scientific reports

OPEN

# Long-term trends and variability in sugarcane production: a five-district comparative analysis with meteorological context in Maharashtra and Karnataka, India

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**The climate-resilient planning and policy development for major cane-growing regions depends on the understanding of sugarcane production patterns which exist over long time periods and show fluctuations at the district level. The study analyzes sugarcane production data from five Indian districts by comparing the 22 years of crop-year data which includes records from 1999 to 2021 for Ahmednagar, Solapur, and Nashik in Maharashtra and Bellary and Dharwad in Karnataka. Parametric and non-parametric methods (linear regression, Mann–Kendall test, Sen's slope) are applied to quantify trends; period-wise summaries, structural-break detection (Pettitt test), and coefficient-of-variation and extreme-year statistics are reported for all five districts. Ahmednagar and Nashik show significant positive yield trends; Solapur has the largest scale and lowest yield variability; Bellary has the highest mean yield (89.46 t/ha). Period-wise analysis identifies three regimes (1999–2006, 2007–2013, 2014–2020) with rising mean yields in most districts. Yield is relatively more stable than area and production (lowest CV in yield). For Ahmednagar, combining meteorological data to identify very good crop years shows that the drought index, moisture sufficiency, heat stress days, and yield are closely related. Extreme high and low yield years can be explained by the variations in these indices. The comparative framework and the district-level evidence enable providing distinct inputs for water-risk management, climate services, and stabilization measures in the water-limited sugarcane systems of the Deccan Plateau.**

**Keywords** Sugarcane, Production trend, Yield, Time series decomposition, Variability analysis

Sugarcane cultivation serves as vital agricultural activity which helps tropical and subtropical regions throughout the world achieve economic progress because it provides the primary source of sugar production and bioenergy generation and agricultural industries use it as their main base for food and feed production[1]. In India, sugarcane serves as a vital commercial crop that covers extensive farming areas while generating high market value because it sustains numerous farming families and enables the operation of a complete agro-industrial system through sugar and ethanol production, which includes sugar as a calorie source and bagasse and molasses as valuable byproducts[2]. The production of sugarcane has experienced significant changes during the past 30 years because of technological advancements, new agricultural policies, and rising climate change impacts (Intergovernmental Panel on Climate Change[3,4].

The sugarcane belts of India contain their most vital regions in Maharashtra and Karnataka. The five districts of Ahmednagar, Solapur and Nashik in western Maharashtra and Bellary and Dharwad in northern Karnataka

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extend across the Deccan Plateau from dry agro-climatic zones to transition agro-climatic zones. Bellary and Solapur fall in drier zones which receive less than 780 millimeters and more than 500 millimeters of annual rainfall. Ahmednagar and Nashik span scarcity and plains zones which receive between 500 and 1200 millimeters of annual rainfall. Dharwad lies in a transition zone which receives between 620 and 1300 millimeters of annual rainfall. All five locations display significant variations in their rainfall patterns which occur both throughout the year and between different years[2]. The various districts show differences in their irrigation systems and soil types and their milling facilities which results in different production conditions and various risk levels that exist both within the districts and between the states.

The district scale requires long-term agricultural production trends and their variability sources because this information helps develop agricultural policies and infrastructure funding decisions and climate-resilient agricultural production methods[5]. The assessment of agricultural production data through time allows researchers to discover hidden patterns and track changes and evaluate long-term production stability. The analyses prove their worth because they enable researchers to understand climate variability effects on agricultural practices which create slow structural changes that short-term environmental changes would hide. The study presents area and production and yield trends that researchers need for their policy work because total production grows through area expansion and yield improvement.

The existing research studies document sugarcane production trends at both national and state levels in India while also presenting specific case studies from individual farms. However, there is a lack of complete district-level studies which track sugarcane production changes over multiple decades while considering weather conditions[1,2]. Only a small number of research studies exist that use extended panel data from several districts to measure climatic variability and study drought conditions and moisture levels and heat stress through their multiple indicators.

The current study investigates this research gap through the analysis of two decades of uninterrupted operational data from five districts which include Ahmednagar as the primary district and Solapur and Nashik and Bellary and Dharwad. The analysis encompasses more than basic trend identification through its assessment of variability and comparison of data across different time periods and detection of structural breaks and integration of meteorological context for years with high-quality weather records. The study developed a comprehensive analytical framework which combines multiple methods to help study production patterns within water-restricted sugarcane agricultural systems that exist in the Deccan Plateau region.

The main goals of this study are to (1) use parametric and non-parametric methods to determine long-term changes in sugarcane area and production and yield during all five districts; (2) discover and define different production phases and their possible structural changes; (3) evaluate production consistency and its variations throughout different districts and historical times; (4) use weather data to explain production patterns which they can study from available data; and (5) investigate how extreme production years relate to weather patterns through their weather index associations. The study examines Ahmednagar with complete meteorological analysis while its results are compared to Solapur and Nashik and Bellary and Dharwad through statistical data and visual representations.

The study offers a new contribution to existing research by presenting a five-district study which analyzes time-based changes through various statistical methods while using specific weather data at the district level. The study outcomes provide essential guidance for agricultural planning and resource management and policymaking in sugarcane production systems which face water shortages throughout the Deccan Plateau region.

## Literature review

Research on sugarcane production trends has been conducted at various scales, from farm-level studies to national and global analyses. The study of agricultural production patterns requires temporal analysis as an essential tool to determine the elements which cause yield differences in farming operations.

Research studies have investigated sugarcane production trends in India which showed national and state-level production patterns as their main focus. Reddy[1] conducted a national-level production trend analysis which showed substantial area and production increases during the past several decades. Kumar and Jain[6] showed that Indian agricultural productivity at the district level experienced both growth and instability while different districts showed varying levels of crop-sector productivity which depended on fertiliser application and rainfall and irrigation and infrastructure development. Murtaza and Masood[7] studied how agricultural productivity differs between Indian districts and how productivity levels between those districts reach equilibrium. The existing district-level studies on sugarcane production fall short of providing complete insights into production patterns and their variations at specific locations. Research has progressed to state and multi-state territories through the work of Indumathi et al.[8] who studied sugarcane production in 19 Indian states from 2014 to 2022 through panel data analysis. The researchers discovered that climate factors, which included annual precipitation and maximum temperature and rainfall, negatively impacted sugarcane production according to their findings. The researchers showed that irrigation and technology and farm management methods together with climate conditions also contribute to sugarcane yield variations. The researchers from Sengupta and Thangavel[9] conducted their research in a district of Uttar Pradesh through statistical methods and GIS mapping to demonstrate that rainfall and temperature and evapotranspiration changes all affect sugarcane production and sugar extraction processes which show the need for district-level climate impact studies. Misra et al.[10] reviewed AI-driven innovations in sugarcane farming and the sugar industry in India, highlighting potential for productivity and sustainability alongside fragmented adoption and research gaps in scalable, climate-resilient systems.

Researchers have conducted comprehensive investigations into how different weather patterns affect farming results. The study conducted by Kelkar et al.[2] revealed that seasonal rainfall patterns in Maharashtra directly affected sugarcane yield outcomes through their impact on rainfall variability. The research conducted by Kumar et al.[11] demonstrated that sugarcane plants require specific temperature ranges to achieve their maximum growth potential in various regions of India. The research by Mall et al.[12] assessed how climate change affects agricultural practices in India. The study by Birthal et al.[13] examined how climate changes affect the production of India's main food crops. The research by Attri and Rathore[14] predicted how climate change will affect wheat production in India. The study conducted by Guhan et al.[4] examined how climate change affects sugarcane water needs and crop production throughout various Tamil Nadu agro-climatic zones, showing that sugarcane yields decrease 3–9% with every 2–4 °C temperature increase and higher water requirements, which affects semi-arid sugarcane farming systems. Dingre and Gorantiwar[15] established water needs and crop coefficients for sugarcane in semiarid India by using field water balance measurement, while[16] offered crop coefficients and water-use rates for sugarcane. Wakchaure[17] showed that reduced tillage, trash retention and fertigation in drip-irrigated sugarcane improved productivity and water-energy-carbon outcomes in water-scarce systems. Behnia et al.[18] evaluated energy use and life-cycle environmental impacts in sugarcane production, finding ratoon cycles more energy efficient than plant cane and recommending reduced tillage and efficient irrigation to improve sustainability. The researchers of Tripathy et al.[19] demonstrated how Indian sugarcane districts can use agrometeorological data with remote-sensing data to estimate regional crop yields through their work on district-level crop yield estimation that used crop evapotranspiration data and vegetation indices, which showed how meteorological data and production information should be matched at the same spatial and temporal levels.

There have been major advances in statistical methods which enable researchers to find patterns in agricultural time series data. The Mann–Kendall test[20,21] developed for environmental data has become a standard method for assessing agricultural production trends. Theoretical basis for non-parametric trend testing was established by Hirsch et al.[20] while Sen[22] developed a regression-coefficient estimator based on Kendall's tau which researchers use with Sen's slope for measuring robust trend magnitude. Researchers have developed new methods which enable them to analyze data for both serial correlation and seasonal patterns. The non-parametric method which Pettitt[23] developed for change-point detection allows researchers to find structural breaks in their investigations. Agricultural studies use period-based analysis together with structural break detection to find changes which occur in production patterns. The statistical methods which Bai and Perron[24] developed for detecting multiple structural breaks in time series have been used to study agricultural production data which shows when policies and technological advancements caused structural changes in the industry.

Agricultural economics research has dedicated substantial resources to studying production variability analysis. Anderson[25] demonstrated that understanding production variability serves as a fundamental requirement for assessing risk and making managerial decisions. Knapp and Heijden[26] applied coefficient of variation and variance instability methods to assess the differences between conventional and organic cropping systems. Researchers have established coefficient of variation as a standardized measurement tool which enables them to assess variability differences among various crops and geographical areas.

Researchers have studied the combination of meteorological data with production analysis in multiple research settings. Thornton et al.[5] showed that weather data must meet specific quality standards together with proper time alignment requirements to enable scientists to conduct effective weather–production relationship studies. Scientists developed multiple aggregation techniques to solve the problem of temporal mismatch between crop years and calendar years.

Recent studies have demonstrated that climate variability now plays a more critical role in determining agricultural output. The research of Intergovernmental Panel on Climate Change[3] showed how climate change affects agricultural systems and what adaptation measures farmers need. The study by Challinor et al.[27] showed that climate change together with adaptation research created effects which decreased crop yields whereas Ray et al.[28] found that climate change drives all geographical differences in agricultural output worldwide. The research of Lobell et al.[29] showed that scientists must conduct specific regional studies to comprehend how climate change affects agricultural production. The researchers conducted a global assessment of climate change effects on food security and agricultural systems according to the findings of Wheeler and Braun[30]and Porter et al.[31]. The studies of Knox et al.[32], and Roudier et al.[33], and Naylor et al.[34], and Olesen and Bindi[35] investigated how climate change affects crop yields in tropical and semi-arid regions. The study of global economic effects and adaptation methods by Mendelsohn and Dinar[36] was supported by the research on extreme weather patterns and adaptation strategies for developing nations which Mirza[37]conducted. The authors of Lipper et al.[38] established climate-smart agriculture as a method to achieve food security while the studies of Venkateswarlu and Shanker[39] and Jat et al.[40] examined adaptation and mitigation methods for agriculture in India and South Asia. In semi-arid Karnataka, Giridhar et al.[41] showed that conjunctive use of rainwater harvesting and groundwater raised farm income and that institutional and social factors influence adoption. The study by Descheemaeker et al.[42] examined how climate change impacts both livestock production and mixed farming operations. The combination of long-run district-level production series with explicitly qualified meteorological context, however, remains scarce for multi-district comparative settings.

Researchers have conducted their studies about weather patterns and different statistical methods at the district level for multiple districts. The study offers complete time-based examination of sugarcane production across five districts which include Ahmednagar and Solapur and Nashik and Bellary and Dharwad. The study utilized trend detection methods and variability assessment methods and period-wise and structural-break evaluation techniques and weather data integration methods to achieve its results.

# Methods
## Study area and data
The study investigates five primary sugarcane cultivation areas in India which include three western Maharashtra districts of Ahmednagar and Solapur and Nashik and two northern Karnataka districts of Bellary and Dharwad which all lie on the Deccan Plateau. The two states contain two sugarcane production districts which exhibit

| District | $N$ (years) | Area mean (min–max) | Production mean (min–max) | Yield mean; CV (%) |
|---|---|---|---|---|
| Ahmednagar | 22 | 87.13 (17.00–134.49) | 7.20 (1.00–12.78) | 78.88; 19.68 |
| Solapur | 22 | 117.41 (36.40–215.00) | 10.01 (2.63–22.61) | 83.56; 15.53 |
| Nashik | 22 | 22.20 (11.22–50.20) | 1.73 (0.67–4.31) | 78.17; 16.99 |
| Bellary | 21 | 4.98 (1.36–10.10) | 0.44 (0.12–0.80) | 89.46; 17.37 |
| Dharwad | 21 | 4.65 (0.87–8.65) | 0.32 (0.06–0.66) | 68.84; 18.44 |

**Table 1**. Summary of sugarcane production series by district (1999–2000 to 2020–2021). Area is reported in thousands of hectares ($10^3$ ha) and production in million tonnes ($10^6$ t) to improve readability.

| District | Station (code) | Any weather years | High-quality years | HQ crop-year starts |
|---|---|---|---|---|
| Ahmednagar | Rahuri (RHI) | 22 | 8 | 2002, 2003, 2004, 2005, 2006, 2007, 2009, 2015 |
| Solapur | Solapur (SLP) | 22 | 19 | 2002–2020 (excluding 1999–2001) |
| Nashik | Niphad (NPD) | 15 | 9 | 1999, 2005, 2007–2013 |
| Bellary | Bellary (BLY) | 12 | 5 | 1999, 2000, 2002, 2007, 2012 |
| Dharwad | Dharwad (DHR) | 8 | 4 | 1999, 2000, 2001, 2002 |

**Table 2**. Meteorological data coverage by district and station (1999–2000 to 2020–2021). "Any weather years" counts crop years with non-missing seasonal rainfall totals; "High-quality years" applies the completeness threshold described in the text.

different agricultural climate conditions and farming practices. The two areas stretch from dry to transition zones which include Bellary and Solapur in dry areas and Dharwad in a transition area with higher rainfall. The study uses Ahmednagar as the central district to perform statistical tests and weather analysis while the other four districts serve as reference points to study long-term changes and different patterns of variability and regime differences between specific time periods.

## Production data

The Directorate of Economics and Statistics (DES) provided district-level sugarcane production data through their official online data portal at the website https://data.desagri.gov.in for the crop years between 1999 and 2020. The dataset contains three main variables which are cultivation area measured in hectares and total production measured in tonnes and yield measured in tonnes per hectare which is calculated by dividing production by area. The agricultural periods which start in December of the first year and end in November of the second year represent the crop years which follow the sugarcane growing cycle for the region. The district-level series for Ahmednagar and Solapur and Nashik and Bellary and Dharwad were standardized to use the same crop-year definition to enable comparison between different states and districts.

The complete production series data from the five districts enable analysis of 22 crop years for each district during the study period while delivering complete data on area and production and yield information. The data represents district-level annual totals which combine the effects of changes in sugarcane cultivation area and average district productivity across different types of farms.

The Table 1 presents an overview of sugarcane production, which shows its distribution and variations across five districts during the study period. Solapur has the highest average cultivated area and total production output, while Nashik and Bellary and Dharwad demonstrate smaller production systems that operate at different yield levels and production variations.

The production dataset contains all data points which span 22 years and three variables without any missing values. This complete dataset enables accurate time-based assessment because it contains all necessary information without needing data imputation or interpolation methods. The data present district-level total sugarcane production figures which show the entire district production instead of specific farm production data.

## Meteorological data

The India Meteorological Department (IMD) provided daily meteorological data for the study districts through its agrometeorological network, accessed using the Climate Research and Services portal at this link https://www.imdpune.gov.in/. Five district-representative stations were used which included Rahuri for Ahmednagar (station code RHI) and Solapur for Solapur (SLP) and Niphad for Nashik (NPD) and Bellary for Bellary (BLY) and Dharwad for Dharwad (DHR). The stations offer daily observations which extend over several decades to support agricultural monitoring activities. The IMD data underwent a process of quality checking and harmonisation before it was converted from daily data to crop-year data to create production series.

The daily records for each station extend from 1996 to 2021 for a period of two decades at minimum but different locations show varying degrees of record completeness and time span. The weather data from Rahuri and Solapur provides continuous coverage throughout the production season but Niphad, Bellary, and Dharwad present shorter weather records which contain intermittent data. Table 2 provides a summary of the district and station data which shows the total crop years that have usable seasonal rainfall data and the total number of HQ crop years which meet the study's completeness requirements.

The study uses core meteorological variables which include daily rainfall measurements together with maximum temperature, minimum temperature, and mean temperature values and evaporation rates and evapotranspiration rates and sunshine hours and relative humidity measurements taken at standard observation times. The study used these series to derive seasonal and crop-year indices which included total rainfall and drought index and moisture adequacy index and heat-stress days. The definition of high-quality crop years requires farmers to achieve 80% accomplishment in both complete crop availability and the specific index-based crop assessment variables. The districts show different weather coverage and quality because Solapur has many HQ crop years while Ahmednagar offers limited but useful weather information and Nashik Bellary and Dharwad face weather interpretation challenges because they have fewer HQ years.

The Table 2 presents weather coverage information for each district according to the high-quality standard. All weather–yield relationships are interpreted as descriptive associations rather than causal effects, and the study results depend on the years which reached the complete data collection requirement.

*Parameters used for each district*

The meteorological parameters for each district were obtained from the designated IMD agrometeorological station which provided data for all districts and this data was combined into crop-year periods. The daily measurement system includes the following elements: rainfall (mm); maximum, minimum, and mean air temperature ($^\circ$C); evaporation (mm); evapotranspiration (mm); sunshine hours; and relative humidity at 07:00 and 14:00 IST (%). The crop-year aggregates were calculated from these daily variables which include the total seasonal rainfall and total evaporation and total evapotranspiration and average daily maximum and minimum and average temperature and average sunshine hours and average relative humidity. The analysis employs derived indices which include drought index (DI) $= (R - E)/E$, where $R$ is crop-year rainfall and $E$ is crop-year evaporation; moisture adequacy index (MAI) $= R/\mathrm{ET}$, where ET is crop-year evapotranspiration; and heat-stress days (count of days with maximum temperature $\geq 35^\circ$C). The exploratory analysis includes additional counts of dry days which receive less than 1 mm of rainfall and heavy-rain days which receive 50 mm or more of rainfall.

*District-wise availability*

Ahmednagar: Rahuri (RHI) provides the full set of parameters above; eight crop years meet the high-quality completeness threshold and are used for DI, MAI, and heat-stress days in the meteorological context (Table 18). Solapur: Solapur station (SLP) provides the same variables with the best coverage (19 HQ crop years from 2002 to 2020), allowing the most robust district-level weather–yield description. Nashik: Niphad (NPD) provides the same parameters; 9 HQ years (e.g. 1999, 2005, 2007–2013) are available, so meteorological interpretation is limited to that subset. Bellary: Bellary station (BLY) supplies rainfall, temperature, evaporation, evapotranspiration, sunshine (when available), and relative humidity; 5 HQ crop years (1999, 2000, 2002, 2007, 2012) were used. Dharwad: Dharwad station (DHR) supplies the same core variables; only 4 HQ crop years (1999–2002) meet the completeness criterion, so weather–yield interpretation for Dharwad is the most limited.

The same calculation methods for DI and MAI and heat-stress days were used in all districts where there existed sufficient daily data. The study selected eight crop years for their quantitative analysis because those years had weather data availability which exceeded 80%. The researchers selected these years to obtain trustworthy statistical results while recognizing that weather data for the entire study period remained incomplete. The researchers aggregated meteorological variables at the crop-year level to create a time structure that matched the production data.

The weather data for the period from October to December in the first calendar year and the period from January to September in the second calendar year was used to establish crop-year alignment. The alignment ensures that weather variables correspond to actual sugarcane growing periods which exist outside of calendar year boundaries thus resolving the time discrepancy between crop-year production records and calendar-year weather data.

## Data preprocessing

All production data and meteorological records were brought into the system, which allowed their synchronization with the crop-year key that was established baseding on district and crop-year start dates. The study assessed unit consistency by examining all sources and states, while areas were measured in hectares and production used tonnes and weather parameters employed degrees Celsius and millimetres. The working dataset creates a panel structure that contains one row for each distinct district-crop-year pairing.

The production series began with a review of raw DES records to identify duplicate entries and visible coding mistakes which affected area and production data, including instances of zero or negative values during documented cultivation periods. The screening process established that all records could be kept unchanged because there was no need for deletion or correction. The calculation of yield in tonnes per hectare was performed by dividing production for each district and crop year through the total area. The study excluded all years which fell outside the 1999–2000 to 2020–2021 period while the five districts were confined to this established temporal range for analysis.

The meteorological series used daily IMD observations which underwent basic integrity tests by checking their temperature and rainfall and radiation variable values and testing internal consistency between maximum and minimum and mean temperature measurements. The process of transforming daily data into crop-year data required two distinct stages. The first stage involved calculating total daily rainfall and evaporation and evapotranspiration for the crop-year period while averaging temperature and sunshine hours and relative humidity. The team calculated completeness metrics through two measurements which involved counting available daily records and comparing this total to the complete number of crop year days. A crop-year was classified as high-quality if at least 80% of days had non-missing values for both the overall record and the subset of variables used in the climate indices; otherwise it was retained only for “any weather years” counts. The study calculated daily totals and average values for all existing days while using the 80% threshold to protect against bias that would result from extensive data gaps.

The preprocessing of production data and meteorological data was done separately before their integration through district and crop year matching to create the analysis panel. The merged panel presents complete production data for all five districts throughout the study period together with weather indices that match IMD coverage areas. Ahmednagar has a complete 22-year production record which includes eight years of excellent weather conditions. Solapur has an equivalent production history to Ahmednagar but with more years of excellent weather conditions. Nashik Bellary and Dharwad possess complete production records yet their records show fewer years of excellent weather conditions. The study processed raw series data through moving-average filters and statistical method decompositions. The study derived all trend and variability measurements from the unmodified series which had been preprocessed but remained in its original state.

## Statistical methods

*Descriptive statistics*

The study calculated descriptive statistics for three production variables which included area and production and yield to determine the central tendency and data dispersion and distribution characteristics of the dataset. The following measures were computed:

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \quad (1)$$

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} (x_i - \mu)^2} \quad (2)$$

$$\mathrm{CV} = \frac{\sigma}{\mu} \times 100 \quad (3)$$

where $\mu$ represents the mean, $\sigma$ is the standard deviation, CV denotes the coefficient of variation, $x_i$ are individual observations, and $n$ is the sample size.

*Trend analysis*

Multiple approaches were employed for trend detection to ensure robustness of results. Linear regression was used to estimate trend slopes:

$$Y_t = \alpha + \beta t + \epsilon_t \quad (4)$$

where $Y_t$ represents the variable of interest at time $t$, $\alpha$ is the intercept, $\beta$ is the trend slope, and $\epsilon_t$ is the error term. The null hypothesis $H_0 : \beta = 0$ was tested using t-statistics.

The Mann-Kendall test, a non-parametric method for trend detection, was applied to assess monotonic trends without assuming data distribution. The test statistic $S$ is calculated as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathrm{sgn}(x_j - x_i) \quad (5)$$

where $\mathrm{sgn}(x)$ is the sign function:

$$\mathrm{sgn}(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x = 0 \\ -1 & \text{if } x < 0 \end{cases} \quad (6)$$

For $n > 10$, the standardized test statistic $Z$ is computed as:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\mathrm{Var}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\mathrm{Var}(S)}} & \text{if } S < 0 \end{cases} \quad (7)$$

where $\mathrm{Var}(S) = \frac{n(n-1)(2n+5)}{18}$ under the null hypothesis of no trend.

Sen’s slope estimator[22], a robust non-parametric method for estimating trend magnitude, was calculated as:

$$\beta_s = median\left(\frac{x_j - x_i}{j - i}\right) \quad for\ all\ i < j \quad (8)$$

### Time series decomposition
Time series decomposition was performed to separate trend, seasonal, and residual components. The additive decomposition model is:

$$Y_t = T_t + S_t + R_t \tag{9}$$

where $T_t$ represents the trend component, $S_t$ is the seasonal component, and $R_t$ denotes the residual component at time $t$. Given the annual frequency of our data, seasonal components represent cyclical patterns rather than calendar seasonality.

### Breakpoint detection
The Pettitt test[23] was employed to detect potential structural breaks in the time series. This non-parametric test identifies the most significant change point by maximising the absolute value of the test statistic:

$$U_t = \sum {}_{i=1}^{t} \sum {}_{j=t+1}^{n} \mathrm{sgn}(x_i - x_j) \tag{10}$$

The test statistic $K_T$ is:

$$K_T = \max_{1 \le t < n} |U_t| \tag{11}$$

The approximate p-value is calculated as:

$$p \approx 2\exp\left(\frac{-6K_T^2}{n^3 + n^2}\right) \tag{12}$$

### Period-wise analysis
The 22-year study window was divided into three assessment periods which enabled to study production regime changes while maintaining necessary observation levels for each regime: Period 1 (crop-year starts 1999–2006), Period 2 (2007–2013), and Period 3 (2014–2020). The boundaries were established because production series showed level shifts and statistical tests confirmed structural break points which were documented in the Section on breakpoint detection. The district data for each time period used the same crop-year definition to calculate all statistical measurements.

The study used analysis of variance (ANOVA) and Kruskal-Wallis test to determine whether there were different average values between periods for Ahmednagar district which included three measurement areas (area, production, yield). The study presented period-based comparisons between three districts through descriptive data and visual data which included boxplots and rankings while acknowledging that formal inference was affected by differences in irrigation and soils and station coverage.

$$Y_{ij} = \mu + \tau_i + \epsilon_{ij} \tag{13}$$

where $Y_{ij}$ is the observation $j$ in period $i$, $\mu$ is the grand mean, $\tau_i$ is the effect of period $i$, and $\epsilon_{ij}$ is the error term.

The F-statistic is:

$$F = \frac{\mathrm{MS}_{\mathrm{between}}}{\mathrm{MS}_{\mathrm{within}}} = \frac{\sum n_i(\bar{Y}_i - \bar{Y})^2/(k-1)}{\sum\sum (Y_{ij} - \bar{Y}_i)^2/(n-k)} \tag{14}$$

where $k$ is the number of periods, $n_i$ is the number of observations in period $i$, and $n$ is the total sample size.

The Kruskal-Wallis test, a non-parametric alternative to ANOVA, was also applied:

$$H = \frac{12}{n(n+1)} \sum {}_{i=1}^{k} \frac{R_i^2}{n_i} - 3(n+1) \tag{15}$$

where $R_i$ is the sum of ranks in group $i$.

### Variability analysis
Multiple measurement methods were needed to assess production variability which required their respective calculations. The coefficient of variation defined in Eq. (3) delivers a consistent assessment of variability between different data sets. The volatility index calculation used standard deviation to measure annual percentage changes from year to year.

$$\mathrm{VI} = \sqrt{\frac{1}{n-1} \sum {}_{i=2}^{n} \left(\frac{Y_i - Y_{i-1}}{Y_{i-1}} \times 100 - \bar{\Delta}\right)^2} \tag{16}$$

where $\bar{\Delta}$ is the mean year-over-year percentage change.

Stability was assessed by calculating the proportion of years within $\pm 10\%$ of the mean:

$$\text{Stability} = \frac{\text{Count}\left(\left|\frac{Y_i-\mu}{\mu}\right| \leq\ 0.10\right)}{n} \times\ 100 \tag{17}$$

Autocorrelation was calculated to assess temporal dependencies:

$$r_k = \frac{\sum\ _{i=1}^{n-k}(Y_i - \bar{Y}\ )(\ Y_{i+k} - \bar{Y})}{\sum\ _{i=1}^{n}(Y_i - \bar{Y})^2} \tag{18}$$

Climate Indices.

Several climate indices were calculated from meteorological data to provide context for production patterns. The drought index was computed as:

$$\text{DI} = \frac{R - E}{E} \tag{19}$$

where $R$ is total annual rainfall and $E$ is total annual evaporation. Negative values indicate drought conditions, with values less than −0.5 indicating severe drought.

The moisture adequacy index was calculated as:

$$\text{MAI} = \frac{R}{\text{ET}} \tag{20}$$

where ET is total annual evapotranspiration. Values greater than 1.0 indicate adequate moisture, while values less than 1.0 indicate moisture deficit.

### Comparative district analysis

The study conducted comparative assessments between Ahmednagar, Solapur and Nashik to overcome the restrictions of single-district inference and to deliver more relevant policy insights. First, constructed multiple time-series visualizations which displayed area and production and yield information to investigate long-term development patterns. The researchers used period-wise boxplots of yield data to conduct central tendency and dispersion analysis across different districts and time periods. The researchers used mean yield values to determine district rankings for all time periods which they established through their study.

The study measured production growth by establishing separate periods to assess how different factors affected agricultural development. The study employed symmetric decomposition to summarize changes in each district during different periods according to period average values.

$$\Delta\ P \approx\ \Delta\ A \cdot\ \bar{Y} + \Delta\ Y\ \cdot\ \bar{A},$$

where $A$ is area, $Y$ is yield, and bars denote period averages. This decomposition is used to support interpretation of whether observed production growth is more closely associated with area expansion or yield improvement.

The radar-style structural summary figure was used to create a compact comparative snapshot of district data. The three districts used standardized 0 to 1 scale metrics to measure both their level of indicators and their measurement variation. The radar summary exists to provide descriptive information which supports the variable-specific results instead of serving as a replacement for them.

## Results

### Descriptive statistics

The five districts were analyzed through descriptive statistics which evaluated area and production and yield across the entire study period from 1999 to 2020. Table 3 provides a summary of average area measurements which exist in thousands of hectares and average production values which are recorded in million tonnes and average yield figures which are expressed in t/ha and yield coefficient of variation results for each district. Ahmednagar shows mean area 87.13 × $10^3$ ha, mean production 7.20 million tonnes, and mean yield 78.88 t/ha with yield CV 19.68%. The Solapur area (117.41 × $10^3$ ha, 10.01 million tonnes) shows the highest scale of operations while its yield CV (15.53%) remains the lowest among all regions. Bellary has the highest mean yield (89.46 t/ha) while Nashik produces a smaller area and production scale which results in a mean yield of 78.17 t/ha. Dharwad exhibits the lowest mean yield (68.84 t/ha) together with the highest yield CV (18.44%).

| District | $N$ | Area mean | Prod. mean | Yield mean | Yield CV (%) |
|---|---|---|---|---|---|
| Ahmednagar | 22 | 87.13 | 7.20 | 78.88 | 19.68 |
| Solapur | 22 | 117.41 | 10.01 | 83.56 | 15.53 |
| Nashik | 22 | 22.20 | 1.73 | 78.17 | 16.99 |
| Bellary | 21 | 4.98 | 0.44 | 89.46 | 17.37 |
| Dharwad | 21 | 4.65 | 0.32 | 68.84 | 18.44 |

**Table 3.** Descriptive statistics by district (1999–2020). Area in $10^3$ ha, production in $10^6$ t.

| Variable | Mean | Median | SD | Min | Max | CV (%) | IQR |
|---|---|---|---|---|---|---|---|
| Area (ha) | 87,126 | 85,500 | 34,773 | 17,000 | 134,486 | 39.91 | 52,346 |
| Production (tonnes) | 7,197,342 | 6,238,400 | 3,654,668 | 1,001,800 | 12,776,170 | 50.78 | 6,517,371 |
| Yield (t/ha) | 78.88 | 77.31 | 15.53 | 47.65 | 108.61 | 19.68 | 22.21 |

**Table 4**. Descriptive statistics for Ahmednagar (1999–2020): full metrics.

| District | Variable | Slope | $R^2$ | Linear *p* | MK *p* | Sen's Slope |
|---|---|---|---|---|---|---|
| Ahmednagar | Area (ha) | 3,091 | 0.33 | 0.005 | 0.032 | 3,157 |
| Ahmednagar | Production (t) | 339,515 | 0.36 | 0.003 | 0.005 | 361,471 |
| Solapur | Area (ha) | 5,471 | 0.41 | 0.001 | 0.004 | 5,962 |
| Solapur | Production (t) | 509,510 | 0.38 | 0.002 | 0.018 | 459,350 |
| Nashik | Area (ha) | −546 | 0.15 | 0.080 | 0.022 | −593 |
| Nashik | Production (t) | −28,004 | 0.06 | 0.29 | 0.071 | −36,541 |
| Bellary | Area (ha) | 79 | 0.04 | 0.37 | 0.38 | 86 |
| Bellary | Production (t) | 1,822 | 0.003 | 0.81 | 0.41 | 9,068 |
| Dharwad | Area (ha) | 298 | 0.54 | <0.001 | 0.006 | 264 |
| Dharwad | Production (t) | 20,048 | 0.45 | 0.001 | 0.020 | 19,820 |

**Table 5**. Trend analysis (area and production) by district: linear slope, $R^2$, linear p-value, Mann–Kendall p-value, Sen's slope.

| District | Slope | $R^2$ | *p* | Sen's Slope |
|---|---|---|---|---|
| Ahmednagar | 1.12 | 0.21 | 0.032 | 1.39 |
| Solapur | 0.47 | 0.05 | 0.30 | 0.62 |
| Nashik | 1.08 | 0.26 | 0.014 | 1.28 |
| Bellary | −0.52 | 0.04 | 0.38 | −0.51 |
| Dharwad | −0.23 | 0.01 | 0.63 | −0.13 |

**Table 6**. Trend analysis (yield) by district: linear slope (t/ha/year), $R^2$, p-value, Sen's slope.

Table 4 shows all descriptive statistics for Ahmednagar which serve as a reference point; Table 3 shows equivalent statistics for all districts in a summary format.

## Trend analysis

The study used trend analysis methods which included linear regression and Mann–Kendall test and Sen's slope to analyze area and production and yield data from all five districts (Table 5). The results for Ahmednagar show significant positive area trends with a slope of 3,091 ha/year and p value of 0.005 and production growth of 339,515 t/year and p value of 0.003 and yield growth of 1.12 t/ha/year and p value of 0.032. The yield-trend results for each district appear in Table 6 while Table 5 shows area and production trend results for all five districts. The study found Ahmednagar and Nashik to have significant positive yield trends with p values less than or equal to 0.032 while Solapur Bellary and Dharwad showed non-significant yield slopes with p values greater than 0.23. The land and production growth in Ahmednagar, Solapur, and Dharwad shows positive and significant results according to Table 5. Nashik exhibits a major decline in land area according to results from the Mann–Kendall test which showed a p value of 0.022 (Table 5). The differences between districts demonstrate how their particular growth patterns developed, which requires to present complete statistical data for each individual district.

The temporal trends for all three variables in Ahmednagar are presented through observed values, 5-year moving averages, and fitted trend lines according to Fig. 1. The visual representation confirms the positive trends identified through statistical tests and reveals periods of acceleration and deceleration in growth. The district-specific series for all five districts which include 5-year moving averages are presented in Fig. 2 to display their long-term patterns which show both similarities and differences between the cities of Ahmednagar, Solapur, Nashik, Bellary, and Dharwad (Fig. 3).

## Period-wise comparison

The statistical data for the five districts was analyzed across three time intervals which included Period 1 from 1999 to 2006 and Period 2 from 2007 to 2013 and Period 3 from 2014 to 2020 (Tables 7 and 8). Ahmednagar data appears in Table 9 while Table 8 displays average yield (t/ha) data which was gathered through district

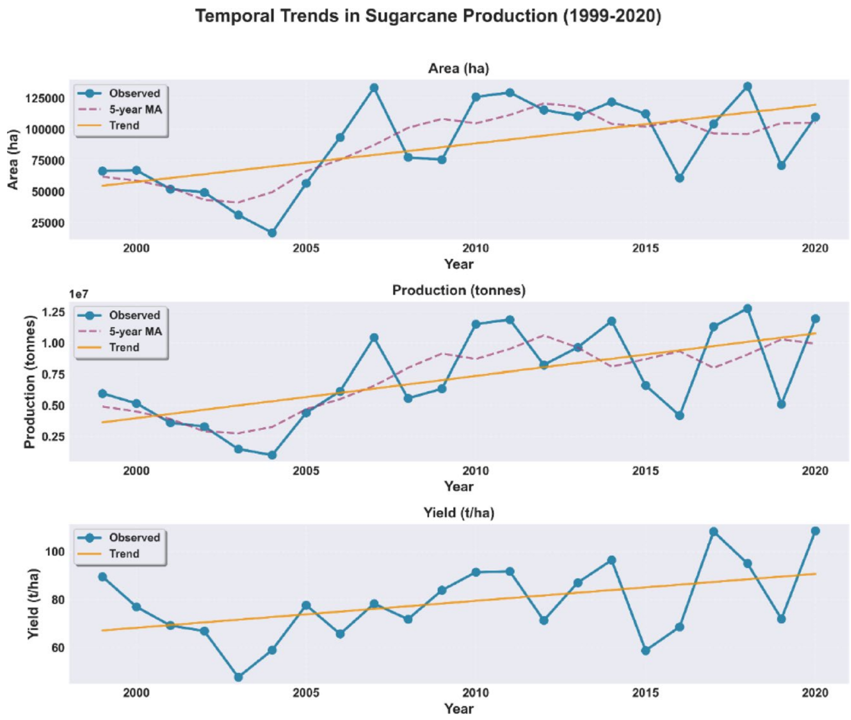


**Fig. 1**. Temporal trends in sugarcane area, production, and yield in Ahmednagar district (1999–2020). Solid lines represent observed values, dashed lines show 5-year moving averages, and orange lines indicate fitted linear trends.

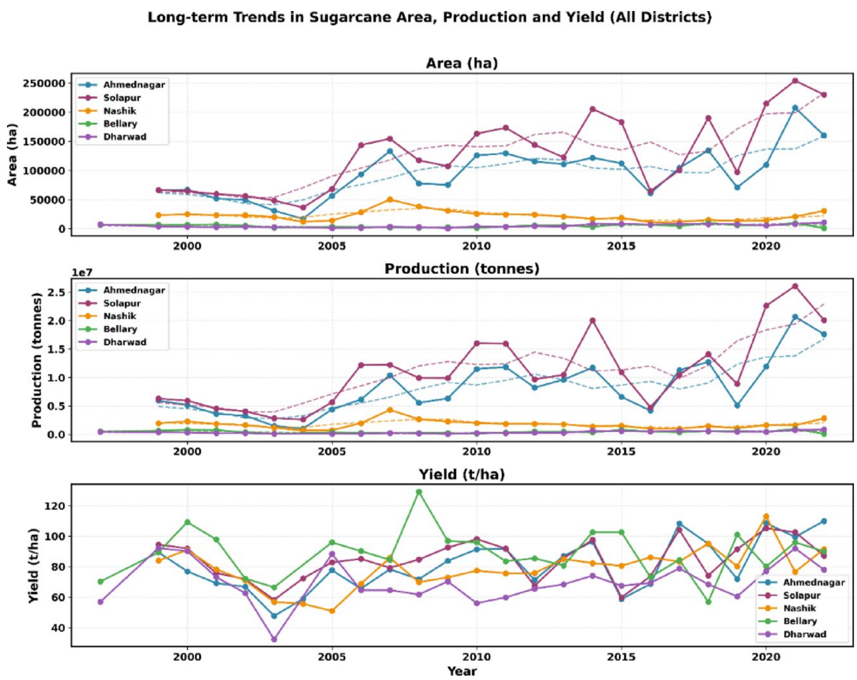


**Fig. 2**. Comparative temporal trends in sugarcane area, production, and yield across Ahmednagar, Solapur, Nashik, Bellary, and Dharwad districts (1999–2020).

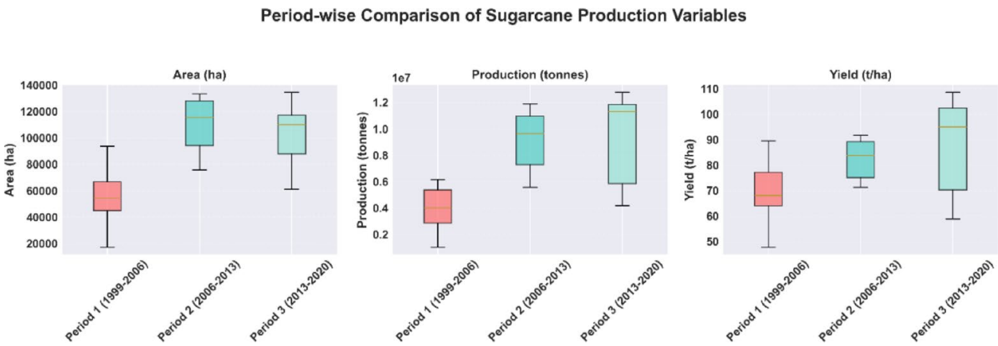


**Fig. 3**. Period-wise distributions of area, production, and yield for Ahmednagar district.

| Variable | Linear Slope | $R^2$ | Linear *p* | MK Z | MK *p* | Sen's slope |
|---|---|---|---|---|---|---|
| Area (ha) | 3,091 | 0.333 | 0.005 | 2.14 | 0.032 | 3,157 |
| Production (tonnes) | 339,515 | 0.364 | 0.003 | 2.82 | 0.005 | 361,471 |
| Yield (t/ha) | 1.12 | 0.210 | 0.032 | 2.14 | 0.032 | 1.39 |

**Table 7**. Trend analysis for Ahmednagar: area, production, and yield.

| District | *N* (P1; P2; P3) | Period 1 | Period 2 | Period 3 |
|---|---|---|---|---|
| Ahmednagar | 8; 7; 7 | 69.05 | 82.20 | 86.81 |
| Solapur | 8; 7; 7 | 79.10 | 85.64 | 86.57 |
| Nashik | 8; 7; 7 | 69.55 | 77.49 | 88.70 |
| Bellary | 7; 7; 7 | 88.76 | 93.78 | 85.85 |
| Dharwad | 7; 7; 7 | 71.93 | 63.79 | 70.80 |

**Table 8**. Period-wise mean yield (t/ha) by district.

| Period | *N* | Area (ha) | Production (t) | Yield (t/ha) | SD (yield) | CV (yield, %) |
|---|---|---|---|---|---|---|
| Period 1 (1999–2006) | 8 | 54,175 | 3,880,975 | 69.05 | 12.72 | 18.42 |
| Period 2 (2007–2013) | 7 | 109,743 | 9,087,243 | 82.20 | 8.60 | 10.47 |
| Period 3 (2014–2020) | 7 | 102,167 | 9,097,574 | 86.81 | 20.15 | 23.21 |

**Table 9**. Period-wise statistics for Ahmednagar.

| District | ANOVA F | ANOVA *p* | KW H | KW *p* |
|---|---|---|---|---|
| Ahmednagar | 3.05 | 0.071 | 5.13 | 0.077 |
| Solapur | 0.70 | 0.51 | 1.52 | 0.47 |
| Nashik | 5.21 | 0.016 | 6.91 | 0.032 |
| Bellary | 0.42 | 0.66 | 0.14 | 0.93 |
| Dharwad | 0.79 | 0.47 | 3.48 | 0.18 |

**Table 10**. ANOVA and Kruskal–Wallis p-values for yield by district (period comparison).

and period analysis. All districts show an increase in mean yield from Period 1 to Period 3 except for Dharwad which recorded its highest mean yield during Period 1 with 71.93 t/ha and experienced a decrease in mean yield during Periods 2 and 3 which resulted in 63.79 t/ha and 70.80 t/ha respectively. The two districts of Nashik and Bellary demonstrate obvious yield improvements throughout all three periods while Solapur and Ahmednagar demonstrate identical yield growth patterns which lead to improved yields during Period 3.

The study conducted ANOVA and Kruskal-Wallis tests to investigate period effects in each individual district (Table 10). Nashik demonstrates significant period effects for yield because the ANOVA test produced a p value

| District | Variable | ANOVA F | ANOVA $p$ | KW H | KW $p$ |
|---|---|---|---|---|---|
| Ahmednagar | Area (ha) | 11.40 | 0.001 | 12.03 | 0.002 |
| Ahmednagar | Production (t) | 9.24 | 0.002 | 10.29 | 0.006 |
| Solapur | Area (ha) | 8.77 | 0.002 | 10.78 | 0.005 |
| Solapur | Production (t) | 6.98 | 0.005 | 9.43 | 0.009 |
| Nashik | Area (ha) | 9.87 | 0.001 | 12.54 | 0.002 |
| Nashik | Production (t) | 5.71 | 0.011 | 9.70 | 0.008 |
| Bellary | Area (ha) | 3.52 | 0.051 | 5.50 | 0.064 |
| Bellary | Production (t) | 2.76 | 0.090 | 5.22 | 0.074 |
| Dharwad | Area (ha) | 42.20 | $<0.001$ | 13.90 | 0.001 |
| Dharwad | Production (t) | 34.04 | $<0.001$ | 13.38 | 0.001 |

**Table 11**. ANOVA and Kruskal–Wallis p-values for area and production by district (period comparison).

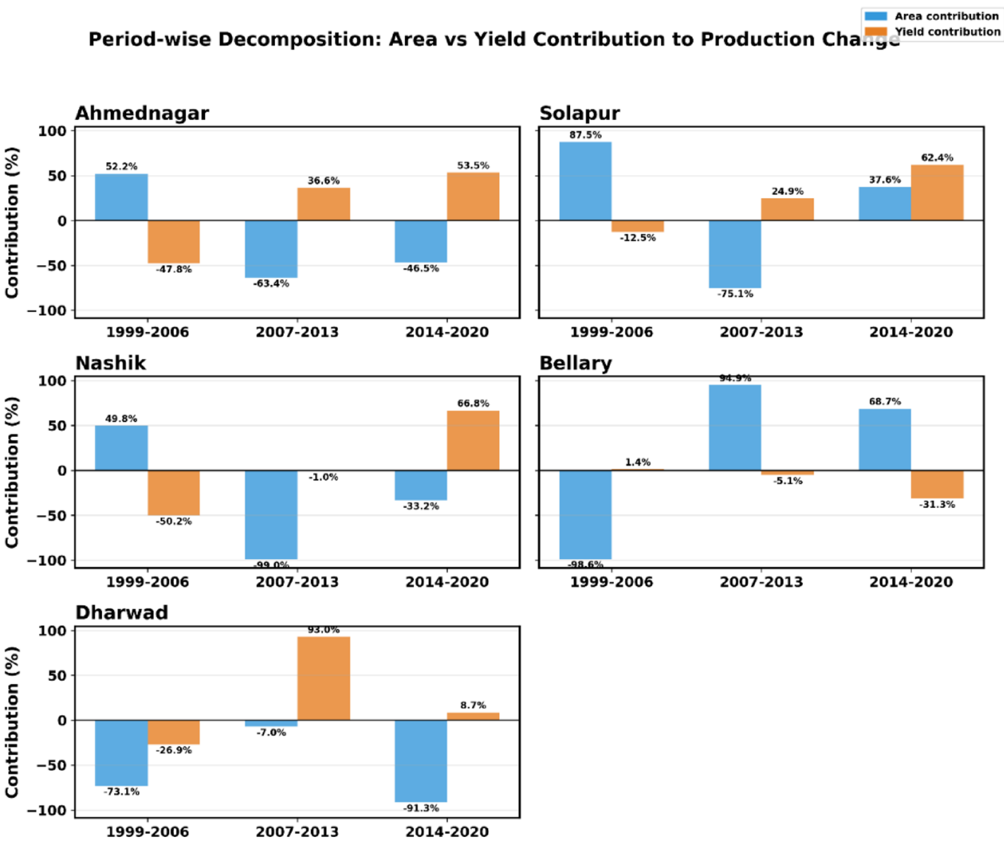


**Fig. 4**. Comparative period-wise change decomposition across Ahmednagar, Solapur, and Nashik.

of 0.016 and the KW test produced a p value of 0.032 ($p < 0.05$). Ahmednagar shows suggestive yield differences ($p$ = 0.071); Solapur, Bellary, and Dharwad do not show significant yield differences across periods. The area and production period effects exhibit statistical significance in Ahmednagar, Solapur, Nashik, and Dharwad (Table 11) because Dharwad displays the strongest period effect with ANOVA p value of less than 0.001 for area and production. The production growth details for five districts are shown in Fig. 4 which shows how production growth is divided between area growth and yield growth for each of the five districts. The yield distributions by district and period are shown in Fig. 5 while Figure [fig/district_ranking] displays district rankings which use mean yield data to show performance across different time periods with rank numbers added for easier comparison (Table 12).

Figure 3 shows box plots which display yield distribution differences between three periods in Ahmednagar, showing how yields developed from Period 1 to better results in later periods.

The comparison method allows to find out which agricultural expansion comes from new farmland development and which agricultural yield enhancement comes from improved crop yields. The method shows how different areas and agricultural systems achieve their growth through a combination of increasing farmland area and advancing crop yield production (Fig. 6).

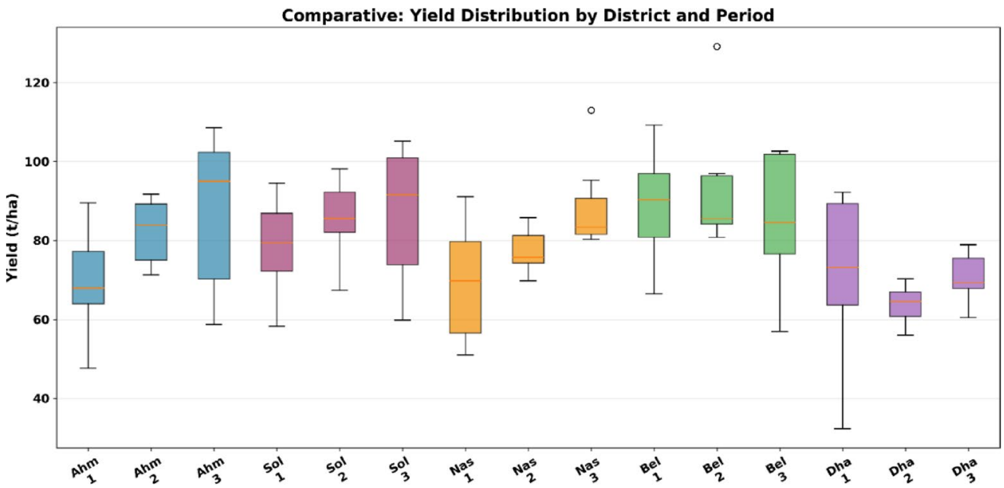


**Fig. 5**. Comparative yield distributions by district and period.

| Variable | ANOVA F | ANOVA *p* | KW H | KW *p* |
|---|---|---|---|---|
| Area (ha) | 11.40 | 0.001 | 12.03 | 0.002 |
| Production (tonnes) | 9.24 | 0.002 | 10.29 | 0.006 |
| Yield (t/ha) | 3.05 | 0.071 | 5.13 | 0.077 |

**Table 12**. ANOVA results for Ahmednagar (area, production, yield).

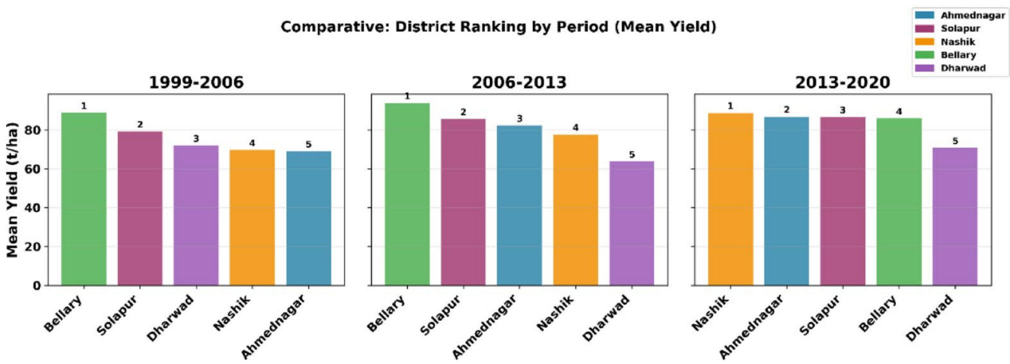


**Fig. 6**. Comparative district ranking by period based on mean yield.

## Time series decomposition

The yield time series data in Fig. 7 shows three distinct components which include trend and seasonal and residual components. The trend component shows a persistent upward movement although it experiences occasional downward movements. The seasonal component establishes cyclical patterns while the residual component detects annual changes which exist beyond both trend and cyclical movements.

## Variability analysis

The study performed variability calculations using five different methods which included coefficient of variation, volatility index, stability within $\pm 10\%$ of mean, and lag-1 autocorrelation to analyze area production and yield data for all five districts. Table 13 shows yield variability data which was collected from different districts. Nashik shows the highest yield stability (59.1% of years within $\pm 10\%$ of mean), followed by Bellary and Dharwad (52.4%); Solapur and Ahmednagar show lower stability (36.4% and 31.8%). Nashik and Solapur show the lowest levels of yield volatility while Dharwad and Ahmednagar experience the highest levels. Table 14 provides complete variability measurements for Ahmednagar while Table 13 shows summary measurements of all districts for yield. Figure 8 shows how district yield paths developed through the study period with each district panel showing distinct patterns of yield level and yield variability throughout the study period.

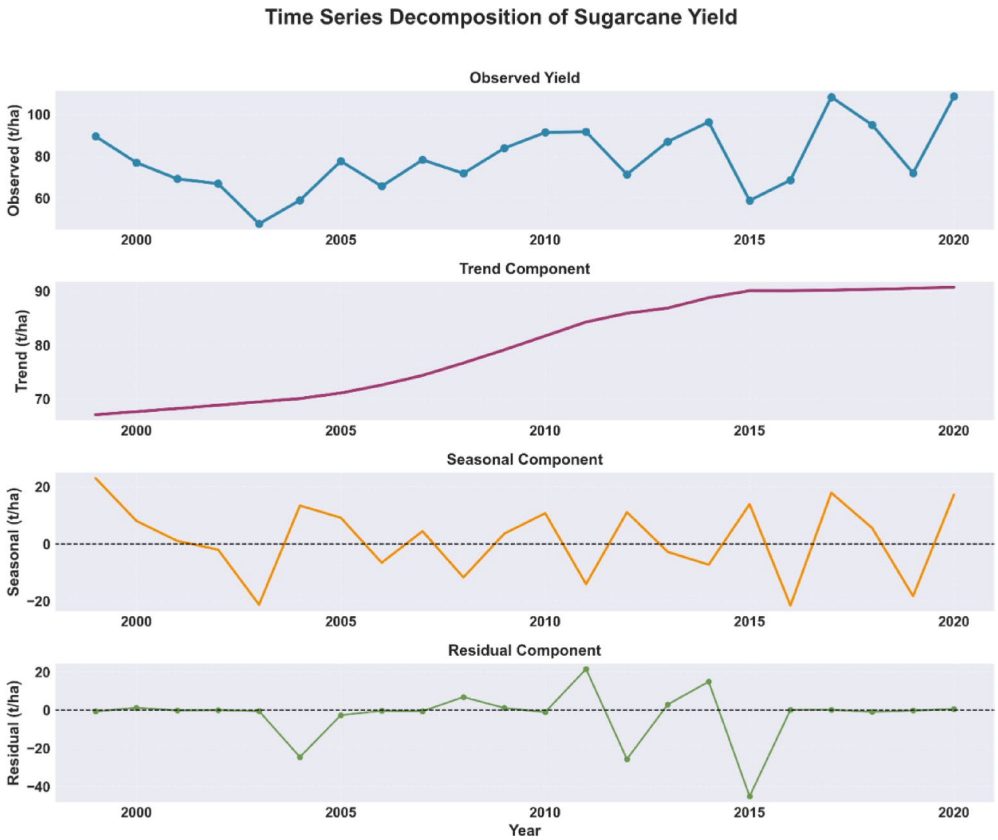


**Fig. 7**. Time series decomposition of sugarcane yield in Ahmednagar district.

| District | CV (%) | Volatility | Stability (%) | Autocorr. |
|---|---|---|---|---|
| Ahmednagar | 19.68 | 24.90 | 31.82 | 0.22 |
| Solapur | 15.53 | 20.23 | 36.36 | 0.12 |
| Nashik | 16.99 | 15.83 | 59.09 | 0.56 |
| Bellary | 17.37 | 28.38 | 52.38 | 0.01 |
| Dharwad | 18.44 | 42.14 | 52.38 | 0.02 |

**Table 13**. Yield variability by district: CV (%), volatility index, stability (%), autocorrelation.

| Variable | CV (%) | Volatility Index | Stability (%) | Autocorrelation |
|---|---|---|---|---|
| Area (ha) | 38.99 | 61.56 | 4.55 | 0.55 |
| Production (tonnes) | 49.61 | 91.83 | 4.55 | 0.44 |
| Yield (t/ha) | 19.68 | 24.90 | 31.82 | 0.22 |

**Table 14**. Variability analysis for Ahmednagar (area, production, yield).

## Extreme years analysis

The three best and three worst yield years were determined for each district as shown in Table 15. Ahmednagar's highest yields occurred in 2020–2021 at 108.61 t/ha and in 2017–2018 at 108.32 and in 2014–2015 at 96.40 while the lowest yields happened in 2003–2004 at 47.65 and in 2015–2016 at 58.78 and in 2004–2005 at 58.93. The peak yields for Solapur and Nashik occurred in 2020–2021 when Solapur reached 105.16 t/ha and Nashik reached 113.03 t/ha. Bellary's highest yield occurred during 2008–2009 when it reached 129.20 t/ha while Dharwad's highest yield happened during 1999–2000 at 92.15 t/ha. The lowest yield across all districts was in Dharwad in 2003–2004 when it reached 32.30 t/ha. Table 16 provides complete information about the highest and lowest three results which apply to Ahmednagar. Table 15 displays the year with highest yield and the year with lowest yield for all five districts. Figure 9 shows annual percentage differences which apply to Ahmednagar. Figure 10 displays yearly yield data for all five districts while marking periods of severe yield decline and yield recovery.

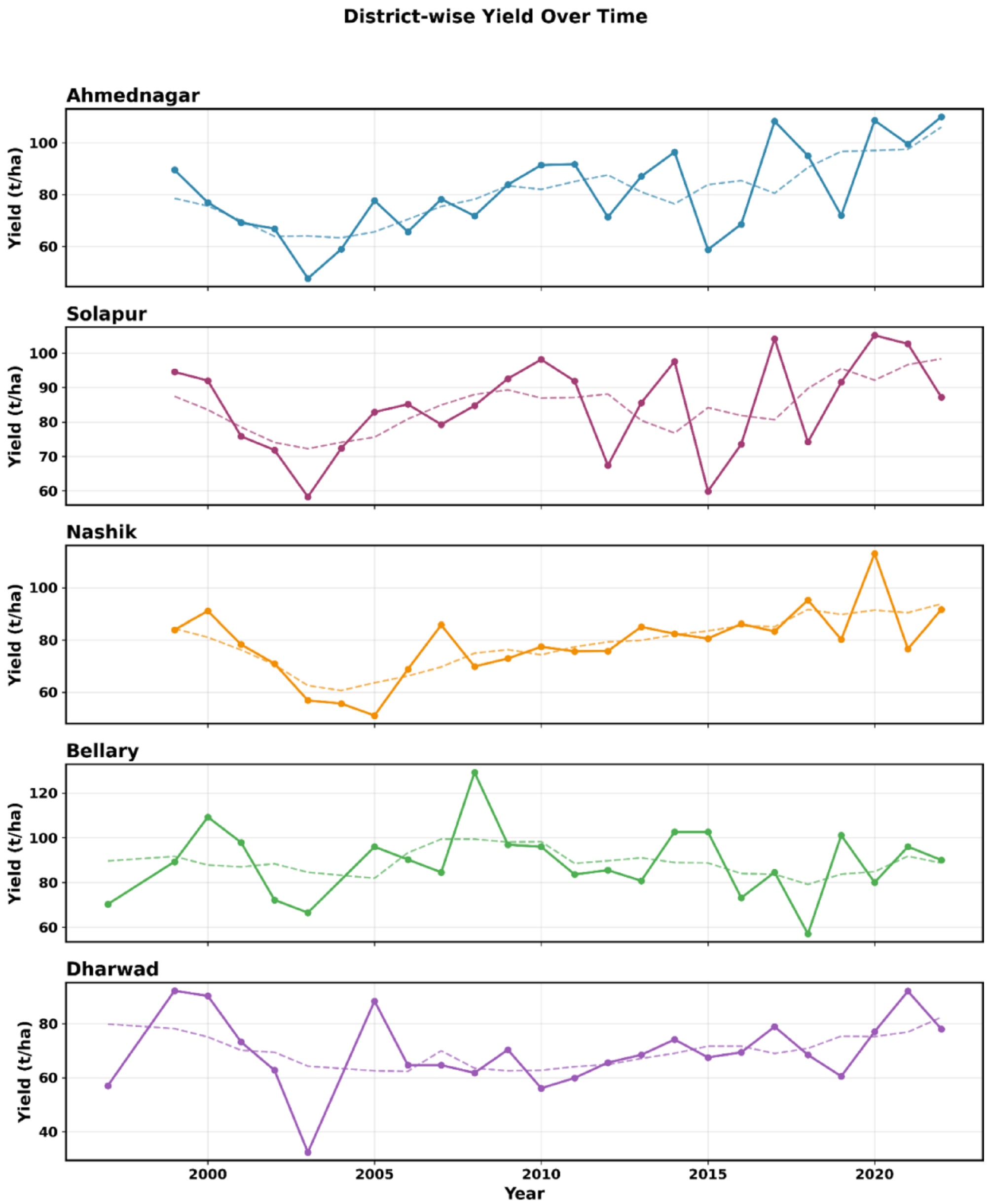


**Fig. 8**. District-wise yield trajectories over time for each district.

| District | Max year | Max yield | Min year | Min yield |
|---|---|---|---|---|
| Ahmednagar | 2020–21 | 108.61 | 2003–04 | 47.65 |
| Solapur | 2020–21 | 105.16 | 2003–04 | 58.26 |
| Nashik | 2020–21 | 113.03 | 2005–06 | 51.01 |
| Bellary | 2008–09 | 129.20 | 2018–19 | 57.00 |
| Dharwad | 1999–00 | 92.15 | 2003–04 | 32.30 |

**Table 15**. Extreme yield years by district: year of maximum and minimum yield (t/ha).

The radar chart in Fig. 11 shows standardised indicators which allow districts to be compared through their structural data.

## District profiles for Nashik, Solapur, Bellary, and Dharwad

The comparative summaries receive additional support through district-specific profiles that present Nashik, Solapur, Bellary, and Dharwad data to demonstrate trend patterns and period-wise averages and extreme-year

| Category | Year | Yield (t/ha) | Area (ha) |
|---|---|---|---|
| Top 3 | 2020–2021 | 108.61 | 109,977 |
| | 2017–2018 | 108.32 | 104,404 |
| | 2014–2015 | 96.40 | 122,000 |
| Bottom 3 | 2003–2004 | 47.65 | 31,200 |
| | 2015–2016 | 58.78 | 112,400 |
| | 2004–2005 | 58.93 | 17,000 |

**Table 16**. Top three and bottom three yield years: Ahmednagar.

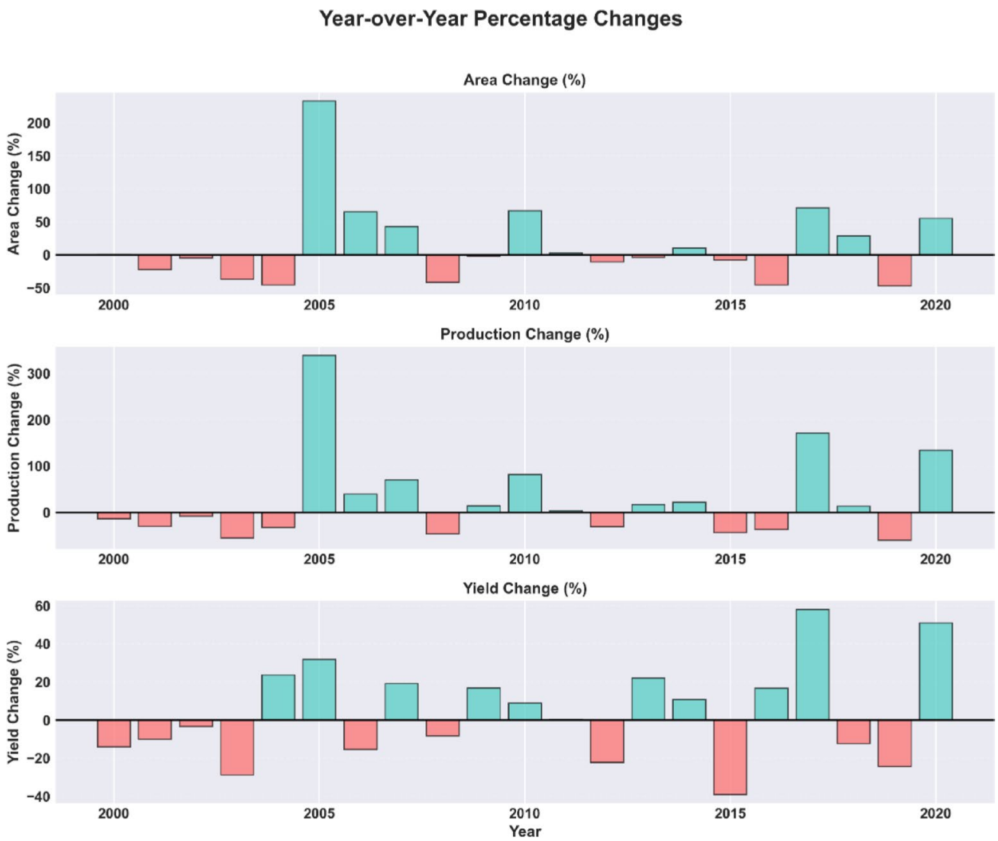


**Fig. 9**. Year-over-year percentage changes in area, production, and yield for Ahmednagar district.

behavior according to the same definitions used in Ahmednagar. The district yield trend profiles for the four districts appear in Fig. 12 while Fig. 13 shows period-based average yield results and Fig. 14 presents extreme-year yield data for each district.

## Meteorological context

Meteorological data integration helps to understand production patterns observed at the district level. High-quality (HQ) weather–yield years are defined as those meeting the 80% completeness rule for both the core weather variables and the derived indices (drought index, moisture adequacy index, and heat-stress days). The study summarized all available complete HQ years for Ahmednagar and Nashik and Solapur while Bellary and Dharwad provided weather coverage information (see Table 2) although their corresponding yield–weather file failed to deliver adequate HQ years with full data for complete analysis. The Table 17 displays district-level data about average drought index values and moisture adequacy indexes and heat-stress days and yield ranges using HQ years as the time reference point.

The drought conditions in Ahmednagar during the eight HQ years show a mean DI of approximately – 0.79 while the region experiences low moisture adequacy with a mean MAI of approximately 0.38 and 90 days of heat stress across each crop year. Nashik HQ years show similarly negative drought indices but moderate yields and a shorter run of years with complete indices. Solapur has the largest number of HQ years with complete indices; on average it exhibits somewhat less severe drought (mean DI $\approx -0.62$), higher moisture adequacy (mean MAI $\approx 1.69$), and more heat-stress days than Ahmednagar which demonstrates the need for proper water

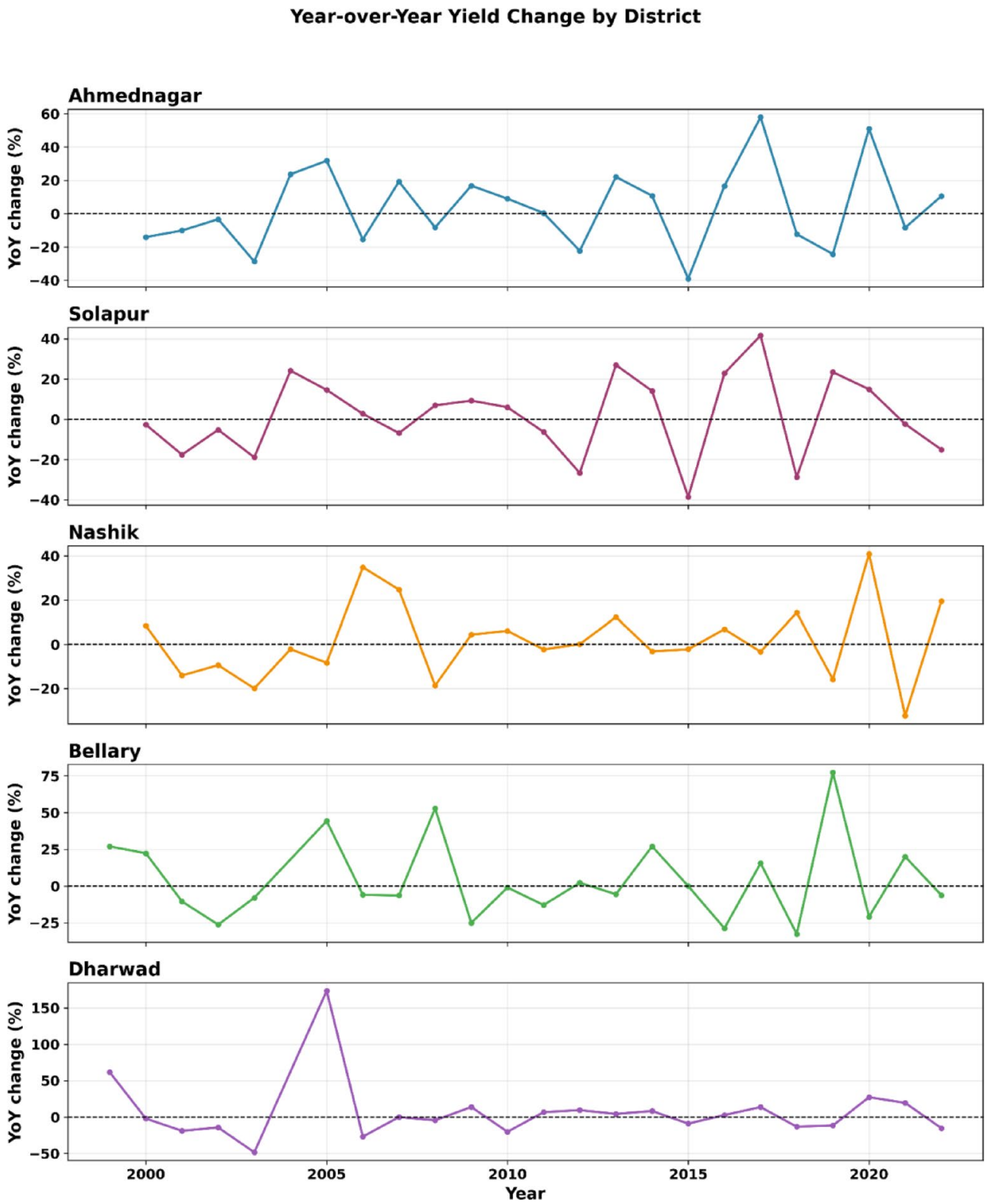


**Fig. 10**. Year-over-year yield change by district.

management and irrigation systems to achieve better yield results. Bellary and Dharwad have HQ weather years according to Table 2, but the matched yield–weather file contains missing indices which stop proper DI/MAI/heat-stress estimation; thus meteorological information for these districts can only show what weather elements exist together with their basic regional climate information.

The meteorological data from eight high-quality years in Ahmednagar enables better understanding of the production patterns. The climate indices for the studied years appear in Table 18 as calculated values. The study period experienced constant drought conditions according to negative drought indices which remained present throughout all study years. The drought index values decreased from − 0.54 in 2009–2010 to −0.97 in 2004–2005 with more severe drought conditions represented by the more negative drought index values.

Ahmednagar's moisture adequacy index showed substantial changes during the 2009–2010 period which reached a moisture value of 1.31 while most other years showed moisture values below 0.5. The period from 2015 to 2016 recorded the most heat stress days which ranged between 79 and 109 days throughout the year.

Table 18 presents climate indices which demonstrate how water availability affects yield production. The drought index shows a positive association with yield, which means that less severe drought conditions (higher index values) lead to better crop production. The moisture adequacy index also shows a positive relationship with yield, which confirms that proper moisture levels are essential for crop production, while years with many heat-stress days result in decreased yields.

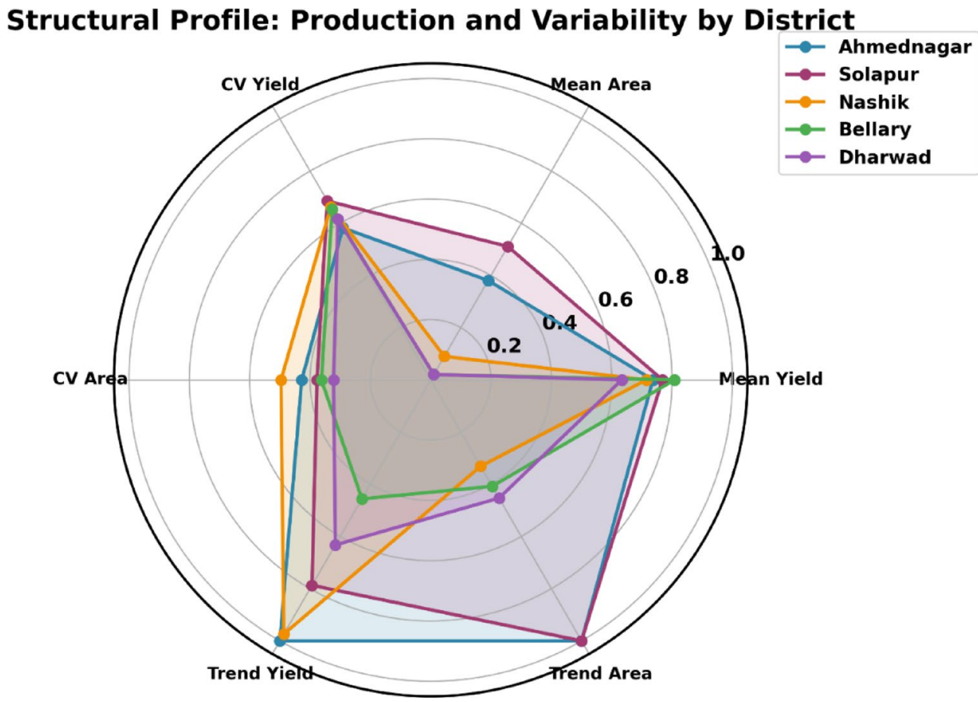


**Fig. 11**. Structural comparison across districts using a radar summary of standardized indicators.

## Discussion

The study examines sugarcane production patterns between five districts in Maharashtra and Karnataka through statistical analysis which includes descriptive statistics, trend analysis, period-wise comparison, variability study, and extreme year assessment for all five districts as shown in Tables 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14 and 15. The long-term time series data show that production growth varies across different districts because Solapur functions as a large-scale production system with a mean area of 117,000 hectares and a mean production of 10 million tonnes while Ahmednagar operates at intermediate scale with major annual production variations at its mean area of 87,000 hectares and production of 7.2 million tonnes and Nashik functions as a small-scale production system which has a mean area of 22,000 hectares and a production capacity of 1.7 million tonnes whereas Bellary and Dharwad operate at even smaller production capacities which lead to their distinct yield patterns (Table 1; Fig. 2).

### Ahmednagar compared to other districts

Ahmednagar occupies an intermediate position among the five districts in both scale and performance. The area and production of this region exceed those of Nashik and Bellary and Dharwad, while it remains smaller than Solapur. The region has a mean yield of 78.88 t/ha, which is similar to Nashik's yield of 78.17 t/ha but lower than Solapur's yield of 83.56 t/ha and Bellary's yield of 89.46 t/ha, while it exceeds Dharwad's yield of 68.84 t/ha. Ahmednagar shows a strong upward yield trend with a statistical significance of $p = 0.032$, which contrasts with the yield trends observed in Solapur, Bellary, and Dharwad. The two districts of Ahmednagar and Nashik show significant yield growth during the study period, while Nashik and Ahmednagar produce the only yield results that statistically differ from each other during this time. The agricultural output of Ahmednagar shows greater instability than Nashik and Solapur because Ahmednagar achieves yield stability for 31.8% of years which falls within 10% of its mean yield while Nashik and Solapur achieve 59.1% and 36.4% respectively. The region demonstrates higher yield fluctuations than Nashik and Solapur while showing yield patterns that match those of Dharwad. The year-over-year change series for Ahmednagar (Fig. 9) demonstrates the extent of these observed changes. Ahmednagar shows yield differences across periods which are not statistically significant because the p-value stands at 0.071 while Nashik displays statistically significant period effects with Solapur Bellary and Dharwad showing no such effects. The results in Table 18 present detailed meteorological information which includes drought index and moisture adequacy and heat-stress days for all districts except Ahmednagar who is the only district which received this detailed meteorological information. Ahmednagar district achieves major yield growth but experiences high yield fluctuations because it exists between Solapur which shows stable large-scale farming and Nashik which displays stable smaller-scale farming. The smaller Karnataka districts of Bellary and Dharwad exhibit stable yield patterns that display non-significant changes while their extreme annual variations show substantial development.

### Comparative yield levels and stability

The average yield for different districts shows variation because Bellary achieves the highest long-term yield of 89.46 t/ha while Solapur has the most consistent yield with a CV of 15.53% and a high average yield of


**Fig. 12**. District-specific yield trend profiles for Nashik, Solapur, Bellary, and Dharwad.

83.56 t/ha which demonstrates stable productivity throughout major land changes. (Table 3; Fig. 8). Dharwad displays lower average yields which measure 68.84 t/ha while exhibiting higher yield fluctuations according to data presented in Table 13. Ahmednagar and Nashik both establish long-term average yields which measure 78.88 t/ha and 78.17 t/ha respectively while Nashik demonstrates superior yield consistency through 59.1% of

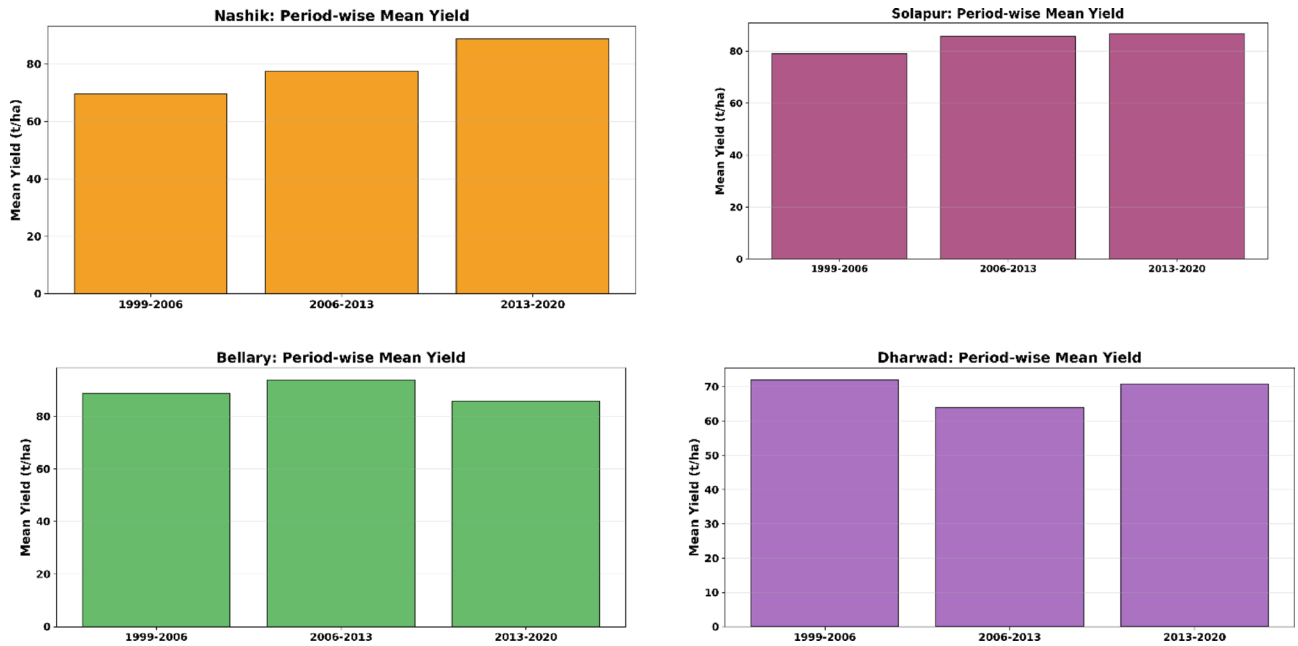


**Fig. 13**. Period-wise yield summaries for Nashik, Solapur, Bellary, and Dharwad.

years maintaining yields within $\pm$ 10% of the average. Ahmednagar displays lower yield stability through its 31.8% of years which exceed this range while the higher yield stability in Nashik derives from its lower risk to agricultural disturbances. The comparative figures for each time period together with the official yield table for each time period (Table 8) show that different districts display different yield levels which create different yield patterns across the time periods. The radar chart (Fig. 11) provides a compact structural comparison of these district-level differences.

## Interpreting period-wise regimes and production-growth mechanisms

The period-based summaries and district-wise ANOVA/Kruskal–Wallis results (Table 10) show that significant yield period effects ($p < 0.05$) occur only in Nashik; Ahmednagar shows suggestive period differences ($p$ = 0.071), while Solapur, Bellary, and Dharwad do not show statistically significant yield differences across periods. The area and production period effects are significant in Ahmednagar and Solapur and Nashik and Dharwad according to Table 11. The decomposition results (Fig. 4) demonstrate that production growth in some districts occurs through land expansion while other districts achieve better results through yield improvements because of their irrigation development and management practices. The time-series decomposition of yield in Ahmednagar shows the trend and cyclical patterns that cause the yield variations shown in Fig. 7. The district ranking figure demonstrates how different periods show varying performance results which shows why policy design requires multiple periods of data instead of relying on one period (Fig. 6).

## Trends and extreme years

The formal trend analysis which examines all districts through Table 6 demonstrates that Ahmednagar and Nashik show significant positive yield trends whereas Solapur Bellary and Dharwad display non-significant yield slopes which indicate that yield growth patterns differ across these five districts. The extreme-years summary (Table 15) shows that the lowest yield across all districts occurred in Dharwad in 2003–2004 (32.30 t/ha) and the highest in Bellary in 2008–2009 (129.20 t/ha). The year-over-year yield change series shows that districts experience abrupt yield decreases which do not happen simultaneously across all areas, resulting in consequences for sugarcane supply planning and state-level risk-sharing activities (Fig. 10). The district-specific profiles for Nashik, Solapur, Bellary, and Dharwad provide complementary detail on local trend patterns, period-wise behaviour, and extreme years (Figs. 12, 13 and 14). The lowest yield year for Ahmednagar occurred in 2003–2004 which showed both low moisture adequacy index values and a drought index that strongly indicated drought conditions. Higher yields occur during years which show improved moisture adequacy together with milder drought conditions as demonstrated in Table 18. The results show that water availability together with heat stress serves as important factors which affect yield results in semi-arid environments while technological and varietal and institutional elements also stay responsible for creating enduring yield patterns.

## Meteorological integration and limits to inference

The districts show significant differences in both weather coverage and weather quality according to the data presented in Table 2. Solapur presents more high-quality weather years during the study period than Nashik which only has partial weather records for the production period and Bellary and Dharwad have lower total numbers of high-quality years. The study calculated climate indices which included the drought index and

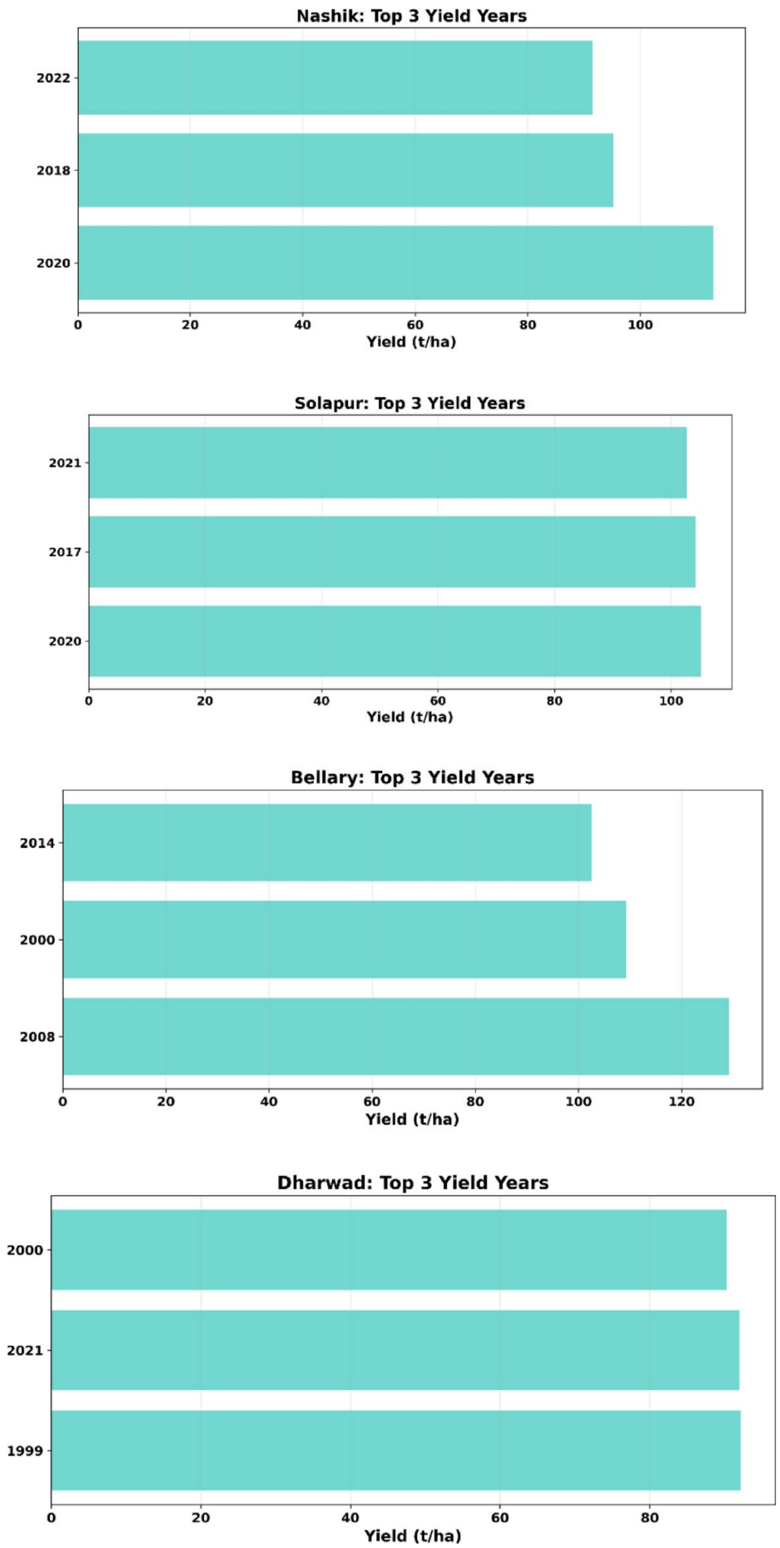


**Fig. 14**. Extreme-year yield profiles for Nashik, Solapur, Bellary, and Dharwad.

moisture adequacy index and heat-stress days for districts and years from matched yield–weather files which contained complete indices for Ahmednagar and Nashik and Solapur (Table 17) while providing detailed yearly data for Ahmednagar (Table 18). The meteorological context for Bellary and Dharwad includes only documented meteorological coverage and general climatic conditions without any quantitative data. The meteorological results are interpreted as descriptive associations which depend on the existing years and the representativeness of weather stations. The analysis does not estimate causal effects of climate variables on yield; therefore, the study

| District | HQ years | Mean DI | Mean MAI | Mean HS days | Yield range (t/ha) |
|---|---|---|---|---|---|
| Ahmednagar | 8 | $-0.79$ | 0.38 | 89 | 47.65–83.85 |
| Nashik | 5 | $-0.71$ | – | 80 | 72.70–77.94 |
| Solapur | 13 | $-0.62$ | 1.69 | 127 | 61.23–105.23 |
| Bellary | 0 | – | – | – | – |
| Dharwad | 0 | – | – | – | – |

**Table 17**. Summary of climate indices for high-quality weather–yield years by district. Mean drought index (DI), moisture adequacy index (MAI), and heat-stress days (HS; count of days with $T_{max} \geq 35^{\circ}$ C) are computed over HQ years with complete indices. Yield range is the minimum and maximum district mean yield (t/ha) over those HQ years.

| Crop year | Yield (t/ha) | Drought Index | MAI | Heat stress days |
|---|---|---|---|---|
| 2002–2003 | 66.86 | −0.86 | 0.22 | 93 |
| 2003–2004 | 47.65 | −0.95 | 0.07 | 86 |
| 2004–2005 | 58.93 | −0.97 | 0.05 | 87 |
| 2005–2006 | 77.66 | −0.96 | 0.05 | 82 |
| 2006–2007 | 65.64 | −0.60 | 0.53 | 79 |
| 2007–2008 | 78.26 | −0.72 | 0.46 | 82 |
| 2009–2010 | 83.85 | −0.54 | 1.31 | 96 |
| 2015–2016 | 58.78 | −0.73 | 0.31 | 109 |

**Table 18**. Climate indices for high-quality weather years.

can only report documented relationships which exist between indices and yield outcomes in the high-quality subset of data.

## Climate-change context
The study shows how heat-stress indicators relate to moisture levels which directly impact crop yield despite its failure to predict future climate scenarios. Warming temperatures increase crop water requirements while raising the chances of sugarcane systems experiencing yield losses under water limitations according to this existing study[43]. The results show that proactive adaptation planning through efficient irrigation and heat-risk advisories and drought-contingency measures provides valuable benefits to district which experience high production variability and drought sensitivity.

## Implications for policy and management
The statistical evidence from all-district data (which includes trends and period tests and variability and extreme years) supports the need for different district priorities. The agricultural data from Ahmednagar shows that farmers should implement water stress management programs which help them to achieve stable production results through improved irrigation methods and drought contingency planning and timely climate advisories. The agricultural output of Solapur shows that its high production capacity and steady yield pattern create a situation where even minor yield variations result in substantial supply changes, which makes it necessary to implement water governance and risk monitoring systems at the basin and command-area level. The combination of Nashik's continuous yield growth and its major yearly yield fluctuations together with its highest yield consistency proves that targeted extension work and varietal selections together with water management adjustments will help maintain productivity growth. The yield patterns in Bellary and Dharwad show non-significant trends while extreme-year patterns reveal different patterns for each region which includes Dharwad's extremely low yield in 2003–2004. The situation requires scientists to study all weather risk factors which affect small-scale farming operations between their two study locations.

## Limitations
Several limitations should be acknowledged. First, district-level aggregates do not capture farm-level heterogeneity in irrigation access, cultivar choice, and input use. Second, one station per district cannot represent microclimatic variation within large districts, and weather completeness varies across districts and years. The third period classification functions as rule-based regime assessment but its results require additional testing to confirm their effects on policies. The research studies three elements which include studying population patterns and studying variability patterns and studying relationship patterns between variables. The study establishes a transparent five-district baseline which enables future research to create more detailed results through higher resolution data and direct causal modeling.

## Conclusion

The study establishes a comprehensive assessment which examines sugarcane production trends and production fluctuations between 1999 and 2021 across five districts in Maharashtra and Karnataka. The study presents formal statistics which include descriptive data and trend analysis and period assessment and variability measurement and extreme year documentation for all five districts to establish conclusions based on uniform evidence contesting evidence from a single primary district. The study includes Ahmednagar as its most detailed meteorological integrated district to compare its weather patterns directly with four other districts: the district shows positive yield trend results which match Nashik but the district shows different results from Solapur and Bellary and Dharwad; the district has intermediate scale which lies between Solapur and Nashik and Bellary and Dharwad; the district shows higher yield volatility combined with lower stability compared to Nashik and Solapur while showing yield differences between periods that reach borderline statistical significance ($p = 0.071$). The yield trends show importance only in Ahmednagar and Nashik while Nashik shows period effects which impact yield and both regions exhibit different levels of yield stability and volatility (Nashik and Solapur more stable, Ahmednagar and Dharwad more volatile). The district-level results which include direct comparisons between Ahmednagar and other districts require different policy and management solutions.

### Recommendations

Based on the all-district statistical evidence and variability profiles, the following actions are directly supported:

- *District-targeted water-risk management*: The districts which experience extreme climate variations and drought risks need to focus on efficient irrigation systems while their drought management strategies should be their second most important task. The smaller districts of Dharwad need to improve their water governance system while their monitoring system should become better. The Solapur region requires better water governance and monitoring systems to handle production increases which create more severe water supply interruptions.
- *Operational climate services*: District-level advisory system for planting and ratoon management and harvest scheduling needs seasonal rainfall monitoring together with heat-stress indicators which include days when the maximum temperature reaches or exceeds 35 degrees Celsius. The system provides critical support during high-risk periods identified by drought and moisture adequacy indices.
- *Stabilisation and resilience measures*: The districts which experience extreme weather conditions and irregular weather patterns should adopt risk management solutions which reduce environmental uncertainty through water conservation agricultural practices and weather-dependent insurance products.

### Future work

The existing baseline assessment can be enhanced through the inclusion of additional districts and more detailed spatial data at the taluka and farm level and through the application of econometric models and process-based models which enable to determine how different factors impact weather patterns and irrigation systems and technology adoption and policy implementation. The meteorological context of Nashik would benefit from extended weather records which include data from multiple weather stations that operate within the boundaries of large districts.

## Data availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Received: 8 January 2026; Accepted: 6 April 2026
Published online: 22 April 2026

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## Acknowledgements

The authors extend their appreciation to the Deanship of Research and Graduate Studies at King Khalid University for funding this work through Large Research Project under grant number RGP2/354/46. The authors acknowledge the support of data providers and agricultural departments for making production and meteorological data (IMD Pune) available for this analysis. Production and area data were obtained from the Directorate of Economics and Statistics (DES) via https://data.desagri.gov.in. Meteorological data were obtained from the India Meteorological Department, Climate Research and Services, Pune (IMD Pune) via https://www.imdpune.gov.in/.

## Author contributions

P.B.: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization, Visualization. I.J.: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. K.K.: Writing – review & editing, Investigation, Formal analysis. C.A.S.: Writing – review & editing, Funding acquisition, Formal analysis. S.K.: Writing – review & editing, Project administration, Supervision. S.A.K.: Writing – review & editing, Project administration, Supervision.

## Funding
The authors extend their appreciation to the Deanship of Research and Graduate Studies at King Khalid University for funding this work through Large Research Project under grant number RGP2/354/46.

## Declarations

## Competing interests
The authors declare no competing interests.

## Additional information
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