Journal of Food Legumes
38(2): 318-327, 2025
DOI: 10.53550/jfl.v38.i2.274

Research Paper

Time series analysis and forecasting of pigeonpea [*Cajanus cajan* (L.) Millsp.] area, production and yield in eastern Uttar Pradesh using ARIMA

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***Received;** January 16, 2025*
***Accepted:** April 2, 2025*

ABSTRACT

This study examines trends, variability, and forecasting of pigeonpea cultivation in Eastern Uttar Pradesh, India, from 1960 to 2022, focusing on area, production, and yield across three periods: Period I (1960–1980), Period II (1981–2000), and Period III (2001–2022). Using descriptive statistics, the Cuddy-Della Valle instability index, trend models, ARIMA modeling, and evaluation metrics (RMSE, MAPE, R^2, AIC), the analysis reveals key findings. The cultivated area declined from 206.35 thousand hectares in Period I to 155.03 thousand hectares in Period III, with a negative CAGR of -0.41%. Production peaked at 134.04 thousand tonnes in Period II but fell to 90.87 thousand tonnes in Period III, despite a marginally positive CAGR of 0.21%. Yield rose to 15.75 quintals/hectare in Period II but dropped to 13.43 quintals/hectare in Period III, showing a positive CAGR of 0.80%. Variability increased in area and production, while yield stabilized. Quadratic trend models captured non-linear patterns effectively, with R^2 of 0.839, 0.675, and 0.573 for area, production, and yield, respectively. ARIMA (1,1,10) models provided accurate forecasts, emphasizing policy and technological measures for sustainable cultivation.

Key words: Area, ARIMA, CAGR, Cuddy-Della Valle index, Forecasting, Instability, Production, Pigeonpea, Yield

INTRODUCTION

Pigeonpea [*Cajanus cajan* (L.) Millspaugh], a significant leguminous crop, plays an important role in global agricultural systems, especially in the tropical and subtropical regions (Uwamariya and Ndanguza 2018). Its high protein content and adaptability to diverse environmental conditions make it indispensable in addressing food security and nutritional needs (Paul *et al.* 2020). Globally, pigeonpea ranks among the top grain legumes, although it occupies a smaller area compared to crops like chickpea and beans. Its utility extends beyond human consumption to include livestock feed, fuelwood, and green manure, underscoring its multifaceted contributions to agriculture and sustainability (Sridhara *et al.* 2023, Shukla *et al.* 2015).

India stands as the global leader in pigeonpea production, contributing nearly 77.61% of the world's output. The crop is integral to the country's agricultural landscape, particularly due to its prominence in the Indian diet as dal (Kumari *et al.* 2021). In the 2021-2022 agricultural year, India cultivated pigeonpea over an area of approximately 5.05 million hectares, yielding a production of 4.34 million tonnes, with an average productivity of 859 kg/ha (Paul *et al.* 2022, Kumari *et al.* 2021). Uttar Pradesh emerges as a significant contributor to this production, leading among the states with a production of 0.47 million tonnes from an area of 0.49 million hectares, and an average yield of 944 kg/ha, accounting for 34.87% of the national production.

Other major pigeonpea-producing states include Madhya Pradesh (0.44 million tonnes, 34.55% of national production), West Bengal (10.53%), Bihar (8.84%), and Jharkhand (4.53%) (Sayipathap *et al.* 2024, Kumari *et al.* 2018). Pigeonpea's resilience to drought and adaptability to rainfed conditions make it a preferred choice among farmers. However, challenges such as erratic rainfall, pest infestations, and market price volatility have influenced its production trends over time. The state's diverse agro-climatic zones provide both opportunities and constraints for pigeonpea cultivation (Banakara *et al.* 2023).

Eastern Uttar Pradesh, a critical agricultural region within the state, holds substantial potential for pigeonpea cultivation. The region's predominance of rainfed farming and marginal soils aligns well with the crop's requirements (Rahman *et al.* 2022). Farmers in this area rely on pigeonpea not only as a dietary staple but also as a cash crop, benefiting from its soil-enriching properties and tolerance to adverse conditions. Despite its importance, pigeonpea production in Eastern Uttar Pradesh has faced challenges such as declining productivity, market fluctuations, and resource constraints, necessitating a deeper understanding of its production dynamics (Chitikela 2022, Ajit and Gupta 2020).

Forecasting agricultural trends, particularly for essential crops like pigeonpea, is crucial for informed decision-making. Accurate predictions enable policymakers to address production challenges, ensure food security, and stabilize markets. Time series analysis, specifically the ARIMA (Auto Regressive Integrated Moving Average) model, offers a robust framework for forecasting agricultural trends (Pandit *et al.* 2021, Pandit *et al.* 2022). By analyzing historical data and identifying patterns, ARIMA provides reliable projections that help stake holders plan for the future.This study employs the ARIMA model to predict the area, production, and yield of pigeonpea in Eastern Uttar Pradesh. By looking at past trends and estimating future patterns, the research aims to provide valuable guidance to improve pigeonpea farming. The results can help allocate resources better, boost farmers' incomes, and promote the sustainable growth of this important crop in the region.

MATERIALS AND METHODS

This study focused on forecasting the area, production, and yield of pigeonpea in Eastern Uttar Pradesh by analyzing historical data from specific districts. A total of 15 districts were included in the analysis: Allahabad, Azamgarh, Bahraich, Ballia, Basti, Deoria, Faizabad, Ghazipur, Gonda, Gorakhpur, Jaunpur, Mirzapur, Pratapgarh, Sultanpur, and Varanasi. These districts were chosen based on the availability of reliable data. Conversely, 13 districts-Ambedkar Nagar, Amethi, Balrampur, Chandauli, Kaushambi, Kushinagar, Maharajganj, Mau, Sant Kabir Nagar, Sant Ravidas Nagar, Shravasti, Siddharth Nagar, and Sonbhadra were excluded due to data limitations.

Figure 1 shows the selected districts in Eastern UP, high lighting regions from the North East Plain, Eastern Plain, and Vindhyan regions. The dataset

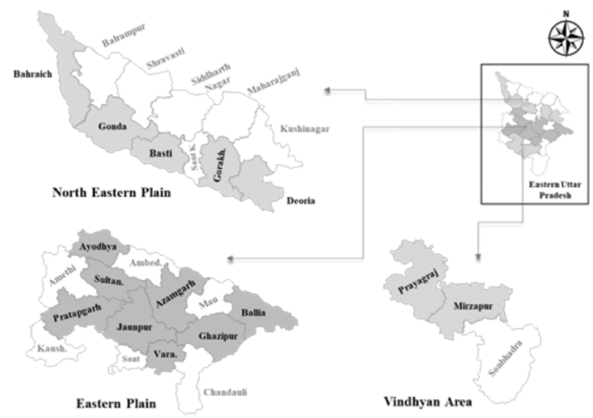

Fig. 1. Highlighted districtsin Eastern UP selected for area, production, and yield forecasting of pigeonpea (Source: Author's compilation).

spanning the years 1960 to 2022 has been classified into three distinct sub-periods. Period I (1960–1980) represents the pre-liberalization era. Period II (1981–2000) is marked by the introduction of modern farming techniques. Period III (2001–2022) is characterized by the adoption of precision agriculture, digital farming, and sustainable practices. This dataset was sourced from reputable institutions such as the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Sankhyakiya Patrika, and the Directorate of Economics & Statistics and has been utilized for analysis and forecasting up to the year 2035. Descriptive statistical methods, including calculations of maximum and minimum values, mean, skewness, and kurtosis, were applied to identify historical trends in pigeonpea area, production, and yield. Previous studies, such as those by Kathayat and Dixit (2021), Dheer *et al.* (2018), Mishra *et al.* (2023), and Bharati and Singh (2019), informed the analytical approach.

The data was subjected to several trend models to capture the dynamics effectively. These models included linear, quadratic, compound, cubic, exponential, logarithmic, and growth models, each designed to explore specific patterns in the dataset.The instability of the data was assessed using the Cuddy-Della Valle instability index, a method widely employed in agricultural studies (Prabakaran *et al.* 2013, Darekar and Reddy 2017, Dharmaraja *et al.* 2020, Kumar *et al.* 2025, Srivastava *et al.* 2022). This index quantifies variability over time and is calculated using:

$$CV_t = (CV) \times \sqrt{(1 - R^2)} \text{............} (1)$$

Where CV is the coefficient of variation

$\left(\frac{\sigma}{\bar{x}} \times 100\right)$, σbeing the standard deviation and $\bar{x}$ the mean.

The compound annual growth rates (CAGRs) for the area, production and yield of the pigeonpea across three distinct phases were calculated using the following growth model:

The growth model here is $Y = \alpha\beta^t$

Where,

Y= Production of the crop for the year t

t = Time variable (1, 2...... n) for each period.

α = Constant

β = Growth coefficient

Log transformation of above function is:

$\ln Y_t = \ln \alpha + t(\ln \beta)$

Where, $\ln \beta = \ln(1 + r)$ and

$t = [antilog(\ln \beta) - 1]$

Then the percent compound growth rate (g) was computed using the relationship (Mishra *et al.* 2025).

CAGR (%) = $[antilog(\ln \beta) - 1] \times 100$

To model and forecast the pigeonpea trends, several trend models were applied (Table 1).

Table 1. These models applied in the present study

Linear Model	$Y_t = b_0 + (b_1 t)$
Quadratic Model	$Y_t = b_0 + (b_1 t) + (b_2 t^2)$
Compound Model	$ln(Y_t) = ln(b_0) + t\, ln(b_1)$
Cubic Model	$Y_t = b_0 + (b_1 t) + (b_2 t^2) + (b_3 t^3)$
Exponential Model	$Y_t = b_0 e^{(b_1 t)}$ *or* $\ln(Y_t) = \ln(b_0) + (b_1 t)$
Logarithmic Model	$Y_t = b_0 + b_1 \ln(t)$
Growth Model	$ln\,(Y_t) = b_0 + b_1 t\, Y_t$

To analyze the time series data, the Autoregressive Integrated Moving Average (ARIMA) model was utilized, incorporating autoregressive (AR) and moving average (MA) components, with differencing for data stabilization. The ARIMA model expressed as ARIMA (p, d, q), determined autoregressive terms, degrees of differencing, and lagged forecast errors. The dataset from 1960 to 2009 was used for model building, while data from 2010 to 2022 served for validation, enabling projections through 2035. This methodology aligns with approaches in studies by Choudhury *et al.* (2017), Derekar and Reddy (2017), Khaemba *et al.* (2021), and Kumar *et al.* (2024).

Model performance was evaluated using metrics such as Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), R-squared (R^2), and Akaike's Information Criterion (AIC). RMSE and MAPE measured error magnitude, while R^2 assessed model fit. AIC provided insights into model adequacy by balancing fit and complexity (Kumar *et al.* 2023, Chaudhari and Tingre, 2014). Residual diagnostics, including auto correlation function (ACF) and partial autocorrelation function (PACF) plots, confirmed the residuals were white noise, validating model suitability. This diagnostic procedure has been endorsed in studies by Ahmar *et al.* (2023), Umesh *et al.* (2023), and Kulkarni *et al.* (2018).

RESULTS AND DISCUSSION

Performance of pigeonpea

Table 2 provides an extensive overview of the performance of pigeonpea in Eastern Uttar Pradesh from 1960 to 2022. The table includes important statistics on area, production, and yield, segmented into three periods.Table 2 reveals that the average area under pigeonpea cultivation over the entire period was 189.97 thousand hectares. This figure reflects a decrease from 206.35 thousand hectares in Period I (1960-1980) to 155.03 thousand hectares in Period III (2001-2022), with Period II (1981-2000) showing an intermediate value of 211.20 thousand hectares. The CAGR for the area under cultivation is negative at -0.41% across the whole period, indicating a declining trend. The negative CAGR is consistent across all periods, with Period III experiencing the steepest decline at -0.73%. The standard deviation of the area increased over time, from 11.65 thousand hectares in Period I to 16.33 thousand hectares in Period III, suggesting increased variability in the area under cultivation. The skewness values for the area are predominantly negative, especially in Period I (-1.96), indicating a leftward skew and suggesting that lower values of the area were more common during this period. The kurtosis values reflect a varying distribution shape, with Period I being highly leptokurtic (4.78), indicating a peakier distribution compared to other periods.

The average production of pigeonpea was 117.28 thousand tonnes over the entire period. Production peaked in Period II (1981-2000) at 134.04

Table 2. Performance of pigeonpea area, production and yield in Eastern UP during 1960-2022

Particulars	Whole period (1960-2022)	Period I (1960-1980)	Period II (1981-2000)	Period III (2001-2022)
		Area ('000 ha)		
Mean	189.97	206.35	211.20	155.03
Standard error	3.69	2.54	2.93	3.48
Standard deviation	29.26	11.65	13.10	16.33
Kurtosis	-0.98	4.78	-0.26	-1.14
Skewness	-0.61	-1.96	-0.06	0.48
Minimum	130.99	168.50	185.70	130.99
Maximum	235.51	217.40	235.51	183.79
CAGR	-0.41%	-0.27%	-0.34%	-0.73%
		Production ('000 tonnes)		
Mean	117.28	128.98	134.04	90.87
Standard error	3.44	4.58	3.51	4.39
Standard deviation	27.30	20.99	15.68	20.57
Kurtosis	-0.79	-0.49	3.56	2.34
Skewness	-0.22	-0.71	1.20	1.25
Minimum	54.26	86.60	109.15	54.26
Maximum	181.40	160.80	181.40	146.59
CAGR	0.21%	0.75%	0.66%	0.82%
		Yield (ton/ha)		
Mean	14.25	13.69	15.75	13.43
Standard error	0.29	0.54	0.42	0.38
Standard deviation	2.28	2.46	1.90	1.80
Kurtosis	-0.38	-1.27	0.00	-0.30
Skewness	0.18	0.24	0.70	-0.02
Minimum	9.80	9.80	13.18	9.95
Maximum	20.21	18.11	20.21	16.90
CAGR	0.80%	2.97%	1.26%	0.25%

thousand tonnes but decreased to 90.87 thousand tonnes in Period III (2001-2022). The CAGR for production is relatively low but positive at 0.21% across the whole period, with Period III showing a slight increase of 0.82%. The standard deviation of production, which increased to 20.57 thousand tonnes in Period III, reflects higher variability in production levels over time. The skewness values for production are positive in the more recent periods, especially in Period III (1.25), indicating a rightward skew and suggesting higher production values were more common. The kurtosis values, particularly high in Period II (3.56) and Period III (2.34), indicate a leptokurtic distribution with more frequent extreme values.

The average yield of pigeonpea over the entire period was 14.25 tonnes per hectare. Yield showed a slight increase from 13.69 tonnes per hectare in Period I to 15.75 tonnes per hectare in Period II, but a decrease to 13.43 tonnes per hectare in Period III. The CAGR for yield was positive at 0.80% for the entire period, with Period I exhibiting a high growth rate of 2.97% and Period III showing a modest increase of 0.25%. The standard deviation of yield was relatively stable, with the lowest value in Period III (1.80 tonnes/ha), reflecting less variability in yield during this period. Skewness values are relatively low, with a positive skew in Period II (0.70) and a near-zero skew in Period III (-0.02), suggesting a balanced distribution of yield values. The kurtosis values are generally low, indicating a distribution that is close to normal, with slight deviations in the earlier periods.

Trends in area, production, and yield of pigeonpea

The trend analysis of pigeonpea in Eastern Uttar Pradesh, as presented in Table 3, provides a comprehensive understanding of the patterns observed in the area, production, and yield of this crop over time. The analysis also references Figures 2, 3, and 4, which visually depict these trends and substantiate the discussion.

For the area under pigeonpea cultivation, the quadratic model emerges as the most suitable, with an R^2 value of 0.839, indicating a strong correlation between the area and time. The significance level is 0.00, underscoring the model's statistical reliability. The constant (b) is estimated at 227.99, with coefficients b_1 at -6.98, b_2 at 0.55, and b_3 at -0.01 (Table 2 and Figure 2). The negative b_1 coefficient suggests an initial decline in the area under pigeonpea cultivation, but the positive b_2 coefficient indicates a subsequent slowing of this decline, potentially leading to a stabilization or slight increase in the future. This trend may reflect shifts in cropping patterns, possibly due to changes in farmer preferences or external factors such as market demand and climatic conditions. The cubic model also shows a relatively strong fit with an R^2 value of 0.749, but the quadratic model is preferred due to its higher R^2. The linear model, with an R^2 value of 0.575, although significant, does not capture the non-linear nature of the trend as effectively. The logarithmic model has a much lower R^2 value of 0.301, indicating a weaker fit. The exponential, compound, and growth models all exhibit an R^2 of 0.539, which is insufficient to accurately model the trend in pigeonpea area.

In terms of production, the quadratic model again provides the best fit, with an R^2 value of 0.675, which is significantly higher than that of

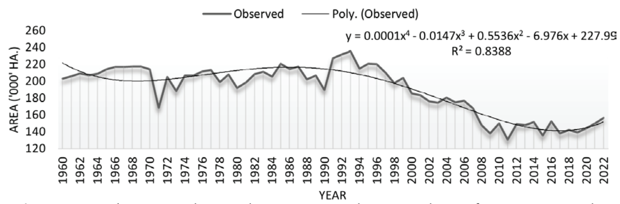

Fig. 2. Observed and expected trends of area under pigeonpea

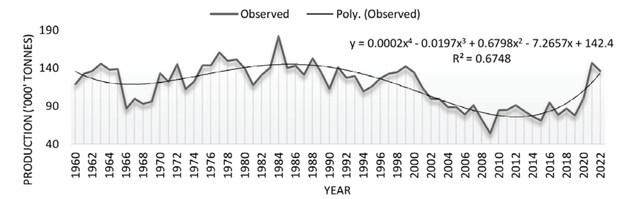

Fig. 3. Observed and expected trends of production under pigeonpea

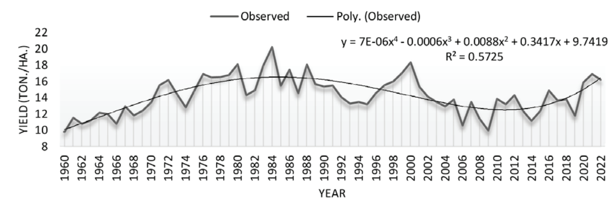

Fig. 4. Observed and expected trends of yield under pigeonpea

Table 3. Trends in area, production and yield of pigeonpea

Model Summary and Parameter Estimates						
Area ('000 ha)						
Equation	**Model summary**		**Parameter estimates**			
	R^2	**Significance**	**constant (b)**	**b_1**	**b_2**	**b_3**
Linear	0.575	0.00	228.72	-1.21	-	-
Exponential	0.539	0.00	0.00	-0.01	-	-
Logarithmic	0.301	0.00	246.64	-17.76	-	-
Quadratic	**0.839**	**0.00**	**227.99**	**-6.98**	**0.55**	**-0.01**
Cubic	0.749	0.00	197.46	1.93	-0.06	-
Compound	0.539	0.00	0.00	-0.01	-	-
Growth	0.539	0.00	0.00	-0.01	-	-
Production ('000 tonnes)						
Linear	0.268	0.00	141.94	-0.77	-	-
Exponential	0.251	0.00	0.00	-0.01	-	-
Logarithmic	0.128	0.00	151.76	-10.81	-	-
Quadratic	**0.675**	**0.00**	**142.40**	**-7.27**	**0.68**	**-0.02**
Cubic	0.457	0.00	97.95	5.71	-0.22	-
Compound	0.251	0.00	0.00	-0.01	-	-
Growth	0.251	0.00	0.00	-0.01	-	-
Yield (ton/ha)						
Linear	0.005	0.00	13.97	0.01	-	-
Exponential	0.005	0.00	0.00	0.00	-	-
Logarithmic	0.094	0.00	11.79	0.77	-	-
Quadratic	**0.573**	**0.00**	**9.74**	**0.34**	**0.01**	**0.00**
Cubic	0.519	0.00	7.91	0.88	-0.03	-
Compound	0.005	0.00	0.00	0.00	-	-
Growth	0.005	0.00	0.00	0.00	-	-

other models. The significance level remains at 0.00, confirming the model's robustness. The constant (b) is estimated at 142.40, with b_1 at -7.27, b_2 at 0.68, and b_3 at -0.02 (Table 3 and Figure 3). The negative b_1 coefficient suggests a decline in pigeonpea production over time, while the positive b_2 indicates a possible future stabilization or slight increase. This trend may be influenced by various factors, including agricultural practices, pest and disease management, and environmental conditions. The cubic model, with an R^2 value of 0.457, also captures some of the production trends but is less effective than the quadratic model. The linear model, with an R^2 of 0.268, and the logarithmic model, with an R^2 of 0.128, are both inadequate in explaining the production trends comprehensively. The exponential, compound, and growth models, each with an R^2 of 0.251, further corroborate the inadequacy of these models in capturing the complexity of pigeonpea production trends.

For pigeonpea yield, the quadratic model once again proves to be the best fit, with an R^2 value of 0.573, the highest among all the models tested. The significance level is 0.00, demonstrating the model's reliability. The constant (b) is estimated at 9.74, with coefficients b_1 at 0.34, b_2 at 0.01, and b_3 at 0.00 (Table 3 and Figure 4). The positive b_1 coefficient suggests a gradual increase in yield over time, while the small positive b_2 indicates that this trend is likely to continue at a modest pace. This trend may be attributed to improvements in farming practices, the adoption of high-yielding varieties, and better pest and disease management strategies. The cubic model, with an R^2 value of 0.519, also shows a good fit but does not surpass the quadratic model in explaining yield trends. The linear model, with an R^2 value of 0.005, is particularly ineffective, as is the exponential model with the same R^2 value, indicating that these models fail to capture the yield trend accurately. The logarithmic model, with an R^2 of 0.094, also falls short of providing a satisfactory explanation of the yield trends. The compound and growth models, with R^2 values of 0.005, confirm their inadequacy in analyzing pigeonpea yield trends.

Instability analysis

In Eastern Uttar Pradesh, the Cuddy and Della (1978) approach was applied to assess instability in the area, production, and yield of pigeonpea as detailed in Table 4. While a more general alternative is to use the coefficient of variation (CV) value, its proper application requires careful consideration of the trend variable in time series data (Hasan *et al.* 2008). The Cuddy and Della method is based on the assumption of a linear trend. However, identifying a linear trend in long-term time series data can be challenging. In this analysis, nonlinearity was incorporated into the trend model, and the coefficient of determination from the best-fitting model was used to calculate the CV_t value for various sequences. This adjusted method is referred to as the modified Cuddy and Della measure. Consequently, the R^2 values in the original Cuddy and Della model and the modified version may differ due to the consideration of nonlinearity.

The analysis of instability involved calculating the de-trended coefficient of variation across four periods: the entire period from 1960 to 2022, Period I (1960–1980), Period II (1981–2000) and Period III (2001–2022).

The R^2 value for the area under pigeonpea cultivation was 0.005 for the entire period, reflecting a negligible correlation and indicating high instability. In Period I, the R^2 significantly increased to 0.842, suggesting more stability during this phase, whereas Periods II and III showed low R^2 values of 0.021 and 0.093, respectively, indicating inconsistent stability across these intervals. The CV for the area was 16.025% over the entire period, with the highest instability observed in Period I at 17.973%. The CV reduced in Period II to 12.045%, and slightly increased in Period III to 13.380%, reflecting some level of variability in pigeonpea cultivation. Throughout the entire period, the CV_t was 16.115, reflecting moderate instability. The highest instability occurred in Period I, while Period II and III experienced slightly lower variations.

Table 4. Instability in area, production and yield of pigeonpea

Statistics	**Whole Period**	**Period I**	**Period II**	**Period III**
	Area ('000 ha)			
R^2	0.005	0.842	0.021	0.093
CV	16.025	17.973	12.045	13.380
CV_t	16.115	7.333	12.246	13.054
	Production ('000 tonnes)			
R^2	0.268	0.134	0.063	0.057
CV	23.277	16.277	11.697	22.634
CV_t	20.079	15.542	11.631	22.520
	Yield (ton/ha)			
R^2	0.575	0.060	0.003	0.515
CV	15.402	5.647	6.203	10.531
CV_t	10.119	5.618	6.364	7.517

Regarding production, the R^2 value for the entire period was 0.268, indicating moderate instability. Period I had a low R^2 of 0.134, which further decreased in Period II (0.063) and Period III (0.057), suggesting an increasing instability over time. The CV for production was highest during the entire period at 23.277%, with noticeable fluctuations across the periods—16.277% in Period I, 11.697% in Period II, and a substantial increase to 22.634% in Period III. The consistent rise in CV from Period II to Period III underscores the challenges in stabilizing pigeonpea production. The CV_t for pigeonpea production indicated more stability during Periods I and II, with increased instability in Period III, reflecting fluctuations in output.

The yield instability analysis revealed a moderate R^2 value of 0.575 for the entire period, indicating a reasonable level of stability. However, this stability was not uniform across the periods, with Period I showing a low R^2 of 0.060, a negligible 0.003 in Period II, and a higher 0.515 in Period III. The CV for yield was 15.402% for the whole period, with the lowest variability in Period I at 5.647%. This variability increased slightly in Period II (6.203%) and more noticeably in Period III (10.531%), indicating growing instability in yield over time. The CV_t suggested relatively stable production across periods, with the lowest variation in Period I, indicating consistent productivity levels during that time.

Modelling and forecasting

Table 5 presents the results of the best ARIMA models used for forecasting the area, production, and yield of pigeonpea in Eastern Uttar Pradesh. The ARIMA (1,1,10) model emerged as the most effective across all parameters. For area forecasting, it recorded the highest R^2 value of 0.878, alongside the lowest RMSE of 10.385, indicating high predictive accuracy. Similarly, in terms of production, the ARIMA (1,1,10) model achieved the best results with an R^2 value of 0.755 and the lowest RMSE of 13.557, MAPE of 9.466, and MAE of 10.145, showcasing its robustness. Yield prediction also favoured the ARIMA (1,1,10) model, as evidenced by an R^2 of 0.630 and minimal RMSE (1.398), MAPE (7.903), and MAE (1.145). The ACF and PACF plots, illustrated in Figures 5 through 7, confirmed the selection of optimal model parameters, with p = 1 and q = 10 for area, production, and yield.

Table 5. Best-fitted ARIMA model for area, production and yield under pigeonpea

	ARIMA Model	R^2	RMSE	MAPE	MAE	AIC
Area	ARIMA (1,1,10)	0.878	10.385	4.148	7.577	497.312
Production	ARIMA (1,1,10)	0.755	13.557	9.466	10.145	537.802
Yield	ARIMA (1,1,10)	0.630	1.398	7.903	1.145	256.756

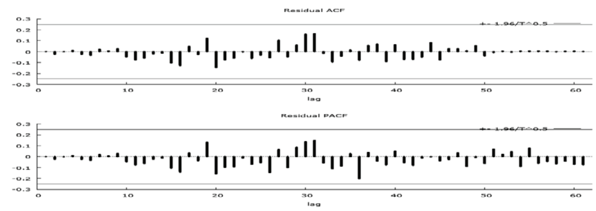

Fig. 5. ACF and PACF graphs of residuals for the best fitted models of area under pigeonpea

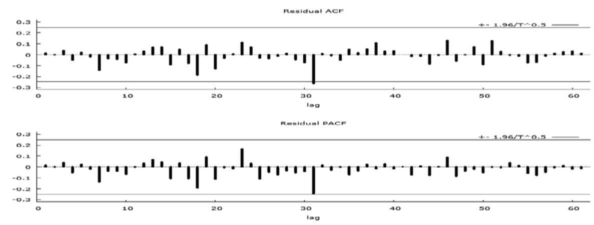

Fig. 6. ACF and PACF graphs of residuals for the best fitted models of production under pigeonpea

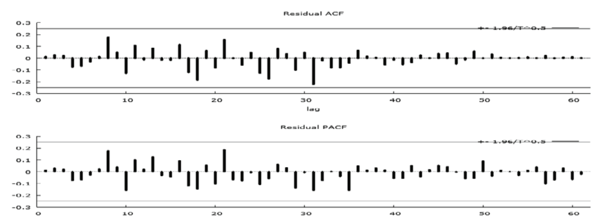

Fig. 7. ACF and PACF graphs of residuals for the best-fitted models of yield under pigeonpea

The analysis of pigeonpea production in Eastern Uttar Pradesh showed a decline in both observed and predicted values from 2010 to 2035 (Table 6). In 2010, the observed data indicated that the area under pigeonpea cultivation was 150.180 thousand hectares, with a production of 84.750 thousand tonnes and a yield of 13.865 tonnes per hectare. Projections for 2035, however, suggest an increase in the area to 155.208 thousand hectares and a rise in production to 114.166 thousand tonnes. Additionally, the yield is expected to increase modestly to 16.244 tonnes per hectare. The figures, illustrated in Figures 8 through 10, highlight a consistent upward trend in the forecasted data, contrasting with the observed values from 1960 to 2022 and forecast up to 2035. This indicates a positive shift in the production dynamics of pigeonpea in Eastern Uttar Pradesh, reflecting improved agricultural practices and environmental conditions.

Table 6. Model validation and forecasting of area, production and yield under pigeonpea

Year	Area ('000 ha)		Production ('000 tonnes)		Yield (ton/ha)	
	Observed	**Predicted**	**Observed**	**Predicted**	**Observed**	**Predicted**
2010	150.180	134.056	84.750	67.325	13.865	12.899
2011	130.990	137.149	85.200	77.085	13.198	13.766
2012	149.070	136.462	91.040	89.638	14.304	14.723
2013	148.090	136.308	83.430	74.585	12.372	12.772
2014	151.850	150.156	76.410	77.784	11.162	11.983
2015	135.930	142.501	70.960	78.814	12.373	12.280
2016	152.550	139.520	94.750	59.869	14.864	12.359
2017	138.207	141.451	78.640	97.433	13.656	14.391
2018	142.158	143.188	86.949	100.128	13.790	13.359
2019	139.420	138.340	77.669	80.648	11.770	12.310
2020	144.428	149.240	100.566	96.255	15.870	14.732
2021	150.111	141.357	146.588	117.996	16.900	15.491
2022	156.555	152.675	136.346	120.702	16.210	15.914
2023	-	158.649	-	156.061	-	14.974
2024	-	156.764	-	131.141	-	14.866
2025	-	154.431	-	123.341	-	15.366
2026	-	156.830	-	115.781	-	17.366
2027	-	154.410	-	107.270	-	15.489
2028	-	155.509	-	121.147	-	16.121
2029	-	156.251	-	134.260	-	14.990
2030	-	154.903	-	139.715	-	15.727
2031	-	157.885	-	136.337	-	15.923
2032	-	157.193	-	128.303	-	16.048
2033	-	156.539	-	122.251	-	16.092
2034	-	155.871	-	117.665	-	16.180
2035	-	155.208	-	114.166	-	16.244

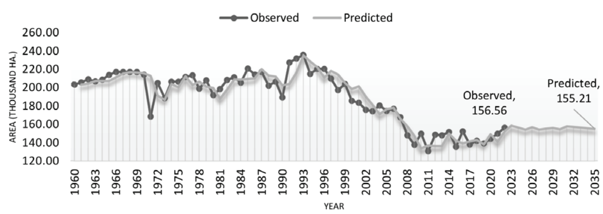

Fig. 8. Observed and forecasting of the area of pigeonpea

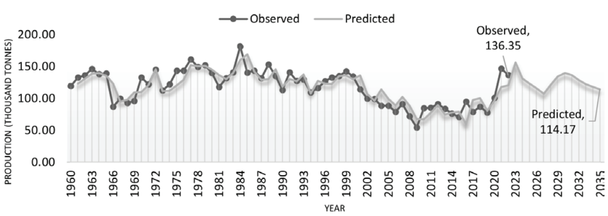

Fig. 9. Observed and forecasted production of pigeonpea

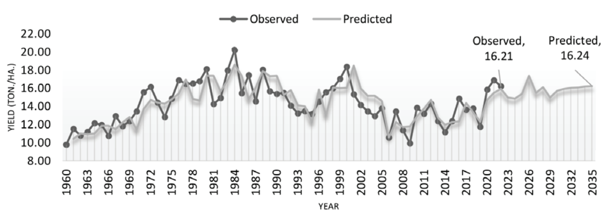

Fig. 10. Observed and forecasted yield of pigeonpea

CONCLUSION

The analysis of pigeonpea production in Eastern Uttar Pradesh reveals both challenges and opportunities for the future. From 1960 to 2022, the data showed fluctuating trends in the area, production, and yield of pigeonpea. The area under cultivation, which was 227.47 thousand hectares in 1991, declined significantly to 130.99 thousand hectares by 2011. This drop was followed by some recovery, with projections suggesting an increase to 155.208 thousand hectares by 2035. Similarly, production decreased from 181.40 thousand tonnes in 1984 to 70.96 thousand tonnes in 2015 but is expected to rise to 114.166 thousand tonnes by 2035. The yield trends indicate a more positive outlook. While the yield per hectare remained relatively steady, it is expected to see a modest rise from 13.865 tonnes per hectare in 2010 to 16.244 tonnes per hectare by 2035. This reflects improvements in farming practices, such as the adoption of better seed varieties, improved pest management, and better access to irrigation. Despite the positive growth in projections, the study highlights the need for continued research and investment in agricultural technologies. To further boost productivity, strategies such as precision agriculture, soil health management, and crop diversification should be prioritized. Additionally, improving market access, storage, and value chain infrastructure can help reduce post-harvest losses and ensure that farmers get better returns.

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