24	28	25	20	24
E (P)	26.67	26.67	26.67	26.67	26.67	26.67
V(P)	7.14	7.14	7.14	7.14	7.14	7.14
τ_{cal}	0.25	1.00	0.50	0.62	2.49	1.00
Inference	Random	Random	Random	Random	Trend	Random
Outlier	No	No	No	No	Yes	No
Production						
P	26	24	26	23	27	28
E (P)	26.67	26.67	26.67	26.67	26.67	26.67
V(P)	7.14	7.14	7.14	7.14	7.14	7.14
τ_{cal}	0.25	1.00	0.25	1.37	0.12	0.50
Inference	Random	Random	Random	Random	Random	Random
Outlier	Yes	No	No	Yes	No	No
Productivity						
P	26	22	25	24	21	26
E (P)	26.67	26.67	26.67	26.67	26.67	26.67
V(P)	7.14	7.14	7.14	7.14	7.14	7.14
τ_{cal}	0.25	1.75	0.62	1.00	2.12	0.25
Inference	Random	Random	Random	Random	Trend	Random
Outlier	No	No	No	No	No	No

3.3 Sustainability Analysis of Mung Productivity

Sustainability in yield of mung in different states along with whole India has been measured with the help of sustainability indices which are already in literature and by using proposed two methods i.e., SI-1 and SI-2 as described in the materials and methods section. From the Table 3, it is clear that whole India is showing higher sustainability in yield of mung as per the indices of Pal and Sahu and proposed two methods and Bihar according to [6] and [7] Whole India placed second and third according index given by Singh *et al*. and Sahu *et al.* respectively. According to all the indices including developed two methods Rajasthan is having comparatively lower sustainability to produce mung among the states under study. So from the table it is clear that results of existing measures and proposed measure are almost in conformity with each other.

3.4 Modeling and Forecasting

After testing the each and every series for presence of outlier, randomness our next task is to forecast the series for the year to come. For this purpose we adopted the [10] ARIMA and GARCH for the data series of area and ARIMA, GARCH and ARIMAx techniques for the data series of production and yield under various crops under study as discussed in the materials and methods section. In the first step, if outlier/s is detected in the data series, it is made free from outlier using suitable measure as mentioned in the material and methods section. Once the data series is made free from outliers, each and every series are examined for stationarity condition through ADF, KPSS test Whole data series is divided into two parts, one is model building and another part, used for model validation in all the forecasting techniques used.

For each and every data series various ARIMA models has been fitted. Among the significant competitive models, best model is selected based on minimum value of AIC, BIC, ME, RMSE, MAE, MPE, MAPE and maximum value of R^2. Best fitted models are put under diagnostic checks through Ljung–Box test; In modeling the data series using GARCH, first the data series is checked for presence of heteroscedasticity. Various GARCH models are fitted; best GARCH model is selected in similar way as in case of ARIMA. In ARIMAx, first all the independent variables which are contributing significantly (stepwise regression) to the crop production are modeled individually and forecasted up to 2022 using ARIMA technique. Then these forecasted values are used as independent/auxiliary variables in the ARIMAx models, various ARIMAx models has been fitted. Among the various competitive ARIMAx model, best model is selected by following the same procedure mentioned above. Among the best ARIMA, GARCH and ARIMAx model, one model has been selected based on minimum value of AIC, BIC, ME, RMSE, MAE, MPE, MAPE and maximum value of R^2 and the forecasting has been made up to 2022 using the best among the ARIMA, GARCH and ARIMAx models. The crop wise results of the modeling and forecasting exercise are presented in this section.

3.5 Modeling and Forecasting of Area under Mung

Results of stationarity test of area, production and productivity data series of mung in major states of India are presented in the Table 4. From the table one can find that both KPSS and ADF test for the data series of area under mung rejected the hypothesis of stationary data. First order differencing was necessary for all the series under study to make it stationary. After achieving stationarity, various ARIMA models are tried for each series and only best models among the competitive model for each series is selected. On the other hand various GARCH models have been fitted and best GARCH model for each series is selected and presented in Table 5. Developed models are also put under diagnostic checking through Ljung–Box test of residuals (Table 5).

Table 3. Sustainability analysis of mung productivity

Sustainability index	Rajasthan	Maharashtra	Andhra Pradesh	Karnataka	Bihar	India
Singh et al.	0.1446	0.3688	0.3890	0.2463	0.5728	0.4494
Sahu et al.	1.7586	0.8119	0.9036	1.4522	0.3748	0.8522
Pal and Sahu	0.0041	0.0022	0.0018	0.0027	0.0014	0.0011
SI-1	0.0069	0.0225	0.0298	0.0150	0.0428	0.0506
SI-2	0.0041	0.0018	0.0015	0.0035	0.0015	0.0006

Table 4. Test of stationarity of area, production and productivity of mung in India

	ADF Value	P Value	Conclusion	KPSS Value	P Value	Conclusion
Area						
Rajasthan	-1.039	0.919	Non Stationary	1.672	0.01	Non Stationary
Maharashtra	-0.516	0.976	Non Stationary	0.866	0.01	Non Stationary
Andhra Pradesh	-1.553	0.749	Non Stationary	0.699	0.01	Non Stationary
Karnataka	-2.812	0.255	Non Stationary	1.846	0.01	Non Stationary
Bihar	-1.129	0.906	Non Stationary	1.043	0.01	Non Stationary
India	-1.574	0.740	Non Stationary	1.384	0.01	Non Stationary
Production						
Rajasthan	-2.478	0.386	Non Stationary	0.986	0.01	Non Stationary
Maharashtra	-0.207	0.989	Non Stationary	1.257	0.01	Non Stationary
Andhra Pradesh	-1.531	0.757	Non Stationary	0.376	0.04	Non Stationary
Karnataka	-2.084	0.540	Non Stationary	0.721	0.01	Non Stationary
Bihar	-0.938	0.935	Non Stationary	1.494	0.01	Non Stationary
India	-1.686	0.696	Non Stationary	1.005	0.01	Non Stationary
Yield						
Rajasthan	-2.649	0.319	Non Stationary	0.695	0.01	Non Stationary
Maharashtra	-0.791	0.954	Non Stationary	1.520	0.01	Non Stationary
Andhra Pradesh	-2.138	0.519	Non Stationary	0.942	0.01	Non Stationary
Karnataka	-1.685	0.697	Non Stationary	0.791	0.01	Non Stationary
Bihar	-1.290	0.852	Non Stationary	1.729	0.01	Non Stationary
India	-1.700	0.691	Non Stationary	0.489	0.04	Non Stationary

From the Table 5, for area under mung in Bihar and whole India, ARIMA (0,1,2) is found to be best ARIMA model; while ARIMA (0,1,4) is best fitted for Rajasthan. ARIMA (1,1,2) is found to be best fitted ARIMA model for Andhra Pradesh and Karnataka where as Maharashtra is best fitted with higher order ARIMA (4,1,4) model. On the other hand, area under mung in all the states and whole India except Andhra Pradesh are bested fitted with GARCH (1) model whereas data series of area under mung for Andhra Pradesh is found not to have GARCH effect. The results of Ljung–Box test of residuals also reject the presence of significant auto correlation in the residuals for the best fitted model both in ARIMA and GARCH. Comparing best fitted ARIMA and GARCH models for area under mung in various states under study revealed that in all the states including India, ARIMA model has outperformed GARCH (Table 5) with satisfying maximum criteria of minimum value of AIC, BIC, RMSE, MAE and other values. It can also be noted that expect MAPE criteria all other criteria signifies ARIMA as best model than GARCH model for modeling mung area in India. These models are used for forecasting mung area up to 2022 (Fig. 1 & Table 5). The selected models are also validated for accuracy using last three years and observed that the actual and predicted values are in range (Table 6) for all the states except for Karnataka. The best fitted model, ARIMA (1,1,2) in Karnataka fails to catch the sudden decrease in area during 2012. From the forecasted values obtained, it can be noted that area under mung in Rajasthan and Karnataka would increase continuously in future which would reach up to 1398.22 thousand hectares and 447.43 thousand hectares respectively in 2022.There would be marginal increase in area towards mung in Maharashtra, Andhra Pradesh, Bihar and whole India in 2022 (Fig. 1).

3.6 Modeling and Forecasting of Mung Production

From stationarity test for the production series of mung, it is observed that, all the data series are non-stationary in nature (Table 4). The non-stationary data series are made stationary by first order differencing. After achieving stationarity, various ARIMA model are tried for each and every series, the significant model which satisfies the maximum criteria of minimum value AIC, BIC, ME, RMSE, MAE, MPE, MAPE and maximum value of $R^2$are selected as best ARIMA model and presented in Table 5. From the table, it is clear that ARIMA (0,1,2) for Karnataka and Bihar; ARIMA (1,1,2), ARIMA (3,1,2), ARIMA (2,1,3) and ARIMA (4,1,4) for Rajasthan, Maharashtra, Andhra Pradesh and whole India respectively are found to be best fitted ARIMA model for modeling mung production. Similarly, among the various GARCH models, GARCH (1) is found to be best fitted for modeling mung production in all states including whole India. In ARIMAx, first all the independent variables which are found to contribute significantly to mung productivity are modeled and forecasted up to 2022 using ARIMA technique (Fig. 3). Then these forecasted values are used as independent variables in the ARIMAx model. As in case of ARIMA and GARCH, here also best ARIMAx model has been selected based on minimum value of various error criteria and maximum value of R^2. From the Table 4.4.3.B1, it can be noted that ARIMAx (0,1,2) for Karnataka and Bihar; ARIMAx (4,1,2), ARIMAx (2,1,2), ARIMAx (1,1,2), ARIMAx (4,1,3) for Rajasthan, Maharashtra, Andhra Pradesh and whole India respectively are the best ARIMAx models among the various competitive ARIMAx models for modeling mung production. The results of Ljung–Box test of residuals also reject the presence of significant auto correlation in the residuals of the best fitted ARIMA, GARCH and ARIMAx model (Table 5).

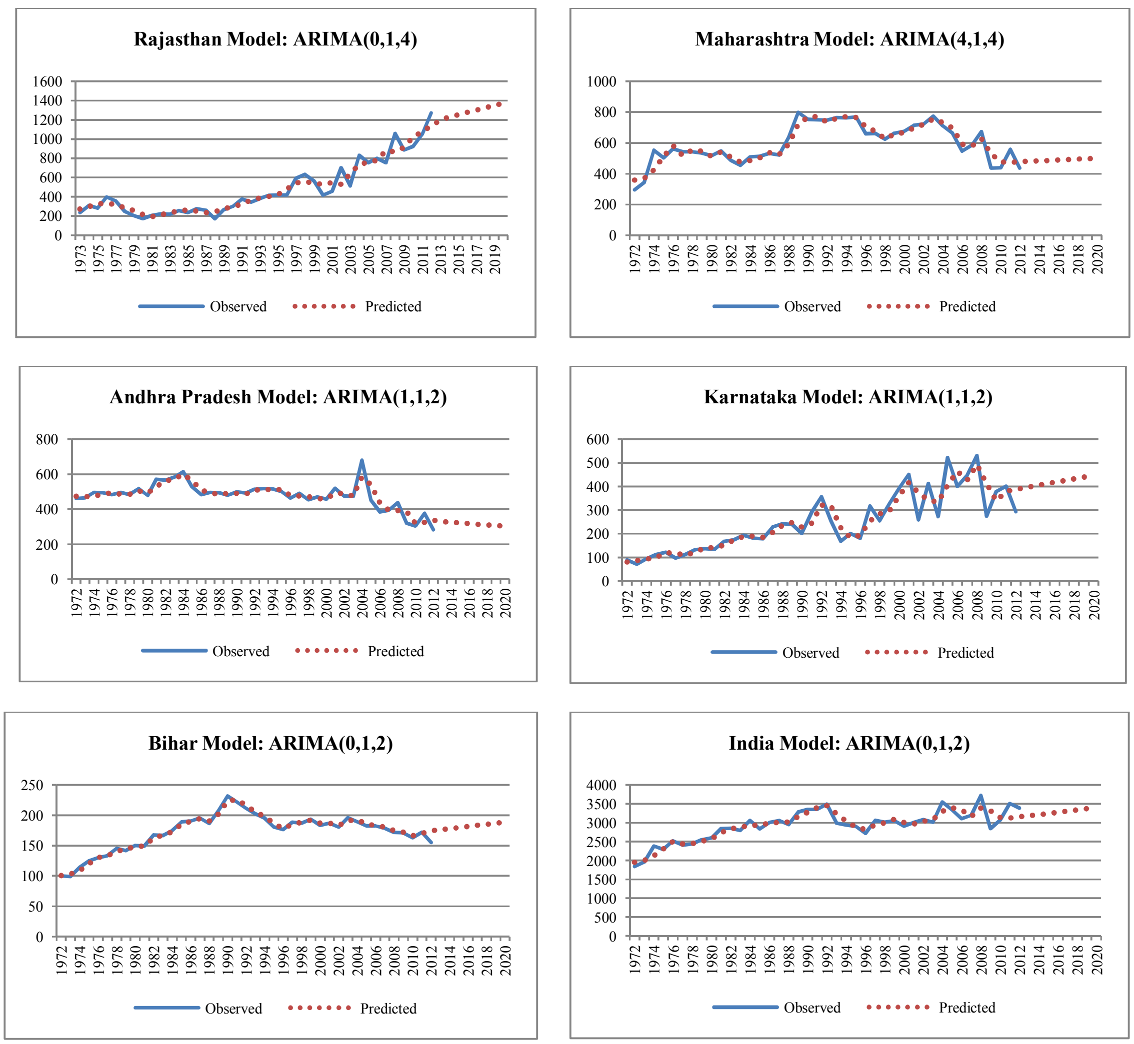

Fig. 1. Observed and forecasted area ('000 ha) under mung cultivation using best selected model in India

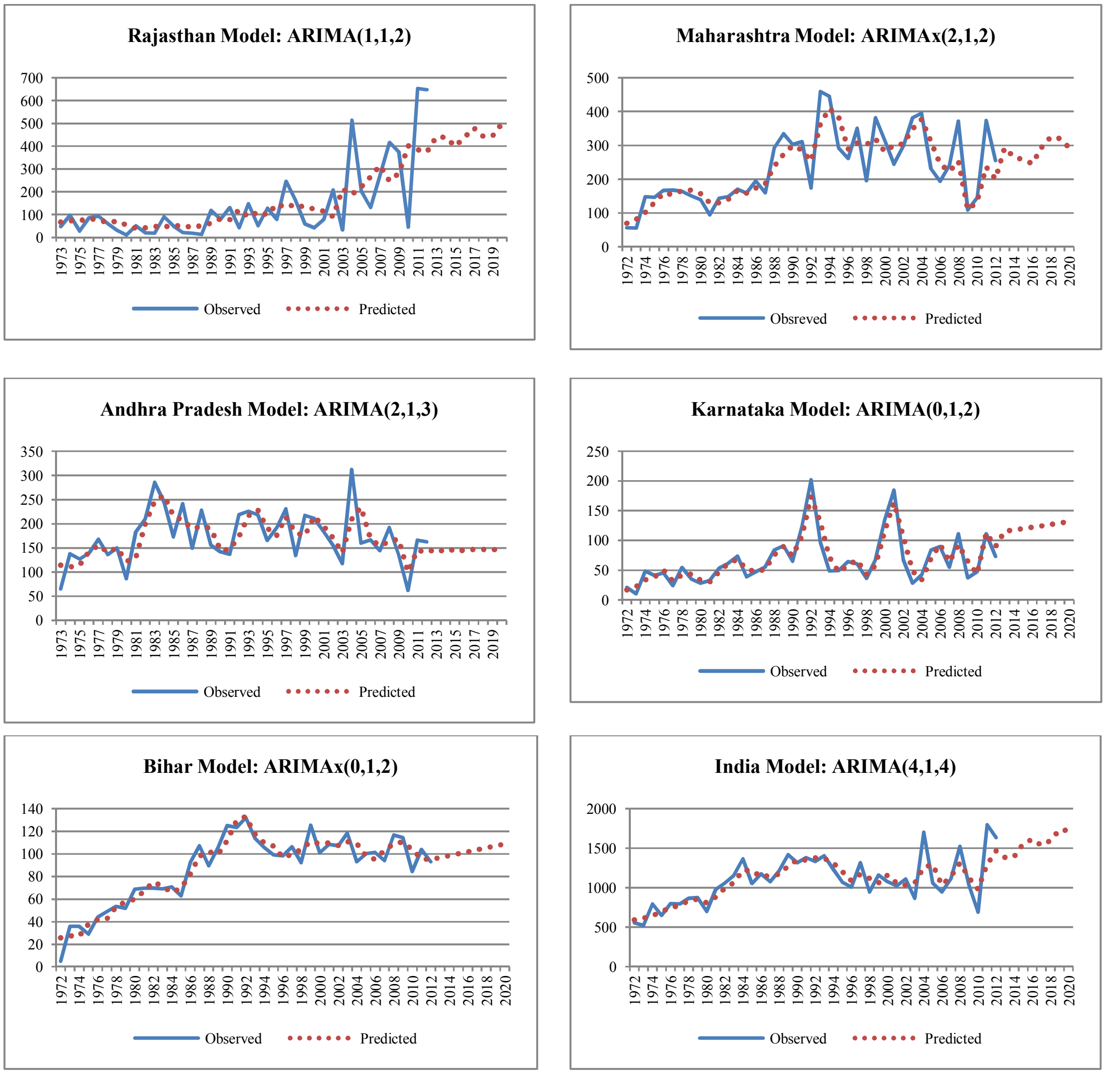

Fig. 2. Observed and forecasted mung production ('000 tonnes) using best selected model in India

By using the same error and R^2 criteria, best among the best selected ARIMA, GARCH and ARIMAx models has been selected. From the Table 5, for modeling mung production, except for Maharashtra and Bihar for all other states and whole India, best fitted ARIMA model outperformed the GARCH and ARIMAx model where as in case of Maharashtra and Bihar ARIMAx model over takes ARIMA and GARCH. From the Fig. 2, it can be noted that the observed and predicted values are almost close in all the states except for mung production series of Rajasthan. The selected models are also validated for accuracy by using last three years data and observed that the actual and predicted values are in range (Table 6) for all the states including whole India expect for Rajasthan. From the forecasted figures, it can be seen that mung production would increase marginally in 2022 as compared to 2012 in all the states expect Rajasthan and Andhra Pradesh which has shown tendency to decrease its production capacity in future.

3.7 Modeling and Forecasting of Mung Productivity

From the stationarity tests for the series of mung productivity, both the ADF and KPSS test rejects the hypotheses of stationarity (Table 4) i.e., mung productivity of all the states under study is non stationary in nature. First order differencing was necessary to make it stationary. After achieving stationary, we proceeds in similar way as in case of production and selected best ARIMA, GARCH and ARIMAx models for all the states under study and results of the same is presented in the Table 5. From the Table 5, for mung productivity in Maharashtra and Karnataka ARIMA (3,1,2) is found to be best ARIMA model; while ARIMA (4,1,2), ARIMA (3,1,3), ARIMA (1,1,2) and ARIMA (1,1,1) are found to be best fitted ARIMA model for Rajasthan, Andhra Pradesh, Bihar and India respectively. On the other hand, mung productivity in Maharashtra, Karnataka and whole India is bested fitted with GARCH (1) model whereas data series of mung productivity for remaining states are found not to have GARCH effect. In similar fashion, best ARIMAx model among various competitive models are also been selected for all states productivity series of mung under study. From the Table 5, it can be noted that among the various ARIMAx models, ARIMAx (1,1,2) for Andhra Pradesh and Bihar; ARIMAx (4,1,2), ARIMAx (2,1,2), ARIMAx (3,1,2), ARIMAx (4,1,3) for Rajasthan, Maharashtra, Karnataka and whole India respectively are found to be best fitted ARIMAx model for modeling productivity of mung in respective states. The residuals of all the best selected models of ARIMA, GARCH and ARIMAx are put under Ljung–Box test (Table 5) and results revealed that there is no significant auto correlation for residuals in the all the cases.

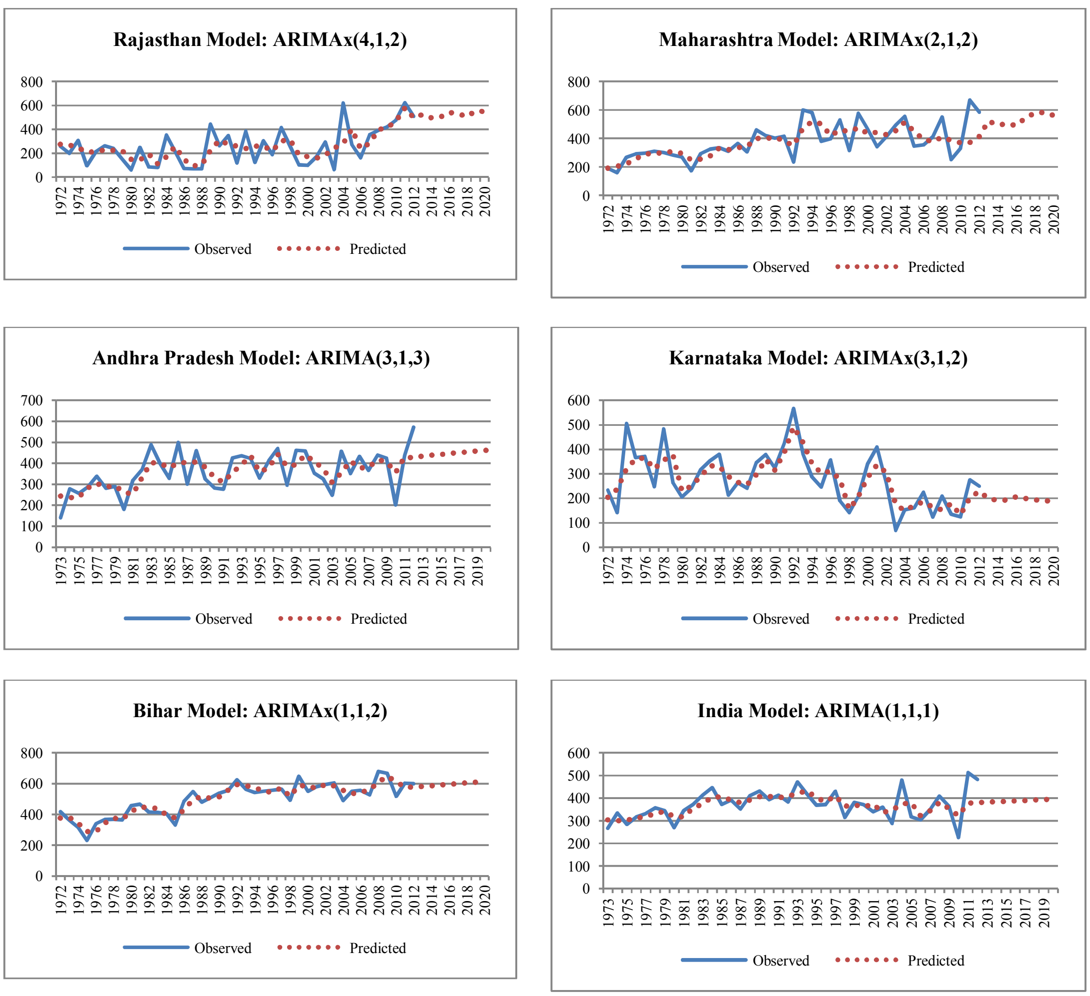

Fig. 3. Observed and forecasted mung productivity (kg per hectare) using best selected model in India

Table 5. Best selected ARIMA and GARCH models for in India

State	Model	Model selection criteria								Ljung-Box test for residuals	
		AIC	BIC	ME	RMSE	MAE	MPE	MAPE	R^2	χ^2	P Value
	Area (‘000 Ha)										
Rajasthan	ARIMA(0,1,4)*	339.33	348.99	-0.105	19.728	15.124	-0.54	3.375	0.99	2.528	0.991
	GARCH(1)	473.903	483.884	-7.472	102.945	72.827	17.827	-6.506	0.788	1.198	0.32
Maharashtra	ARIMA(4,1,4)*	358.19	374.56	0.846	20.31	16.409	0.236	2.769	0.969	3.211	0.976
	GARCH(1)	383.866	392.054	3.883	35.866	26.772	4.553	0.704	0.893	1.261	0.262
Andhra Pradesh	ARIMA(1,1,2)*	337.87	346.05	0.162	19.307	12.816	-0.036	2.638	0.871	5.342	0.867
	No GARCH										
Karnataka	ARIMA(1,1,2)*	358.2	366.39	0.128	25.556	17.428	0.061	6.383	0.95	4.563	0.918
	GARCH(1)	405.158	413.346	-4.018	41.226	29.345	12.289	-5.331	0.693	0.383	0.536
Bihar	ARIMA(0,1,2)*	206.35	212.9	0.027	3.208	2.71	0.122	1.553	0.99	2.882	0.984
	GARCH(1)	247.463	255.517	-0.072	6.035	4.549	2.753	0.294	0.959	1.952	0.162
India	ARIMA(0,1,2)*	434.61	441.17	-0.371	75.594	57.995	0.068	1.98	0.963	1.951	0.997
	GARCH(1)	544.38	552.698	-1.399	232.939	177.501	6.068	-0.705	0.686	0.547	0.46
	Production (000’tonnes)										
Rajasthan	ARIMA(1,1,2)*	-27.52	-19.21	0.001	0.137	0.109	-0.121	6.02	0.839	5.423	0.861
	GARCH(1)	354.383	362.438	0.168	28.922	18.906	18.363	-8.17	0.877	0.678	0.411
	ARIMAx(4,1,2)	398.15	413.12	-0.155	32.344	24.374	-13.208	29.122	0.905	9.583	0.478
Maharashtra	ARIMA(3,1,2)	364.87	376.34	0.302	25.304	19.741	0.357	8.491	0.917	2.208	0.995
	GARCH(1)	379.824	388.012	4.643	32.905	27.745	11.858	1.713	0.85	1.585	0.208
	ARIMAx(2,1,2)*	353.58	366.46	0.078	24.195	19.012	0.116	8.084	0.926	1.977	0.997
Andhra Pradesh	ARIMA(2,1,3)*	292.2	303.48	0.072	10.583	8.398	0.014	4.757	0.875	10.044	0.437
	GARCH(1)	355.014	363.202	5.009	22.973	17.769	10.207	1.652	0.565	0.051	0.821
	ARIMAx(1,1,2)	340	349.82	0.246	18.571	14.733	0.161	8.652	0.895	8.261	0.603
Karnataka	ARIMA(0,1,2)*	314.97	321.52	0.003	13.926	10.462	0.985	14.869	0.85	4.99	0.892
	GARCH(1)	327.006	335.194	3.866	19.041	13.231	19.665	-0.456	0.616	1.216	0.27
	ARIMAx(0,1,2)	323.09	331.28	0.012	13.517	10.221	1.145	14.583	0.858	0.44	0.507

Table 5 continued…..

Bihar	ARIMA(0,1,2)	225.81	232.36	-0.032	4.404	3.536	0.373	4.275	0.979	4.553	0.919
	GARCH(1)	317.084	325.402	2.115	11.886	8.718	13.247	-1.426	0.807	1.692	0.24
	ARIMAx(0,1,2)*	234.05	243.87	-0.03	4.096	3.371	0.357	4.235	0.982	4.358	0.93
India	ARIMA(4,1,4) *	425.69	441.8	0.711	56.627	43.508	0.194	3.971	0.935	1.93	0.997
	GARCH(1)	531.985	540.303	2.368	212.04	167.863	16.206	-3.982	0.349	3.29	0.07
	ARIMAx(4,1,3)	448.9	465.28	0.711	59.302	47.657	0.169	4.396	0.927	4.832	0.68
	Productivity (kg/hectare)										
Rajasthan	ARIMA(1,1,2)*	-27.52	-19.21	0.001	0.137	0.109	-0.121	6.02	0.839	5.423	0.861
	GARCH(1)	354.383	362.438	0.168	28.922	18.906	18.363	-8.17	0.877	0.678	0.411
	ARIMAx(4,1,2)	398.15	413.12	-0.155	32.344	24.374	-13.208	29.122	0.905	9.583	0.478
Maharashtra	ARIMA(3,1,2)	364.87	376.34	0.302	25.304	19.741	0.357	8.491	0.917	2.208	0.995
	GARCH(1)	379.824	388.012	4.643	32.905	27.745	11.858	1.713	0.85	1.585	0.208
	ARIMAx(2,1,2)*	353.58	366.46	0.078	24.195	19.012	0.116	8.084	0.926	1.977	0.997
Andhra Pradesh	ARIMA(2,1,3)*	292.2	303.48	0.072	10.583	8.398	0.014	4.757	0.875	10.044	0.437
	GARCH(1)	355.014	363.202	5.009	22.973	17.769	10.207	1.652	0.565	0.051	0.821
	ARIMAx(1,1,2)	340	349.82	0.246	18.571	14.733	0.161	8.652	0.895	8.261	0.603
Karnataka	ARIMA(0,1,2)*	314.97	321.52	0.003	13.926	10.462	0.985	14.869	0.85	4.99	0.892
	GARCH(1)	327.006	335.194	3.866	19.041	13.231	19.665	-0.456	0.616	1.216	0.27
	ARIMAx(0,1,2)	323.09	331.28	0.012	13.517	10.221	1.145	14.583	0.858	0.44	0.507
Bihar	ARIMA(0,1,2)	225.81	232.36	-0.032	4.404	3.536	0.373	4.275	0.979	4.553	0.919
	GARCH(1)	317.084	325.402	2.115	11.886	8.718	13.247	-1.426	0.807	1.692	0.24
	ARIMAx(0,1,2)*	234.05	243.87	-0.03	4.096	3.371	0.357	4.235	0.982	4.358	0.93
India	ARIMA(4,1,4) *	425.69	441.8	0.711	56.627	43.508	0.194	3.971	0.935	1.93	0.997
	GARCH(1)	531.985	540.303	2.368	212.04	167.863	16.206	-3.982	0.349	3.29	0.07
	ARIMAx(4,1,3)	448.9	465.28	0.711	59.302	47.657	0.169	4.396	0.927	4.832	0.68

*Note: * indicates the best model and used further for forecasting purpose*

Table 6. Validation and forecasting of area under mung in India on the basis of selected best model

State	Model	2010		2011		2012		2016	2020	2022
		Observed	Predicted	Observed	Predicted	Observed	Predicted	Predicted	Predicted	Predicted
Area (‘000 Ha)										
Rajasthan	ARIMA(0,1,4)	922.85	1023.73	1050.04	1073.29	1272.23	1139.93	1277.4	1372.88	1398.22
Maharashtra	ARIMA(4,1,4)	437.89	475.21	558	474.33	436.13	478.12	488.98	499.83	506.12
Andhra Pradesh	ARIMA(1,1,2)	306	318.75	378	326.29	283	338.66	318.37	302.79	301.21
Karnataka	ARIMA(1,1,2)	379	338.55	402	380.28	293	387.79	417.6	447.43	457.56
Bihar	ARIMA(0,1,2)	163.14	166.26	172.4	170.25	155.08	174.61	181.6	188.59	192.19
India	ARIMA(0,1,2)	3070.06	3138.1	3508.19	3124.1	3387.08	3155.54	3277.08	3398.62	3421.34
Production (000’tonnes)										
Rajasthan	ARIMA(1,1,2)	43.98	400.98	652.53	384.86	647.18	374.62	440.15	498.96	512.27
Maharashtra	ARIMAx(2,1,2)	145.21	133.21	374	236.29	255.39	200.61	245.71	293.61	326.01
Andhra Pradesh	ARIMA(2,1,3)	62	99.64	166	145.66	162	140.46	143.49	149.26	177.66
Karnataka	ARIMA(0,1,2)	47	43.5	111	112.8	73	89.49	122.24	131.68	154.56
Bihar	ARIMAx(0,1,2)	84.43	103.75	104.12	95.72	93.06	95.02	101.91	108.92	119.23
India	ARIMA(4,1,4)	692.31	981.29	1800.23	1297.07	1634.33	1466.82	1612.22	1726.51	1766.16
Productivity (kg/hectare)										
Rajasthan	ARIMAx(4,1,2)	476.56	469.43	621.43	578.75	508.7	497.24	540.73	549.94	571.96
Maharashtra	ARIMAx(2,1,2)	331.61	369.91	670.25	370.03	585.58	412.87	490.77	561.26	598.32
Andhra Pradesh	ARIMA(3,1,3)	202.61	356.47	439.15	430.15	572.44	426.42	447.7	462.65	481.78
Karnataka	ARIMA(3,1,2)	124.01	133.18	276.12	202.49	249.15	229.22	206.17	192.07	189.80
Bihar	ARIMAx(1,1,2)	517.53	613.37	603.94	575.27	600.08	578.07	595.21	613.58	629.75
India	ARIMA(1,1,1)	225.5	322.25	513.15	376.99	482.52	381.41	388.22	395.53	408.84

Best of the best selected ARIMA, GARCH and ARIMAx models are selected based on minimum value of AIC, BIC, ME, RMSE, MAE, MPE, MAPE and maximum value of R^2. For modeling mung productivity in Rajasthan, Maharashtra, Karnataka and Bihar ARIMAx models are found to be best than ARIMA and GARCH while in case of Andhra Pradesh and whole India ARIMA is found to be the best model. The selected best of the best models are validated by using recent three years data (Table 6) and found that predicted values are close to actual values for Rajasthan, Karnataka and Bihar during validation periods. In other hand, models have failed to catch the sudden changes in mung productivity of Maharashtra, Andhra Pradesh and whole India during the validation period. The forecasted figures indicate that, mung productivity would increase marginally in Rajasthan and Bihar whereas remaining all the states under study including whole India has tendency to loss their present capacity to produce mung in future. Even though, in India forecasted figures for mung area and production would increase marginally in future, this increase in production is no match with projected demand for 2022 which is 2840 thousand tonnes (Singh, 2013). Hence, for the food and nutritional security of huge population, India needs to arrest the tendency of decrease in productivity.

4. CONCLUSION

Thus from the study of area, production and productivity of mung the following salient features are emerge out:

1. By and large there has been considerable expansion in area, production and productivity of mung in all the states under study including whole India during the study period. Among the states under study, the maximum annual growth in area (9.75%) and production (14.55%) of mung was observed in Rajasthan.Bihar stands first in productivity of mung among the states under study.Rajasthan, Karnataka and Andhra Pradesh have fails to reach national average per hectare production of 367.37 kg/ha.
2. In case of area, production and productivity of mung for selected states and whole India, none of the series is found stationary and hence first order differencing is done to achieve stationarity. For modeling and forecasting mung area, ARIMA models are found to be best compared to GARCH for all the states under study including while whole India.Except in Maharashtra and Bihar, ARIMA models overtakes the GARCH and ARIMAx for modeling mung production.In maximum cases of mung productivity series under study, inclusion of independent variable in ARIMA models has given better result than univariate ARIMA and GARCH. Forecasted figures indicate that, area and production of mung would increase marginally in India whereas productivity has tendency to decrease in future.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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