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Forecasting of Maize Yield in Bihar through Auto Regressive Integrated Moving Average (ARIMA) Models

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ABSTRACT

The experiment was conducted during March, 2023 at Dr Rajendra Prasad Central Agricultural University, Samastipur, Bihar, India based on secondary maize yield data from 1990 to 2021, sourced from the Department of Economics and Statistics and India Agristat databases to investigate the forecasting of yield of maize. Various ARIMA models were developed based on Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots at different lags. Data from 1990 to 2019 were used for model development, while data for 2020 and 2021 were reserved for validation. Among several ARIMA models tested-namely ARIMA (0,0,1), ARIMA (1,0,0), ARIMA (1,0,1), ARIMA (0,1,1), ARIMA (1,1,1), ARIMA (0,1,2), and ARIMA (2,0,1)-the ARIMA (2,0,0) model provided the best fit for forecasting maize yield in Bihar. The significance of model parameters was assessed, and diagnostic checks, including tests for model adequacy, invertibility, stationarity, and forecast accuracy (MAPE, MAE, RMSE, % forecast error, and BIC), were conducted using t-tests and chi-square tests. The forecasted maize yields for the years 2021, 2022, 2023, and 2024 were 357 kg ha^{-1}, 358 kg ha^{-1}, 355 kg ha^{-1}, and 358 kg ha^{-1}, respectively. The forecast errors for 2021 and 2022 were 31.7% and 32.3%, respectively. These results suggested that the ARIMA(2,0,0) model was a reliable tool for short-term yield forecasting of maize in Bihar. The final ARIMA model used for forecasting was represented by the following equation: $Z_t – Z_{t-1} = 22.810 + 0.29 (z_{t-1} - z_{t-2}) + 0.20 (z_{t-2} - z_{t-3}) + a_t$.

KEYWORDS: Forecasting, ARIMA model, time series, statistical model

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Data Availability Statement: Legal restrictions are imposed on the public sharing of raw data. However, authors have full right to transfer or share the data in raw form upon request subject to either meeting the conditions of the original consents and the original research study. Further, access of data needs to meet whether the user complies with the ethical and legal obligations as data controllers to allow for secondary use of the data outside of the original study.

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1. INTRODUCTION

Maize, often referred to as the "Queen of Cereals," holds a prominent position globally due to its higher genetic yield potential compared to other cereal crops (Kumar and Kumar, 2017). The present study, entitled Forecasting of Maize Yield in Bihar through Auto Regressive Integrated Moving Average (ARIMA) Models, were utilizes data from 1990 to 2021 sourced from credible platforms including the Department of Economics and Statistics and India Agri Stat. (Esther et al., 2017) study was made to predict the output of pulses in Kenya using the ARIMA model for the observed data from 1960 to 2012. (Poyyamozh et al., 2017) discussed the ARIMA model for predicting the area and output of cotton in India for the observed data have been taken from 1955–2015. (Mrinmoy Ray et al., 2018) have been discussed ARIMA-ANN hybrid models for India's sugar cane yield forecast. After comparing both models it was concluded that the hybrid model's predictive accuracy is superior to ARIMA. (Shah et al., 2018) discussed the ARIMA model for forecasting major crop production in Pakistan for data collected from 1984 to 2015. Results have shown that ARIMA (0, 2, 1) was found to be a better suited model for forecasting major crops. (Sabzikar et al., 2019) presented a methodology for estimating the parameters of the ARTFIMA model. (Dharmaraja et al., 2019) discussed the linear regression and time-series models for forecasting the efficiency of bajra crop yield in the Alwar district of Rajasthan. The study found that ARIMAX is the best predictor of Alwar's bajra yield model. (Gopinath and Kavithamani, 2019) study were made to analyse and forecast the output of sugar cane by using the ARIMA with Exogenous Variable Model (ARIMAX). Sohan et al., 2023 discussed about Forecasting of Onion price in Patna District through ARIMA model" .(Chattopadhyay et al., 2021). (Wiri and Tuaneh, 2022) applied the Autoregressive Fractionally Integrated Moving Average (ARFIMA) model to analyse the Nigerian exchange rate.

2. MATERIALS AND METHODS

The current study was conducted during March-July, 2023 at Dr Rajendra Prasad Central Agricultural University, Samastipur, Bihar, India in order to investigate the yield forecasting of Maize in the Indian states of Bihar.

The methodology were outlined as Description of the research area; Data source; Techniques and tools used in the analysis.

2.1. Description of the research area

The research area was yield forecasting of Maize in Bihar. The state of Bihar is geographically situated between latitudes 24°20'10" and 27°31'15" North, and longitudes 83°19'50" and 88°17'40" East.

2.1.1. Location

Bihar lies in the subtropical to tropical climatic zone, sharing its borders with the Ganga Delta and Assam. The Himalayan Mountain range, located to the north of the state, plays a significant role in influencing the region's precipitation patterns. Bihar encompasses a geographical area of approximately 93.6 lakh hectares, which constitutes about 3% of India's total land area.

2.1.2. Climate

Positioned in eastern India, Bihar experiences a subtropical climate characterized by hot summers and cool winters. During the peak summer months of March to May, the average temperature rises to nearly 40°C. In contrast, winter temperatures between December and January can drop to around 8°C. The state sits at an average elevation of 173 feet above sea level and covers an area of approximately 94,163 square kilometres. On average, Bihar receives rainfall on about 52.5 days annually, with total precipitation amounting to approximately 976 mm per year. These climatic and geographical conditions play a crucial role in shaping the state's agricultural productivity and crop performance.

2.2. Source of the data

The present study was based on the secondary data on area, production and productivity of maize. These data were collected from the authenticated portals like Directorate of Economics and statistics and India Agri stat.

2.3. Techniques and tools used in the analysis

2.3.1. ARIMA models for forecasting of yield

The Box and Jenkins (1976) model was used for yield forecasting. The basic group of models for forecasting a time series is Auto Regressive Integrated Moving Average (ARIMA). The "Auto-Regressive" process refers to the various series that appear in forecasting equations. The "Moving Average" process was used to demonstrate the lags of forecast errors in the model. ARIMA (p, d,q) denotes the ARIMA model, where 'p' is the order of the auto regressive process, 'd' is the order of the data stationary process, and 'q' is the order of the moving average process.

Auto Regressive process of order (p) is,

$$Y_t=\mu+\varphi_1 Y_{t-1}+\varphi_2 Y_{t-2}+\ldots+\varphi_p Y_{t-p}+\varepsilon_t$$

Moving Average process of order (q) is,

$$Y_t=\mu-\theta_1\varepsilon_{t-1}-\theta_2\varepsilon_{t-2}-\ldots-\theta_q\varepsilon_{t-q}+\varepsilon_t$$

The basic formulation of ARIMA (p, d,q) could be described as,

$$Y_t=\varphi_1 Y_{t-1}+\varphi_2 Y_{t-2}+\ldots+\varphi_p Y_{t-p}+\mu-\theta_1\varepsilon_{t-1}-\theta_2\varepsilon_{t-2}-\ldots-\theta_q\varepsilon_{t-q}+\varepsilon_t$$

where, Y_t= yield (dependent variable) of groundnut at year t

$Y_{t-1}, Y_{t-2}\ldots, Y_{t-p}$=response variable at time lags t-1, t-2..., t-p respectively μ=constant mean of the process

$\varepsilon_{t-1}, \varepsilon_{t-2}\ldots, \varepsilon_{t-q}$=errors in the previous time periods

φ_s=coefficients to be estimated of AR process

θ_s=coefficients to be estimated of MA process

ε_t=forecast error, independently and normally distributed with zero mean & constant variance for t=1, 2,…, n

d=fraction differenced during the interpretation of AR and MA

2.3.2. The box-jenkins modelling procedure

For forecasting, the mathematically sound and reliable Box-Jenkins method was used instead of any other traditional econometric methods. To create a model, this method employs a series of stages in the ARIMA modelling procedure. The built models were then tested for accuracy using historical data. The model fits better if the residues are small, contain useless information, and are distributed irregularly. If the model is not satisfactory, the entire process should be repeated to improve on the basic model using the new available model. This procedure was repeated until the best-fitting model was found. The following are the iterative phases in developing an ARIMA forecasting technique are as; Model specification; Model estimation; Diagnostic checking; Forecasting.

2.3.3. Model specification

The primary goal of ARIMA modelling was to find the best values for p, d, and q. This could be partially resolved by examining the time series data's Auto Correlation Function (ACF) and Partial Auto Correlation Functions (PACF) .The ACF indicates the order of the model's autoregressive component 'q,' whereas the PACF indicates the component 'p.' The first step were to determine whether the data are stationary. The degree of homogeneity, (d), i.e., the number of time series data to be differenced to produce a stationary series. It was determined by where the ACF fall out to zero. After deciding 'd', a stationary series, its ACF and PACF are analysed to determine the suitable values of p and q.

2.3.4. Model estimation

The model was then estimated using a computer package. In step 1, the goal was to obtain estimates of the ARIMA model parameters that were tentatively constructed. The ARIMA coefficients (φ's and θ's) should be calculated using a nonlinear least squares method. The most important method for estimating ARIMA models is known as "Marquardt's compromise."

2.3.5. Diagnostic checking

The output was obtained through diagnostic checks. The first diagnostic check is residual analysis, which involves creating a graph of a time series plot of residuals. If the plot produces a rectangular scatter around a zero-horizontal level with no trend, the applied model is declared normal. Normality testing is the second diagnostic check. Normal scores are compared to residuals in the first normality test. If it formed a straight line, the applied model is declared to be a good fit. The residuals histogram is plotted as the second normality test. The third check was determining the fitness of the good. The residuals are marked against the corresponding fitted values for this purpose. When the plot shows no pattern, the model is declared to be a perfect fit.

2.3.6. Forecasting

Following an evaluation of the fitted ARIMA model's predictive capability, along with 95% confidence interval values. Forecasting was done for four years or less because forecasting errors increase rapidly if we go too far into the review and Literature. Several studies have demonstrated the effectiveness of ARIMA models for agricultural forecasting. (Kumar et al., 2017) applied the ARIMA (0,1,1) model to forecast sugarcane productivity in Bihar using data from 1939–40 to 2014–15. Model validation with 2011–15 data showed good accuracy, with productivity increases of 4.22% and 5.05% in 2016 and 2017, respectively. Similarly, (Suresh et al., 2011) used ARIMA models to forecast sugarcane area, production, and productivity in Tamil Nadu from 1950–2007. ARIMA (1,1,1) was found suitable for area and yield, while ARIMA (2,1,2) best predicted production. (Sharma et al., 2018) used ARIMA to forecast maize production in India from 2018 to 2022, selecting models based on ACF and PACF analyses. (Biswas et al., 2019) applied ARIMA (1,1,2) to predict sunflower seed prices in Kadiri market, Andhra Pradesh, achieving low error rates (MAPE: 2.30%, RMSPE: 3.44%).

3. RESULTS AND DISCUSSION

Data on maize yield in the states of Bihar were gathered to help with the research's stated aims. The secondary data for the years 1990 to 2021 was retrieved from reliable websites like the Department of Economics and Statistics and India Agri Stat. For the purpose of forecasting maize, data up to the year 2019 were used to build the prediction model, and data from the following two years were retained for the forecast model's validation.

3.1. Forecasting the yield of maize in Bihar through ARIMA models

In this study, we have used different models to find out the perfect model for the forecast of maize yield in Bihar. For the model comparison, yearly yield of maize was taken into consideration. The detailed analysis of maize yield forecasting in Bihar has been presented as below.

3.1.1. Model identification

The essential initial stage in the exploration of an ARIMA model involves assessing the stationarity characteristics of the time series process involved. The data exhibit non-stationary behaviour, indicating the lack of constancy of mean and its variance, as represented by the maize yield data of non-differentiated plot in figure 1. Consequently, the figure 2 depicts the first-order differenced series plot of Bihar's maize yield. Notably, the first-order difference of the data demonstrates stationary attributes, characterized by a steady mean and variance, as depicted by the plot. The study of Table 1 and Table 2 shows Auto Correlation Function and Partial Auto Correlation Function of original (Z_t) and first order difference series (ΔZ_t) for Bihar up to lag 16 (sixteen), respectively.

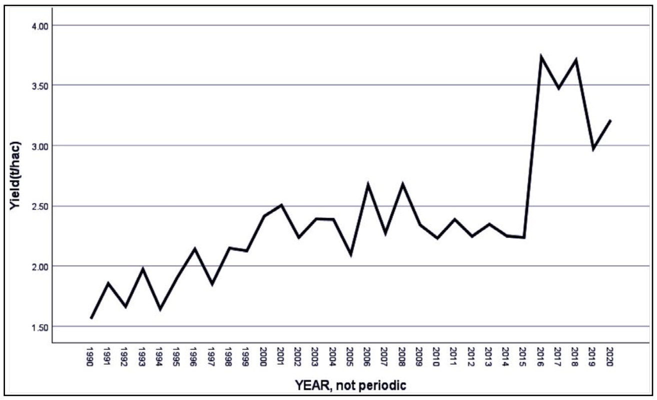

Figure 1: Maize yield time series plot of Bihar

3.1.2. Parameter estimation

Across a range of output tables spanning in Table 3, diverse models' parameter estimates have been furnished. Calculations for model parameters, standard deviation (SD) and t-statistic has been carried out for all models. The suitable auto regressive factor and Moving Average factor for forecast models have been documented in the output tables. Furthermore, to facilitate model diagnosis, the autocorrelation function has been analyzed for the residuals of the fitted models its statistical-significance is evaluated through the application of the Ljung-Box test using Q-statistics. The parameters of ARIMA (2,0,0) has been provided in the Table 3. Owing to its notable performance in terms of low Root Mean Square Error (RMSE), Mean absolute Percentage Error (MAPE),

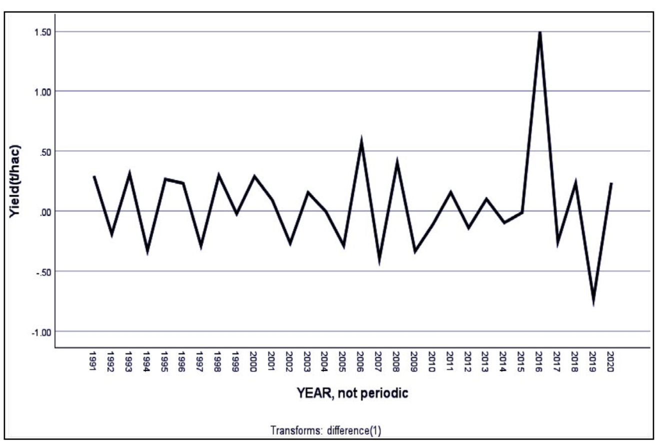

Figure 2: First order difference time series plot of maize yield in Bihar

Table 1: Auto-correlation function of original (Z_t) and first-ordered difference series (ΔZ_t) for maize yield in Bihar

Lag	Z_t	t-value	ΔZ_t	Δt-value
1	0.631	0.171	-0.367	0.174
2	0.546	0.168	0.057	0.171
3	0.444	0.165	-0.171	0.168
4	0.326	0.162	-0.161	0.165
5	0.272	0.159	0.434	0.161
6	-0.003	0.156	-0.183	0.158
7	0.020	0.153	-0.063	0.155
8	0.041	0.150	0.184	0.155
9	-0.016	0.147	-0.275	0.151
10	0.054	0.143	0.351	0.148
11	-0.034	0.136	-0.264	0.144
12	0.019	0.133	0.008	0.141
13	0.027	0.129	0.071	0.137
14	-0.041	0.125	-0.229	0.133
15	0.041	0.121	0.205	0.129
16	-0.056	0.125	-0.071	0.121

Table 2: Partial auto-correlation function of original (Z_t) and first order difference series (ΔZ_t) for maize yield in Bihar

Lag	Z_t	t-value	ΔZ_t	Δt-value
1	0.631	0.180	-0.367	0.183
2	0.245	0.180	-0.090	0.183
3	0.051	0.180	-0.211	0.183
4	-0.058	0.180	-0.366	0.183
5	0.018	0.180	0.281	0.183
6	-0.380	0.180	0.047	0.183
7	0.115	0.180	-0.255	0.183
8	0.188	0.180	0.338	0.183
9	-0.031	0.180	-0.053	0.183
10	0.126	0.180	-0.022	0.183
11	-0.093	0.180	0.049	0.183
12	-0.109	0.180	-0.050	0.183
13	0.005	0.180	-0.167	0.183
14	-0.029	0.180	-0.162	0.183
15	0.112	0.180	-0.095	0.183
16	-0.043	0.180	-0.053	0.183

Table 3: Output of ARIMA (2, 0, 0) fitted for maize yield in Bihar

Model parameters			
Parameters	Estimates	SE	t-Value
Constants	-109.634	22.810	-4.806
j_1	0.29	0.20	1.45
j_2	0.13	0.20	0.06

AR factor: $j(B)=1-0.29B-0.20B^2$
Forecast model: $Z_t–Z_{t-1}=22.810+0.29\ (z_{t-1}-z_{t-2})+0.20\ (z_{t-2}-z_{t-3})+a_t$

Diagnostic check		
Lags	Residual ACF	t-value
1	0.016	0.177
2	0.025	0.177
3	-0.068	0.177
4	-0.039	0.178
5	0.345	0.198
6	-0.234	0.206
7	-0.148	0.210
8	0.020	0.210
9	-0.212	0.216
10	0.143	0.219
11	-0.247	0.228
12	-0.089	0.229
13	-0.014	0.239
14	-0.204	0.234
15	0.130	0.237
16	-0.050	0.237
17	0.051	0.237
18	0.042	0.237
19	-0.165	0.237
20	0.104	0.238
21	0.041	0.241
22	-0.040	0.242
23	0.034	0.243
24	-0.111	0.243

Model fit parameter				
R-squared	RMSE	MAPE	MAE	BIC
0.691	0.359	10.473	0.265	-1.625

Q-Statistics: 19.140; Degrees of freedom: 16

Mean absolute Error (MAE) and Bayesian Information Criterion (BIC) values, the ARIMA (2,0,0) emerged as the most suitable model for forecasting maize yield in Bihar. (Kumar and Verma, 2020) forecasted mustard production in Haryana's Bhiwani and Hisar districts using ARIMA, evaluating model performance with MAPE, AIC, and BIC. (Yadav et al., 2020) used ARIMA (1,1,0) to forecast fish production in Assam with data from 1980–2018, showing consistent growth from 336.97 to 358.21 thousand tonnes. Figure 3 shows auto correlation function and partial auto correlation function of original (Z_t) and first order difference series (ΔZ_t) for Bihar up to lag 16 (sixteen).

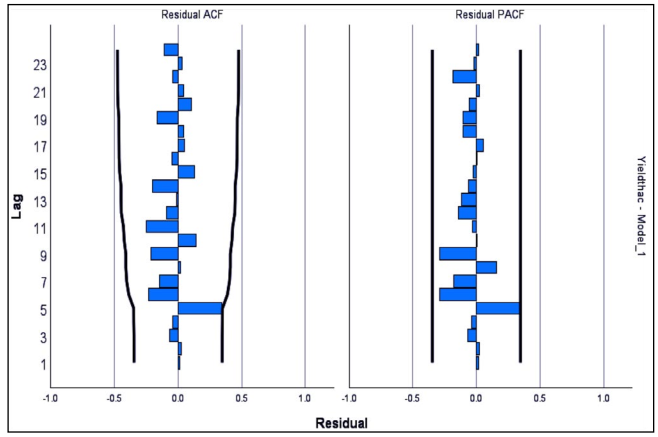

Figure 3: ACF and PACF plot of residuals of ARIMA (2,0,0) fitted yield for maize of Bihar

3.1.3. Best fitted model selection

An effective model possesses the stationarity and parsimony attributes. The estimated coefficients' parameters have demonstrated exceptional quality and stability. Interestingly, even though p=0 for ARIMA (0,0,1), ARIMA (0,1,1), and ARIMA (0,1,2), models essentially represent pure moving average models or white noise-series. However, it is worth noting that, in such cases, further assessment of stationarity conditions is not necessary. Similarly, observed q=0 for processes which are purely AR, like ARIMA (1, 0, 0) and ARIMA (2, 0, 0), which are also recognized as white-noise series. In line with existing literature, it is recognized that every pure AR process possesses inherent invertibility, obviating the need for further checks (Box and Jenkins., 1976). The guiding principle put forth by Box and Jenkins was adhered to when selecting a parsimonious model. Contrasting models such as ARIMA (1,1,1), ARIMA (0,1,2), and ARIMA (2,0,1) all these models were failed to meet the parsimony criterion. The models like ARIMA (0,0,1), ARIMA (1,0,0), ARIMA (1,0,1), ARIMA (0,1,1), and ARIMA (2,0,0) which possess lesser parameters and thereby fulfill the condition of parsimony Table 4. For every individual model, both the t-statistic and chi-square statistics were computed. Upon comprehensive comparison of diverse models, ARIMA (2,0,0) demonstrated the most optimal fit. Notably, the Root Mean Square Error (RMSE),

Table 4: Selection of good model for maize yield of Bihar

Models	RMSE	MAPE	MAE	BIC	Statio-nary	Inver-tible	Parsi-mony	Stable/ R^2	Diagnostic check		% Forecast Error	
									t-test	X^2 test	1st step (2021-22)	2nd step (2022-23)
0,0,1	0.67	11.12	0.28	1.71	NA	✔	✔	0.67	NS	NS	27.3	2.48
1,0,0	0.36	10.83	0.27	1.74	✔	NA	✔	0.68	NS	NS	29	8.45
1,0,1	0.36	10.58	0.27	1.61	✔	✔	✔	0.69	NS	NS	32.8	15.92
0,1,1	0.37	11.15	0.29	1.63	NA	✔	✔	0.64	NS	NS	31.1	13.18
1,1,1	0.36	11.56	0.29	1.57	✔	✔	X	0.67	NS	NS	31.5	11.7
0,1,2	0.37	11.82	0.29	1.54	NA	✔	X	0.66	NS	NS	28.1	6.5
2,0,0	0.36	10.30	0.26	1.42	✔	NA	✔	0.69	**	NS	31.7	10.9
2,0,1	0.37	10.39	0.26	1.46	✔	✔	X	0.69	**	NS	32.31	11.9

✔ : Condition is satisfied; X: Condition is not satisfied; NA: Not applicable. i.e., if p=0 and q=0, for all pure MA and AR processes (or white noise) are respectively stationary and invertible and no further checks are required; NS: Non-significant; **: Highly significant

Mean Absolute percentage Error (MAPE), Mean Absolute error (MAE), Bayesian information Criterion (BIC) values were least which was also supported by the cross-validation process of the selected best-fit ARIMA (2,0,0) model. (Beyaztas and Shang, 2022) proposed a robust Bootstrap algorithm for constructing PIs and forecast regions for the univariate and multivariate autoregressive TS. The proposed procedure was based on the weighted likelihood estimates and weighted residuals. (Wankhade and Kale, 2021) utilized ARIMA in MINITAB19 to predict groundnut area and yield in India (1970–2017), finding a declining area trend but increasing yield for 2018–2033. These studies collectively affirm ARIMA's reliability in agricultural forecasting across diverse crops and regions (Figure 4).

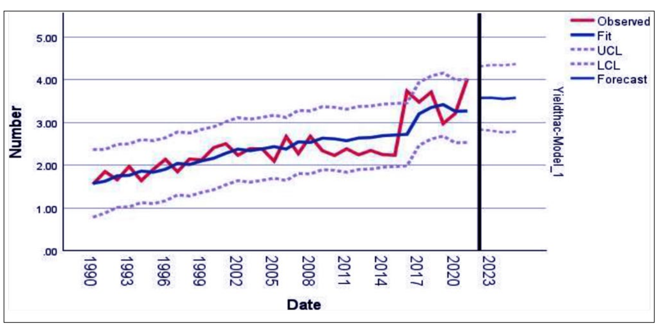

Figure 4: Graph of time (year) v/s yield for ARIMA (2,0,0) in Bihar

3.1.4. Diagnostic check

A statistically reliable model was distinguished by unpredictable fluctuations that display no self-dependence and uphold steady average and variability. In the result tables mentioned in this research, calculations were conducted to ascertain and furnish the ACF of residuals.

Each coefficient of residual autocorrelation underwent hypothesis testing, specifically the null hypothesis Ho: pk(a)=0, using a t-test. To calculate the appropriate standard errors, Bartlett's approximation formulas were utilized. The verification of the randomness of the unforeseen fluctuations finds support in the observation that all t-values associated with the residual Auto Correlation Function (ACF) for the model being examined hold no statistical significance, indicating they are below the critical thresholds. This notion gains further strength from the implementation of a χ^2 test by Ljung and Box, utilizing Q-statistics. In the case of the chosen ARIMA model, specifically ARIMA (2,0,0), the Ljung and Box test resulted in a Q-statistics value of 19.753. This calculated value stands lower than the critical chi-square value corresponding to 16 degrees of freedom, as demonstrated in Table 4. As a result, the appropriateness of the selected ARIMA model with an order of (2,0,0) is substantiated. Additionally, forecast errors for one step ahead and two steps ahead were computed, yielding values of 12.93% and 0.83%, respectively, (Barman et al., 2024) extended the concept of predictive roots, previously applied in linear and non-linear autoregressive models, to artificial neural network (ANN) models for the purpose of constructing prediction intervals (PIs).

Forecasting the maize yield in Bihar using ARIMA models Yield forecasts and their confidence intervals: Following the establishment of the model's credibility, it was utilized to anticipate future yields within the existing time series.

These prognostications are projected over a defined interval, commonly known as the "lead time," encompassing several years into the future. Employing the selected ARIMA model, ARIMA (2,0,0), the prediction for the forthcoming 4 years' yield was formulated, along with its associated confidence interval. Remarkably, this duration witnessed a consistent

Table 4: Selection of good model for maize yield of Bihar

Models	RMSE	MAPE	MAE	BIC	Stationary	Invertible	Parsimony	Stable/ R^2	Diagnostic check		% Forecast error	
									t-test	X^2 test	1st step (2021-22)	2nd step (2022-23)
0,0,1	0.67	11.12	0.28	1.71	NA	✔	✔	0.67	NS	NS	27.3	2.48
1,0,0	0.36	10.83	0.27	1.74	✔	NA	✔	0.68	NS	NS	29	8.45
1,0,1	0.36	10.58	0.27	1.61	✔	✔	✔	0.69	NS	NS	32.8	15.92
0,1,1	0.37	11.15	0.29	1.63	NA	✔	✔	0.64	NS	NS	31.1	13.18
1,1,1	0.36	11.56	0.29	1.57	✔	✔	X	0.67	NS	NS	31.5	11.7
0,1,2	0.37	11.82	0.29	1.54	NA	✔	X	0.66	NS	NS	28.1	6.5
2,0,0	0.36	10.30	0.26	1.42	✔	NA	✔	0.69	**	NS	31.7	10.9
2,0,1	0.37	10.39	0.26	1.46	✔	✔	X	0.69	**	NS	32.31	11.9

✔: Condition is satisfied; X: Condition is not satisfied; NA: Not applicable. i.e., if p=0 and q=0, for all pure MA and AR processes (or white noise) are respectively stationary and invertible and no further checks are required; NS: Non-significant; **: Highly significant

reduction in maize yield within the region of Bihar, Table 5. (Barman et al., 2022) proposed the robust unconditional sieve bootstrap and robust sieve bootstrap techniques, which utilize weighted least squares estimation to address the impact of outliers when constructing prediction intervals (PIs) for both returns and volatilities within the ARCH model framework. (Seba et al., 2023) proposed a hybrid approach for forecasting temperature and moisture levels in greenhouses by integrating ARIMA, ARTFIMA, and support vector machine (SVM) methods. (Kumar and Chaturvedi, 2023) provide an extensive examination of ARFIMA and ARTFIMA models, emphasizing their ability to capture both long-memory and tempered long-memory features in time series data. (Muhhamed et al., 2024) sugarcane yield prediction in Bihar using biometric characteristics.

Table 5: Values of forecast and their confidence intervals of ARIMA (2,0,0) Fitted for maize yield of Bihar

Years	Fore-casted yield	95% confidence interval limits		Actual yield	Forecast error (%)
		Lower	Upper		
2021-22	3.57	2.84	4.31	5.23	31.7
2022-23	3.58	2.81	4.34	4.02	32.3
2023-24	3.55	2.77	4.34	-	-
2024-25	3.58	2.79	4.36	-	-

4. CONCLUSION

The maize yield trends in Bihar, ARIMA models-an effective alternative to traditional forecasting methods-were applied to 30 years of yield data (1990–2021). Among them, ARIMA (2,0,0) was identified as the best fit, being stationary, parsimonious, stable, and having minimal error. The model forecasted maize yields for 2021 to 2024 as 357, 358, 355, and 358 kg ha^{-1} respectively table 5. The model thus provides a reliable basis for short-term yield forecasting and agricultural planning in the state.

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