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COMPARISON OF ARIMA, ARIMAX AND GARCH MODEL FOR FORECASTING THE GRAM PRODUCTION SCENARIO OF INDIA.

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ABSTRACT

Pulses are known as poor man's meat as these are comparatively cheaper sources of protein in balancing human diet. In a populous developing country like India, production of pulses play pivotal role in nutritional security of the country. The most important pulse crop in India is gram which occupied an area of about 8958.50 thousand hectares and contributes 44.33 percent of total pulse production during 2012. Production of gram depends on many production factors like rainfall, temperature, relative humidity, fertilizer etc. Analysis of production behaviour, modelling and forecasting of production taking all these factors in to consideration play vital role in human nutritional security. Hence an attempt has been made to analyse and forecast the production scenario of gram in major growing states of India using the best model among Autoregressive Integrated Moving Average (ARIMA) with and without inclusion of exogenous variables and Generalised Autoregressive Conditional Heteroscedastic (GARCH) models. From the forecasted value, it can be said that, gram productivity of India would increase to 969.84 kg/ha in 2018 as compared to 2012. But these increased productivity would still be about 1/6th of present productivity of Israel (6119.80 Kg/ha) and 1/3rd of China (3333.30 kg/ha). On the other hand, forecasting figures for gram area indicates, area would decrease in future and also due to ever increasing population and urbanization area will remains limiting factor of production. Hence, India needs to augment productivity of gram for nutritional security of its huge population.

Keywords: ARIMA, ARIMAx, forecasting, GARCH and production

1. Introduction

Agriculture plays an important role in Indian economy, 58% of Indian population depend upon the agriculture and allied sector (Anonymous, 2015). 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 contributor to Indian agriculture. Pulses are known as poor man's meat as these are comparatively cheaper sources of protein in balancing human diet. In a populous developing country like India, production of pulses play pivotal role in nutritional security of the country. The most important pulse crop in India is gram which occupied an area of about 8958.50 thousand hectares and contributes 44.33 per cent of total pulse production during 2012. It constitutes nearly two-fifth share of the area of total pulses. It may be noticed that gram is extensively cultivated as a winter crop in India especially in the states of Madhya Pradesh (33.88 %), Rajasthan (19.41 %), Maharashtra (15.60 %), Karnataka (10.44 %), Andhra Pradesh (6.34 %) and Uttar Pradesh (6.20 %). These states together accounted for 91 per cent of all India area under gram. These are also leading states in terms of production but Uttar Pradesh crossed Karnataka and Andhra Pradesh due to highest productivity. The state of Uttar Pradesh was leading with a yield rate of 930 kg/ha followed by Andhra Pradesh with 920 kg/ha.

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As gram occupies a significant position among the pulse crops in India, a proper forecast of production of such important pulse crops is very important in terms of food and nutritional security of its people. Thus, from this point of view study of production and other behaviour for the past and assessment of the same in future play vital role. The present study focus on the modelling and forecasting of area, production and yield of gram for major gram growing states of India.

In the arena of time series modelling and forecasting, Box-Jenkins ARIMA technique has come in a great way. Attempts have been made to forecast various crops using ARIMA techniques. Among these, the works of Sahu (2006) for forecasting of irrigated crops like Potato, Mustard and Wheat. Mishra *et al.,* (2013) for onion production in India. Niaz. *et al.,* (2013), forecasting of lentil pulses production in Bangladesh and Vishwajith *et al.,* (2016) for sugarcane production in major growing states of India are few to mentioned.

Though ARIMA models have got wide application in modeling time series data, this is being criticized for its assumption of linearity, and homoscedaticity. As such researchers were in search of better models. Generalised Auto Regressive Conditional Heteroscedastic (GARCH) models was thought of and in literature one can find its use in time series modeling. Paul *et al.* (2009) studied India's volatile spice export data through the

Box-Jenkins Auto Regressive integrated moving average (ARIMA) approach and also through, GARCH nonlinear time series model along with its estimation procedures. Yaziz *et al.* (2011) studied ARIMA and GARCH expand models in forecasting crude oil prices and found that the GARCH model was better than ARIMA model. Vishwajith *et al.* (2014) analyzed trend and forecasted production pulse production in India using ARIMA and GARCH models.

All the above studies and other related studies have mostly considered modelling taking only the time series data of a particular phenomenon, but production of any crops depends on many production factors like rainfall, temperature, relative humidity, fertilizer etc. There is not enough work on forecasting production by taking care of factors of production using ARIMAx model in Indian context. The present study is a sincere attempt to use the factors of production in the model. As such the study attempts to examine the production scenario, growth and forecast the production of gram in major growing states of India using best model among ARIMA, GARCH and ARIMAx model.

2. Materials and methods

Based on their relative contributions to Indian gram basket during 2011, five major states *viz.* Madhya Pradesh, Rajasthan, Maharashtra, Andhra Pradesh and Karnataka, along with whole India are considered for the present study. Data related to area, production and yield of gram in four 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.

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:

$$G = \frac{\max_{i=1,\dots n} \left| y_i - \bar{y} \right|}{s}$$

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. If more number of outlier was detected due to particular cause, we used suitable transformation of data before further analysis. Analysis has been carried out using Graphpad Software (http://graphpad.com).

Examination of behavior of the series under consideration starts with randomness test. Test of randomness is a technique to have an idea whether the values of series under examination have changed haphazardly or followed a definite pattern. The present test for randomness is a non-parametric test based on the number of turning points used when sample size is large. The process is to count peaks and troughs in the series. A "peak" is a value greater than the two neighbouring values and a "trough" is a value, which is lower than of its two neighbours. Both the peak and trough are treated as turning points of the series. Thus, to get a turning point, one needs at least three data points. The number of turning points is clearly one less than the number of runs up and down in the series. The interval between two turning points is called a "phase." Three consecutive observations are required to define a turning point, μ_1, μ_2, μ_3. If the series is random these three values could have occoured in any order of six possibilities. In only four of these ways would there be a turning point (when the greatest or least value is in the middle). Hence the probability of a turning point in a set of three value is 2/3.

Let us consider now a set of values $\mu_1, \mu_2, \dots, \mu_n$ and let us define a "marker" variable X_i by

$$X_i = \begin{cases} 1, & \begin{cases} \mu_i < \mu_{i+1} > \mu_{i+2} \\ \mu_i > \mu_{i+1} < \mu_{i+2}; i = 1, 2, \ldots, n-2 \end{cases} \\ 0, & otherwise \end{cases}$$

The number of turning points p is then simply

$$p = \sum_{i=1}^{n-2} X_t$$

on simplification one can work out

$$E(p) = \sum E(X_i) = \frac{2}{3}(n-2)$$

$$E(p^2) = E\left(\sum_{i=1}^{n-2} X_i\right)^2 \text{, on simplification}$$

$$E(p^2) = \frac{40n^2 - 144n + 131}{90} \text{ and}$$

$$V(p) = \frac{16n - 29}{90}$$

It can easily be verified that as the number of observation increases (n), the distribution of 'p' tends to normal. Thus, for testing the null hypothesis, *i.e.,* series is random

we have the test statistic, $\tau = \dfrac{p - E(p)}{s_p} \sim N(0,1)$

Where s_p is the standard deviation of 'p'.

Thus if the calculated value of τ is greater than 1.96, we reject H_0 that the series is random otherwise accept it.

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.

ARIMA models 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 $\alpha_1, \alpha_2 \ldots \alpha_p$ 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 $\theta_1, \ldots, \theta_q$ 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, $X_t - \phi_1 X_{t-1} - \ldots\ldots - \phi_p X_{t-p} = Z_t + \theta_1 Z_{t-1} + \ldots\ldots + \theta_q Z_{t-q}$ where, $\{Z_t\} \sim WN(0, \sigma^2)$ and the polynomials $(1 - \phi_1 Z - \ldots\ldots - \phi_p Z^p)$ and $(1 + \theta_1 Z + \ldots\ldots + \theta_q Z^q)$ 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

$$\phi^*(B) X_t \equiv \phi(B)(1-B)^d X_t = \theta(B) Z_t, \text{ where, } \{Zt\} \sim WN(0, \sigma^2)$$

$\phi_{(z)}$ 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 Bollerslev (1986) 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 . . . . 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 Bollerslev (1986), "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 $_t$ 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 $L(\theta)$ 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.

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

$$\left(L^s y_t = y_{t-s}\ ' L^s x_t = x_{t-s}, \text{etc.}\right)$$

$\mu \in R, \alpha_s \in R, \beta_s \in R^k$ 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 2020.

$$AIC = 2k - 2\ln(L) \qquad BIC = -2{*}\ln(L) + k{*}\ln(n)$$

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

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

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

where $X, \bar{X}, \hat{X}$ are the value of the i[th] observation, mean and estimated value of the i[th] 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.

3. RESULTS AND DISCUSSION

Gram is the most important pulse crop grown in India with a production of 8220.00 thousand tonnes in 2010-11 covers almost 45 percent of total pulses production of India. Also it contains 18-22% of proteins, 280 mg calcium per 100g, 61-62% of carbohydrates, 12.3mg iron per 100g and *etc.* As such the performance of gram is largely associated with food and nutritional security of not only India but also the World. In this section, an attempt has been made to examine the performance of gram production in India and its major states during the period under consideration. Table 1 provides the *per se* performance of gram in India during 1950-2012. From the table one can find that, during the period under study average area under gram is 7626.68 thousand hectare. The maximum area sown was 10326.00 thousand hectare in 1959-60 which clearly indicates that during the green revolution the area under gram is replaced by food crops like rice and wheat. Same is being reflected in compound growth rate of -0.40 percent per annum. Platykurtic and positive nature of skewness clearly indicates that area under gram became steady after the green revolution period. The maximum annum growth in area was observed in Karnataka (6.41%), followed by Andhra Pradesh (4.41%) and Rajasthan (2.81%). Though average area under gram in Madhya Pradesh is more compare to all other states, Madhya Pradesh has registered a comparatively less annual growth rate of 2.38 per cent. In Karnataka area under gram has increased from a mere 132.00 thousand hectare to 972.00 hectare while in Madhya Pradesh, gram cultivation shows a mere increase from 1303.00 thousand hectare to 3223.00 thousand hectare. The positive value skewness and kurtosis for all states expect Madhya Pradesh reveals that maximum changes in area under gram has taken place during initial period under study. While in case of Madhya Pradesh positive value of skewness and platykurtic nature reveals that there has been steady increase of area under gram during initial period and remained almost same during other half part of the study.

Gram production in India has increased from a mere 3360.00 thousand tonnes to 8220.00 thousand tonnes during study period and has registered simple growth rate of 1.74 per cent per annum. Madhya Pradesh with an average production of 1476.87 thousand tonnes (1/4th of all India production) ranked first followed by Rajasthan, Maharashtra, Andhra Pradesh and Karnataka. Although average production of Madhya Pradesh was highest, maximum annual growth in gram production has observed in Andhra Pradesh (16.23%) followed by Karnataka (12.63%). The higher growth rate in Andhra Pradesh was also noticed during 1981-2002 which was mainly due to high productivity coupled with favourable prices, good monsoon and availability of improved variety seeds and efficient extension services (Tuteja, 2006). In addition, there are evidences to show (NSSO Report, 451) that pulse growers in Andhra Pradesh are using improved seeds for pulse cultivation and adoption rate is as high as 70.96 per cent against an all India average of 47 per cent during 1999. Reddy *et al.* in 2013 reported that the area under gram is shifting from northern states to southern states due many institutional and technological factors includes introduction of gram into black cotton soils, availability of plenty of rabi fallow lands, adoption of short duration and high yielding varieties (KAK-2 and JG-11), stable yield and prices, well developed land lease market and wider availability of highly subsidized cold storage warehouse.

Table 1: *Per se* performance of gram production in major states of India during 1950-2012.

	Madhya Pradesh	Rajasthan	Maharashtra	Andhra Pradesh	Karnataka	India
			Area ('000 hectare)			
Minimum	1303.00	449.70	242.00	46.00	132.00	4987.20
Maximum	3223.00	2815.70	1438.00	647.00	972.00	10326.00
Mean	2051.50	1356.61	597.93	160.92	277.82	7626.68
SE	64.73	55.16	35.12	21.31	25.47	153.47
CV (%)	24.84	32.02	46.25	104.25	72.18	15.84
Kurtosis	-0.89	1.23	1.65	2.50	3.97	-0.29
Skewness	0.40	0.25	1.50	1.94	2.08	0.17
SGR%	2.38	2.81	2.04	4.41	6.41	0.30
CGR%	1.30	0.20	1.90	2.40	2.50	-0.40
			Production ('000 tonnes)			
Minimum	593.00	162.00	41.00	14.00	20.00	3360.00
Maximum	3304.10	2073.80	1300.00	912.00	631.00	8220.00
Mean	1476.87	885.82	309.56	141.26	129.10	5234.52
SE	92.55	51.37	35.41	30.06	16.46	133.50
CV (%)	13.54	22.47	17.39	22.61	25.07	6.02
Kurtosis	-0.41	0.58	3.24	3.44	5.04	0.25
Skewness	0.78	0.73	1.88	2.13	2.24	0.49
SGR%	7.34	6.99	7.04	16.23	12.63	1.74
CGR%	3.60	2.60	0.80	5.20	3.70	0.40
			Productivity (kg ha^{-1})			
Minimum	377.00	347.00	168.00	241.00	148.00	453.00
Maximum	1081.00	909.00	904.00	1591.00	670.00	915.00
Mean	684.87	634.77	445.27	555.79	411.24	685.84
SE	22.67	18.04	21.63	46.52	14.36	14.86
CV (%)	13.54	22.47	17.39	22.61	25.07	6.02
Kurtosis	-0.66	-0.59	0.05	0.53	-0.24	-0.63
Skewness	0.46	-0.14	0.94	1.30	0.36	0.04
SGR%	2.22	1.60	2.10	2.92	0.85	1.44
CGR%	1.20	0.60	1.60	2.70	1.10	0.80

On other hand, gram's competitive edge has weakened in the northern states mainly in Madhya Pradesh due to shift towards more profitable crops like wheat in the irrigated area and mustard in unirrigated areas (Tuteja, 2006). Positive nature of skewness in all the states and India reveals that changes in gram production has taken place during the early half and remained almost same during other part of the study. Leptokurtic nature of all data series except for Madhya Pradesh indicates that there has been a significant effort in maintaining the production during study period; gram production of Madhya Pradesh is observed negative kurtosis indicating platykurtic nature.

Gram productivity of India is varied from 453.00 kg ha^{-1} to 915.00 kg ha^{-1} with an annual simple and compound growth rate of 1.44 per cent and 0.80 per cent respectively. On average gram productivity remained 685.84 kg ha^{-1} during the study period. Madhya Pradesh has recorded the average highest productivity (684.87 kg ha^{-1}) and lowest of Karnataka (411.24 kg ha^{-1}). Productivity in case of Andhra Pradesh has increased by six and half times over the minimal value their by registering the highest annual simple and compound growth rate of 2.92 percent and 2.70 percent respectively among the major contributing states under study. Average gram productivity of all the major contributing states is below than the national average of 685.84 kg ha^{-1} thereby indicating the productiveness other states which contributes comparatively less to Indian gram baskets. Positive skewness and kurtosis nature of Andhra Pradesh and Maharashtra, where the growth rate is comparatively higher than other states under study indicates that a maximum improvement in productivity has taken place during early period under study and remained almost same in later half. Gram productivity of Madhya Pradesh, Karnataka and India are positively skewed and platykurtic in nature which reveals that steady changes in productivity has taken place during early half of period under study and remained almost same thereafter.

Table 2: Test of outliers and randomness for area, production and productivity of gram in India

	Madhya Pradesh	Rajasthan	Maharashtra	Andhra Pradesh	Karnataka	India
			Area			
No. of Obs.	62	62	62	62	62	62
P	38	42	36	27	31	36
E (P)	40.00	40.00	40.00	40.00	40.00	40.00
V(P)	10.70	10.70	10.70	10.70	10.70	10.70
τ_{cal}	0.61	0.61	1.22	3.97	2.75	1.22
Inference	Random	Random	Random	Trend	Trend	Random
Outlier	No	Yes	No	No	Yes	No
			Production			
P	40	40	40	22	35	38
E (P)	40.00	40.00	40.00	40.00	40.00	40.00
V(P)	10.70	10.70	10.70	10.70	10.70	10.70
τ_{cal}	0.00	0.00	0.00	5.50	1.53	0.61
Inference	Random	Random	Random	Trend	Random	Random
Outlier	No	No	Yes	Yes	Yes	No
			Productivity			
P	45	41	38	38	44	44
E (P)	40.00	40.00	40.00	40.00	40.00	40.00
V(P)	10.70	10.70	10.70	10.70	10.70	10.70
τ_{cal}	1.53	0.31	0.61	0.61	1.22	1.22
Inference	Random	Random	Random	Random	Random	Random
Outlier	No	No	No	No	No	No

Analysis of data for different series rejected the presence of outliers in most of the cases (Table 2). A few outliers are detected in case of area of Rajasthan and Karnataka; production of Maharashtra, Andhra Pradesh and Karnataka indicating significant deviation from the aggregate pattern and thereby differential potentialities of growth. Outlier incase of gram production in Karnataka is mainly attributed to sudden increase in area under gram during 2006-07. The main reason for presence of outlier in case of Andhra Pradesh production is sudden increase in productivity of gram coupled with area during 2001-02 and thereafter. These data series are made free from outliers either by suitable transformation or by replacing the outlier by median of the respective series before further analysis as discussed in material and methods section.

From the test of randomness one can see that area under gram in case of Andhra Pradesh and Karnataka followed definite trend while Madhya Pradesh, Rajasthan, Maharashtra and whole India have changed randomly. In case of production of gram, excluding Andhra Pradesh, all other major states including whole India have changed randomly. The results show that randomness nature of gram productivity in all the states under study including India. The main reasons behind randomness nature of area in most of data series may be due to very less area under assured irrigation (only 29.57 %, average of 2001-2011, computed from data available at indiastat.com) and high level of fluctuation in prices (in absence of an effective government price support mechanism, Anonymous, 2014) farmers are not very keen on taking up gram cultivation in a flow. Poor spread of improved varieties, high breeds and technology, abrupt climatic changes, vulnerability to pest and diseases may have resulted in randomness nature of productivity in all major states and in whole India. It has been reported that the coverage of high yielding varieties of gram was of the order 3449.11 thousand hectare or 46.29 percent of total area under gram (average of 1996-97, 1997-98 and 1998-99, Anonymous, 2002); seed replacement rate estimated for the year 2006-07 was only 9.48 % for gram (Anonymous, 2009). The randomness nature of productivity and area has resulted in randomness of production in most of the major states and in whole India. By and large there is absence of clear cut policies in major contributing states towards gram production or it has fails to execute in proper manner. By keeping food and nutritional security of ultimate mate consumer in mind, for the benefit of farmers and country as a whole, clear cut policies should be made.

Modeling and forecasting of area under gram

Results of stationarity test of area, production and productivity data series of gram in major states of India are presented in the table 3. From the table one can find that both KPSS and ADF test for the data series of area under gram reject the hypothesis that data are stationary. First order differencing was necessary for the series to make it stationary. After achieving stationarity, various ARIMA and GARCH models are tried for each series and only best models among the competitive models for each series is selected and presented in table 4. 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 gram in various states under study revealed that except for Rajasthan, in all other states including India, ARIMA model has outperformed GARCH (Table 4) with satisfying maximum criteria of minimum value of AIC, BIC, RMSE, MAE and other values. The best selected models are used for forecasting gram area up to 2020. The selected models are also validated for accuracy using last three years and observed that the actual and predicted values are in range (Table 5.). From the forecasted values obtained, it can be noted that area of gram in Madhya Pradesh, Rajasthan, Maharashtra, Andhra Pradesh and Karnataka would be 3021.23, 757.65, 1438.92, 853.32 and 1025.36 thousand hectare respectively in 2020 as result of which whole India's gram area would be 8062.34 thousand hectare in 2020. The forecasted figures indicates that area under gram in case of Karnataka, Maharashtra and Andhra Pradesh would increase in future where as in Madhya Pradesh, Rajasthan and whole India it would decrease in future (Fig. 1). Thus proper measures should be taken to arrest the decrease in area under gram in future.

Modeling and forecasting of gram production

From stationarity test for the production series of gram, it is observed that, all the data series are non-stationary in nature except the production series of Rajasthan (Table 1) same can be visualized through figure 2. The non-stationary data series are made stationary by first order differencing. After achieving stationarity, in similar manner as in case of area best ARIMA and GARCH model are selected, while for fitting ARIMAx, first all the independent variables which are found to contribute significantly to the productivity of gram are modeled and forecasted up to 2020 using ARIMA technique. Then these forecasted values are used as independent variables in the ARIMAx model and comparative best model are selected and presented in table 4.

Best among the best selected ARIMA, GARCH and ARIMAx models is selected based on minimum value of AIC, BIC, ME, RMSE, MAE, MPE, MAPE and maximum value of R^2 and used for forecasting purpose. For modeling gram production in Madhya Pradesh, Andhra Pradesh and whole India ARIMAx model is found to be best than ARIMA and GARCH, while in case of Rajasthan, Maharashtra and Karnataka ARIMA outperformed the GARCH and ARIMAx. 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 5). From the forecasted figures, it can be seen that gram production would increase marginally in 2020 as compared to 2012 in all the states expect Madhya Pradesh which has tendency to decrease its production capacity in future. The same can also be visualized through figures (Fig 2).

Modeling and forecasting of gram productivity

From the stationarity tests for the series of gram productivity, both the ADF and KPSS test rejects the hypotheses of stationarity (Table 1). 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 4. Best of the best selected ARIMA, GARCH and ARIMAx models are selected in similar manner as earlier. For modeling gram productivity in Madhya Pradesh, Rajasthan, Andhra Pradesh and Karnataka ARIMA models are found to be best than GARCH and ARIMAx while in case of Maharashtra and whole India, GARCH and ARIMAx respectively found to be the best models. Although ARIMAx model is found to be best for modeling gram productivity only for whole India, it has lowest value of AIC and BIC criteria for all the gram productivity series of states under study. From the figure, we can note that observed and predicted value are very close during model building stage.

The selected best of the best models are validated by using recent three years data (Table 5) and found that predicted values are close to actual values for Maharashtra, Madhya Pradesh and whole India during validation periods. In other hand, forecasted value deviates from the 2012's actual value for Andhra Pradesh, Karnataka and Rajasthan due to sudden change in the productivity of the gram in these states during 2012. From the figure 3, we can note that actual and forecasted values in all the states under study are close to each other during the model building stages. The forecasted figures indicate that, gram productivity would increase marginally in all the states under study and whole India expect for Madhya Pradesh where it would remain constant.

4. Conclusion

From the present study one can conclude that there has been increase in production of gram in India during the present study. ARIMA, GARCH and ARIMAx

Table 3: Test of stationarity of area, production and productivity of gram in India.

State	ADF Value	P-value	Conclusion	KPSS Value	P-value	Conclusion
			Area			
Madhya Pradesh	-3.251	0.088	Non Stationary	2.910	0.010	Non Stationary
Rajasthan	-3.589	0.089	Non Stationary	0.349	0.019	Non Stationary
Maharashtra	-1.141	0.909	Non Stationary	2.319	0.010	Non Stationary
Andhra Pradesh	4.230	0.990	Non Stationary	1.216	0.010	Non Stationary
Karnataka	-1.064	0.920	Non Stationary	2.261	0.010	Non Stationary
India	-2.627	0.322	Non Stationary	1.652	0.010	Non Stationary
			Production			
Madhya Pradesh	-2.470	0.385	Non Stationary	2.780	0.010	Non Stationary
Rajasthan	-3.721	0.021	Stationary	0.448	0.137	Stationary
Maharashtra	-0.891	0.947	Non Stationary	2.028	0.010	Non Stationary
Andhra Pradesh	0.082	0.990	Non Stationary	1.727	0.010	Non Stationary
Karnataka	-2.000	0.575	Non Stationary	2.332	0.010	Non Stationary
India	-3.078	0.139	Non Stationary	0.250	0.010	Non Stationary
			Productivity			
Madhya Pradesh	-2.547	0.354	Non Stationary	2.516	0.010	Non Stationary
Rajasthan	-3.407	0.093	Non Stationary	1.447	0.010	Non Stationary
Maharashtra	-0.715	0.964	Non Stationary	2.459	0.010	Non Stationary
Andhra Pradesh	-0.536	0.977	Non Stationary	2.190	0.010	Non Stationary
Karnataka	-2.108	0.531	Non Stationary	2.111	0.010	Non Stationary
India	-3.683	0.034	Non Stationary	2.440	0.010	Non Stationary

Table 4: Best fitted ARIMA, GARCH and ARIMAx models for area, production and productivity of gram in India. India.

State	Model	Model selection criteria								LB test	
		AIC	BIC	ME	RMSE	MAE	MPE	MAPE	R2	x^2	PValue
						Area					
Madhya	ARIMA(2,1,1)*	**640.530**	**650.740**	-5.193	**65.103**	**48.504**	**-0.461**	2.323	**0.978**	0.127	0.722
Pradesh	GARCH(1)	661.862	672.164	**-2.368**	69.616	53.916	2.621	**-0.252**	0.974	0.451	0.502
Rajasthan	ARIMA(0,1,3)	720.390	730.610	**0.359**	129.017	93.752	**0.074**	6.967	**0.871**	4.507	0.921
	GARCH(1)*	**718.656**	**728.872**	9.115	**123.197**	**93.214**	7.113	**0.466**	0.793	0.021	0.884
Maharashtra	ARIMA(0,1,2)*	**559.180**	**567.350**	**0.247**	**30.934**	**21.145**	**-0.268**	3.682	**0.982**	8.006	0.662
	GARCH(1)	706.395	716.782	-1.937	88.196	57.921	10.708	-3.121	0.854	0.000	0.990
Andhra	ARIMA(3,1,2)*	**433.620**	**447.920**	**0.197**	**9.643**	**6.394**	**-0.932**	5.747	**0.995**	7.368	0.690
Pradesh	GARCH(1)	540.769	551.156	7.921	40.176	21.732	14.704	**-0.580**	0.917	3.854	0.178
Karnataka	ARIMA(0,1,2)*	**505.560**	**513.730**	**0.144**	**20.078**	**12.671**	**-1.179**	4.762	**0.982**	7.410	0.686
	GARCH(1, 1)	618.304	630.770	3.128	51.624	29.897	11.138	**-1.465**	0.849	2.851	0.212
India	ARIMA(0,1,3)*	**798.550**	**808.760**	**1.860**	**258.999**	**195.540**	**0.014**	2.640	**0.946**	0.429	0.513
	GARCH(1)	861.549	871.851	56.101	373.803	305.077	4.185	**0.600**	0.883	1.018	0.313
						Production					
Madhya	ARIMA(4,1,2)	681.290	697.640	**0.258**	**84.892**	**61.809**	-0.624	4.445	**0.981**	1.905	0.997
Pradesh	GARCH(1)	720.654	730.956	-10.666	110.799	83.076	6.125	-1.643	0.967	0.104	0.747
	ARIMAx(4,1,2)*	**557.780**	**574.240**	-0.618	88.656	64.015	**-0.592**	**4.170**	0.979	5.276	0.872
Rajasthan	ARIMA(1,0,4)*	673.770	688.070	**-0.822**	**78.717**	**60.699**	**0.270**	6.755	**0.915**	8.340	0.596
	GARCH(1)	761.647	771.949	14.926	160.206	126.729	14.864	**0.926**	0.712	0.024	0.877
	ARIMAx(2,1,2)	**585.070**	**597.870**	-2.037	128.619	104.929	-1.013	11.921	0.811	0.458	0.498
Maharashtra	ARIMA(2,1,4)*	574.140	590.490	**-0.054**	**31.913**	**21.308**	-2.523	7.996	**0.978**	2.110	0.995
	GARCH(2)	683.313	695.778	31.568	104.721	66.212	25.093	**-0.837**	0.787	0.037	0.848
	ARIMAx(1,1,2)	**459.600**	**472.320**	0.487	35.352	24.669	**-2.024**	8.556	0.976	2.493	0.991
Andhra	ARIMA(1,1,4)	499.950	514.250	0.192	**16.492**	**9.363**	-6.222	12.052	0.993	7.101	0.716
pradesh	GARCH(1)	517.231	527.619	14.474	64.395	28.098	27.418	-8.783	0.891	0.000	0.983
	ARIMAx(1,1,4)*	**432.280**	**447.090**	**0.060**	19.129	11.515	**-3.195**	**10.491**	**0.994**	9.362	0.498
Karnataka	ARIMA(0,1,2)*	468.120	476.290	**0.098**	**13.725**	**9.576**	**-2.443**	**9.026**	0.977	5.008	0.891
	GARCH(1,1)	477.133	489.496	4.375	21.246	13.553	11.019	-0.911	0.940	3.371	0.132
	ARIMAx(0,1,2)	**399.370**	**410.340**	0.142	15.016	10.967	-2.576	9.125	**0.983**	2.073	0.355
India	ARIMA(0,1,3)	811.480	821.700	4.393	**291.287**	234.198	**-0.080**	4.585	0.792	0.027	0.870
	No GARCH Effect										
	ARIMAx(2,1,2) *	**659.130**	**671.780**	**0.696**	293.579	**223.562**	-0.176	**4.370**	**0.819**	3.421	0.490
						Productivity					
Madhya	ARIMA(2,1,2)*	554.420	566.680	**0.053**	**28.983**	**22.785**	-0.108	**3.482**	**0.964**	4.221	0.937
Pradesh	No GARCH										
	ARIMAx(1,1,2)	**450.920**	**461.890**	0.165	29.317	24.451	**-0.058**	3.542	0.963	5.724	0.838
Rajasthan	ARIMA(1,1,2)*	607.390	617.700	-0.341	**42.531**	**32.669**	-0.095	**5.133**	**0.821**	4.856	0.901
	GARCH(1)	635.754	646.056	7.922	52.658	40.555	6.605	0.617	0.662	0.098	0.755
	ARIMAx(1,1,2)	**487.390**	**498.360**	**0.008**	43.753	33.991	**-0.058**	5.192	0.767	5.889	0.825
Maharashtra	ARIMA(2,1,4)	552.560	569.050	**0.175**	25.593	19.501	**-0.483**	4.619	0.970	1.051	0.878
	GARCH(1)*	513.896	524.111	0.199	**20.308**	**16.539**	3.817	**-0.582**	**0.978**	1.815	0.178
	ARIMAx(2,1,3)	**432.930**	**449.190**	-2.290	24.098	18.985	-1.099	4.560	0.973	6.407	0.780
Andhra	ARIMA(4,1,4)*	622.820	643.420	**-0.220**	**43.388**	**30.586**	-1.423	**6.144**	**0.984**	4.131	0.941
Pradesh	GARCH(1)	780.977	793.442	-1.333	174.250	113.597	21.508	-6.663	0.743	0.956	0.466
	ARIMAx(4,1,4)	**507.220**	**527.340**	0.278	47.240	34.832	**-1.384**	6.605	0.983	3.525	0.966
Karnataka	ARIMA(1,1,2)*	558.250	568.550	**0.128**	**28.543**	**21.954**	**-0.091**	**5.557**	**0.910**	9.385	0.496
	No GARCH										
	ARIMAx(1,1,2)	**461.020**	**473.820**	-0.450	28.783	23.824	-0.200	5.700	0.885	4.671	0.198
India	ARIMA(2,1,2)	541.750	554.110	**-0.104**	23.786	18.518	**-0.090**	2.838	0.936	10.916	0.364
	GARCH(1,1)	562.617	574.980	-0.287	28.027	22.398	3.434	-0.266	0.902	0.000	0.986
	ARIMAx(2,1,3)*	**423.900**	**438.360**	1.896	**21.192**	**16.075**	0.232	**2.327**	**0.944**	2.652	0.753

Note: * indicates the best model and used further for forecasting purpose; LB: Ljung Box test for residuals

Table 5: Validation and forecasting of area, production and productivity of gram in India

State	Model	2010		2011		2012		2016	2018	2020
		Obs.	Pred.	Obs.	Pred.	Obs.	Pred.	Pred.	Pred.	Obs.
					Area ('000 ha)					
Madhya Pradesh	ARIMA(2,1,1)	3085.50	2854.80	3112.10	2862.42	3223.00	2857.63	2916.28	2969.05	3021.23
Rajasthan	GARCH(1)	884.40	1234.99	1783.30	1236.13	1570.00	1237.28	1241.92	1244.29	1246.67
Maharashtra	ARIMA(0,1,2)	1291.00	1249.83	1438.00	1309.40	1023.00	1323.79	1381.35	1410.13	1438.91
Andhra Pradesh	ARIMA(3,1,2)	647.00	643.75	584.00	692.75	534.00	736.76	805.35	807.45	853.32
Karnataka	ARIMA(0,1,2)	972.00	856.93	959.00	913.37	846.00	925.81	975.59	1000.48	1025.36
India	ARIMA(0,1,3)	8169.20	8015.41	9185.60	8229.06	8958.60	7988.95	8025.64	8043.99	8062.34
					Production ('000 tonees)					
Madhya Pradesh	ARIMAx(4,1,2)	3304.10	2925.78	2686.60	2894.03	3290.30	3065.34	3197.89	3336.92	3244.23
Rajasthan	ARIMA(1,0,4)	534.60	987.66	1600.70	1084.23	1061.10	1148.92	1234.51	1270.46	1304.09
Maharashtra	ARIMA(2,1,4)	1114.00	1035.52	1300.00	1222.65	815.00	1193.03	1234.76	1306.52	1309.32
Andhra Pradesh	ARIMAx(1,1,4)	846.00	826.80	720.00	737.38	520.00	586.31	491.52	506.31	521.58
Karnataka	ARIMA(0,1,2)	574.00	514.36	631.00	575.84	583.00	584.62	619.74	637.29	654.85
India	ARIMAx(2,1,2)	7480.00	7115.92	8220.00	7955.74	7580.00	8269.78	8488.79	8637.72	8772.09
					Productivity (Kg ha-1)					
Madhya Pradesh	ARIMAx(4,1,2)	3304.10	2925.78	2686.60	2894.03	3290.30	3065.34	3197.89	3336.92	3244.23
Rajasthan	ARIMA(1,0,4)	534.60	987.66	1600.70	1084.23	1061.10	1148.92	1234.51	1270.46	1304.09
Maharashtra	ARIMA(2,1,4)	1114.00	1035.52	1300.00	1222.65	815.00	1193.03	1234.76	1306.52	1309.32
Andhra Pradesh	ARIMAx(1,1,4)	846.00	826.80	720.00	737.38	520.00	586.31	491.52	506.31	521.58
Karnataka	ARIMA(0,1,2)	574.00	514.36	631.00	575.84	583.00	584.62	619.74	637.29	654.85
India	ARIMAx(2,1,2)	7480.00	7115.92	8220.00	7955.74	7580.00	8269.78	8488.79	8637.72	8772.09

models can be used for modelling gram production in India. Superiority of any model not to be established the emphatically in modelling data of gram. Gram production for whole India is also expected to increase during the years to come. In-spite of growth in all fronts the major concern is that, the productivity of major contributing state as well as whole India would still be about 1/6th of present productivity of Israel (6119.80 Kg ha^{-1}) and 1/3rd of China (3333.30 kg ha^{-1}). On the other hand, forecasting figures for gram area indicates, area would decrease in future and also due to ever increasing population and urbanization area will remains limiting factor of production. Hence, India needs to augment productivity in gram for nutritional security of its huge population.

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Fig. 1: Observed and forecasted area ('000 ha) under gram cultivation using best selected models in India.

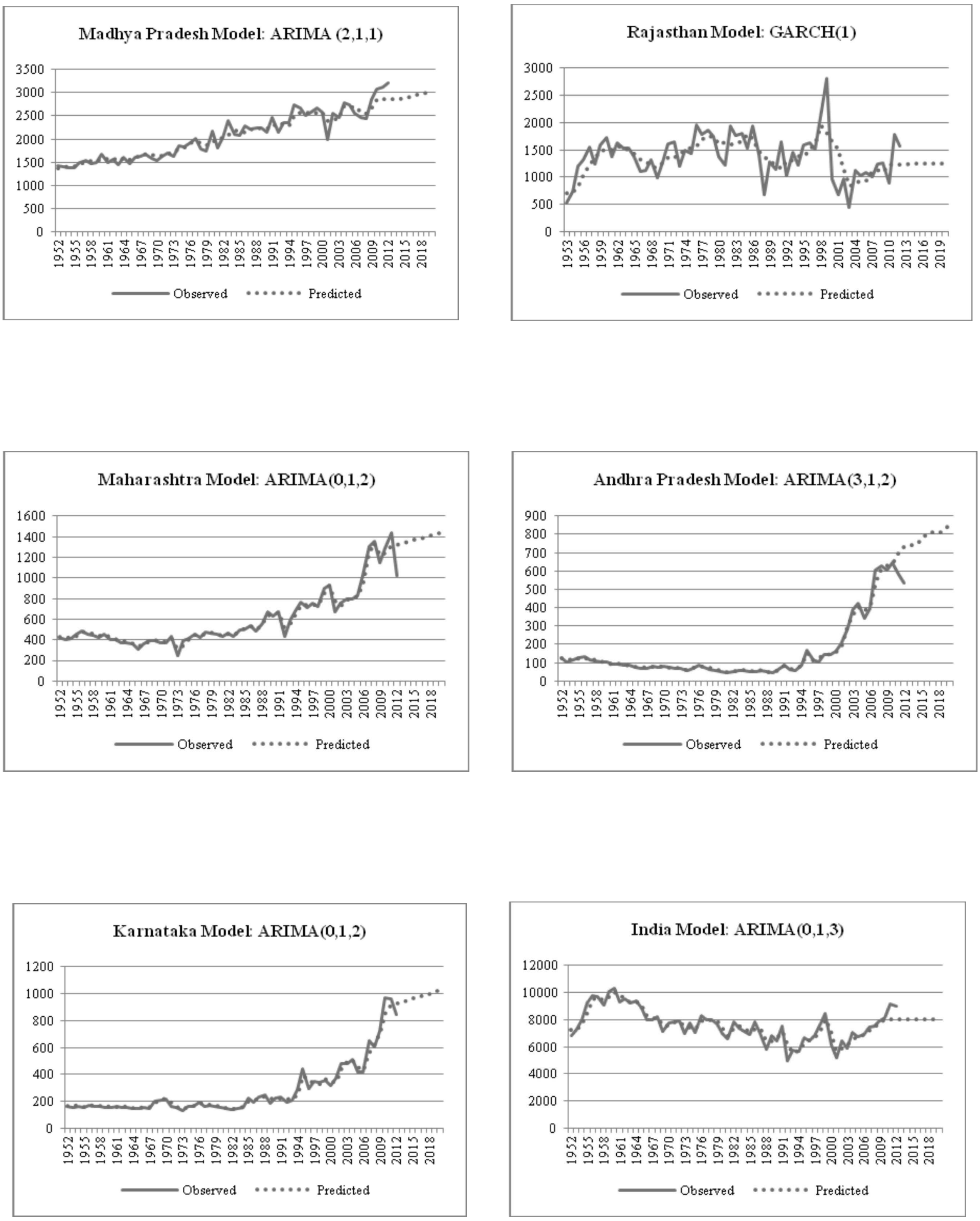
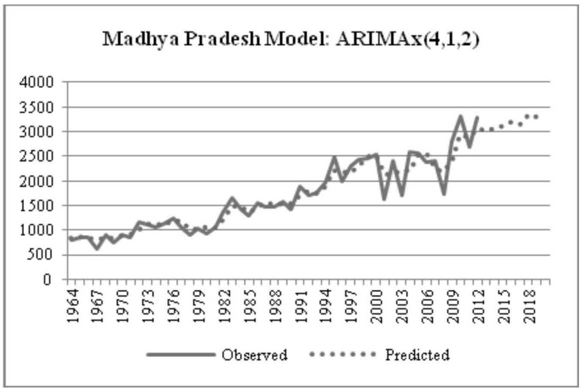
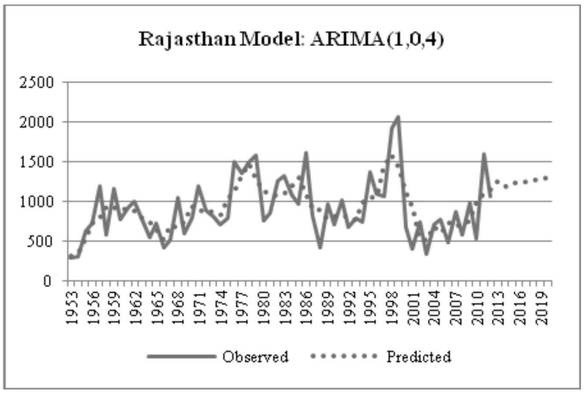
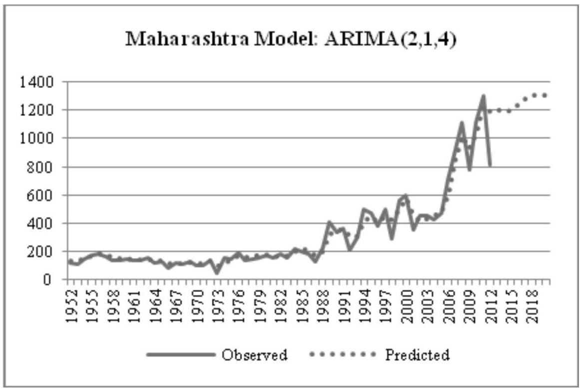
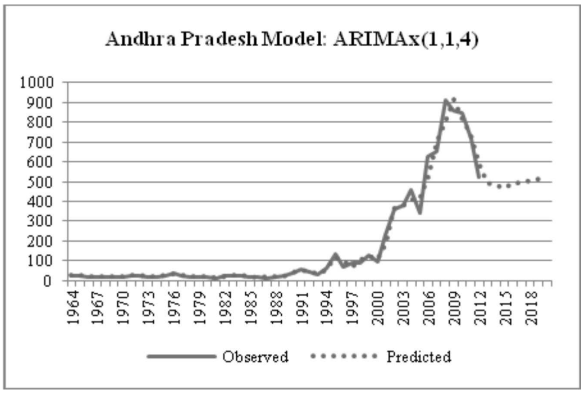


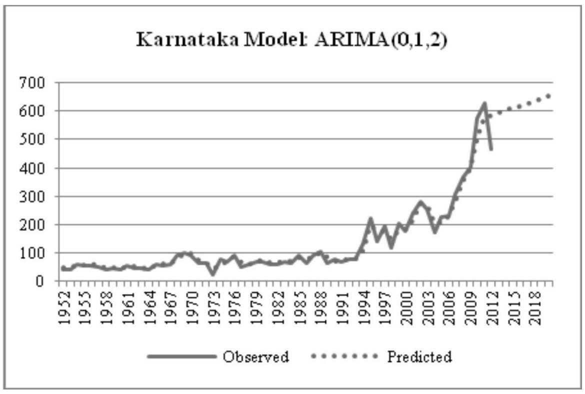
Fig. 2: Observed and forecasted gram production ('000 tonnes) using best selected model in India.











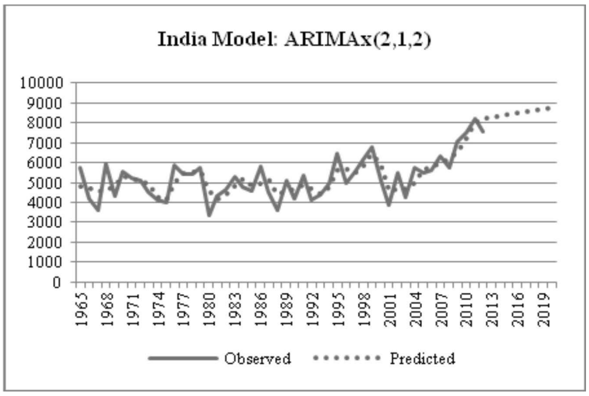
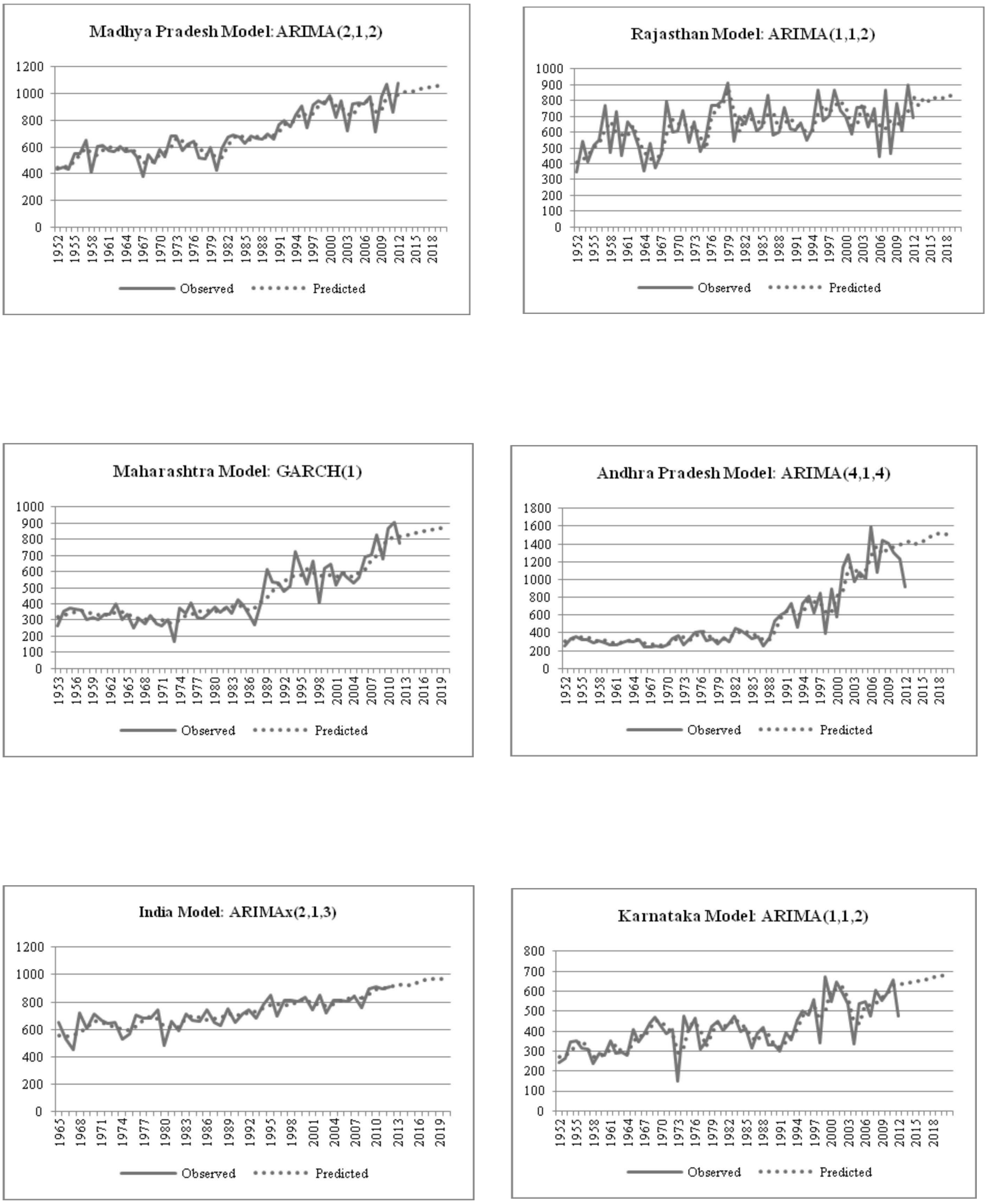


Fig. 3: Observed and forecasted gram productivity (kg per hectare) using best selected models in India.



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