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Trend analysis of India's agricultural exports using linear and nonlinear growth models

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Abstract

This study analyzes the long-term trend of India's agricultural exports using twelve linear and nonlinear growth models applied to annual export data. The models tested include linear, logarithmic, inverse, quadratic, cubic, compound, power, S-curve, growth, exponential, logistic, and Gompertz forms. Model performance was compared using Adjusted R^2 , RMSE, MAPE, AIC, BIC, and Theil's U. The results show that export behavior is nonlinear, and the logistic model gives the best fit. It recorded the highest Adjusted R^2 (0.9176) and the lowest RMSE (38,834.56), MAPE (26.68), and Theil's U (0.0999). The logistic curve shows an S-shaped trend in which exports grow slowly at first, rise faster later, and then move toward a saturation point. Applying the same method to India's total exports also identified the logistic model as the best. Four-year forecasts show steady growth in agricultural exports and faster growth in total exports, supporting the usefulness of nonlinear models for policy decisions.

Keywords: Agricultural exports, growth models, nonlinear trend, forecasting, logistic model, India

1. Introduction

Agricultural exports are an important part of India's trade. They support rural income, value addition, employment, and foreign exchange earnings. Over the years, India has expanded its export basket from traditional items like rice and spices to fruits, vegetables, livestock products, and processed foods. This shows a clear improvement in the structure of agricultural trade (Basu, 2024; Priyanka *et al.*, 2024) ^[1, 2]. Studies also report that India's agricultural exports have increased in value and volume, although the growth pattern often shows periods of rise and fall (Globalization and Indian Agricultural Exports, 2023; Growth Trends and Instability in Agricultural Crops).

Trade liberalisation after 1991 brought major changes to India's export performance. Evidence shows that these policy reforms improved India's competitiveness in global markets. Shinoj and Mathur (2008) ^[5] showed that India gained advantage in many agricultural commodities during the post-reform years. Commodity-specific studies such as Adhikari *et al.* (2016) ^[6] for rice and Bhopala *et al.* (2023) ^[7] for sugar also reported positive export growth. Research on horticultural crops (Keerthika *et al.*, 2024; Growth Trends and Instability in Horticultural Crops, 2023) ^[8, 9] highlights both new export opportunities and instability in some years. These findings show the importance of studying long-term export behaviour. To understand these long-term patterns, suitable analytical tools are needed. Earlier studies mostly used compound or exponential growth models, but recent agricultural research shows that nonlinear models are better at identifying turning points, curvature, and saturation in long-term data. Logistic and Gompertz models are useful for this because they describe S-shaped growth patterns that start slowly, increase quickly, and then stabilise (Winsor, 1932; Franses, 1994; Satoh, 2019) ^[10, 11, 12]. Other agricultural studies also show that nonlinear models fit better when growth changes over time (Srinivasa Chary *et al.*, 2023; Growth and Instability Analysis in Indian Agriculture, 2018) ^[13, 14].

Comparing different growth models requires proper statistical tools. Akaike's Information Criterion (AIC) and Schwarz's Bayesian Information Criterion (BIC) help select the best model by balancing fit and simplicity (Akaike, 1974; Schwarz, 1978) ^[15, 16]. Theil's U statistic also

measures forecasting accuracy. These tools make it possible to choose the most suitable model when several alternatives are available. Although many studies discuss agricultural exports and trend modelling, most of them use only one or two growth models and focus on individual commodities. Very few studies compare a wide range of linear and nonlinear growth models for India's total agricultural exports. This is a gap in the literature because aggregate export data reflect broader structural patterns and policy effects.

The present study fills this gap by applying twelve growth models—linear, logarithmic, inverse, quadratic, cubic, compound, power, S-curve, exponential, logistic, and Gompertz to India's agricultural export data. The models are compared using Adjusted R², RMSE, MAPE, AIC, BIC, and Theil's U. Short-term forecasts are also prepared, and agricultural export trends are compared with total national exports to understand their relative growth behaviour.

2. Materials and Methods

2.1 Data Source and Study Period

The present investigation is based on annual time-series data on India's Agricultural Exports and Total National Exports spanning a period of 36 years, from 1990-1991 to 2025-2026. The data was collected from the Ministry of Agriculture & Farmers Welfare, Government of India in the website <https://www.indiastat.com>. This long study horizon enables an in-depth assessment of both short-term fluctuations and long-term structural trends in agricultural export growth. All subsequent analyses, including model estimation and trend diagnostics, were conducted using the compiled time-series dataset for the specified period.

2.2 Growth Model Specifications

To analyze the underlying trend behavior, twelve alternative linear and nonlinear deterministic growth models were fitted to each export series. These functional forms have been commonly utilized in agricultural and economic trend studies due to their capacity to capture linearity, curvature, acceleration, saturation, and various other structural characteristics. The models, along with their mathematical specifications, are detailed below:

To examine the temporal behaviour of India's agricultural export earnings, two widely used growth models such as Linear Growth Model and Compound Growth Model were employed.

(i) Linear Growth Model

The linear model assumes a constant absolute change in export earnings over time. It is specified as:

$$Y_t = a + bt \quad \dots(1)$$

where

Y_t = Agricultural export earnings in year t ,

t = Time (years),

a, b = Parameters estimated through Ordinary Least Squares (OLS).

The Linear Growth Rate (LGR) is computed using:

$$LGR = \left(\frac{b}{\bar{Y}} \right) \times 100 \quad \dots(2)$$

where $\bar{Y}$ is the mean of the export series.

This indicates the average annual percentage increase in exports.

(ii) Compound Growth Model

The compound model assumes a constant percentage change over time, following an exponential growth pattern:

$$Y_t = ae^{bt} \quad \dots(3)$$

Taking logarithms:

$$\log Y_t = a + bt \quad \dots(4)$$

Parameters are estimated using OLS on the log-transformed values.

The Compound Growth Rate (CGR) is computed by:

$$CGR = (e^b - 1) \times 100 \quad \dots(5)$$

This growth rate captures accelerated or decelerated trends in export performance over the study period.

(iii) Statistical Significance of Growth Rates

The significance of LGR and CGR was verified using the Student's t -test, following:

$$t = \frac{r}{SE(r)} \text{ with degrees of freedom} = N - 2 \quad \dots(6)$$

where

r = estimated growth rate (LGR or CGR),

$SE(r)$ = standard error of the estimated growth rate,

N = number of observations.

A growth rate is considered statistically significant if the calculated t exceeds the critical t value at the 5% probability level.

Table 1: Mathematical Specifications of Growth Models

Sl. No.	Model	Functional Form
1	Linear	$Y = a + bX$
2	Logarithmic	$Y = a + b \ln(X)$
3	Inverse	$Y = a + \frac{b}{X}$
4	Quadratic	$Y = a + bX + cX^2$
5	Cubic	$Y = a + bX + cX^2 + dX^3$
6	Compound	$Y = a \cdot b^X$
7	Power	$Y = a \cdot X^b$
8	S-Curve	$Y = e^{(a + \frac{b}{X})}$
9	Growth	$Y = e^{(a + bX)}$
10	Exponential	$Y = a \cdot e^{bX}$
11	Logistic	$Y = \frac{L}{(1 + e^{-(k(X - X_0))})}$
12	Gompertz	$Y = a \cdot e^{(-b \cdot e^{-cX})}$

where Y represents the export value, X denotes the time period, and a, b, c, d, k, L , and X_0 are model parameters.

Each of these models establishes a unique behavioral pattern over time. Linear and logarithmic models reflect proportional and gradually increasing trends, whereas quadratic and cubic functions facilitate shifts in curvature throughout the time period. Compound, growth, and exponential models represent multiplicative or constant-proportion increases. The logistic and Gompertz models are especially effective for identifying S-shaped trends, where initial growth accelerates before eventually stabilizing.

2.3 Estimation Procedure

To capture the long-term behaviour, direction, and structural pattern of India's agricultural export earnings, a comprehensive trend analysis was conducted by fitting twelve linear and nonlinear growth models. This approach enables comparison across models that differ in their assumptions about curvature, saturation, acceleration, and proportional change. Such multi-model trend evaluation is widely recommended in agricultural economic research and has been applied in earlier studies on production and trade growth. Each functional form was estimated using either Ordinary Least Squares (OLS) for linearizable models or nonlinear least squares (NLS) for intrinsically nonlinear forms. The independent variable in all models was time (t), while the dependent variable was either Agricultural Exports or Total National Exports. The complete list of functional forms fitted in the present study is given below. The estimation process utilized the Python programming language along with the Statsmodels and SciPy libraries, ensuring robust numerical optimization for the nonlinear models. For each export series, fitted values were generated and used to calculate residuals, trend curves, and forecast values. No differencing or transformation was applied to the dependent variable, except where required by the functional specification.

2.4 Model Evaluation Criteria

The adequacy of each fitted trend model was assessed using a set of statistical criteria widely employed in time-series growth studies. Since no single measure is sufficient to judge goodness of fit, multiple indicators were computed to ensure a robust comparison of model performance for both Agricultural Exports and Total National Exports.

2.5 The evaluation criteria used in this study include

(a) Adjusted Coefficient of Determination (Adj. R²)

The Adjusted R² accounts for the number of parameters in the model and provides an unbiased measure of explanatory power. Unlike R², it penalises unnecessary model complexity. It is computed as:

$$\text{Adj. } R^2 = 1 - \left(\frac{(1-R^2)(n-1)}{n-p-1} \right) \quad \dots(7)$$

where

n = number of observations,

p = number of parameters in the model.

A higher Adjusted R² indicates better fit.

(b) Root Mean Square Error (RMSE)

RMSE measures the standard deviation of residuals and reflects the average magnitude of forecast errors:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{t=1}^n (Y_t - \hat{Y}_t)^2} \quad \dots(8)$$

Lower RMSE signifies higher prediction accuracy.

(c) Mean Absolute Percentage Error (MAPE)

MAPE expresses forecast errors in percentage terms and is particularly useful for comparing models when the scale of the dependent variable changes over time:

$$\text{MAPE} = \frac{100}{n} \sum_{t=1}^n \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \quad \dots(9)$$

A smaller MAPE indicates greater reliability.

(d) Theil's U Statistic

Theil's U is used to compare model forecasts with a naive benchmark. It is computed as:

$$U = \frac{\sqrt{\frac{1}{n} \sum_{t=1}^n (A_{t+1} - P_{t+1})^2}}{\sqrt{\frac{1}{n} \sum_{t=1}^n A_{t+1}^2 + \frac{1}{n} \sum_{t=1}^n P_{t+1}^2}} \quad \dots(10)$$

where

A_{t+1} = actual value at time t+1,

P_{t+1} = predicted value at time t+1.

Interpretation

U < 1 → model is better than naïve forecast

U = 1 → equivalent to naïve forecast

U > 1 → model performs worse than naïve forecast

A lower Theil's U indicates a superior model.

(e) Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC)

AIC and BIC incorporate both the goodness of fit and model parsimony:

$$\text{AIC} = n \ln \left(\frac{\text{RSS}}{n} \right) + 2p \quad \dots(11)$$

$$\text{BIC} = n \ln \left(\frac{\text{RSS}}{n} \right) + p \ln(n) \quad \dots(12)$$

Where RSS = residual sum of squares.

Lower AIC and BIC values indicate a better-fitting and more efficient model.

This multi-criteria evaluation ensures that the selected function provides both strong explanatory performance and high predictive accuracy, consistent with best methodological practices in agricultural trend analysis.

2.6 Forecasting Methodology

After identifying the logistic function as the optimal model for both agricultural and national exports, the study proceeded to make projections for the four-year period from 2027 to 2030. The estimated parameters from the best-fitting logistic model were integrated into the trend equation to generate export forecasts.

3. Results and Discussion

3.1 Model Performance for Agricultural Exports

Twelve linear and nonlinear growth models were fitted to the time-series data of Agricultural Exports and Total National Exports of India for the period 1990-91 to 2025-26. The best-fitted model for each series was identified based on the relatively highest Adj.R², lowest MAPE, RMSE, and Theil's U-Statistic. The fitted trend lines and model summaries are described in Table 2.

A. Trends in Agricultural Exports

Among the models, the Logistic model recorded the highest Adj.R² (0.9097) along with the lowest MAPE (26.69), lowest RMSE (38,834.56) and lowest Theil's U-Statistic (0.0999). These diagnostics indicate a superior fit compared to all other functional forms, and the model was statistically significant at

the 1% level.

Hence, the Logistic model was identified as the best-fitting model for Agricultural Exports.

The fitted logistic equation is

$$Y_t = \frac{396004.58}{1 + 145.3564e^{-0.2168t}} \quad \dots(13)$$

where t represents the time in years.

From Fig. 1, agricultural export earnings were observed to increase steadily throughout the study period, exhibiting an S-shaped growth pattern with signs of gradual stabilization in recent years.

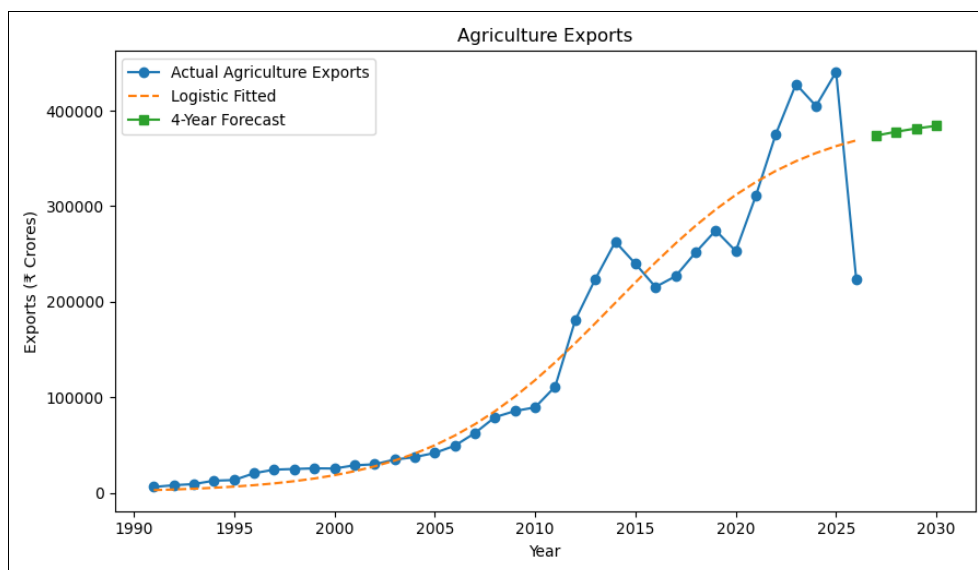


Fig 1: Observed and Modeled Growth in Agricultural Exports: Logistic Fit with 4-Year Forecast

Table 2: Performance of Growth Models for Agricultural Exports

Equation	Model		Parameters				R ²	Adj.R ²	MAPE	RMSE	Theil's U
	F	Sig.	Constant	b1	b2	b3					
Linear	177.15	0.000	-77959.00	11915.10	-	-	0.83898	0.83424	133.13	54225.74	0.14081
Logarithmic	43.39	0.000	-172849.10	118591.06	-	-	0.56067	0.54775	234.89	89569.57	0.24136
Inverse	7.89	0.008	180798.20	-330526.64	-	-	0.18836	0.16449	284.90	121744.23	0.34741
Quadratic	139.23	0.000	-883.08	-254.78	328.92	-	0.89405	0.88763	36.12	43986.62	0.11344
Cubic	106.31	0.000	50456.44	-15847.45	1368.18	-	0.90881	0.90027	52.50	40806.40	0.10505
Compound	75.96	0.000	8027.87	1.1278	-	-	0.69079	0.68170	20.26	75143.21	0.18054
Power	94.68	0.000	1785.63	1.40231	-	-	0.73578	0.72801	40.87	69462.28	0.20467
S-Curve	109.17	0.000	-130289.48	167570.04	13693.43	-	0.86870	0.86075	104.29	48965.55	0.12668
Growth	75.96	0.000	exp(8.9907)	0.12029	-	-	0.69079	0.68170	20.26	75143.21	0.18054
Exponential	96.51	0.000	24306.14	0.08036	-	-	0.85399	0.84515	75.50	51635.79	0.13383
Logistic	118.49	0.000	396004.81	180.5542	0.21685	-	0.91741	0.90967	26.69	38834.56	0.09987
Gompertz	112.34	0.000	461206.05	13.6867	0.11700	-	0.91328	0.90515	41.05	39793.71	0.10239

The results presented in Table 2 demonstrate that the logistic model achieved the highest performance among all evaluated specifications. It recorded the highest Adjusted R² (0.9097) and the lowest values for RMSE (38,834.56), MAPE (26.69), and Theil's U (0.0999). While both the cubic and Gompertz models exhibited satisfactory performance, the logistic model consistently surpassed them across all error and information criteria.

The superior performance of the logistic model indicates that India's agricultural exports follow an S-shaped growth trajectory, characterized by initial slow growth, followed by acceleration, and ultimately stabilization as they approach a carrying capacity. This pattern aligns with the theoretical expectations for mature export sectors nearing market saturation.

3.2 Model Performance for Total National Exports

B. Trends in Total National Exports

The Total National Export data was analyzed using the same set

of growth models, and the results are presented in Table 3.

The Logistic model again outperformed all other models with the highest Adj.R² (0.9173), lowest MAPE (14.68), lowest RMSE (3,25,148.8) and lowest Theil's U (0.1012). These values indicate that the logistic form provides the most accurate representation of the long-term movement in national export earnings.

Accordingly, the following logistic model was selected

$$Y_t = \frac{396004.81}{1 + 180.5542e^{-0.2168t}} \quad \dots(14)$$

Fig. 2 shows that total exports follow a smooth, accelerating trend followed by a period of stabilization, consistent with the characteristics of a logistic curve.

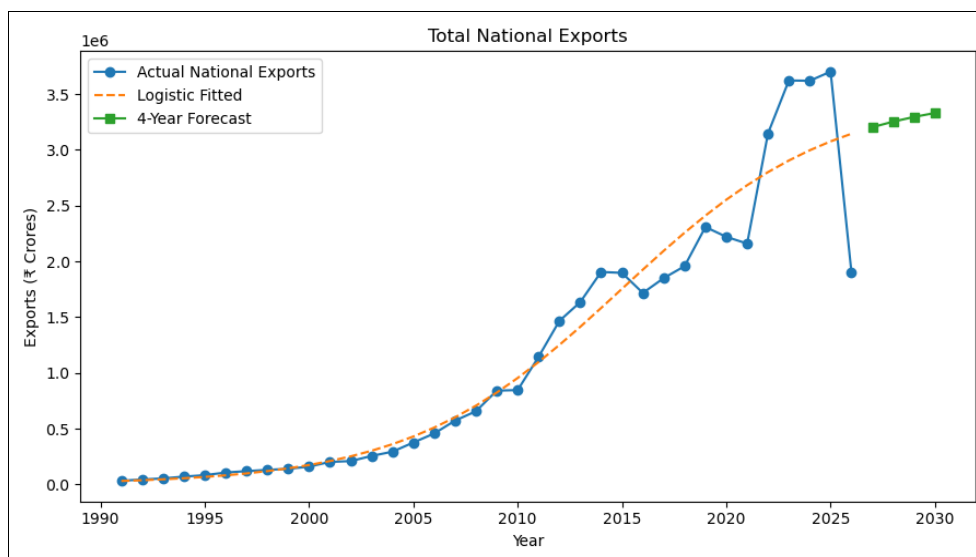


Fig 2: Observed and Modelled Growth in Total National Exports: Logistic Fit with 4-Year Forecast

A comparable modeling exercise was performed for total national exports to allow for a comparison with agricultural export behavior. The findings are shown in Table 3.

Table 3: Performance of Growth Models for Total National Exports

Equation	Model		Parameters				R ²	Adj.R ²	MAPE	RMSE	Theil's U
	F	Sig.	Constant	b1	b2	b3					
Linear	186.83	0.000	-688672.37	100113.78	-	-	0.846	0.84151	179.32	443,665.80	0.13939
Logarithmic	44.06	0.000	-1483771.44	995608.52	-	-	0.564	0.55164	326.11	746,212.90	0.24363
Inverse	7.88	0.008	1484014.50	-2764591.38	-	-	0.188	0.16435	392.19	1,018,737.00	0.35312
Quadratic	154.80	0.000	-28851.22	-4068.51	2815.74	-	0.903	0.89784	39.28	350,917.80	0.10945
Cubic	112.47	0.000	50456.44	-15847.45	1368.18	-99.00	0.913	0.90525	51.72	332,788.40	0.10367
Compound	44.88	0.000	46185.06	1.1433	-	-	0.568	0.55627	23.26	742,348.80	0.20654
Power	112.44	0.000	8248.41	1.57980	-	-	0.767	0.76100	40.09	544,815.50	0.19329
S-Curve	117.52	0.000	-130289.48	167570.04	13693.43	-	0.876	0.86943	136.64	396,730.20	0.12415
Growth	44.88	0.000	exp(a)	0.08	-	-	0.568	0.55627	23.26	742,348.80	0.20654
Exponential	105.68	0.000	185596.16	0.08300	-	-	0.864	0.85676	101.42	415,521.20	0.13023
Logistic	118.32	0.000	396004.81	180.5542	0.21685	-	0.917	0.90955	14.68	325,148.80	0.10124
Gompertz	116.26	0.000	461206.05	13.68670	0.11700	-	0.915	0.90808	32.95	327,782.90	0.10207

The logistic model once again proved to be the best-fitting specification for total national exports, exhibiting the lowest RMSE (325,148.80), the lowest MAPE (14.68), and the highest Adjusted R² (0.9096). These results suggest that national exports also adhere to an S-shaped nonlinear trajectory, aligning with the findings observed in agricultural exports.

3.3 Trend Behaviour Analysis

The fitted curves indicated that agricultural exports have experienced distinct phases of growth throughout the study period. The initial phase showcased moderate expansion, which was subsequently followed by a period of accelerated growth and eventual stabilization, resulting in a logistic-shaped trajectory akin to other agricultural and economic time series. In contrast, total national exports displayed a more pronounced upward trend with greater intensity, yet still reflected a broadly similar growth pattern.

The S-shaped trajectory captured by the logistic model indicates that agricultural exports has three distinct phases

- 1. Initial Phase:** Slow growth during early years due to limited market access and infrastructure constraints.
- 2. Acceleration Phase:** Rapid expansion following trade liberalisation and policy reforms.

- 3. Maturation Phase:** Gradual deceleration as the sector approaches its current carrying capacity.

3.4 Growth Rate Analysis

C. Forecasting of Agricultural and National Exports

Based on the linear model, agricultural exports recorded a linear growth rate of 8.36 per cent, while the compound annual growth rate (CAGR) derived from the compound model was 10.89 per cent. These rates are consistent with the strong upward movement observed in the fitted curves.

The logistic trajectory suggests that agricultural exports may be approaching a steady growth phase, indicating the need for policy interventions to stimulate further acceleration through diversification, value addition, and market expansion.

3.5 Four-Year Forecasting of Exports

Using the best-fitted Logistic models, a four-year ahead projection for both agricultural exports and total national exports was generated for the period 2027 to 2030. The projected values are shown in Table 4 and Table 5. The forecasts indicate a continued increase in export earnings for both categories, though at a diminishing rate, reflecting the bounded nature of logistic growth.

Table 4: Forecast of Agricultural Exports (2027-2030)

Year	Forecasted Exports (₹ Crores)
2027	3,73,881.92
2028	3,77,998.61
2029	3,81,379.21
2030	3,84,145.03

Table 5: Forecast of Total National Exports (2027-2030)

Year	Forecasted Exports (₹ Crores)
2027	32,02,749
2028	32,52,611
2029	32,94,731
2030	33,30,141

D. Growth Rates in Agricultural and National Exports

The Linear Growth Rate (LGR) and Compound Annual Growth Rate (CAGR) were calculated.

Table 6: Growth Rate Estimates for Export Variables

Export Variable	LGR (%)	CAGR (%)
Agricultural Exports	8.363	10.890
Total National Exports	8.589	10.754

The forecasts indicate that agricultural exports will exhibit stable but moderate growth, increasing from ₹3,73,882 crores in 2027 to ₹3,84,145 crores in 2030, representing an average annual increment of approximately ₹3,421 crores. Total national exports demonstrate stronger momentum, projected to increase from ₹32,02,749 crores in 2027 to ₹33,30,141 crores in 2030.

The linear and compound growth rates of agricultural exports and total national exports were computed and are presented in Table 6. Agricultural exports recorded a linear growth rate of 8.363 percent and compound annual growth rate of 10.890 percent, while total national exports exhibited corresponding growth rates of 8.589 percent and 10.754 percent, respectively.

The relatively slower growth trajectory of agricultural exports compared to total national exports underscores the need for targeted policy measures to enhance the competitiveness of India's agricultural export sector.

4. Conclusion

The present study analysed long-term agricultural export trends using twelve alternative growth models and identified the logistic function as the best descriptor of export behaviour. The logistic form captures the nonlinear and saturating nature of export growth more effectively than linear or polynomial functions, as evidenced by superior performance across all evaluation criteria.

The key findings of the study are summarised as follows

1. Among the twelve growth models evaluated, the logistic model provided the best fit for both agricultural exports (Adjusted $R^2 = 0.9097$) and total national exports (Adjusted $R^2 = 0.9096$).
2. Agricultural exports exhibited an S-shaped growth trajectory characterised by initial slow growth, subsequent acceleration, and eventual stabilisation.
3. The linear growth rate of agricultural exports was estimated at 8.36 per cent, while the compound annual growth rate was 10.89 per cent.
4. Forecasts for 2027-2030 indicate continued but moderate increases in agricultural exports, while total national exports demonstrate stronger growth momentum.

The findings carry significant policy implications. The approaching saturation phase in agricultural exports necessitates strategic interventions including: - Diversification of the export basket toward high-value products - Enhancement of processing and value-addition infrastructure - Strengthening of quality certification and compliance mechanisms - Exploration of new markets and trade agreements

The study acknowledges certain limitations including the deterministic nature of the models employed and the assumption of stable policy and market conditions over the forecast horizon. Future research may incorporate stochastic models and structural break tests to enhance predictive accuracy.

In conclusion, nonlinear growth models, particularly the logistic form, prove to be effective analytical tools for trend analysis and export forecasting, offering critical inputs for policymakers, exporters, and development planners.

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Competing Interests

Authors have declared that no competing interests exist.

Authors' contributions

A.Meena designed the study, Roshini Priya C H performed the statistical analysis, S. Madhusudhan Reddy, P. Ramesh, Uttej Dubany and Mullapudi Ram Prasad managed the literature searches.

All authors read and approved the final manuscript.

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