Research Article

Evaluating Dynamic Trends in Oilseed Production in India through Innovative Trend Analysis and Principal Component Analysis

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Abstract | Oilseed crops play a significant role in the Indian agriculture sector, being directly or indirectly related to human diets, country economies, and various industrial applications. This paper was designed with two prominent objectives, employing two different analytical approaches: innovative trend analysis (ITA) and principal component analysis (PCA) on oilseed production data from 1981 to 2022. Initially, ITA was applied to analyse zone-wise variations, visualize hidden trends, and assess the magnitude of the rate of change in long-term production patterns. Later, PCA was performed to identify different production patterns and highlight the key states influencing the production trends. The ITA graphs revealed various types of production patterns (monotonic, non-monotonic, and trendless) among the zones. In addition, the ITA highlighted that Rajasthan (178.2) and Madhya Pradesh (174.4) recorded the highest average growth rates (thousand tons/year), while Andhra Pradesh & Telangana (-18.5), Tamil Nadu (-17.95), and Odisha (-17.05) recorded the sharpest declines. PCA analysis captured five distinct production patterns with 80% of total variation. PC1 (explaining 45% variance) showed strong positive loadings (0.75–0.94) for major states like Maharashtra, Rajasthan, and Madhya Pradesh, while Kerala had a strong negative loading (-0.808), indicating a production decline. Both ITA and PCA analyses offer important information to help understand the differences in oilseed production across regions and over time, which can guide policy choices for sustainable farming and zonal prioritization.

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Introduction

One of the key pillars of India's economy is the agricultural sector, which facilitates different activities such as the manufacturing, distribution, and consumption of goods. Approximately 21% of India's total gross value added is contributed by the agriculture sector, and nearly 50% of the population relies on agricultural activities for their livelihood (Saruk and Rayalu, 2024). This clearly demonstrates that agriculture plays a major role in maintaining the stability of a nation's economy (Kalpana, 2017b; Manoj, 2023). A wide variety of crops are cultivated in India, among which oilseed crops are considered particularly important. Approximately 20.8% of agricultural land is dedicated to oilseed cultivation, contributing nearly 10% to total crop production, making India the fourth-largest producer of oilseeds globally.

Oilseeds are generally categorized as either edible or non-edible according to their industrial and human consumption uses. Edible oilseeds are consumable, and these oils are energy-dense foods rich in oil content, vitamins, and minerals, providing moderate levels of fiber and both saturated and unsaturated fatty acids. These oils are not only important for human consumption but also have a significant role in industrial value. Non-edible oilseeds are used for industrial purposes, for example, the production of products such as paints, soaps, pharmaceuticals, hair oils, textiles, and varnishes (Sittal *et al*., 2019). Simply put, the oilseeds sector plays a crucial role in agriculture as well as national economies globally due to the extensive benefits it offers for human diet and industrial applications. Traditionally cultivated oilseed crops in India include sesame, groundnut, niger, soybean, castor, rapeseed-mustard, safflower, and sunflower (Raghunadha *et al*., 2022).

Several factors, including the steady rise in human consumption, growing domestic demand, and expanding industrial use of vegetable oils, have significantly contributed to the increased demand for oilseed production. To tackle this situation, the Indian government implemented several missions and projects between 1985 and 2014 with the aim of rising oilseed production. Under these programs, nine major oilseed crops were cultivated to support the growth of the oilseed sector and to overcome the gap between demand and supply (Jainuddin *et al*., 2021). In response to the issue of growing demand for oilseed production, various statistical methods (path analysis, annual compound growth rate, decomposition analysis, Cuddy-Della Valle instability index, etc.) were applied. These methods play a role in understanding the trend patterns of oilseed production.

For instance, Raghunadha *et al*. (2022) analyse d various types of oilseed crops such as sunflower, groundnut, castor, niger, sesame, and palm oil in Andhra Pradesh, while Jainuddin *et al*. (2021) extended this analysis to oilseeds across India. Viswanatha and Immanuelraj (2017) assessed the spatiotemporal growth rates of edible oilseeds in India's leading producing states, focusing on area, production, and yield using compound growth rates. Regression models have also been constructed to estimate growth rates for groundnut crops (Kalpana, 2016) and castor oil production (Kalpana, 2017a) in India.

Trend analysis is essential for handling long-term data, which helps to understand the effects of past interventions, patterns, and movements and forecast likely future trends. Most of the researchers are widely applied in many diverse fields, including agriculture, finance, climate studies, healthcare, and more. Trend analysis can be performed either parametric methods (e.g., linear regression, polynomial regression, ARIMA, and exponential smoothing) or non-parametric methods (e.g., Cox-Stuart, Mann-Kendall (MK) test, ITA, Spearman's rho test, and Sen's slope estimator). Non-parametric methods are particularly well-suited to handle any kind of data. Therefore, it is not necessary to make rigorous parametric rules when handling data that has outliers, skewed distributions, and non-linear connections (Khalili *et al*., 2016; Zichen *et al*., 2020). Non-parametric methods, particularly the MK test, ITA and Sen's slope estimator, are widely applied by several researchers to study the trends in rainfall, temperature, and other agricultural variables. For example, Praveen *et al*. (2020), Nur *et al*. (2023), Krushna *et al*. (2024), Muthaiah *et al*. (2024), and Kalpana *et al*. (2020) evaluated trend patterns in rainfall, while Alemu and Dioha (2020), Sarita *et al*. (2020), Monforte and Ragusa (2022), Al-Mutairi *et al*. (2023) and Ghaderpour *et al*. (2024) analysed temperature trends. These methods are expanded in agriculture to study the trend patterns of crop production such as castor (Kalpana *et al*., 2019), wheat (Kalpana and Kiran, 2020), rice (Kalpana *et al*., 2021), food grains (Kalpana *et al*., 2023), and sugarcane (Kalpana and Siva, 2025) have also used trend analysis techniques have also been used. Furthermore, Hemalatha *et al*. (2022) analyzed the hydropower generation trends of SAARC countries, including Bangladesh, Pakistan, India, and Sri Lanka.

ITA is an add-on advanced methodology of the Mann-Kendall test and is increasingly used to study complex structured trends of time series datasets. This method is widely recommended to identify hidden trends in visual form (Yavuz 2018; Caloiero, 2020; Kalpana and Chesneau, 2024). For example, Ishfaq *et al*. (2022) utilized the ITA method to study the variations in climate across high, medium, and low levels of rainfall and air temperature values over recent decades in the Jhelum basin of the Kashmir Valley. Kalpana and Chesneau (2024) used ITA to analyse CO_2 emissions trends across various sectors, such as coal, oil, gas, and cement, in India and China. Sapliogl u *et al*. (2014) investigated streamflow trends in the western Mediterranean basin of Turkey, while Sonali *et al*. (2013) analyse d temperature trends across India using the MK and ITA methods. Kisi (2015) demonstrated that ITA graphical plots are more effective at detecting hidden trends in pan evaporation than the MK and SR tests.

Ay and Kisi (2015) used the ITA method to conduct trend analysis in order to identify rainfall trends in six different regions of Turkey. According to the findings, Samsun and Trabzon showed considerable rising growth, while the other four regions showed no discernible trends. Dabanli *et al*. (2016) highlighted the differences between the MK test and ITA method in their application to hydro-meteorological data from the Ergene basin in Turkey. Air temperature and heatwave trend patterns of northwestern Mexico were assessed using linear data correction, ITA method, and Spearman's rho test. The analysis highlighted that temperature and heat heatwaves indicated rising trends (Martinez-Austria *et al*., 2016). Elouissi *et al*. (2016) investigated monthly rainfall trends across twenty-five locations in the MACTA watershed, Algeria, using the ITA method. The results revealed that northern region followed decreasing trends, and the southern region indicated increasing trends during the period 1970–2011. In the Coruh River basin of Turkey, trends in maximum hydrologic drought variables for nine stations were analyse d. While the MK test showed no significant trends, both the modified MK test and the ITA method detected positive and negative trends at different stations, with the results aligning well with each other (Tosunoglu and Kisi, 2017).

Nayana *et al*. (2022) applied multivariate adaptive regression splines to forecast wheat yield through principal component analysis, which helps to identify the top wheat-producing states based on key factors such as cultivation area, yield, and production from 1962 to 2018. This approach helped improve prediction accuracy by focusing on the most influential features. Neetu *et al*. (2024) forecasted yield using PCA and OLS regression on cotton crop data from 1964 to 2015. PCA enhanced the accuracy of forecasting by reducing dimensionality while retaining key information.

Hence, previous researchers have performed basic statistical methods to analyse the trends of oilseed production. Globally, no one focuses on visualizing trends or identifying key states influencing oilseed production. To address these gaps, this study applies an advanced trend analysis method (i.e., ITA) to examine temporal changes in oilseed production trends. In continuation, a multivariate statistical method (i.e., PCA) is performed to capture distinct production patterns and major influencing states at the zone/state level in India. So, the novelty of this research lies in the combined use of ITA and PCA to provide a more comprehensive understanding of oilseed production dynamics.

Materials and Methods

Data

Data on the annual total production of oilseeds (both edible and non-edible) has been collected from the Reserve Bank of India, covering 24 Indian states over a 42-year period (1981–2022). This extensive time series is considered adequate for examining patterns and tracking variations in oilseed production. Annual trend analysis is conducted to explore regional differences in output.

Innovative trend analysis

The ITA method, which was first introduced by Sen (2012). Unlike traditional methods, ITA does not rely on statistical assumptions such as serial correlation, normality of distribution, and data length. This nonparametric approach is specifically designed to visually inspect and identify both monotonic trends (increasing or decreasing) and non-monotonic trends within time series datasets. Sen (2017) enhanced the ITA method by introducing a calculation framework for deriving monotonic trends and conducting significance tests. Simply put, ITA not only graphically visualizes the trend but also estimates slope of trend, similar to the Theil-Sen estimator.

However, Theil-Sen remains a widely accepted method for quantifying trend magnitude, particularly for linear trends, whereas ITA is more effective in detecting nonlinear trend patterns (Junli *et al*. 2018; Zhou *et al*., 2018; Malik *et al*., 2019; Ali *et al*., 2019; Kuriqi *et al*., 2020; Pour *et al*., 2020; Jayanta *et al*., 2020; Liaqat *et* *al.*, 2022). This makes it an effective tool for analysing the strength and direction of trends, especially in complex datasets like agricultural production data. The detailed procedure for constructing the ITA plot is discussed below.

Step 1: The time-series data (1981–2022) is divided into two equal periods such as 1981-2001 and 2002-2022.
Step 2: The data in each half is arranged separately in ascending order.
Step 3: Consider, the first half (y_1) of the data is plotted on the X-axis, and the second half (y_2)is plotted on the Y-axis of a Cartesian coordinate system. A 45-degree line (also called the 1:1 line) is draw on the scatter plot.
Step 4: Control Limits (CL): The CLs for the plot are defined as $y_1 \pm 0.05(\bar{y}_1)$ at 95% confidence.
Step 5: The scatter plot is analysed by the following ways:

If the data points lie on the 1:1 line, it indicates that there is no trend in the data.
If the data points are positioned above the 1:1 line, it suggests a monotonic increasing trend.
If the data points fall below the 1:1 line, it indicates a monotonic decreasing trend.
If the data points are scattered above and below the 1:1 line, it indicates a non-monotonic trend.

Step 6: Significance of trend is verified by the following rules:

If the data points (few or all) fall outside the control limits, it implies that the data exhibits a significant trend (either monotonic or non-monotonic).
If all points are within these limits, it suggests that there is no trend over period.
Sen (2017) the magnitude of the trend slope (*S*) form is defined as

$$S = \frac{2(\bar{y}_2 - \bar{y}_1)}{n}$$

Where *n* is the number of data points in each period, $y_1$and y_2 represent the averages of the first and second halves of the series, respectively. The value of *S* represents the trend indicator and positive value of *S* indicates an increasing trend, while a negative value indicates a decreasing trend. The confidence limits of the trend slope follow a standard normal probability density function with zero mean and standard deviation (σ_s) are given as follows:

$$CL_{(1-a)} = 0 \pm S_{cri} X \sigma_s$$

Where

$$\sigma s = \frac{2\sqrt{2}}{n\sqrt{n}} \sigma \sqrt{1 - \rho \bar{y}_2 \bar{y}_1}$$

$\rho\ \bar{y}_2\ \bar{y}_1$ = The correlation between the two average values in stochastic nature

Principal component analysis

Principal component analysis (PCA) is a statistical technique used to reduce the dimensionality of datasets with interrelated quantitative variables while retaining the maximum possible variance. It transforms correlated variables into a smaller set of uncorrelated principal components, ranked by the variance they explain. This method helps reveal underlying patterns, making complex datasets easier to interpret. PCA is widely applied in pattern recognition, where it identifies key variables that represent most of the dataset's variability (Jackson *et al.*, 1991; Helena *et al.*, 2000; Chowdhury and Husain, 2020; Gaurav *et al.*, 2021; Ahmed, 2023). By simplifying high-dimensional data, it enhances analysis efficiency and supports data-driven decision-making across various fields. PCA provides valuable insights with minimal information loss by arranging principal components (PC) in descending order of variance, with PC1 capturing the highest share than the remaining PC's. Here, factor loadings classify variables as strong (≥0.75), moderate (0.75–0.50), or weak (0.50–0.30), reflecting their relative contribution within a component rather than their overall importance (Liu *et al.*, 2003; Vieira *et al.*, 2012). Principal components are interpreted based on loading scores. In the context of production, suppose states with high positive loading scores indicate key contributors to production trends; states with high negative loading scores suggest the decline trend of production, and states with loading scores near zero are considered to have minimal influence on the components. PCA is a commonly used method for selecting independent variables and discarding highly correlated or redundant variables. The PCA involves five main steps as follows:

The original data matrix is listed as given by:

$$X = [x_{ab}]_{mxn} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}$$

Where x_{ab} = production of oilseeds in the a^{th} state during the b^{th} year; a = 1, 2, ..., m and the originally measured data are standardized to mitigate the impact of dimension with Z score standardization:

$$Z_{ab} = \frac{(x_{ab} - x_b)}{s_b}$$

Where Z_{ab} represents the standardized variable, x_b and s_b are the mean and standard deviation production across all states for year b Correlation coefficient matrix is determined based on the following equation

$$R = mxn = [r_{ab}]_{nmx} = \frac{1}{n-1}\sum_{t=1}^{n} x_{ta} * \times x_{tb} *$$

The eigenvalues and eigenvectors are then calculated as follows

$$Fi = v_{i1}x_1^* + v_{i2}x_2^* + \ldots + v_{in}x_n^*$$

Where v_i is eigen vectors and is the standardized parameter.

Results

The fundamental descriptive statistics are computed for zone-wise oilseed production from 1981 to 2022 in India and presented in Table 1. The results revealed that substantial zonal variations. It means the states with the lowest production are Kerala (0.2 thousand tons), Manipur (0.4 thousand tons), and Mizoram (0.6 thousand tons). On the other hand, Gujarat and Rajasthan stood out as the top producers, with output levels of 7132.1 thousand tons and 9295.8 thousand tons, respectively. When considering average production, Kerala recorded the smallest average output at 5.969 thousand tons, whereas Madhya Pradesh achievedthe highest average production with 5047.1905 thousand tons of oilseed. According to Yitea *et al*.,(2021), the variability of oilseed production is classified using the coefficient of variation (CV).

The states of Bihar, Assam, and Uttar Pradesh belong to the low variability (CV < 20%) category. Karnataka,

Table 1: *Descriptive statistics of zone-wise annual oilseed production from 1981 to 2022*

Zones	States	Min.	Max.	Average	Standard Deviation	Coefficient of Variation
Northern	Jammu & Kashmir	2.7	124.2	46.3582	17.8638	38.5343
	Haryana	117.2	1431	756.8262	335.0254	44.2672
	Himachal pradesh	3.1	12	6.9905	1.9962	28.5559
	Punjab	56.8	306.1	128.7452	73.1076	56.7847
	Uttar Pradesh	787.2	1713	1133.5929	208.5732	18.3993
	Rajasthan	625.6	9295.8	4031.2476	2328.5171	57.7617
Northeastern	Arunachal pradesh	6.6	37.8	24.9357	8.671	34.7735
	Assam	112	215.2	163.75	25.7661	15.735
	Manipur	0.4	32.8	9.842	13.2775	134.9066
	Meghalaya	3.4	15.3	7.8958	3.8616	48.9064
	Mizoram	0.6	12.3	4.0663	2.7552	67.7564
	Nagaland	1.6	84.6	41.8086	28.2564	67.5851
	Tripura	2.4	14.4	6.767	3.7751	55.7871
	Sikkim	4.3	15.1	7.8104	2.3946	30.6589
	Madhya pradesh	833.3	9276	5047.1905	2432.4595	48.1943
Eastern	Bihar	104.9	173.9	133.5762	14.1445	10.5891
	Odisha	91.1	940.9	326.831	285.2835	87.2878
	West Bengal	170	1277.5	609.8881	301.3257	49.4067
Western	Gujarat	398.2	7132.1	3574.031	1750.7029	48.984
	Maharashtra	839.8	6937.8	3017.2357	1660.4236	55.0313
Southern	APT	1093.6	3390	1840.7774	563.9854	30.6384
	Karnataka	749.7	1888.7	1257.1262	323.2149	25.7106
	Kerala	0.2	18.6	5.969	5.4588	91.4515
	Tamil nadu	461.8	1968.3	1171.6952	322.3443	27.5109

Himachal Pradesh, and Tamil Nadu are classified as having medium variability (20% < CV < 30%), and the remaining states fall into the high variability category (CV > 30%).

Next, the ITA method was applied using R, and the results are visually presented in Figures 1 and Figure 2, while the estimated slopes are summarized in Table 2. Based on Figure 1, eleven states—Arunachal Pradesh, Assam, Gujarat, Maharashtra, Meghalaya, Manipur, Haryana, Madhya Pradesh, Nagaland, Rajasthan, and West Bengal—exhibit monotonic increasing trends.

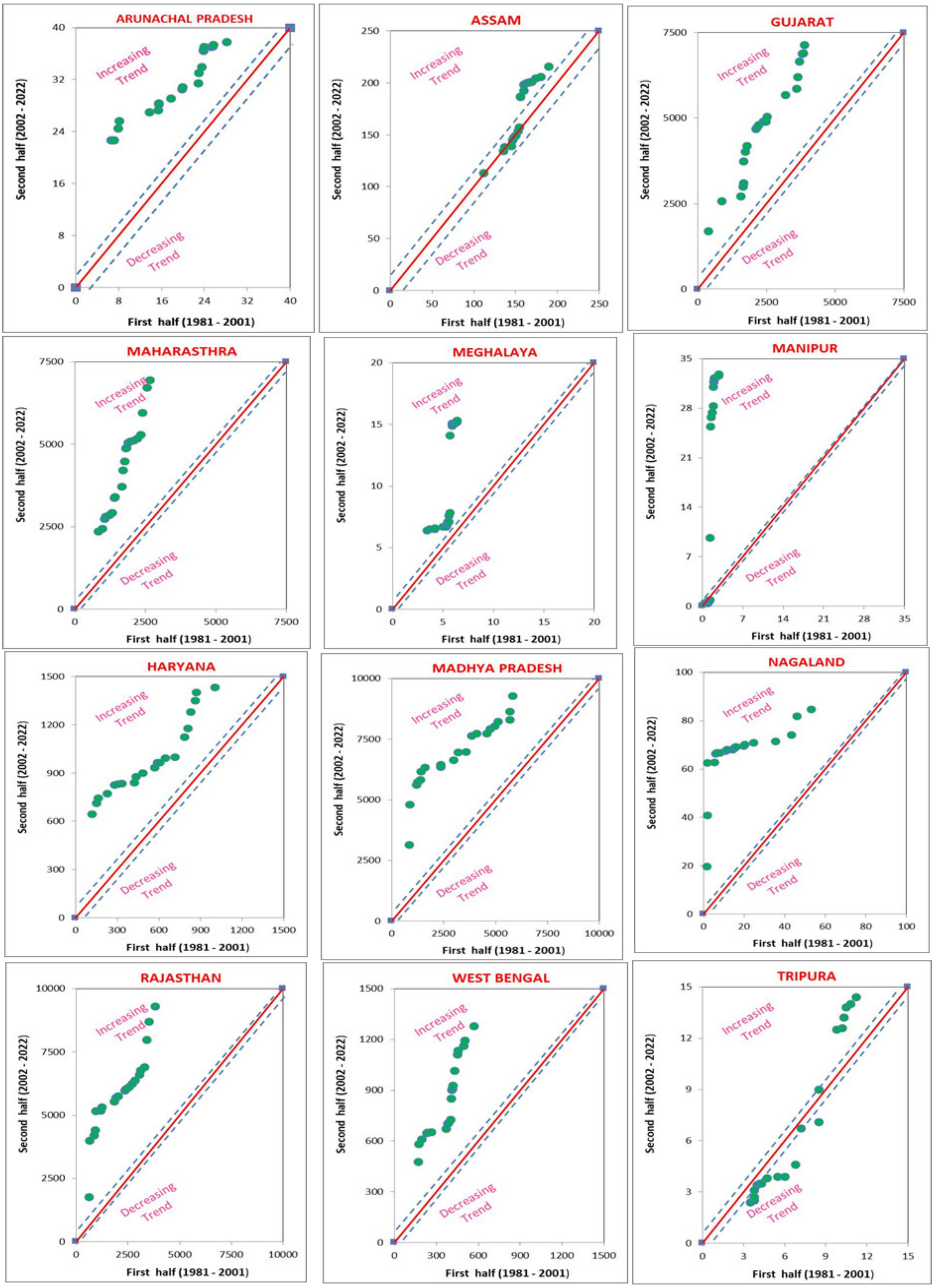

Figure 1: *Monotonic and non-monotonic increasing trends - ITA method*

increasing trends. The scatter plots reveal that the data points for these states are far away above the +5% line and 1:1 line. These observations indicate a consistently increasing monotonic trend with a high tendency. However, Assam displays a lower tendency for monotonic increase, as its data points are near to the above +5% range and the 1:1 line. This suggests a less pronounced but still positive monotonic trend in Assam. In continuity, 1 state (Tripura) only follows a non-monotonic increasing trend.

Furthermore, from Figure 2 results, a monotonic decreasing trend is observed across 7 states: Kerala, Karnataka, Odisha, Punjab, Uttar Pradesh, Andhra Pradesh & Telangana (APT), and Tamil Nadu. Of these, Karnataka and Uttar Pradesh displayed only a slight declining tendency because the data points are plotted marginally below the -5% threshold and the 1:1 reference line. In contrast, Kerala, Odisha, Punjab, APT, and Tamil Nadu exhibited a pronounced declining tendency, evidenced by a greater scatter of data points below the -5% threshold from the 1:1 reference line. Three states (Mizoram, Sikkim, and Himachal Pradesh) demonstrated non-monotonic decreasing trends, and two states (Jammu & Kashmir and Bihar) showed no significant trend at the 95% confidence level.

Table 2 presents the average growth and decline rates of production trends across all zones of India. The findings indicate that 3 out of 24 (12.5%) states, such as Jammu & Kashmir, Himachal Pradesh, and Tamil Nadu, do not exhibit any significant trends at the 5% level of significance. The majority of the states, 21 (87.5%), exhibit statistically significant trends. Of these, 11 (52.38%) states follow a rising trend, while the remaining 10 (47.62%) states show a decreasing trend in oilseed production.

Table 2: *Zone-wise trend slopes estimated using the ITA method*

Zones	States	Slope (ITA)	Control limit (95%)		Nature of trend	Sig.
			Lower	Upper		
Northern	Jammu & Kashmir	-0.0706	-0.1534	0.1534	↓	NO
	Haryana	21.2673	-1.4921	1.4921	↑	YES
	Himachal pradesh	0.0009	-0.0136	0.0136	↑	NO
	Punjab	-5.2347	-0.2234	0.2234	↓	YES
	Uttar Pradesh	-8.505	-0.6589	0.6589	↓	YES
	Rajasthan	178.1995	-14.379	14.379	↑	YES
Northeastern	Arunachal pradesh	0.5921	-0.0339	0.0339	↑	YES
	Assam	0.7902	-0.1589	0.1589	↑	YES
	Manipur	0.7827	-0.1064	0.1064	↑	YES
	Meghalaya	0.2359	-0.0402	0.0402	↑	YES
	Mizoram	-0.0771	-0.0191	0.0191	↓	YES
	Nagaland	2.3069	-0.3394	0.3394	↑	YES
	Tripura	0.0046	-0.0129	0.0129	↑	NO
	Sikkim	-0.0788	-0.0163	0.0163	↓	YES
	Madhya pradesh	174.429	-13.3264	13.3264	↑	YES
Eastern	Bihar	-0.2449	-0.0783	0.0783	↓	YES
	Odisha	-17.0524	-1.3599	1.3599	↓	YES
	West bengal	22.7367	-1.9455	1.9455	↑	YES
Western	Gujarat	109.7145	-5.8596	5.8596	↑	YES
	Maharashtra	122.6025	-4.7921	4.7921	↑	YES
Southern	APT	-18.5037	-4.1965	4.1965	↓	YES
	Karnataka	-12.3254	-1.5779	1.5779	↓	YES
	Kerala	-0.4451	-0.0381	0.0381	↓	YES
	Tamil nadu	-17.9501	-1.3444	1.3444	↓	YES

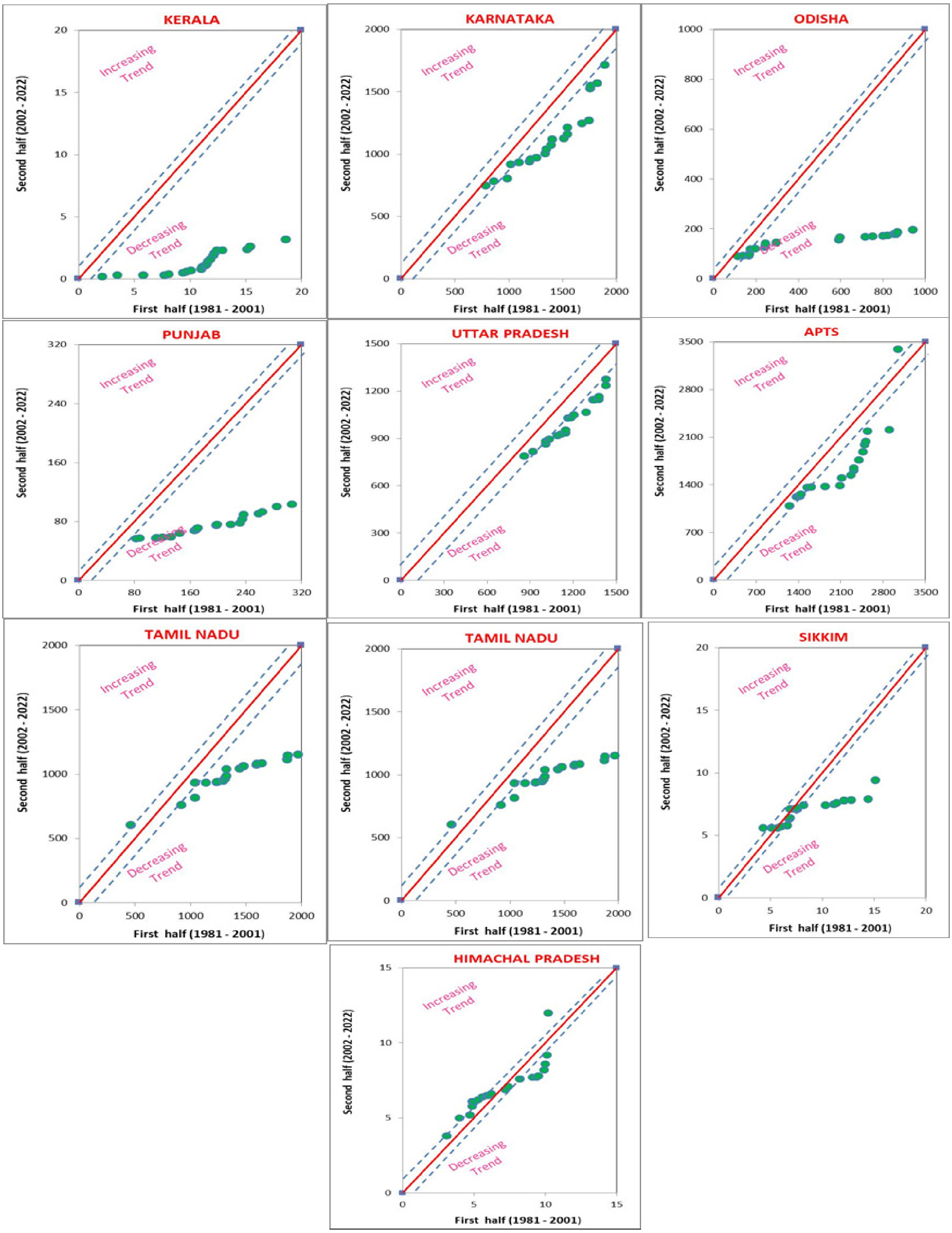

Figure 2: *Monotonic and non-monotonic decreasing trends - ITA method*

In addition to that, the analysis further highlights that Rajasthan (Northern) experiences the most significant increase trend in oilseed production, with the highest positive slope of 178.2 thousand tons/year, followed by Madhya Pradesh (174.4290 thousand tons/year) in northeastern and Maharashtra (122.6025 thousand tons/year) in western. Also, Western (Gujarat=109.7145), northern (Haryana=26.27), and eastern (West Bengal=22.7367) zones emerged as the leading regions in oilseed production, surpassing other zones. Conversely, the largest decline trend in production is observed in APT, with a negative slope of -18.5 thousand tons/year, trailed by Tamil Nadu (-17.9501 thousand tons/year) and Odisha (-17.0524 thousand tons/year). The average rate of change in thousand tons per year varies from -18.5037 for the state of APT to 178.1995 for Rajasthan.

After assessing zonal trends through ITA, PCA was applied to uncover inter-state relationships and dominant production structures. Table 3 provides strong evidence supporting the suitability of applying principal component analysis (PCA) to the oilseed data using SPSS. The calculated value of Kaiser-Meyer-Olkin (KMO) is 0.75, which indicates that the sample size is adequate for factor analysis. As per Kaiser and Rice (1974), if the KMO value is above 0.6, it is considered acceptable, and values above 0.7 suggest good sampling adequacy. Additionally, Bartlett's test of sphericity is significant when $p < 0.05$ (Polit and Beck, 2016), confirming that the correlation matrix is not an identity matrix, meaning that the variables are sufficiently correlated to justify PCA. Therefore, the results validate the appropriateness of applying PCA to the given dataset.

Table 3: *Results of KMO and bartlett's test*

Kaiser-Meyer-Olkin Measure of sampling adequacy.		0.750
Bartlett's test of sphericity	Approx. Chi-Square	1168.264

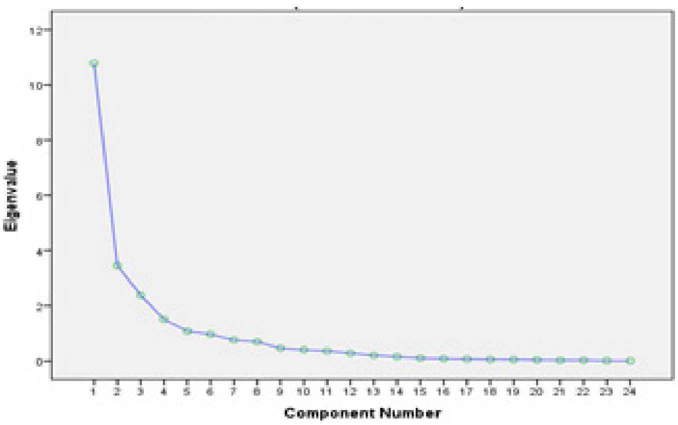

Figure 3: *Scree plot of eigenvalues for oilseed production data*

Figure 3 visually or structurally illustrates the scree plot of eigenvalues, while Table 4 summarizes the eigenvalues and percentage variance of each principal component. These helps to decide how many PCs can be considered for the study. It is observed that the first five components related to eigenvalues only exhibit greater than or equal to one. Also, these five components collectively explain almost 80% of the total variance, demonstrating the suitability of PCA for dimensionality reduction while preserving critical information. So the study is focused on five distinct uncorrelated patterns in oilseed production across states, which are presented in Table 5.

Among these, PC1 emerges as the most dominant, accounting for 45% of the total variation in oilseed production. States are classified based on the magnitude of their factor loadings on PC1. States with high positive loadings in PC1 include Maharashtra (0.946), Rajasthan (0.941), Madhya Pradesh (0.897), West Bengal (0.872), Haryana (0.849), Gujarat (0.805), Arunachal Pradesh (0.785), and Nagaland (0.769), indicating that these states contribute strongly and consistently to national oilseed production.

Table 4: *Component-wise eigenvalues and percentage of variance*

Component	Initial eigenvalues	% of Variance	Cumulative %
1	10.78	44.918	44.918
2	3.459	14.414	59.332
3	2.381	9.922	69.254
4	1.508	6.285	75.538
5	1.086	4.525	80.063
6	0.969	4.037	84.101
7	0.764	3.183	87.283
8	0.698	2.91	90.193
9	0.46	1.916	92.109
10	0.406	1.693	93.801
11	0.364	1.515	95.316
12	0.283	1.18	96.496
13	0.204	0.85	97.346
14	0.155	0.644	97.989
15	0.108	0.449	98.439
16	0.083	0.347	98.786
17	0.071	0.294	99.08
18	0.057	0.236	99.317
19	0.053	0.219	99.536
20	0.041	0.172	99.707
21	0.029	0.121	99.829
22	0.024	0.101	99.93
23	0.01	0.044	99.973
24	0.006	0.027	100

States such as Manipur (0.640) and Meghalaya (0.657) show moderate positive loadings, suggesting a moderate level of influence on overall production. In contrast, Kerala (-0.808) shows a strong negative loading, reflecting a marked decline in oilseed production, while Odisha (-0.720) and Punjab (-0.662) exhibit moderate negative loadings.

Table 5: *Rotated component matrix with factor loadings for selected principal components*

States	Component				
	PC1	PC 2	PC 3	PC 4	PC 5
Maharashtra	0.946				
Rajasthan	0.941				
Madhya pradesh	0.897				
West bengal	0.872				
Haryana	0.849				
Kerala	-0.808				
Gujarat	0.805				
Arunachal pradesh	0.785				
Nagaland	0.769				
Odisha	-0.720			-0.614	
Punjab	-0.662				
Meghalaya	0.657				
Manipur	0.640				
Karnataka		0.855			
APT		0.792			
Bihar		0.722			
Tamil nadu					
Tripura			0.825		
Assam			0.787		
Jammu & Kashmir					
Himachal pradesh				0.840	
Mizoram				0.717	
Sikkim					
Uttar pradesh					0.891

The subsequent components (i.e., PC2, PC3, PC4, and PC5) are captured for additional, distinct production patterns. Here, PC2 explains 14% of the variance, with Karnataka (0.855) and APT (0.792) as major contributors compared to Bihar (0.722), suggesting regional variations. In the case of PC3, it accounts for 10% of the variance, with Tripura (0.825) and Assam (0.787) as key contributors. Next, PC4 (6% variance) is dominated by Himachal Pradesh (0.840) and Mizoram (0.717), while Odisha (-0.614) acted as a declining trend pattern. Lastly, PC5, contributing 5% of the variance, highlights Uttar Pradesh (0.891) as a significant player in oilseed production.

Discussion

ITA results revealed clear zone-wise variations in oilseed production trends across India, with positive trends in some states contrasting sharply with negative trends in others. However, the southern zone states showed declining trends, whereas the western zone states showed rising trends, and the northern, northeastern, and eastern zone states showed mixed trends. Possible reasons include variations in cultivated area, rainfall, irrigation, and technology adoption. This aligns with the quantitative results presented earlier. PCA effectively distinguished high-and low-performing states, and along with ITA, consistently identified Rajasthan, Madhya Pradesh, Maharashtra, West Bengal, Gujarat, and Haryana as the top producers. These findings align with RBI Statistics (2024), confirming the reliability of the analyses. Such spatial differences in oilseed production have important implications for India's agricultural economy, as dependence on a few high-performing states can affect national self-sufficiency and increase vulnerability to climatic or market fluctuations. The persistent decline in oilseed production in Andhra Pradesh, Telangana, Tamil Nadu, and Odisha underscores the urgent need for targeted measures, including improved seed access, better irrigation management, and stronger technical support systems. Over time, the persistence of zonal differences despite national initiatives suggests a renewed focus on technological dissemination and resource-efficient practices. Collectively, these findings emphasize the need to address structural and climatic constraints in lagging states to ensure balanced oilseed production growth across India.

Conclusions

The trend analysis using the ITA method revealed significant regional disparities in oilseed production in India from 1981 to 2022. ITA figures showed that 11 states exhibited a monotonically increasing trend, 1 state showed a non-monotonic increase, 7 states demonstrated a monotonically decreasing trend, 3 states exhibited a non-monotonic decrease, and 2 states showed no significant trend at the 95% confidence level. Andhra Pradesh & Telangana, Tamil Nadu, and Odisha states experienced the sharpest declines, while Rajasthan, followed by Madhya Pradesh and Maharashtra, were key growth leaders. In addition to that, the remaining states showed mixed trends, whereas the southern states faced a consistent decline in production. Next, PCA loadings further indicated that Maharashtra, Rajasthan, Madhya Pradesh, West Bengal, Haryana, Gujarat, Arunachal Pradesh, Nagaland, and Kerala had a strong association with PC1 and were identified as major contributors. These patterns highlight regional disparities in oilseed production, identifying key states driving production growth and others facing declines. Addressing these disparities is vital for achieving equitable and sustainable oilseed production growth across India.

Recommendations

Further studies should integrate climatic and socio-economic variables to strengthen understanding of regional variations. Policy efforts should prioritize region-specific technological dissemination, irrigation improvement, and seed access programs to reduce disparities.

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Data Availability

The data used in this study was obtained from the Reserve Bank of India (RBI) and is available on its official website [https://data.rbi.org.in/BOE/OpenDocument/2409211437/OpenDocument/opendoc/openDocument.jsp?logonSuccessful=true&shareId=3].

Ethics approval

All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors.

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Novelty Statement

This study offers an integrated application of Innovative Trend Analysis (ITA) and Principal Component Analysis (PCA) to systematically examine long-term zonal and state-level oilseed production dynamics in India. The approach reveals latent production patterns and key regional contributors, providing robust insights for targeted policy formulation and sustainable agricultural planning.

Author's Contribution

Girish Kumar S: Study conception and design, data collection, analysis and interpretation of results, draft manuscript preparation.
Kalpana Polisetty: Study conception and design, analysis and interpretation of results, draft manuscript preparation,
All authors reviewed and approved the final version of the manuscript.

Generative AI or AI assisted technology statement
AI tools were used only for language editing and grammar improvement. The authors are fully responsible for the content, results, and conclusions of this manuscript.

Conflict of interest
The authors declare that there is no conflict of interest to disclose.

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