

A Geospatial Framework for Recurrent Kharif Drought Hotspot Mapping Using SPI-4 and Getis-Ord Gi* in Semi-Arid Maharashtra

Nilofar Jamadar^{1*}, Niranjani P V²

¹Department of geography, University of Madras, Guindy campus, Chennai 600025, Tamil Nadu, India

²Department of geography, University of Madras, Guindy campus, Chennai 600025, Tamil Nadu, India

*Corresponding Author: Nilofar Jamadar; jamadarn380@gmail.com

Abbreviation: GESS

Website: www.maned.org/journals

Received: 12-07-2026

Revised: 27-08-2026

Accepted: 16-09-2026

Key Words:

Kharif drought; SPI-4;
CHIRPS; ERA5-Land;
Getis-Ord Gi*;
drought recurrence;
hotspot analysis;
semi-arid Maharashtra;
geospatial analysis

Abstract

Drought is an irregular hydro climatological phenomenon whose incidence varies significantly both spatially and temporally, particularly in the semi-arid areas of Maharashtra. The present study adopts a geospatial methodology for mapping the Kharif drought hotspot areas on a taluka scale using CHIRPS rainfall, SPI-4 and the Getis-Ord Gi* index. The monthly rainfall values from 2000 to 2025 were downloaded for 140 talukas of 14 drought-prone districts using Google Earth Engine. The precipitation amounts occurring from June to September were combined together to capture the Kharif season, and the SPI-4 values for each of the taluka-years were derived based on the gamma distribution. Years with SPI-4 values ≤ -1 were identified as the drought years and the number of drought incidences was calculated to determine the recurrence over the 26-year period. Getis-Ord Gi* was later applied to identify the spatial clustering of the recurrent drought. In all, 3,640 observations of taluka-years were made, out of which, 697 observations experienced drought conditions. There was marked variability in drought frequency in different talukas, with drought being observed in as many as seven consecutive years in some talukas during the study period. Using hotspot analysis, 29 out of 140 talukas (20.7%), which includes 9 talukas at 99% confidence level, 9 talukas at 95% confidence level and 11 talukas at 90% confidence level, were found to be significant high-recurrence drought hotspots. CHIRPS-based drought assessment was validated independently using ERA5-Land rainfall dataset. Correlation between the two datasets was moderate, with Pearson and Spearman correlation coefficients being 0.502 and 0.574, respectively. Agreement between the drought categories was 76.9% with Cohen's Kappa coefficient being 0.348. Validation of historical drought periods using document records was also performed, and agreement was found for 2001-2004, 2008-2009 and 2014-2015. Thus, it can be concluded that Kharif drought has a spatial clustering tendency and not a random distribution pattern in the study region. The proposed framework based on spatial hotspot analysis along with temporal recurrence, independent rainfall data validation and historical agreement can be effectively used for identifying drought hotspots for drought management purposes.

INTRODUCTION

One of the common hydroclimatic hazards associated with prolonged and unusual shortage of precipitation causing adverse impacts on agriculture, water resources, ecosystems and livelihoods of rural populations are droughts. Being among the gradual types of hazards, drought is characterized by variation in terms of duration, severity, frequency and areal extent. Drought in India, where agricultural output depends greatly on southwest monsoon rains, is likely to be strongly associated with monsoon precipitation and its variability. Hence, the assessment of the spatial and temporal variability of drought events is necessary for their monitoring and planning of agriculture and water management.

As for the meteorological drought, it is linked mainly to shortage of rainfall and assessed through the use of precipitation-based drought indices. The Standardized Precipitation Index (SPI) suggested by (McKee et al.,1993) is one of the most widely used indexes that is based only on precipitation and calculated for different time scales. SPI-based researches reveal the presence of considerable spatial and temporal variability of drought conditions in India. (Kumar et al.,2015) identified consider.



Copyright: © 2026 by the authors

Licensee: ManEd Research Foundation.

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY 4.0) license.

the conditions of meteorological drought using SPI calculated for monsoon precipitation and indicated some years with significant drought (e.g. 2002). (Pandit, 2018) evaluated the conditions of meteorological drought in the semi-arid Maharashtra using SPI for June – September rainfall and noted the importance of rainfall variability for assessing the conditions of drought and planning agriculture. Moreover, (Dakhore et al.,2020) analyzed the conditions of drought in Maharashtra using SPI calculated at annual, southwest monsoon and post-monsoon time scales for 326 talukas of Maharashtra, thus demonstrating the value of SPI for the assessment of the frequency, persistence and intensity of drought at administrative scale. In addition, (Prajapati et al.,2021) evaluated meteorological drought in drought-prone Marathwada using multi-time-scale SPI.

Geospatial techniques and remote sensing methods have been widely employed in addition to recent drought studies in order to perform the spatial evaluation of the same. Utilization of gridded rainfall data sets such as CHIRPS has made possible the consistent estimation of rainfall in those regions where there is no station. (Funk et al.,2015) identified CHIRPS as being an archive of long-term high-resolution precipitation data which is quite beneficial in analysis of rainfall variability and climatic hydro extremes. However, even though there have been many drought frequency, severity and temporal pattern related studies done in Maharashtra, not much efforts have been put in the identification of drought prone regions and their statistical significant clusters. The recent studies on drought based on SPI have further added value to multi-time-scale drought characterization and its relation with agriculture yields in Marathwada region, thus emphasizing the importance of SPI based drought analysis at taluka level in drought prone regions (Prajapati et al., 2021; Swain et al., 2022; PCA-based composite drought index study, 2022).

Spatial Statistics is one of the methods which can help identify regions with high recurrence of drought and differentiate them from drought occurrence due to randomness. Getis-Ord Gi* statistics can be used in order to determine statistically significant spatial clustering of high or low values. (Getis and Ord,1992) came up with the distance-based statistic for the spatial association whereas (Ord and Getis, 1995) expanded it into local spatial statistics for hotspots detection. Thus, the use of this method in the detection of recurrence of drought can provide more insights compared to the conventional year-wise drought assessment.

On the other hand, the current paper presents a geospatial methodology for the identification of recurrent Kharif drought hotspots at 140 taluka units of the drought prone regions of Maharashtra from 2000 to 2025. In order to calculate Kharif rainfall and SPI-4 from June to September, CHIRPS data is used whereas $SPI-4 \leq -1$ is considered in order to define drought events. The drought recurrence rate for each taluka unit during the 26 years period is calculated and analyzed in order to determine the recurrent drought hotspots using Getis-Ord Gi* statistic. The results are validated using independent rainfall data sets from ERA5-Land and historical consistency.

STUDY AREA

The analysis concentrates on 14 drought-affected districts from semi-arid Maharashtra in India, and spans a total of 140 taluka level spatial units. The study area comprises the semi-arid regions of Vidarbha, Marathwada, and surrounding semi-arid regions that suffer from high spatial variability of monsoon rainfall and droughts in agriculture. The study location lies approximately between 17°N to 21°N latitudes and 74°E to 79°E longitudes. The selected area was considered appropriate for Kharif drought assessment due to its monsoonal rainfall and high spatial variability of rainfall and dry periods. The selected district and taluka locations are marked on the map.

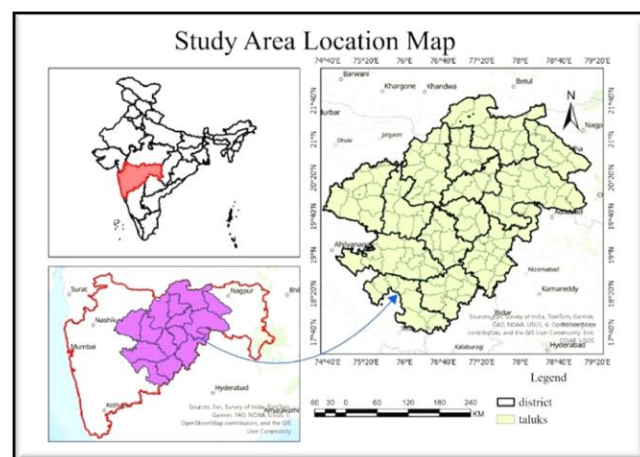


Fig.1: Study Area Map

DATA AND METHODOLOGY

Table 1: Data sources

Data	Source	Period	Spatial/Temporal Resolution	Purpose
Taluka Boundary Shapefile	Survey of India	2025	Taluka level	Study-area delineation and spatial analysis
CHIRPS Rainfall	CHIRPS / Google Earth Engine	2000–2025	Monthly	Kharif rainfall and SPI-4 calculation
ERA5-Land Rainfall	ERA5-Land / Google Earth Engine	2000–2025	Monthly	Independent rainfall validation
Historical drought evidence	Government/official and academic sources	2000–2025	Year-wise	Historical drought consistency

Methodology

This study utilizes geospatial, rainfall, and reanalysis data to investigate Kharif drought recurrence and their spatial clustering in semi-arid Maharashtra. Boundary information on taluka was acquired from Survey of India and used to define the 140 selected taluka polygons. Monthly precipitation data during 2000–2025 were collected from the Climate Hazards Center InfraRed Precipitation with Station data (CHIRPS). CHIRPS is a quasi-global precipitation dataset, which is high resolution, based on the combination of satellite information with the station and is extensively used in precipitation and droughts studies (Funk et al., 2015). Rainfall data were extracted using Google Earth Engine and were arranged on taluka, year, and month basis.

In order to have an independent verification, rainfall data from ERA5-Land rainfall product were considered as a different rainfall dataset. ERA5 is a reanalysis system which provides global coverage of atmospheric and land surface condition for long-term use (Hersbach et al., 2020). The respective Kharif rainfall data were extracted for the same taluka and year combinations as for the CHIRPS dataset.

Monthly rainfall observations were spatially matched with the selected talukas and screened for duplicates and missing values. Rainfall observations were aggregated from June to September months as an indicator of the Kharif season. This gave one seasonal rainfall observation per taluka per year for the period

2000 to 2025, giving in total 3,640 taluka-year observations (140 talukas x 26 years).

Kharif Season Rainfall and SPI-4

For the determination of meteorological drought, the Standardized Precipitation Index (SPI) was used, which was first developed by McKee et al. (1993). SPI is a precipitation-based drought index that converts the cumulative rainfall value into a standardized value, which is a probability-based value, enabling comparability of dry and wet conditions geographically and through time. The process of calculation of SPI was done in accordance with the procedures followed for SPI calculation explained by McKee et al. (1993) and Guttman (1999).

In this study, SPI for four months was chosen, which means that SPI-4 will be determined for the Kharif season. The accumulated rainfall from June to September in each taluka was fitted to a probability distribution. Then, the cumulative probability derived from the fitting was transformed to the standard normal distribution. SPI can be calculated as:

$$SPI = \Phi^{-1}[F(X)]$$

where X denotes the accumulated rainfall, F(X) is the cumulative probability corresponding to rainfall value X and Φ^{-1} is the inverse standard normal distribution.

The resulting values of SPI have an average value close to zero, where values less than zero are below average rainfall and those above zero represent above average rainfall. A threshold of $SPI \leq -1.0$ was considered as drought threshold, where SPI value of ≤ -1.0 represents drought. Hence, each taluka was-

year wise classified as drought or non-drought.

Assessment of Drought Recurrence

To determine the persistence of drought, the number of drought years was calculated per taluka within the 26 years of study. While in a single-year drought analysis, the identification of talukas prone to drought is straightforward, a drought recurrence analysis is capable of detecting the talukas that consistently experience drought conditions in different years.

The drought recurrence percentage per taluka was calculated using the following equation:

$$R_i = (D_i / N) \times 100$$

Where R_i = drought recurrence percentage for taluka i , D_i = number of drought years observed for taluka i and N is the total number of study years (26).

These results were integrated to the taluka boundary layer and taken as the main attribute in hotspot analysis. Apart from the drought recurrence percentage, the individual drought years were also kept to establish the temporal trend of drought recurrence and the important drought years within the study area.

Getis-Ord G_i^* Spatial Hotspot Analysis

A Getis-Ord G_i^* was used to determine the spatial clusterings of recurrent drought events. Getis and Ord (1992) proposed the G -statistic for the determination of spatial association, while Ord and Getis (1995) further improved on the statistics for determination of significant spatial clusters of high and low values. The G_i^* statistic is especially suitable for the current analysis because the intention of the analysis is to test whether the talukas with high drought recurrence form significant spatial clusters and not only map the high recurrence.

Getis-Ord G_i^* statistic was computed using the following equation:

$$G_i = [\sum_j w_{ij}x_j - \bar{X}\sum_j w_{ij}] / [S\sqrt{\{[n\sum_j w_{ij}^2 - (\sum_j w_{ij})^2]/(n-1)\}}]^*$$

Where x_j = the drought recurrence value for feature j , w_{ij} = the spatial weight between features i and j , n is the number of spatial features, $\bar{X}$ is the mean recurrence value and S is the standard deviation of the recurrence values.

The analysis was done in ArcGIS Pro based on the spatial relationship among the neighboring talukas. The resultant z -scores and statistical significance level of the G_i^* values have been used to identify the high value and low value clusters. Positively

significant G_i^* values are identified as clusters of talukas having high recurrence of drought and are hence regarded as recurrent drought hotspots. The G_i Bin Classes have been used to identify the confidence level in the identification of the hotspots, with +1, +2 and +3 denoting the confidence levels of approximately 90%, 95% and 99%, respectively.

Independent Rainfall Validation

The rainfall portion of the drought assessment has been independently validated through ERA5-Land rainfall dataset. CHIRPS and ERA5-Land Kharif rainfall estimates have been compared against each other for the same taluka-year observations. Correlation between the two rainfall datasets has been studied using Pearson correlation and Spearman Rank Correlation. Pearson correlation has been used to test the linear relationship, while Spearman correlation has been used to assess the consistency of the ranking of the rainfall.

Difference in magnitude of the two datasets has been measured using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and mean bias:

$$RMSE = \sqrt{[(1/n)\sum_i (C_i - E_i)^2]}$$

$$MAE = (1/n)\sum_i |C_i - E_i|$$

$$Bias = (1/n)\sum_i (C_i - E_i)$$

where C_i is CHIRPS rainfall, E_i is ERA5-Land rainfall and n is the total number of matching observations. In addition to that, percentage bias has been used to estimate the relative systematic difference between the two rainfall datasets. Agreement in drought/non-drought classification between the two datasets has been tested using percentage agreement and Cohen's Kappa statistic. Cohen (1960) defined the Kappa statistic for measuring agreement between categorical classification and taking into account the possibility of agreement due to chance. The Kappa coefficient has been calculated as:

$$\kappa = (P_o - P_e) / (1 - P_e)$$

where P_o is the observed agreement and P_e is the expected agreement by chance.

Historical Consistency of Droughts

A corresponding historical consistency evaluation was carried out in order to find out whether the identified main drought years according to the analysis of SPI-4 are consistent with the drought and rainfall-deficit years recorded in Maharashtra. The years with the highest percentage of drought-stricken talukas were compared with the scientific literature,

official documents, and historic records of drought, rainfall shortage, agriculture pressure, and water scarcity in Maharashtra.

In particular, special attention was paid to the identified main drought periods, namely 2001–2004, 2008–2009, and 2014–2015. Such a comparison was applied as an additional qualitative validation of the temporal consistency of drought identification through SPI. Rainfall data were extracted using Google Earth Engine, rainfall processing, SPI calculation, drought classification, and recurrence analysis, and Getis-Ord Gi* hot spots were created using Python. ArcGIS Pro was used for spatial analysis.

RESULTS AND DISCUSSION

Temporal Characteristics of Kharif Drought

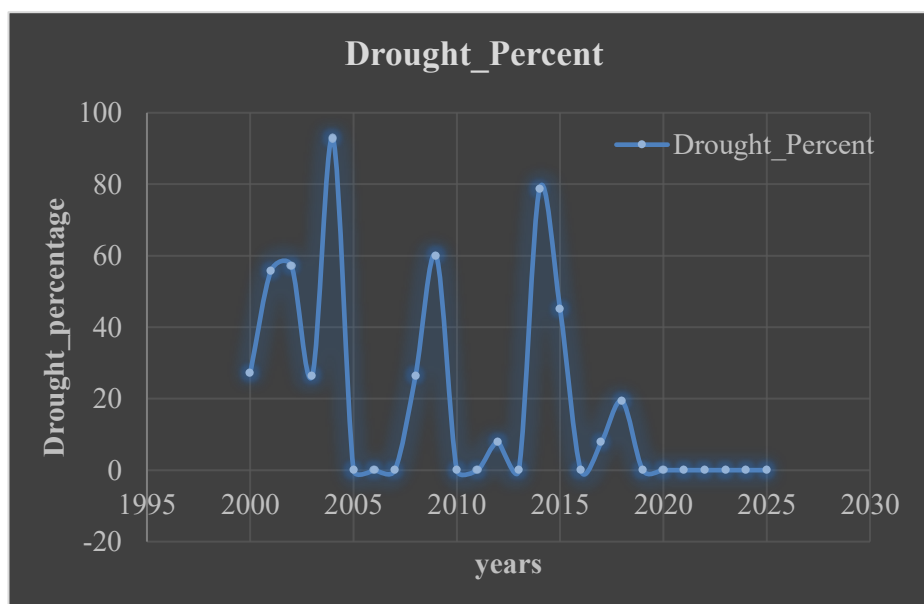


Fig.2: Year-wise percentage of talukas affected by Kharif drought based on SPI-4 (2000–2025).

This temporal distribution demonstrates the fact that droughts occur in certain years more often compared to other years. For instance, high drought frequencies were detected during the early 2000s, 2008–2009, and 2014–2015. On the contrary, some years, such as 2005–2007, 2010–2011, 2013, and 2016, were characterized by a lack of taluka-level drought at the defined SPI-4 threshold. It should be mentioned that such variability proves the effectiveness of SPI-4 in detecting differences between Kharif precipitation conditions for particular years. It is also worth noting that widespread drought years defined using SPI-4 demonstrate historical agreement with drought and rainfall deficit conditions for Maharashtra,

The analysis based on the SPI-4 method gave rise to 3,640 observations in terms of taluka-year, involving 140 talukas for 26 years between 2000 and 2025. SPI scores varied between -2.11 and 2.87 , with an average score close to zero and the standard deviation of about 1, which means that the proper standardization of the precipitation time series has been achieved. Taking into account the criterion of $SPI-4 \leq -1.0$ as drought indicator, 697 taluka-year observations (19.4%) have been characterized by drought, and 2,934 observations – by no drought. The distribution of drought occurrence over years is highly variable (Figure 2). The maximum share of drought-affected talukas has been observed in 2004 (92.86%), 2014 (78.57%), 2009 (60.00%), 2002 (57.14%), and 2001 (55.71%). Drought occurrence has also been fairly high in 2015 (45.00%).

especially during 2001–2004, 2008–2009, and 2014–2015.

Spatial Distribution of Kharif Drought Recurrence

In the drought recurrence map, there are numbers of drought years for each taluka under Kharif drought conditions over the 26-year study period, ranging from 2000 to 2025, based on the SPI-4 threshold of ≤ -1.0 . The drought recurrence ranged from three to seven years among the 140 talukas, suggesting the variation of drought occurrences within the study area.

Some talukas had drought recurrence, and the highest drought recurrence was six to seven years for Partur, Paithan, Jalna, Badnapur, Jafrabad, Chickli, Washi, Ambejogai, Ahmadpur, Kandesh, Udgir,

Palam, and Ked. This taluka is an indication of locations that have repeated droughts in terms of rainfall deficit within the Kharif season for the study period. However, the drought recurrence map only provides information about the drought frequency for individual talukas without giving the spatial

clustering of drought occurrences in neighboring talukas with drought recurrences. Consequently, further analysis was carried out on the drought recurrences through the Getis-Ord G_i^* hotspot analysis.

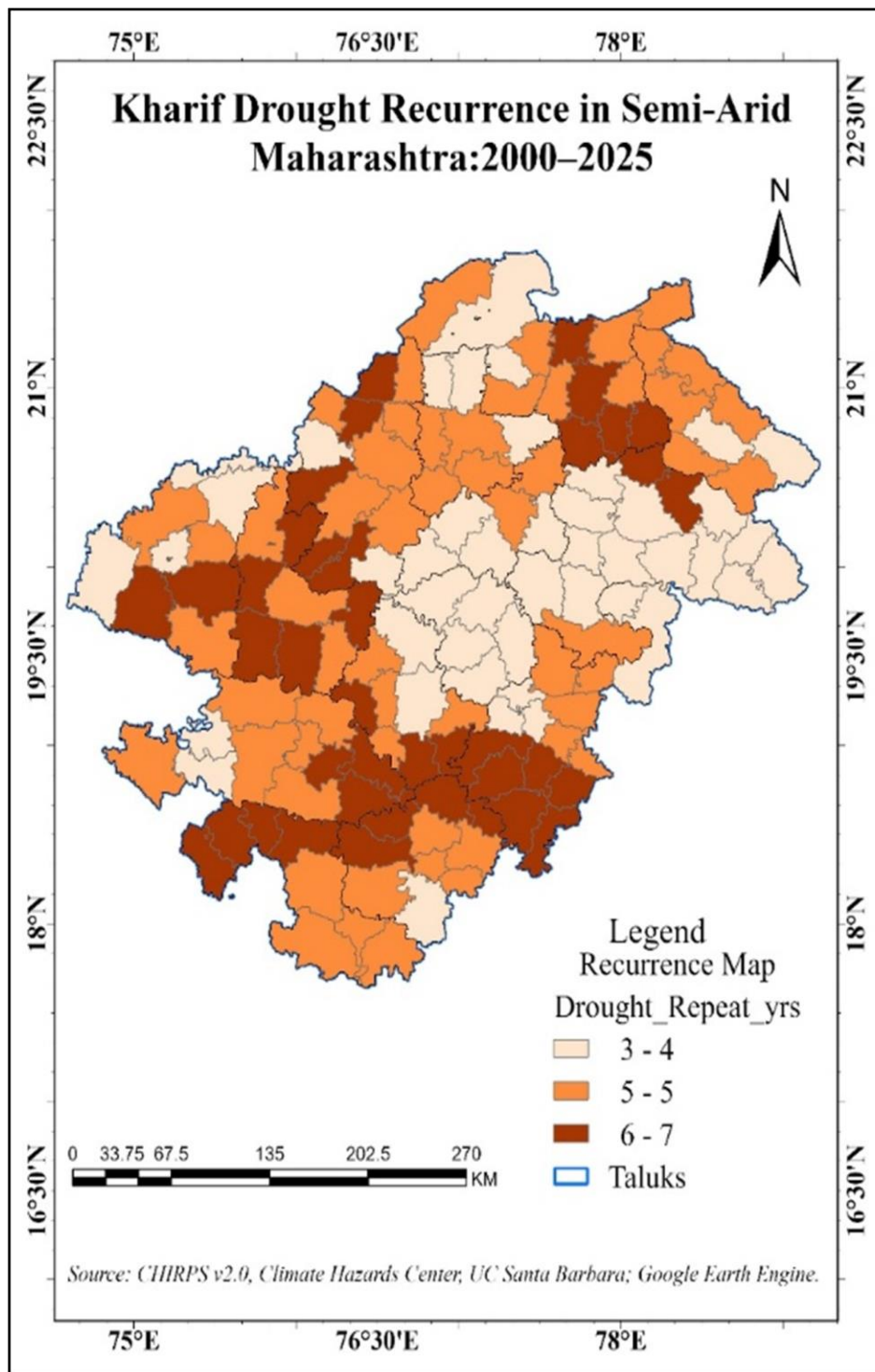


Fig.3: Kharif Drought Recurrence in Semi-Arid Maharashtra (2000–2025)

Getis-Ord Gi* Hotspot Analysis

Gi* statistics of Getis and Ord have been used to test whether the talukas with high drought recurrence values constitute statistically significant spatial clusters. According to the analysis, there are 29 talukas with high drought recurrence values which constitute 20.7% of total talukas that have been tested as statistically significant hotspots in the study region. Among these significant hotspots, 9 talukas constitute statistically significant at 99%, 9 talukas constitute statistically significant at 95%, and 11 talukas constitute statistically significant at 90%

confidence level. These significant hotspot clusters are mostly located in Nanded, Dharashiv, Beed, Perbhani, Jalna, Latur, Amravati, and Buldhana districts. As positive and statistically significant Gi* values show, the talukas with high drought recurrence values are not randomly distributed but rather geographically concentrated. Consequently, it could be stated that a taluka with high drought recurrence constitutes a hotspot only if it is surrounded by other neighboring talukas with high drought recurrence values.

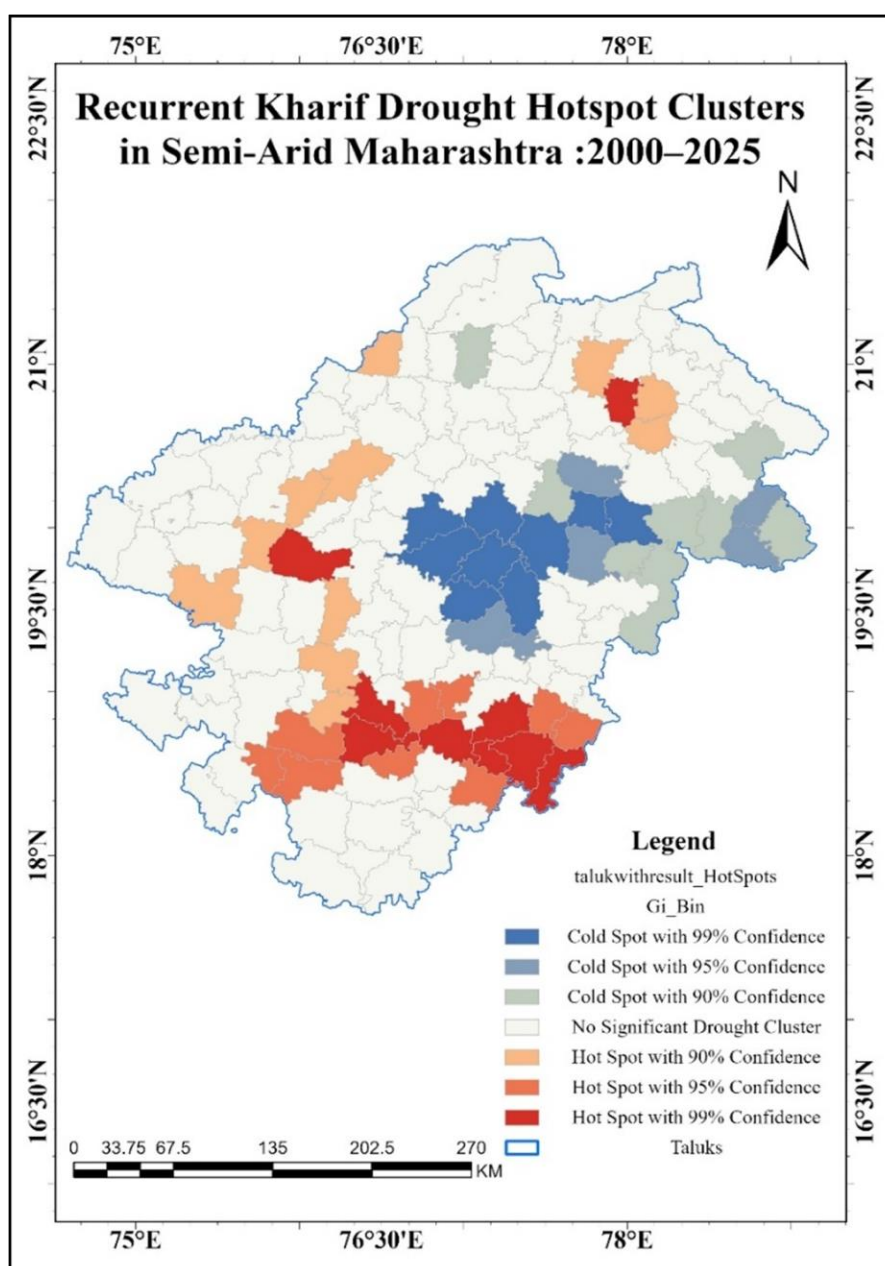


Fig.4: Recurrent Kharif Drought Hotspot Clusters in Semi-Arid Maharashtra (2000–2025).

The hotspot clusters suggest the existence of areas where recurrent drought of Kharif season is spatially clustered. Such areas could receive more attention while monitoring droughts, planning agriculture, managing groundwater resources and implementing drought mitigation measures. As a result, the significance of the G_i^* statistics suggests that recurrent Kharif drought follows a certain pattern of spatial clustering instead of being spatially random.

Independent Validation of CHIRPS Rainfall

The validity of the CHIRPS rainfall database used for calculating SPI-4 was verified by independent comparison with rainfall data from ERA5-Land for the corresponding Kharif periods of 2000–2025. ERA5-Land was used here as an independent rainfall product instead of ground-truth rainfall data. Comparison was made for the same taluka-year data as was used for the analysis of the CHIRPS rainfall.

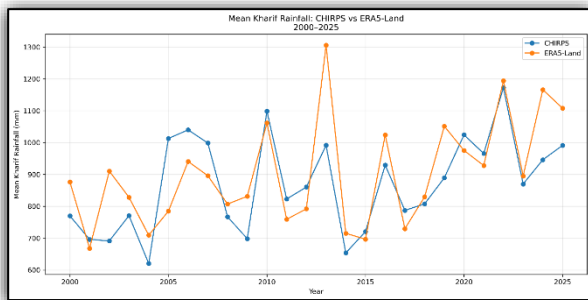


Fig.5: Year-wise Comparison of Mean Kharif Rainfall Derived from CHIRPS and ERA5-Land, 2000–2025.

The year-by-year comparison indicated that there is quite a similarity between the two datasets in respect to the variations of the Kharif rainfall in the study period, although variation in terms of rainfall magnitude was noticed in some years. The two datasets seemed to follow the same pattern of wet and dry spells, suggesting similarity in terms of the time-related behaviour of Kharif rainfall. For more insights into the correlation of the two datasets, a scatter plot was created based on the CHIRPS and ERA5-Land Kharif rainfall records.

A positive relationship can be seen between CHIRPS and ERA5-Land rainfall estimates from the scatterplot. However, the observations are scattered around the 1:1 reference line. The Pearson correlation coefficient ($r = 0.502$) suggests a moderately strong linear relationship while the Spearman rank correlation coefficient ($\rho = 0.574$) shows moderate agreement in rankings of wetter and drier periods. The RMSE value of 258.9 mm shows that there is a difference in magnitude of the rainfall estimates between the two datasets. There was 76.9% agreement in drought classification from the two rainfall datasets, and a Cohen's Kappa value of 0.348 shows fair agreement above chance level.

It is therefore concluded that although there are differences in rainfall amounts estimated from the two products, there is similarity in the identification of drought/non-drought situations in a considerable proportion of cases.

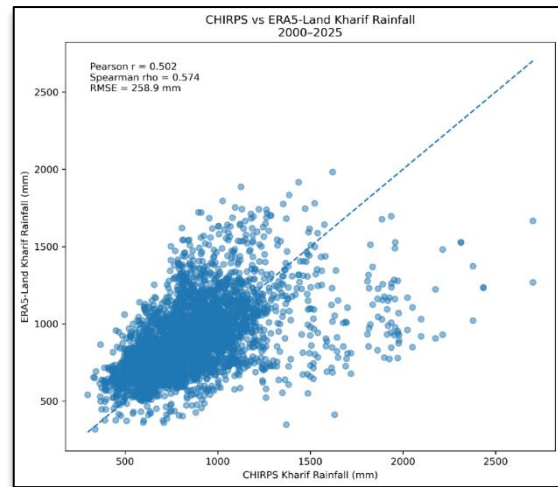


Fig.6: Scatter Plot of CHIRPS and ERA5-Land Kharif Rainfall Estimates, 2000–2025.

Previous comparisons of the precipitation products of satellite and reanalysis data for the Indian region have indicated variability in their performances depending on location and season, implying that estimates of rainfall from different precipitation products are not expected to agree completely (Dubey et al., 2021). CHIRPS was developed specifically for the purpose of monitoring rainfall variability and extremes using satellite data along with station data (Funk et al., 2015), whereas ERA5-Land includes rainfall estimates from reanalysis data (Muñoz-Sabater et al., 2021). Thus, the present comparison is considered cross-dataset validation independent of rainfall accuracy.

In general, the relatively strong correlations, 76.9% agreement in classification, and Kappa value reveal that there is support for the application of CHIRPS rainfall for the current study of droughts. On the other hand, the differences found in the datasets should be considered as the limitation of the study since it shows that validation cannot be taken to mean the equivalence of CHIRPS and ERA5-Land.

Consistency of Major Drought Years in History

Another validation conducted in the study is the verification of major drought years found from the SPI-4 with the recorded history of drought, rainfall deficiency, and agricultural and water stress in the state of Maharashtra. There was consistency found between the drought years found and recorded history.

Drought Year	Official/Authoritative Evidence Source	Consistency
2001	WEEKLY DROUGHT REPORT: No.4 (As on 21-05-2001) Government of India Ministry of Agriculture (Department of Agriculture & Cooperation) www.ndmindia.nic.in GENERAL OVERVIEW OF DROUGHT- 2001	Strong
2002	India: Southwest monsoon 2002 end-of-season report Format: Analysis, Source: Govt. India, Posted 4 Oct 2002 Originally published 4 Oct 2002	Strong
2003	Chavadekar, A., & Kashid, S. S. (2016, December). Historical drought analysis of Maharashtra state by using SPI Index. In <i>Techno-societal 2016, international conference on advanced technologies for societal applications</i> (pp. 1097-1104). Cham: Springer International Publishing.	Consistent
2004	Chavadekar, A., & Kashid, S. S. (2016, December). Historical drought analysis of Maharashtra state by using SPI Index. In <i>Techno-societal 2016, international conference on advanced technologies for societal applications</i> (pp. 1097-1104). Cham: Springer International Publishing.	Strong
2008	REPORT ON THE DYNAMIC GROUND WATER RESOURCES OF MAHARASHTRA (2008-2009) Prepared by Groundwater Surveys and Development Agency, GoM & Central Ground Water Board, Central Region, Nagpur, GoI	Consistent
2009	India: Declaration of drought/drought-like conditions in 2009 by states as on 18 Aug 2009 Format: News and Press Release, Source: Govt. India ,Posted 18 Aug 2009, Originally published 18 Aug 2009	Consistent
2014	2014 drought in Maharashtra worse than the 2012 one Format: News and Press Release, Source: India Water Portal Posted 24 Dec 2014, originally published 23 Dec 2014	Strong
2015	Zachariah, M., Kumari, S., Mondal, A., Haustein, K., & Otto, F. E. (2023). Attribution of the 2015 drought in Marathwada, India from a multivariate perspective. <i>Weather and Climate Extremes</i> , 39, 100546.	Strong

Table 2. Historical Consistency of Major SPI-4 Drought Years, 2000–2025

Comparison of the SPI-4 data was also done with the droughts in the history of Maharashtra. The years when drought occurred based on the results of analysis were found to be consistent with the reported rainfall deficit and agriculture/water shortages for the years 2001-2004, 2008-2009, and 2014-2015 (Table 2). The year with the maximum drought area was 2004 (92.86%) and the year that came second was 2014 (78.57%), which is also consistent with drought in the history.

DISCUSSION

The findings indicate that Kharif drought in semi-arid Maharashtra is characterized by both spatial and temporal recurrence. The identification of widespread drought years with SPI-4 as well as repeated occurrences of droughts in selected talukas is consistent with previous studies indicating spatial and temporal variations of droughts in Maharashtra (Dakhore et al., 2020; Swain et al., 2022a, 2022b). In addition, the use of the Getis-Ord Gi* hotspot analysis helped gain insight into the spatial distribution of recurrent droughts. The statistical test revealed significant high value drought clusters mostly located in the districts of Nanded, Dharashiv, Beed, Perbhani, Jalna, Latur, Amravati, and Buldhana. In this regard, the districts described

above can be referred to as the major drought hot spot areas revealed by the statistical analysis. The distribution pattern of the clusters reveals that the talukas having high recurrence of droughts are geographically linked and occur adjacent to drought prone talukas.

The talukas with high drought recurrence were Partur, Paithan, Jalna, Badnapur, Jafrabad, Chickli, Washi, Ambejogai, Ahmadpur, Kandesh, Udgir, Palam, and Ked. These talukas had drought conditions about six to seven times within the study period. Recurrent drought occurrence in these talukas suggests that these areas are at risk from drought due to rainfall, and that they are prone to recurrent droughts in Kharif season. The majority of the high recurrence talukas are situated within or around the statistically significant hot spots districts. Identification of 29 statistically significant hot spots for high drought recurrence value suggests spatial structure in the recurrence of drought. It is beneficial to use Getis-Ord Gi* method since this will identify places in which high drought recurrence values are clustered around other high values and hence geographically related drought-prone locations (Getis and Ord, 1992; Ord and Getis, 1995). This is more meaningful compared to analyzing drought years separately.

The CHIRPS-ERA5-Land comparison gave more evidence to prove the reliability of the rainfall-based analysis. While moderate correlations and decent classification performance may point to the divergence of the two data sets, the similarity of their temporal behavior proves the general reliability of the drought signal based on CHIRPS data. Historical analysis revealed that there were several years when droughts were registered based on SPI-4 drought analysis and drought and rain deficiency periods were recorded in Maharashtra.

Overall, the combination of SPI-4 drought analysis, recurrence analysis, Getis-Ord Gi* hot spot analysis, rainfall data analysis, and historical information gives a full picture of drought risk in semi-arid Maharashtra. The detected hot spots and high-recurrence regions should be considered priority areas for drought monitoring and management.

CONCLUSION

In this study, the geospatial framework was developed for identifying Kharif drought hotspots in 140 talukas of semi-arid Maharashtra from the year 2000 to 2025. This geospatial framework used CHIRPS rainfall data, SPI-4, drought recurrence, historical drought, validation using ERA5-Land data, and Getis-Ord Gi* to find the hotspots of droughts. In this study, 3,640 taluka-year observations have been studied. Out of these 3,640 observations, 697 taluka-year droughts were identified where the drought threshold was $\text{SPI-4} \leq -1.0$. The findings of this study showed that there is a great deal of variability in Kharif droughts in terms of both time and space. The years when the greatest number of talukas were affected by drought were 2004, in which 92.86% of talukas faced drought conditions, then came 2014 (78.57%), 2009 (60%), 2002 (57.14%), and 2001 (55.71%). There was also considerable variation in drought recurrence in talukas; some talukas experienced drought conditions six to seven times. The talukas with the highest recurrence of drought include Partur, Paithan, Jalna, Badnapur.

According to the Getis-Ord Gi* statistics, there were 29 talukas (20.7% of the area studied) which are statistically significant recurrent drought hotspots at 90%, 95%, and 99% confidence level. The recurrent drought hotspots were mainly clustered in the areas of Nanded, Dharashiv, Beed, Perbhani, Jalna, Latur, Amravati, and Buldhana districts. Therefore, the results reveal that the recurrent drought conditions in semi-arid region of Maharashtra are spatially clustered and not randomly distributed.

The comparison of CHIRPS and ERA5-Land rainfall datasets further helped to establish the reliability of the rainfall-based drought evaluation method.

The moderate Pearson correlation (0.502), Spearman correlation (0.574), and drought-classification agreement of 76.9% show that despite some differences in the two data sources, CHIRPS was able to capture the general temporal trend of drought events. Moreover, the agreement of several widespread SPI-4 drought years with drought and rainfall deficit periods in Maharashtra gave more confidence in the results obtained. Thus, the suggested framework is an efficient way of recurrent Kharif drought-prone area identification through temporal drought analysis and statistically significant spatial hotspots detection. The hotspots districts and highly recurrent drought talukas could be prioritized for development of drought early-warning systems, climate resilient agriculture, groundwater recharge activities, watershed development, and water resource management. Also, this framework can be used for drought evaluation in other semi-arid regions of India with limited available data.

REFERENCES

1. Awasthi, N., Tripathi, J. N., Petropoulos, G. P., Gupta, D. K., Singh, A. K., & Kathwas, A. K. (2023). Performance assessment of Global-EO-based precipitation products against gridded rainfall from the Indian Meteorological Department. *Remote Sensing*, 15(13), 3443.
2. Dakhore, K. K., Karunakar, A., Jadhav, J. D., Kadam, Y. E., Waskar, D. P., & Kumar, P. V. (2020). Analysis of drought in Maharashtra by using the Standardized Precipitation Index. *Journal of Agrometeorology*, 22(Special Issue-1), 43–50.
3. Dubey, S., Gupta, H., Goyal, M. K., & Joshi, N. (2021). Evaluation of precipitation datasets available on Google Earth Engine over India. *International Journal of Climatology*, 41(10), 4844–4863.
4. Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and Psychological Measurement*, 20(1), 37–46.
5. Chuphal, D. S., Kushwaha, A. P., Aadhar, S., & Mishra, V. (2024). Drought Atlas of India, 1901–2020. *Scientific Data*, 11, 7.
6. Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—A new environmental record for monitoring extremes. *Scientific Data*, 2, 150066.
7. Getis, A., & Ord, J. K. (1992). The analysis of spatial association by use of distance statistics. *Geographical Analysis*, 24(3), 189–206.
8. Guttman, N. B. (1999). Accepting the standardized precipitation index: A calculation

- algorithm. *Journal of the American Water Resources Association*, 35(2), 311–322.
9. Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., De Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R. J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., de Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., & Thépaut, J.-N. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730), 1999–2049.
 10. Mahajan, D. R., & Dodamani, B. M. (2015). Trend analysis of drought events over Upper Krishna Basin in Maharashtra. *Aquatic Procedia*, 4, 1250–1257.
 11. McKee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology* (pp. 179–184). American Meteorological Society.
 12. Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., Boussetta, S., Choulga, M., Harrigan, S., Hersbach, H., Martens, B., Miralles, D. G., Piles, M., Rodríguez-Fernández, N. J., Zsoter, E., Buontempo, C., & Thépaut, J.-N. (2021). ERA5-Land: A state-of-the-art global reanalysis dataset for land applications. *Earth System Science Data*, 13(9), 4349–4383.
 13. Naresh Kumar, M., Murthy, C. S., Sessa Sai, M. V. R., & Roy, P. S. (2012). Spatiotemporal analysis of meteorological drought variability in the Indian region using standardized precipitation index. *Meteorological Applications*, 19(2), 256–264.
 14. Ord, J. K., & Getis, A. (1995). Local spatial autocorrelation statistics: Distributional issues and an application. *Geographical Analysis*, 27(4), 286–306.
 15. Swain, S., Mishra, S. K., & Pandey, A. (2022). Assessing spatiotemporal variation in drought characteristics and their dependence on timescales over Vidarbha Region, India. *GeoCarto International*, 1–23.
 16. Swain, S., Mishra, S. K., Pandey, A., & Dayal, D. (2022). Assessment of drought trends and variabilities over the agriculture-dominated Marathwada Region, India. *Environmental Monitoring and Assessment*, 194, 883.
 17. Tabassum, F., & Krishna, A. P. (2022). Spatiotemporal drought assessment of the Subarnarekha River Basin, India, using CHIRPS-derived hydrometeorological indices. *Environmental Monitoring and Assessment*, 194, 902.