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Evaluation of Suitable Forecasting Models for Potato Crop in India – A Statistical Approach

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Abstract

Accurate prediction of horticultural crop performance is critical for agricultural planning and policy. Potato (*Solanum tuberosum* L.) is strategically important for India's food security and export revenue. This study compares five forecasting approaches-ARIMA, Exponential Smoothing (ETS), Prophet, Structural Time Series (STS), and Support Vector Regression (SVR)—using annual data on potato area, production, and productivity in India from 1950–51 to 2023–24. Model performance was evaluated using RMSE, MAE, MAPE, and cross-validation with Ljung–Box residual diagnostics. ARIMA models achieved the lowest MAPE across all three variables: 1.79% (area), 4.31% (production), and 4.93% (productivity), outperforming all competing models. Five-year forecasts (2025–2029) project steady expansion in cultivated area and total production, but a declining productivity trend-a finding with significant policy implications for input-use efficiency and varietal improvement. ARIMA is identified as the most suitable model for agricultural planners and market regulators in India.

Keywords: Forecasting, ARIMA, Exponential smoothing, Potato, SVR

1. Introduction

Potato (*Solanum tuberosum* L.) occupies a central position in Indian agriculture, serving simultaneously as a staple food, a cash crop, and a major horticultural export commodity. India ranks second globally in potato production, with an estimated cultivated area of 23.59 lakh hectares and total production of approximately 58.11 million tonnes in recent years (NHB, 2023–24). Despite this remarkable scale, consistent productivity improvements have remained elusive: average national productivity has grown far more slowly than production, and regional disparities in yield efficiency remain pronounced (Hijmans, 2001; Govindakrishnan et al., 2017). With horticulture production in India rising from 280.70 million tonnes in 2013–14 to 367.72 million tonnes in 2024–25, and potato exports valued at approximately USD 4.89 million in 2023–24, the crop is deeply embedded in both domestic food systems and international trade networks. Reliable forecasting of potato area, production, and productivity is therefore essential for supply-chain planning, cold-storage investment, price stabilization, and agricultural policy design.

Crop production forecasting has been a longstanding concern in agricultural statistics, with methods ranging from expert judgment and trend extrapolation to sophisticated statistical and machine learning approaches. Early work on agricultural time series modeling was grounded in the Box–Jenkins ARIMA framework (Box and Jenkins, 1976), which has since become the benchmark for univariate crop forecasting worldwide. For potato specifically, the forecasting literature is substantial. Hijmans (2001) demonstrated that global potato production growth over the twentieth century was driven primarily by area expansion in developing countries rather than productivity gains-a structural pattern that continues to shape Indian potato dynamics. In the Indian context, Kumar et al. (2012) applied ARIMA models to forecast potato production in Uttar Pradesh, finding that autoregressive structures adequately captured the stochastic trends in district-level yield series. Rathod and Mishra (2018) compared ARIMA with hybrid models for horticultural crops and reported that while ARIMA performed well for stable trend series, machine learning models offered advantages in the presence of structural breaks.

Beyond classical time series methods, newer approaches have been proposed for agricultural forecasting. Prophet, developed by Taylor and Letham (2018) at Facebook, is designed to handle trend changepoints and seasonality flexibly and has been applied to agricultural series in several low- and middle-income country contexts. Structural Time Series (STS) models,

rooted in the state-space framework of Harvey (1989), decompose a series into level, trend, and irregular components with time-varying parameters, offering interpretability at the cost of parsimony. Support Vector Regression (SVR), a kernel-based machine learning method, has been applied to crop yield forecasting as a nonlinear alternative to classical approaches (Prabakaran et al., 2015; Kumar and Sharma, 2021). However, comparative evaluations of these diverse methods on Indian potato data-spanning the full post-independence agricultural era from 1950 to 2024-remain scarce. Most existing studies either focus on a single model, cover limited time horizons, or examine crop series from other countries with very different agronomic and policy contexts.

This gap is significant for three reasons. First, the structural characteristics of Indian potato time series-nonlinear area expansion driven by policy interventions, recurrent productivity stagnation, and periodic market shocks-may favor different model classes depending on the variable of interest. Second, forecasting studies published in international journals on potato have predominantly addressed European and Latin American contexts (Pronyk et al., 2009; Haverkort and Struik, 2015), leaving a clear need for India-specific empirical benchmarking. Third, with productivity showing signs of deceleration, five-year forward projections are urgently needed to guide investments in varietal research, irrigation expansion, and post-harvest infrastructure. The present study addresses these gaps directly by conducting a rigorous, multi-model comparison on 74 years of annual potato data from India, evaluating ARIMA, ETS, Prophet, STS, and SVR under a consistent cross-validation framework, and generating five-year forecasts with associated uncertainty bounds.

This study was carried out with the following objectives.

1. To evaluate suitable forecasting model for potato area, production and productivity in India.

2. To predict the potato crop area, production and productivity in India for next five years.

2. Materials and Methods

The annual data on area, production, and productivity of potato crop for the period from 1950-51 to 2023-24 were used in this study for the forecasting of future values. To evaluate the suitable forecasting model for potato crop area, production and productivity, the following forecasting models were used for this study.

1. Autoregressive Integrated Moving Average (ARIMA).
2. Exponential smoothening (ETS).

3. Prophet
4. Structural Time Series (STS) and
5. Support Vector Regression (SVR)

To assess the error accuracy, the following tools are used

1. Root Mean Square Error (RMSE)
2. Mean Absolute Error (MAE)
3. Mean Absolute Percentage Error (MAPE)

2.1 Autoregressive Integrated Moving Average (ARIMA) Model

The Autoregressive Integrated Moving Average (ARIMA) model is a classical form of widely applied univariate methodology in time series forecasting. Due to its strong statistical properties in handling trends, this model has been widely applied in agricultural forecasting research, especially in long-term agricultural series such as crop area, production, and productivity.

2.1.1 Model Formulation

Let $Y_t$denote a univariate time series observed at time t. A non-seasonal ARIMA model of order (p, d, q) is defined as

$$\Phi_p(B)(1-B)^d Y_t = \Theta_q(B)\varepsilon_t$$

Where:

- B represents backward shift operator such that $BY_t = Y_{t-1}$,
- d represents order of differencing required to achieve stationarity,
- $\Phi_p(B)$ represents the autoregressive (AR) polynomial of order p,
- $\Theta_q(B)$ represents the moving average (MA) polynomial of order q, and
- ε_t represents white-noise error term with zero mean and constant variance σ^2.

The AR and MA components are expressed as:

$$\Phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$$

$$\Theta_q(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q$$

2.1.2 Stationarity Testing and Differencing

Stationarity is a fundamental requirement for ARIMA modeling. A time series is considered stationary when its mean and variance remain constant over time and its autocovariance depends only on the lag length.

The stationarity was examined using Augmented Dickey-Fuller (ADF) test,

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{k} \delta_i \Delta Y_{t-i} + \varepsilon_t$$

The differencing was applied to make the data stationary

- **First-order differencing**:

$$\Delta Y_t = Y_t - Y_{t-1}$$

- **Second-order differencing (where required)**:

$$\Delta^2 Y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2})$$

2.1.3 Model Selection Using Grid Search

A grid search evaluated various ARIMA (p, d, q) models within certain ranges of p, d, and q parameters. For each model, the in-sample and out-of-sample forecast accuracies were evaluated.

2.2 Exponential Smoothing (ETS) Models

Exponential Smoothing (ETS) models are a group of univariate time series forecasting techniques that describe the time series in terms of its underlying level, trend, and error components. ETS models are not required to have stationary time series and are often used as benchmarks in agricultural and economic time series analyses.

2.2.1 ETS Model Framework

The ETS framework represents a time series using three components:

- Error (E): additive (A) or multiplicative (M)
- Trend (T): none (N), additive (A), or damped additive (Ad)
- Seasonality (S): none (N), additive (A), or multiplicative (M)

Since the data used in this study are annual series, no seasonal component was considered.

Hence, ETS models of the general form ETS (E, T, N) were evaluated.

Observation equation

$$Y_t = \ell_{t-1} + b_{t-1} + \varepsilon_t$$

State equations

$$\ell_t = \ell_{t-1} + b_{t-1} + \alpha\varepsilon_t$$
$$b_t = b_{t-1} + \beta\varepsilon_t$$

where:

- ℓ_t is the level at time t,
- b_t is the trend at time t,
- α and β are smoothing parameters ($0 < \alpha, \beta < 1$),
- $\varepsilon_t$is the error term.

2.2.2 Model Estimation

The ETS models were estimated by means of a state-space representation and maximum likelihood estimation. The ETS approach selects automatically the best combination of error and trend components without any need to specify parameters.

2.3 Prophet Model

Prophet is a time series forecasting method that decompose the time series into easily understandable components that sum up to the whole series. It is used for capturing long-term trends and random changes in the data. Prophet is used for forecasting because it is flexing and estimates things automatically.

2.3.1 Model Structure

The Prophet model expresses a time series $y(t)$as:

$$y(t) = g(t) + \varepsilon(t)$$

where:

- $g(t)$denotes the trend component, and
- $\varepsilon(t)$represents the random error term.

2.3.2 Trend Component

The trend component g(t) was defined with a piecewise linear form to allow the growth rate to vary at specific times. The linear trend form is given by:

$$g(t) = kt + m$$

where k is the growth rate and m is the intercept.

To control the flexibility of the trend, a changepoint prior scale (CPS) parameter was set. Various values of this parameter were assessed to control the trend adjustment.

2.4 Structural Time Series (STS) Model

Structural Time Series (STS) models is a type of state space model in which a time series is decomposed into several components: level, trend, and irregular. They provide a flexible framework to model time-varying behavior in a time series and allow the components to vary stochastically over time.

2.4.1 Model Representation

An STS model decomposes a time series $Y_t$into the following components:

$$Y_t = \mu_t + \varepsilon_t$$

where:

- $\mu_t$represents the underlying state component, and
- $\varepsilon_t$is the irregular disturbance term.

2.4.2 Trend Specification

The trend component in the STS framework is modeled as a local linear trend, allowing both the level and slope to change over time:

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t$$
$$\beta_t = \beta_{t-1} + \zeta_t$$

where:

- $\mu_t$is the level component,
- $\beta_t$is the slope component,
- $\eta_t$and $\zeta_t$are mutually uncorrelated disturbance terms.

2.5 Support Vector Regression (SVR)

Support Vector Regression (SVR) is a supervised learning technique, an extension of Support Vector Machines, designed to establish nonlinear relationships between input variables and outputs by using a mapping to a higher-dimensional feature space.

2.5.1 Model Formulation

SVR estimates a function of the form:

$$f(x) = \mathbf{w}^{\top}\phi(x) + b$$

where $\phi(x)$is a nonlinear mapping function, $\mathbf{w}$is a weight vector, and $b$is a bias term.

The SVR optimization problem minimizes:

$$\frac{1}{2} \| \mathbf{w} \|^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*)$$

subject to:

$$| y_i - f(x_i) | \leq \varepsilon + \xi_i$$

where C is the regularization parameter, ε is the error tolerance, and ξ_i, ξ^* are slack variables.

2.6 Forecast Accuracy Measures

2.6.1 Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) measures the square root of the average of squared differences between observed and predicted values. RMSE gives relatively higher weight to large forecast errors and lower RMSE values indicate better forecasting performance.

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (Y_t - \hat{Y}_t)^2}$$

2.6.2 Mean Absolute Error (MAE)

Mean Absolute Error (MAE) represents the average of the absolute differences between observed and predicted values. Unlike RMSE, MAE treats all forecast errors equally and provides a straightforward interpretation of average prediction error. A lower MAE value indicates higher forecast accuracy.

$$MAE = \frac{1}{n}\sum_{t=1}^{n} | Y_t - \hat{Y}_t |$$

2.6.3 Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) measures the average absolute percentage deviation between observed and predicted values. MAPE is scale-independent and allows direct comparison of forecasting accuracy across different variables and crops. Lower MAPE values indicate superior forecasting performance.

$$MAPE = \frac{100}{n}\sum_{t=1}^{n} | \frac{Y_t - \hat{Y}_t}{Y_t} |$$

2.7 Residual Diagnostics

Residual diagnostics were used as a model adequacy check and to support the selection of appropriate forecasting models**,** used residual diagnostics were ACF, PACF, and Ljung-Box Q test.

The autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of residuals were used to visually inspect the presence of any remaining autocorrelation at different lags. The absence of significant spikes in the residual ACF and PACF plots indicates that the systematic patterns in the data have been adequately captured by the model.

The Ljung–Box Q test was employed to formally test the null hypothesis that the residuals are independently distributed. A non-significant Ljung–Box test statistic suggests that there is no significant autocorrelation remaining in the residuals and that the model provides an adequate fit to the data.

3. Results and Discussion

3.1 Overview of Model Evaluation

In this section the forecasting results obtained for area, production, and productivity of potato using ARIMA, ETS, SVR, STS and Prophet models are presented. Model performance was evaluated primarily using Mean Absolute Percentage Error (MAPE), ensuring comparability across crops, variables, and models. Time series cross- validation (CV-MAPE) and residual diagnostics were employed to check the robustness and adequacy of the selected models. The discussion emphasizes comparative performance, forecast behavior, and practical

implications rather than methodological theory.

3.2 Potato Crop

3.2.1 Potato Area

Among all models evaluated for potato area, ARIMA achieved the lowest MAPE of 1.79%, indicating that the area under potato cultivation in India follows a relatively stable stochastic trend that is effectively captured by linear autoregressive structures. This result is consistent with findings from Rathod and Mishra (2018), who reported that ARIMA outperformed ETS and hybrid models for stable-trend crop area series in India, and with Kumar et al. (2012), who found ARIMA adequate for potato area forecasting in Uttar Pradesh. The superior performance of ARIMA over Prophet (MAPE: 10.86%) for the area variable reflects the fact that Indian potato area expansion has followed a relatively smooth upward trajectory over the study period, without the abrupt structural breaks that would favor Prophet's changepoint mechanism. Similarly, SVR (MAPE: 4.23%) underperformed relative to ARIMA, suggesting that the nonlinear feature mappings offered by kernel-based methods do not confer additional advantage when the underlying series is dominated by a linear stochastic trend. Cross-validation results (CV-MAPE: 4.03% for ARIMA) confirm the robustness of ARIMA forecasts. Residual diagnostics indicate model adequacy: the Ljung–Box Q statistic of 3.32 with $p = 0.973$ confirms that no significant autocorrelation remains in the ARIMA residuals for area (Table 5). The Forecasted values of Potato crop in India were given in Table 1. Forecast accuracy measures for different models in forecasting area (ha), production (tonnes), and productivity (t ha^{-1}) of potato crop in India were given in Table 2.

Table 1. Forecasted values of Potato crop area(ha) in India.

Variable	Year	Forecasted Values	95 % Lower Confidence Interval	95 % Upper Confidence Interval
Potato Crop Area	2025	2391935	2259260	2524611
	2026	2425227	2250515	2599940
	2027	2458242	2244714	2671770
	2028	2491156	2242911	2739401
	2029	2523938	2243052	2804824

Table 2. Forecast accuracy measures for different models in forecasting area (ha), production (tonnes), and productivity (t ha^{-1}) of potato crop in India.

S.no.	VARIABLES	MODELS	RMSE	MAE	MAPE	CV-MAPE
1	**Area**	**ARIMA**	52841.79	37731.89	**1.785256**	4.028877
		ETS	78868.7525	61491.0935	2.84112897	3.47132397
		STS	133901.73	101836.544	4.65116432	4.59020951
		Prophet	236390.727	230590.252	10.861565	5.61021103
		SVR	110592.351	93322.1945	4.23012841	3.50691582
2	**Production**	**ARIMA**	2539229	2153019	**4.306307**	7.325845
		ETS	3593682.21	3065726.48	6.18763242	7.03919377
		STS	3414057.99	2925216.54	5.88838424	10.4425179
		Prophet	12872434.4	12471146.3	24.6496221	12.4731302
		SVR	6656060.4	5647215.71	10.7056218	7.55776162
3	**Productivity**	**ARIMA**	1.367912	1.132089	**4.931342**	8.591851
		ETS	3.66426518	3.40440448	14.2343246	5.7079961
		STS	3.00248848	2.78585847	11.6639343	7.73818658
		Prophet	1.53850894	1.34682932	5.68066718	8.21079326
		SVR	2.51506166	2.25807986	9.43793924	5.32462777

3.2.2 Potato Production

For potato production, ARIMA again achieved the best performance with a MAPE of 4.31%, compared to ETS (6.19%), STS (5.89%), SVR (10.71%), and Prophet (24.65%). The exceptionally poor performance of Prophet for production reflects its difficulty in tracking a series characterized by both a strong upward trend and considerable inter-annual variability driven by weather and market conditions. This finding is broadly consistent with Rathod et al. (2020), who noted that data-driven decomposition methods such as Prophet tend to overfit trend changepoints in agricultural production series with irregular fluctuations. The ARIMA production model passed the Ljung-Box diagnostic ($Q = 8.52$, $p = 0.578$), confirming residual independence and model adequacy. The CV-MAPE of 7.33% is somewhat higher than the in-sample MAPE, which is an expected outcome of the conservative rolling-origin evaluation scheme and does not undermine the selection of ARIMA as the best model. The production forecasts (Table 3) indicate an increase from approximately 60.92 million tonnes in 2025 to 64.17 million tonnes in 2029. This modest but sustained growth is driven primarily by area

expansion, given the stagnating productivity trajectory discussed below. Comparative analysis with earlier projections is instructive: Govindakrishnan et al. (2017) projected Indian potato production to reach approximately 55 million tonnes by 2020 under a business-as-usual scenario, a figure that was closely approximated in actual data. The present projections extend this trajectory conservatively, without assuming any step-change improvement in yield-enhancing technology or irrigation access. Forecasted values of Potato crop production (tonnes) in India were given in Table 3.

Table 3. Forecasted values of Potato crop production (tonnes) in India.

Variable	Year	Forecasted Values	95 % Lower Confidence Interval	95 % Upper Confidence Interval
Potato Crop Production	2025	60919684	56675343	65164024
	2026	60956175	56229937	65682414
	2027	61726595	56030162	67423028
	2028	62950065	56000442	69899688
	2029	64173535	56048696	72298375

3.2.3 Potato Productivity

The productivity variable presents the most agronomically significant and policy-relevant findings of this study. ARIMA achieved the lowest MAPE of 4.93% for productivity, outperforming ETS (14.23%), STS (11.66%), SVR (9.44%), and Prophet (5.68%). The comparatively poor performance of ETS for productivity is noteworthy: the exponential smoothing framework assigns exponentially declining weights to past observations, which may cause it to overreact to recent fluctuations in productivity and thereby inflate forecast errors. This limitation of ETS in yield series with complex autocorrelation structures has been noted by Prabakaran et al. (2015) in the context of cashew nut forecasting in India.

A critical observation from the residual diagnostics is that the ARIMA productivity model exhibits a significant Ljung–Box statistic ($Q = 41.80$, $p = 8.13\times10^{-6}$), indicating residual autocorrelation that the selected ARIMA specification has not fully resolved (Table 5). This finding warrants careful interpretation. It is likely attributable to the complex, nonlinear dynamics of potato productivity in India-shaped by episodic technology adoption (e.g., high-yielding variety releases, micro-irrigation expansion), erratic monsoon patterns affecting

rainfed potato areas, and structural shifts in the dominant growing regions from West Bengal and Uttar Pradesh toward newer zones such as Madhya Pradesh and Gujarat. In such circumstances, a purely linear ARIMA model may be insufficient, and hybrid approaches combining ARIMA with machine learning residual correction (as proposed by Zhang, 2003) or the inclusion of relevant covariates (rainfall, fertilizer input, minimum support price) could improve model adequacy. This limitation is acknowledged as a direction for future research.

The productivity forecasts (Table 4) reveal a declining trend, from 23.86 t ha^{-1} in 2025 to 22.19 t ha^{-1} in 2029, representing a reduction of approximately 7% over the five-year horizon. This is a stark finding that deserves policy attention. National potato productivity in India has historically hovered between 20 and 25 t ha^{-1}-well below the global average of approximately 20.7 t ha^{-1} achieved by top producers and far below the 40–50 t ha^{-1} attained in the Netherlands and Belgium (FAO, 2022). The declining forecast trajectory is consistent with recent agronomic observations: soil health degradation from intensive cultivation, inadequate adoption of certified seed potato, low micro-nutrient use efficiency, and climate-induced thermal stress during the critical tuberization period have all been cited as constraints on Indian potato productivity (Govindakrishnan et al., 2017; Haverkort and Struik, 2015). These forecast results thus corroborate field-level diagnoses from the agronomic literature and strengthen the case for urgent targeted investment in productivity-enhancing interventions. Forecasted values of Potato crop productivity (t ha^{-1}) in India were given in Table 4.

Table 4. Forecasted values of Potato crop productivity (t ha^{-1}) in India.

Variable	Year	Forecasted Values	95 % Lower Confidence Interval	95 % Upper Confidence Interval
Potato Crop Productivity	2025	23.86087	19.9303	27.79143
	2026	23.62881	17.01828	30.23935
	2027	23.04886	12.39984	33.69788
	2028	22.69426	7.869121	37.5194
	2029	22.19369	2.494735	41.89264

3.3 Comparative Model Performance

Across all three variables, ARIMA models demonstrated superior in-sample MAPE performance. The failure of Prophet for area (MAPE: 10.86%) and production (MAPE:

24.65%) reflects its design for sub-annual series with strong seasonal patterns—a context not matched by annual agricultural data. STS models performed poorly due to excessive flexibility in level and slope components, leading to over-smoothing of the historical trend and poor generalization. SVR, despite its ability to capture nonlinear input-output relationships, did not outperform ARIMA for any variable, which is consistent with the view that machine learning methods require substantially larger sample sizes than the 74 observations available in this study to realize their theoretical advantages (Liakos et al., 2018). The cross-validation results (Table 2, CV-MAPE column) consistently show higher errors than in-sample MAPE across all models, which is expected under rolling-origin evaluation and does not affect model ranking. Results of Ljung-Box Q test for different models were given in Table 5. The validation of ARIMA models using ACF and PACF plots were given in Figure 1-3.

Table 5. Results of Ljung–Box Q test for different models.

S.no.	MODELS	VARIABLES	STATISTIC	P_VALUE
1	**ARIMA**	Area	3.315275	0.973002
		Production	8.522085	0.577978
		Productivity	41.80279	8.13E-06
2	**ETS**	Area	5.94585712	0.81979139
		Production	11.7386684	0.30292717
		Productivity	8.5020062	0.57992381
3	**STS**	Area	3.17441942	0.97701612
		Production	12.3344706	0.26329507
		Productivity	10.0254847	0.43826027
4	**Prophet**	Area	24.5036949	1.00399E-06
		Production	18.7952496	0.003439489
		Productivity	11.6148466	0.040463917
5	**SVR**	Area	9.24111333	0.50938427
		Production	9.08876984	0.52370026
		Productivity	14.8460857	0.13777487

4.Conclusion and Policy Implications

This study evaluated five forecasting models-ARIMA, ETS, Prophet, STS, and SVR-for

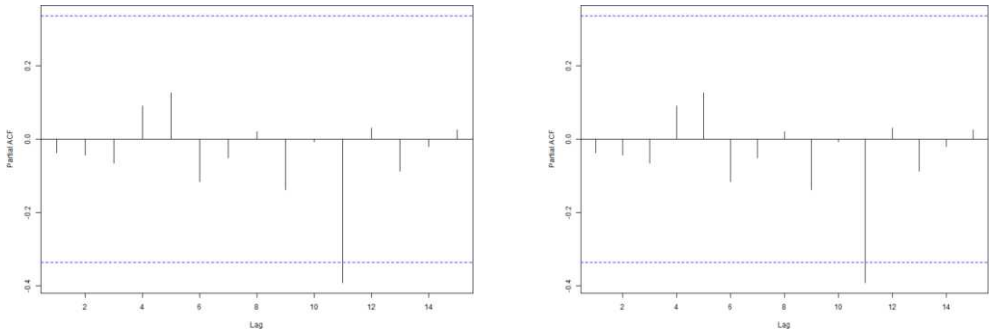
predicting area, production, and productivity of potato in India using 74 years of annual data (1950–51 to 2023–24). ARIMA models consistently outperformed all competing approaches across all three variables based on MAPE, achieving values of 1.79%, 4.31%, and 4.93% for area, production, and productivity respectively. These results align with the established literature on ARIMA for agricultural time series in India and internationally, confirming that stable stochastic trend series are well-captured by the Box–Jenkins framework.

The five-year forecasts project continued growth in potato area (reaching approximately 2.52 million ha by 2029) and production (reaching approximately 64.17 million tonnes), but a declining productivity trend (falling to approximately 22.19 t ha^{-1} by 2029). This divergence between expanding area and contracting yield per unit area is a significant policy signal. It suggests that India's growing potato output is being driven almost entirely by extensification-bringing additional land under cultivation-rather than by intensification or technological upgrading. If sustained, this trajectory will lead to diminishing marginal returns from area expansion and increasing pressure on land and water resources.

Policy interventions are urgently warranted on multiple fronts. Investment in certified seed potato production and distribution, expansion of micro-irrigation in non-traditional potato belts, and targeted micro-nutrient supplementation programs can arrest the productivity decline projected by this study. For market management, the forecast expansion in production implies continued need for cold-chain investment and diversification of export destinations beyond current primary markets. For agricultural insurers and commodity traders, the widening confidence intervals of the five-year productivity forecasts underscore the importance of probabilistic risk assessment rather than point-based planning.

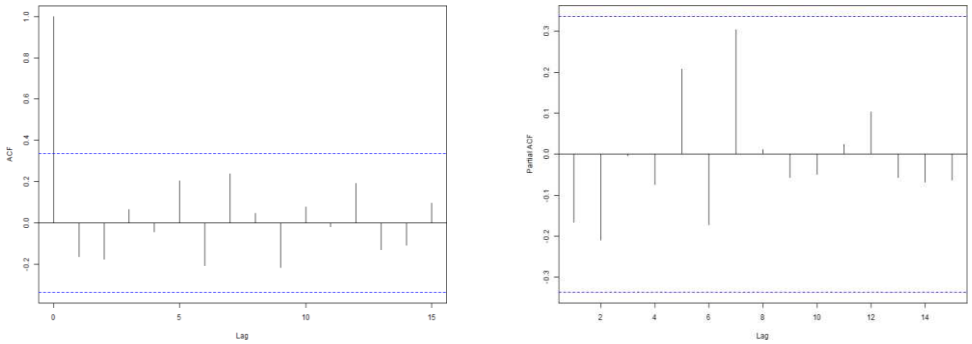
The residual autocorrelation detected in the ARIMA productivity model (Ljung–Box $p = 8.13\times10^{-6}$) identifies an important limitation of the purely linear ARIMA framework for this variable and points to a clear direction for future research: the development of hybrid ARIMA-ML models incorporating weather covariates and input-use variables, or the application of functional data analysis approaches to regional productivity series, may yield improved forecast accuracy. The framework developed in this study provides a rigorous and replicable baseline for such future work.

Figure 1. ACF(a) and PACF(b) plot for potato area residuals for ARIMA.



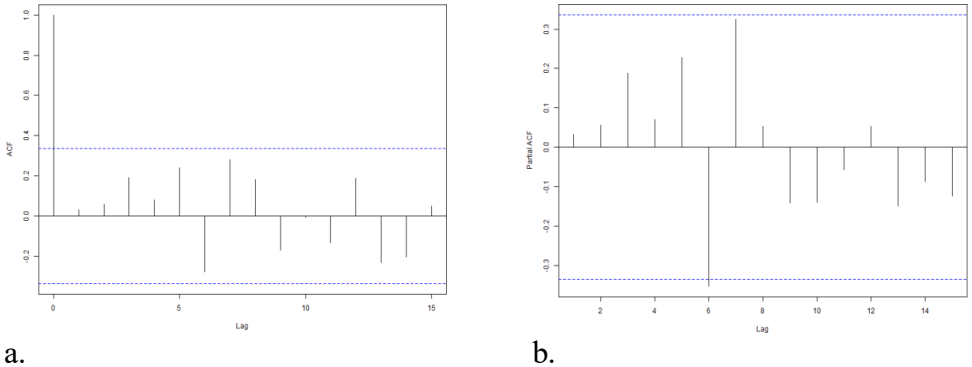
a. b.

Figure 2. ACF(a) and PACF(b) plot for potato production residuals for ARIMA



a. b.

Figure 3. ACF(a) and PACF(b) plot for potato productivity residuals for ARIMA



a. b.

5. Conflict of interest

There is no conflict of interest

6.Usage of AI tools

I hereby declare that I did not use any AI tools for manipulation or fabrication of any results reported in this study. The online platforms used only for language polishing- particularly for grammer corrections.

7. Funding Declaration

There is no funding or any other financial help for this research.

8. Data Availability Statement

The annual data on area, production, and productivity of potato crop for the period 1950–51 to 2023–24 were obtained from published reports and official databases of the National Horticulture Board (NHB) and the Directorate of Horticulture, Government of India. The processed dataset is available from the corresponding author upon reasonable request.

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