Plant Archives **Vol. 25, Special Issue (ICTPAIRS-JAU, Junagadh) Jan. 2025 pp. 537-546**
e-ISSN:2581-6063 (online), ISSN:0972-5210

Plant Archives

Journal homepage: http://www.plantarchives.org
DOI Url : https://doi.org/10.51470/PLANTARCHIVES.2025.SP.ICTPAIRS-076

A COMPARATIVE ASSESSMENT OF OBSERVED AND ERA5 DATA FOR SPEI-BASED DROUGHT ANALYSIS IN THE SAURASHTRA REGION

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ABSTRACT

Estimating meteorological drought parameters such as severity, duration, and frequency to devise appropriate mitigation strategies is a complex task due to the intricate relationships between these parameters. This study compares Standardized Precipitation Evapotranspiration Index (SPEI) values from observed data and ERA5 reanalysis data at four stations in Saurashtra—Amreli, Junagadh, Jamnagar, and Targhadia—across seven-time scales (monthly, three-monthly, and seasonal). Using three comparison methods—Pearson correlation, historical seasonal drought severity, and drought frequency analysis. The correlation coefficients between observed and ERA5 data for the Standardized Precipitation Evapotranspiration Index (SPEI) show strong relationships across all time scales for the four Saurashtra stations. ERA5 performs best at longer time scales, with the highest correlations observed at the 6-month (SPEI6) scale, where it closely aligns with observed drought conditions. These findings suggest that ERA5 is particularly effective for capturing long-term drought trends, although its accuracy may improve with further calibration for short-term predictions. The observed and ERA5 data generally align in capturing broader wet and dry periods, despite occasional discrepancies in specific years, likely due to variations in data sources, modelling, or regional climate. ERA5 provides a good approximation of drought conditions in Saurashtra, especially in identifying “No Drought” and Severe Drought periods, though there are slight differences in Mild and Moderate Drought classifications. These variations suggest that ERA5 is sensitive to short-term fluctuations and can be useful for regional drought monitoring with minor adjustments for local conditions. It was found that ERA5 data closely aligns with observed data, providing reliable insights into drought conditions. The results highlight ERA5’s potential for operational drought monitoring, crop yield prediction and other applications, especially in regions with limited ground-based data.

Key words : ERA5 Reanalysis, SPEI, Drought Monitoring, Saurashtra.

Introduction

Drought is a recurrent natural disaster and climate extreme that significantly impacts humans, ecosystems, and the environment. It often begins as meteorological drought, marked by insufficient rainfall and high evapotranspiration rates. This then leads to agricultural drought, characterized by soil moisture depletion and reduced crop yields, followed by hydrological drought, which affects surface and groundwater supplies and finally socio-economic drought, causing economic losses and social distress.

Several indices are available to characterize meteorological droughts in terms of severity, duration, intensity and frequency, while also linking them to agriculture and water resources. Many commonly used meteorological drought indices, such as the Standardized Precipitation Index (SPI) (McKee *et al.*, 1993), Rainfall Anomaly Index (RAI) (Van Rooy, 1965), Drought Area Index (DAI) (Bhalme and Mooley, 1980), Decile Index (DI) (Gibbs and Maher, 1967), Percent of Normal Precipitation Index (PNPI) (Willeke *et al.*, 1994), Z-Score and China Z Index (CZI) (Ju *et al.*, 1997), rely solely on rainfall as their primary parameter.

Since the rainfall based indices does not account for changes in other climate variables, such as surface air temperature, it has a limitation in fully reflecting the effects of climate change (Won *et al*., 2020). To address this, the Standardized Precipitation Evapotranspiration Index (SPEI) was developed by Vicente-Serrano *et al.* (2010) include not only rainfall (supply) but also the climatic water demand by incorporating potential evapotranspiration (ETo). The SPEI retains all its advantages of SPI which is additional information on and potential evapotranspiration and hence gaining popularity in drought quantification (Adarsh *et al.*, 2018). In the Saurashtra region of Gujarat, India, Pandya *et al.* (2022) showed that SPEI was better corrected with crop yields of cotton and groundnut as compared to other indcies (Pandya, 2023) and it was better linked to agricultural drought (Pandya *et al*., 2022). Pandya *et al.* (2023) also developed drought severity-duration-frequency curves for the Saurashtra region using the Standardized Precipitation Evapotranspiration Index (SPEI).

Gathering information from numerous meteorological stations across a large region like Saurashtra on a monthly and timely basis is not practically feasible. Therefore, the use of open-source climatic data with high spatial and temporal resolution and extensive spatial and temporal coverage, with minimum latency, becomes essential.

In many regions, including large areas of India, the density of ground-based rain gauges is insufficient to capture the spatial and temporal variability of rainfall. This results in significant data gaps, making it challenging to monitor weather patterns, manage water resources and predict agricultural yields. In India, for instance, areas such as Gujarat and Rajasthan suffer from lower rain gauge densities, hindering accurate rainfall monitoring and drought condition assessments. The Bureau of Indian Standards (BIS) recommends specific rain gauge densities based on geographic features, but in rural and remote areas, rain gauge networks are often underdeveloped or poorly maintained, leading to discrepancies between ground-based data and actual conditions.

To address these challenges, several platforms provide access to climate-related data, including IMD Gridded data, NASA POWER, CHIRPS and ERA5, produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). Comparing open-source data products like ERA5 with observed station data is particularly important in regions with sparse rain gauge networks. ERA5, with its high spatial resolution of approximately 31 km and global coverage, offers a reliable solution by filling these data gaps with consistent and accurate climate information. Unlike other data products that may take several months to become available, ERA5 reanalysis data is accessible within a week, making it particularly valuable for time-sensitive applications.

ERA5 has been successfully used in operational drought monitoring tools and SPEI (Standardized Precipitation Evapotranspiration Index) calculations, as demonstrated by researchers such as Saha *et al*. (2021), Vicente-Serrano *et al*. (2022) and Santini *et al*. (2023). Its hourly estimates of precipitation and other climatic variables provide detailed information that complements sparse ground station data, improving the accuracy of climate and hydrological modeling. This is especially useful in areas with complex topographies, such as hilly or coastal regions, where local weather patterns may not be captured by existing rain gauge networks. In Saurashtra, for example, where rain gauge coverage is limited, ERA5 can help generate more accurate predictions of drought conditions, water availability, and crop yields.

Open-source data products like ERA5 also democratize access to high-quality climate data, which is often costly or inaccessible in developing countries. By providing free access to high-resolution climate data, ERA5 ensures that researchers, policymakers, and farmers in regions with low rain gauge densities can make informed decisions. Furthermore, ERA5's integration of data from satellites, ground stations and other sources improves the overall reliability and consistency of the data, making it a valuable resource for global climate and hydrological studies.

Comparing ERA5 with observed station data is crucial for validating the effectiveness of open-source data products in areas with limited ground-based monitoring. ERA5's ability to provide high-resolution, hourly climate data offers a powerful tool for overcoming the challenges posed by sparse rain gauge networks. By leveraging global datasets like ERA5, it is possible to enhance drought monitoring, water resource management, and agricultural planning, particularly in regions like Saurashtra where rain gauge coverage is inadequate. Open-source data products like ERA5 play a vital role in improving the accuracy and reliability of climate predictions, ultimately contributing to better-informed decision-making in regions with limited meteorological infrastructure (WMO, 2020; Hersbach *et al.*, 2020; Ramesh *et al.*, 2021).

The main objective of the present study was to compare observed stations and ERA5 based SPEI for Saurashtra region of Gujarat. This comparison will help improve the precision of drought monitoring, agricultural planning and water resource management by filling significant data gaps with reliable and high-resolution climate information and development of operation drought monitoring systems.

Materials and Methods

Study area and data used

The present study was done in the Saurashtra region of Gujarat, India. The Saurashtra region, located in the westernmost part of Gujarat State, India, lies between 20º30' to 23º N latitude and 69º to 72º E longitude. Spanning an area of 6.49 million hectares, it encompasses 11 districts. The region experiences a dry pre-monsoon period, followed by the southwest monsoon rains, which typically begin in mid-June and last between 20 to 37 days. Over 95% of the region's annual rainfall occurs between June and September. The climate is semi-arid and subtropical, with limited irrigation facilities and no perennial rivers. The present study was conducted using four stations of Saurashtra Amreli, Junagadh, Jamnagar and Targhadia (Fig. 1). The monthly rainfall and minimum and maximum data was collected for above stations were collected from two sources 1. Observed data of 1981 to 2023 (44 years) from June to November were collected from four Research Stations of Junagadh Agricultural University 2. ERA5 Reanalysis data downloaded

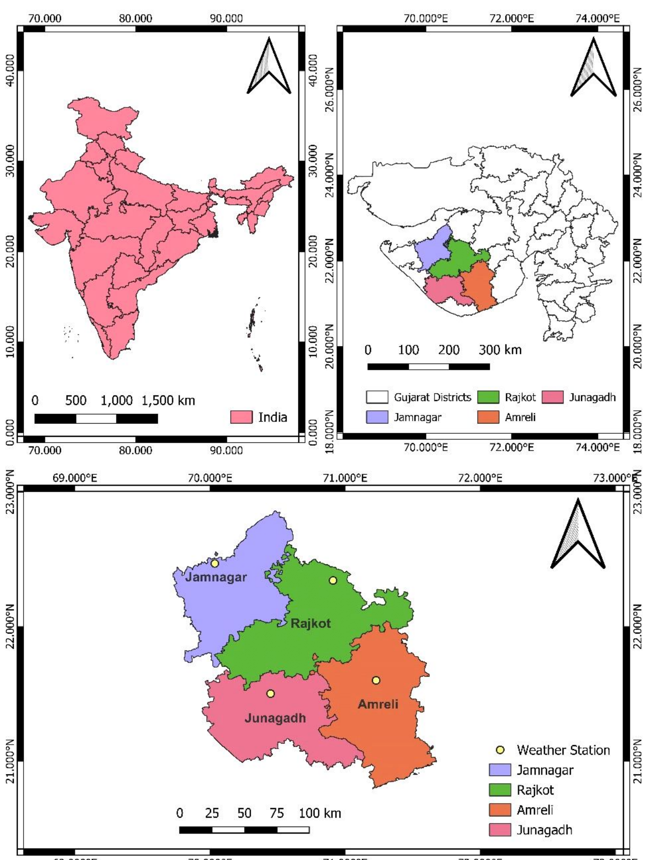


Fig. 1 : Study Area map.

Table 1 : Average Monthly Rainfall (mm) of various Stations.

S. no.	Station name	June	July	August	September
1	Amreli	130	215	136	128
2	Junagadh	202	357	211	165
3	Jamnagar	92	250	156	109
4	Targhadia	111	253	151	128

(Hersbach *et al*., 2020). The details of average monthly observed rainfall of various stations are given in the Table 1.

Computation of SPEI

The SPEI computation method given by Vicente-Serrano *et al*. (2010) is described below.

In the first step, Thornthwaite method (Thornthwaite, 1948) was used to estimate PET as shown in Equation (1).

$$PET = 16 \times \left(\frac{N}{12}\right) \times \left(\frac{NDM}{30}\right) \times \left(\frac{10T}{H}\right)^m \tag{1}$$

N is the mean hours of sunshine

NDM is the number of days in a month

H in the above Equation is the heat index, which can be calculated using Equation (2).

$$H = \sum_{j=1}^{12} \left(\frac{T_i}{5}\right)^{1.514} \tag{2}$$

T is the average temperature of each month in ^{0}C.

m is a coefficient used whose value depends on H.

The coefficient m can be obtained using Equation (3).

$$m = 6.75 \times 10^{-7} H^3 - 7.71 \times 10^{-5} H^2 + 1.79 \times 10^{-2} H + 0.492 \tag{3}$$

The difference between monthly precipitation and potential evapotranspiration is used for obtaining SPEI as given in Equation (4).

$$D_i = P_i - PET_i \tag{4}$$

Here, i represent the month. The D_i values so obtained are combined at various time scales. To standardize the original series, the log-logistic distribution function is applied following the approach of Vicente-Serrano *et al.* (2010). The probability density function used for characterizing the log-logistic function is provided in Equation (5).

$$f(x)=\frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1}\left[1+\left(\frac{x-\gamma}{\alpha}\right)^{\beta}\right]^{-2} \quad (5)$$

Here, α is the scale parameter, β is the shape parameter and γ is the origin parameter. Also, $\gamma > D < \infty$. The distribution parameters were determined using the L-moments procedure in Equations (6) to (8). The L-moments method is considered an easy but robust method (Ahmad *et al.*, 1988).

$$\alpha=\frac{(w_0-2w_1)\beta}{\left[\left(1+\frac{1}{\beta}\right)\right]\left[\left(1-\frac{1}{\beta}\right)\right]} \quad (6)$$

$$\beta=\frac{2w_1-w_0}{6w_1-w_0-6w_2} \quad (7)$$

$$\gamma=(w_0-\alpha\left[\left(\frac{1+1}{\beta}\right)\right]\left[\left(\frac{1-1}{\beta}\right)\right] \quad (8)$$

Here, [(β) is the gamma function of β.

The D series follows the log-logistic distribution whose probability distribution function is expressed in Equation (9).

$$F(x)=\left[1+\left(\frac{\alpha}{x-\gamma}\right)^{\beta}\right]^{-1} \quad (9)$$

Now, SPEI can be obtained using Equation (10)

$$SPEI=W-\frac{C_0+C_1W+C_2W^2}{1+d_aW+d_2W^2+d_3W^3} \quad (10)$$

where, $W=\sqrt{-2\ln(P)}$ for P ≤ 5 and P is the probability of exceeding a determined D value. The constants are $C_0 = 2.515517$, $C_1=0.802853$, $C_2= 0.010328$, $d_1=1.432788$, $d_2=0.189269$ and $d_3= 0.001308$.

The Drought severity classifications of SPEI in terms is given in Table 2.

Comparison of observed and ERA5 based SPEI

The SPEI was calculated for seven different time scales, including four monthly intervals (June, July, August and September), two three-month periods (June to August and July to September), and one six-month period (June to November, representing the seasonal scale). Three methods were used for comparison: 1) Pearson correlation between observed and ERA5-based SPEI values, 2) Historical seasonal drought severity based on the theory of run concept and 3) Drought frequency analysis across various categories.

Table 2 : Drought severity classifications of SPEI.

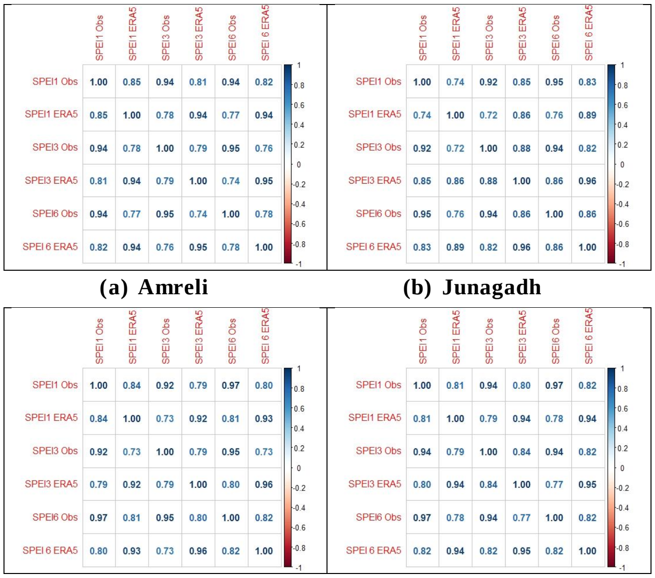
Category	SPEI
Extremely wet	≥ 2.0
Severely wet	1.5 to 1.99
Moderately wet	1.0 to 1.49
Mild wet	0.5 to 0.99
Near normal	-0.49 to 0.49
Mild drought	-0.5 to -0.99
Moderate drought	-1.0 to -1.49
Severe drought	-1.5 to -1.99
Extreme drought	≤ -2.0

Results and Discussion

Correlation between observed and ERA5 based SPEI

The correlation coefficients between observed and ERA5 data for the Standardized Precipitation Evapotranspiration Index (SPEI) for 1, 3 and 6 months across four stations in Saurashtra—Amreli, Junagadh, Jamnagar and Targhadia—reveal consistent relationships between the datasets (Fig. 2). In general, the observed and ERA5 data show strong correlations for all time scales, with the highest correlations typically found in the 6-month (SPEI6) time scale, followed by the 3-month (SPEI3) and 1-month (SPEI1) scales. For instance, in Amreli, the correlation between observed and ERA5 data for SPEI1 is 0.85, which rises to 0.94 for SPEI6, indicating that ERA5 is particularly effective in capturing long-term drought trends. Similar patterns are observed in the other stations, with the correlation between ERA5 and observed data improving for longer time scales.

In Junagadh, the correlation between observed and ERA5 data is slightly lower than in Amreli, especially for the 1-month scale, where it is 0.74. However, as the time scale increases, the correlation strengthens, reaching 0.95 for SPEI6. This suggests that ERA5 is more reliable for capturing longer-term drought conditions in Junagadh, similar to what is observed in Amreli. Additionally, ERA5 appears to be slightly more sensitive to variations in the 3-month and 6-month time scales compared to the 1-month scale. The pattern of correlation in Junagadh is consistent with the other stations, where ERA5 tends to perform better at longer time scales, capturing more of the broader drought trends.



(a) Amreli **(b) Junagadh**

(c) Jamnagar (d) Rajkot

Fig. 2 : Pearson Correlation Coefficient (r) between observed and ERA5 based SPEI for various stations.

particularly for longer durations, where it aligns well with observed drought data. The consistency of ERA5's performance across all four stations indicates that it is capable of tracking drought conditions, especially over longer periods, but may require further calibration to improve short-term drought predictions.

Targhadia follows a similar trend, with correlations between observed and ERA5 data reaching 0.81 for SPEI1, 0.94 for SPEI3 and 0.97 for SPEI6. The strongest correlation is again observed at the 6-month time scale, supporting the idea that ERA5 is better at capturing longer-term drought events. The correlation coefficients across all time scales indicate that ERA5 can reasonably replicate observed drought patterns in Targhadia, with the most reliable predictions occurring over extended time frames. The performance of ERA5 in Targhadia is consistent with the other stations, reinforcing the general trend that ERA5 is more effective at capturing drought conditions over longer periods.

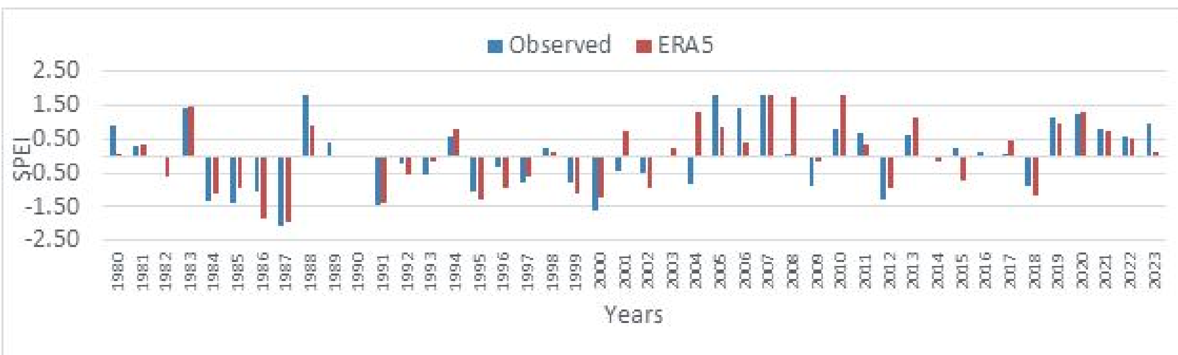


Fig. 3 : Seasonal SPEI drought severities based on observed and ERA5 data for Amreli station.

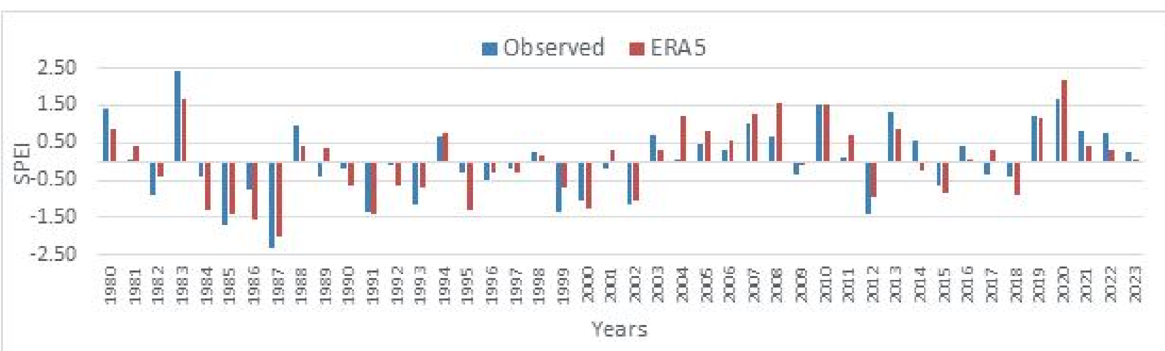


Fig. 4 : Seasonal SPEI drought severities based on observed and ERA5 data for Junagadh Station.

In Jamnagar, the correlation between observed and ERA5 data for the 1-month scale is 0.84, which is also relatively strong but slightly lower than in Amreli. The correlation strengthens significantly at the 6-month scale, reaching 0.97. Similar to Junagadh, ERA5's performance is less reliable at the 1-month scale but improves with longer time scales. This suggests that ERA5 can be an effective tool for drought monitoring in Jamnagar,

Overall, ERA5 data can be reasonably used to capture drought conditions in Saurashtra, especially for longer time scales. While the correlation between ERA5 and observed data is weaker at the 1-month scale, it improves significantly at the 3-month and 6-month scales, making ERA5 a useful tool for monitoring long-term drought trends. The high correlations for the 3-month and 6-month periods indicate that ERA5 effectively captures the broader patterns of drought in the region. Therefore, ERA5 data can be a valuable resource for drought monitoring and forecasting in Saurashtra, though it may be necessary to refine the model for short-term drought predictions, especially for the 1-month scale.

Historic Drought Severities by Theory of Run

The Theory of Run is a hydrological framework used to analyze historic drought severities by identifying and quantifying drought episodes based on cumulative deficits in variables like precipitation, soil moisture, or streamflow. A drought "run" is defined as a sequence of values consistently below a predefined threshold, with severity measured as the cumulative deficit, duration as the length of the run and intensity as the average deficit per time step. Here, the drought severity thresholds used are given in Table 2. This approach enables the detection of extreme drought events, trends in frequency and persistence, and localized impacts in specific regions, offering a robust method for assessing past droughts. While sensitive to threshold selection and requiring high-quality data, the Theory of Run provides valuable insights into the nature and impact of historic droughts, aiding in the development of future resilience strategies.

The Seasonal SPEI drought severities based on observed and ERA5 data for Amreli station is given in Fig. 3. Upon comparing the observed and ERA5 data, some notable patterns emerge. Generally, the two datasets exhibit similarities in capturing the overall trend of wetter or drier conditions for each year. For instance, in 1983, both observed and ERA5 data show positive SPEI values, indicating a wetter period. Similarly, in 1986 and 1987, both datasets portray severe drought conditions with negative SPEI values. However, discrepancies between the observed and ERA5 data are evident in certain years. Notable differences can be seen in 2004, where the observed data reports a notably negative SPEI value, indicative of drought, while the ERA5 data suggests a wetter condition with a positive SPEI value. Another instance is in 2010, where the observed data indicates wetter conditions, while the ERA5 data suggests drier conditions. Overall, while there are instances of divergence in specific years, the observed and ERA5 data generally align in capturing the broader trends of wetter and drier periods.

Upon examining the observed and ERA5 data for Junagadh Station (Fig. 4), several patterns emerge. Generally, both datasets show consistent trends in the severity of drought or wet conditions for most years. In 1983, 2007, 2010 and 2020, both observed and ERA5 data indicate notably positive SPEI values, suggesting wetter conditions. Conversely, in years like 1987 and 1998, both datasets reflect negative SPEI values, signaling drier conditions. However, discrepancies exist in certain years. Notably, in 2004, the observed data reports a positive SPEI value, indicating wetter conditions, while the ERA5 data suggests a drier situation with a negative SPEI. Similarly, in 2014, the observed data indicates positive SPEI, while the ERA5 data suggests a drier scenario.

Fig. 5 represents a comparison between observed and ERA5 data for Jamnagar, focusing on Standardized Precipitation Evapotranspiration Index (SPEI) values for various years. SPEI quantifies the deviation of precipitation and evapotranspiration from their long-term averages, offering insights into drought or wet conditions. Upon analyzing the observed and ERA5 data, both datasets generally exhibit consistent trends in the severity of drought or wet conditions for most years. In 1987, 1991 and 1999, both observed and ERA5 data indicate notably negative SPEI values, suggesting drier conditions. Conversely, in 2007, 2010 and 2019, both datasets reflect positive SPEI values, signaling wetter conditions.

However, discrepancies exist in certain years. Notably, in 2014, the observed data indicates a negative SPEI, implying drier conditions, while the ERA5 data suggests a less severe drought with a higher SPEI value. Similarly, in 2008, the observed data suggests a drier period, while the ERA5 data indicates a wetter condition.

Fig. 6 provides a comparison between observed and ERA5 data for Traghadia, focusing on Standardized Precipitation Evapotranspiration Index (SPEI) values for various years. SPEI quantifies the deviation of precipitation and evapotranspiration from their long-term averages, offering insights into drought or wet conditions. Upon analyzing the observed and ERA5 data, both datasets generally exhibit consistent trends in the severity of drought or wet conditions for most years. In 1983, 2004, 2007, 2010 and 2019, both observed and ERA5 data indicate notably positive SPEI values, suggesting wetter conditions. Conversely, in 1985, 1986 and 1991, both datasets reflect negative SPEI values, signaling drier conditions. However, discrepancies exist in certain years. Notably, in 1994, the observed data indicates a positive SPEI, implying wetter conditions, while the ERA5 data suggests a less severe wet period with a lower SPEI value. Similarly, in 2001, the observed data suggests a wetter period, while the ERA5 data indicates a drier condition.

Overall, the observed and ERA5 data generally align in capturing the broader trends of wetter and drier periods, despite instances of divergence in specific years. These

Fig. 5 : Seasonal SPEI drought severities based on observed and ERA5 data for Jamnagar Station.

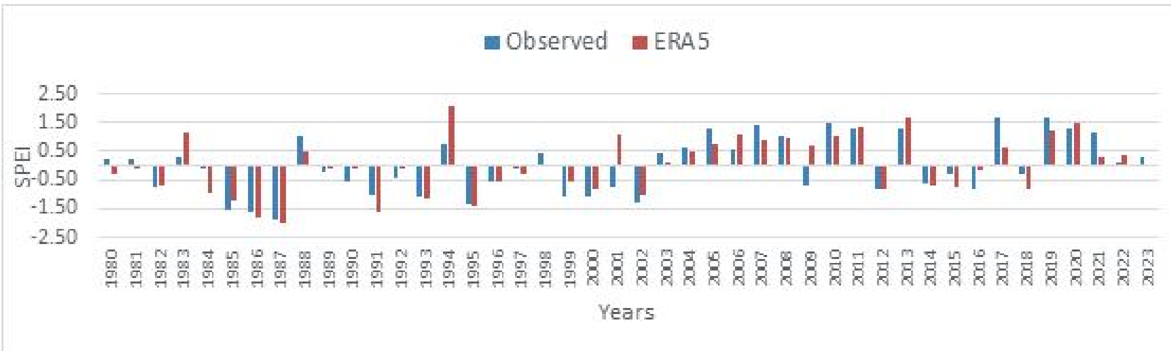


Fig. 6 : Seasonal SPEI drought severities based on observed and ERA5 data for Targhadia Station.

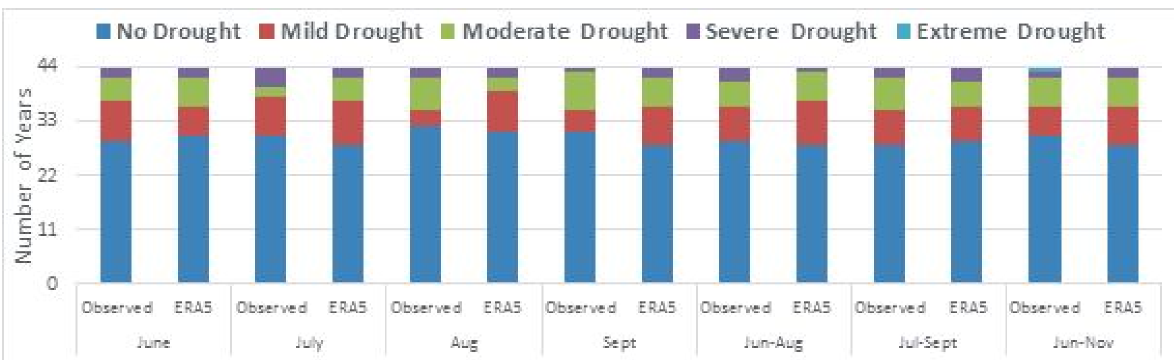


Fig. 7 : Drought frequency under various drought categories for observed and ERA5 based SPEI for Amreli station**.**

differences may result from variations in data sources, modeling approaches, or regional climate characteristics. The comparison highlights the importance of using multiple datasets to account for uncertainties and enhance the reliability of drought assessments, particularly for specific regions like Saurashtra.

Drought Frequency under various categories by observed and ERA5 data

The seasonal drought severities comparison was given in previous section. Here with drought frequency under various classes such as no drought or mild/ moderate/severe or extreme drought is discussed. Figs. 7 to 10 present drought frequencies across various categories for four stations in Saurashtra—Amreli, Junagadh, Jamnagar, and Targhadia—based on the Standardized Precipitation Evapotranspiration Index (SPEI) for different time scales (1, 3 and 6 months). Both observed data and ERA5 reanalysis data are provided, and the comparison highlights the consistency and differences between these two sources. The general trend across all stations shows "No Drought" as the dominant category, with most variations observed in the Mild and Moderate Drought categories, where ERA5 data sometimes deviates from the observed data.

In Amreli, the drought classification shows a good overall alignment between the observed and ERA5 datasets, with "No Drought" being the most common classification in both datasets. However, in the Mild Drought category, ERA5 tends to slightly under represent instances compared to the observed data in some months, especially in June and July. The Moderate Drought category also exhibits some variations, with ERA5

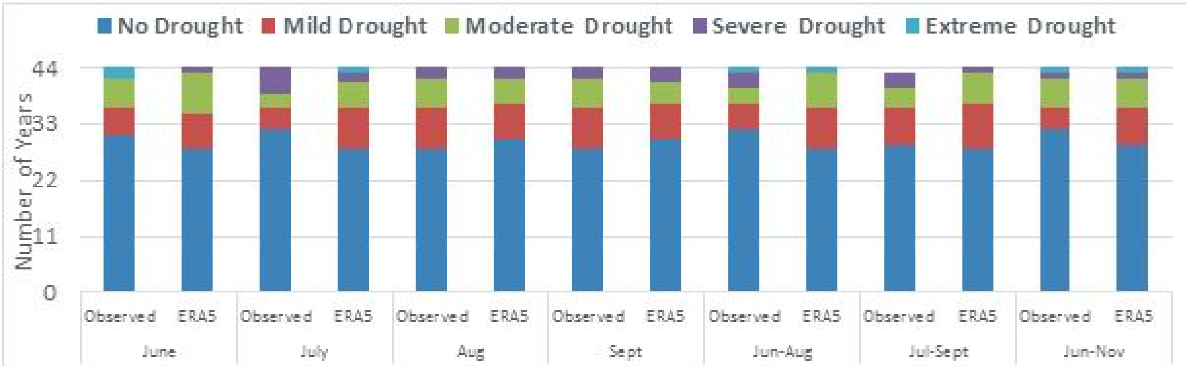


Fig. 8 : Drought frequency under various drought categories for observed and ERA5 based SPEI for Junagadh station.

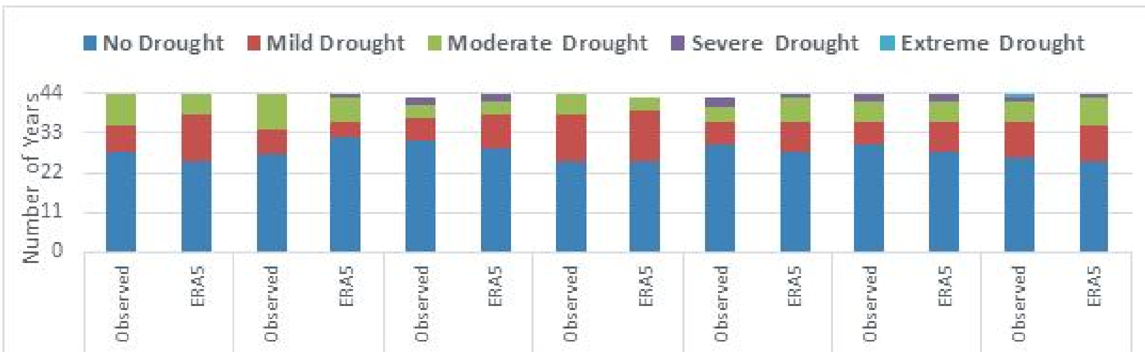


Fig. 9 : Drought frequency under various drought categories for observed and ERA5 based SPEI for Jamnagar station.

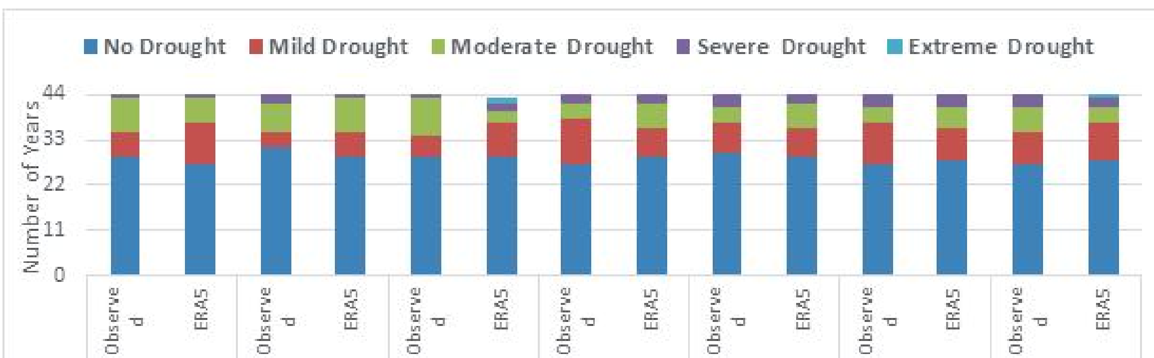


Fig. 10 : Drought frequency under various drought categories for observed and ERA5 based SPEI for Targhadia station.

showing slightly fewer occurrences. Severe and Extreme Droughts are rare in both datasets, with ERA5 slightly overestimating them in some periods. Overall, ERA5 can reasonably capture the trends observed in Amreli but slightly underestimates the frequency of mild drought conditions.

Junagadh shows a somewhat different pattern, particularly in the Severe Drought category. ERA5 data reports more instances of Severe Drought, especially in July and September, where the observed data shows significantly fewer occurrences. Similarly, the Mild Drought category is over represented in ERA5 for several months, such as in June and September. However, for the "No Drought" category, both datasets align well, with only minor differences. The Moderate Drought category shows some variation, with ERA5 data tending to report slightly more instances than the observed data. Despite these discrepancies, ERA5 still provides a reasonable estimate of drought conditions in Junagadh, though some adjustments might be needed to better capture the frequency of Severe Drought.

Jamnagar exhibits notable differences between the observed and ERA5 data, particularly in the Mild Drought category, where ERA5 overestimates the frequency in June and July. In contrast, the Moderate Drought category is reported more frequently in the observed data, particularly in August and September, while ERA5 tends to report fewer instances. Severe Drought conditions are relatively rare in both datasets, with ERA5 showing slightly more occurrences in June and August. Despite these discrepancies, ERA5 captures the broader drought trends in Jamnagar, though it may overestimate certain drought categories and underrepresent others. ERA5's higher frequency of Mild Drought events, especially in June, suggests that it may be more sensitive to precipitation variability than the observed data.

Finally, Targhadia presents a relatively consistent picture between observed and ERA5 data, with both datasets agreeing on the dominance of "No Drought" in all time scales. ERA5, however, tends to slightly overestimate Mild Drought conditions, especially in June and July. In contrast, the Severe Drought category is consistent across both datasets, with rare occurrences noted in both the observed and ERA5 data. The Moderate Drought category shows slight variations, but overall, ERA5 closely tracks the observed drought conditions in Targhadia, with minor differences in the frequency of Mild Drought events. The consistency in Targhadia suggests that ERA5 can reasonably replicate drought conditions for this station, but like other stations, slight adjustments may be needed to fine-tune its predictions.

In conclusion, ERA5 reanalysis data provides a reasonable approximation of the observed drought conditions in Saurashtra across the four stations, especially for capturing the broader trends in "No Drought" and Severe Drought categories. While there are variations in Mild and Moderate Drought classifications, ERA5 generally captures the major drought patterns observed in the region. Minor discrepancies, particularly in the frequency of Mild Drought, suggest that ERA5 may be more sensitive to short-term fluctuations in precipitation and evapotranspiration, making it a useful tool for monitoring drought at the regional scale with some adjustments for local nuances.

For countries like India, where approximately 70 to 90% of annual rainfall occurs during the southwest monsoon (June to September) (Kumar *et al*., 2021), drought characterization and monitoring are crucial. The comparison between observed and ERA5 data for drought categories across various months and cumulative periods provides valuable insights into the agreement and discrepancies between the two datasets. In general, the observed and ERA5 data align closely, particularly in reporting the absence of extreme drought events. Discrepancies are evident in specific categories and months, with ERA5 sometimes indicating more years with mild to moderate drought while the observed data reporting more severe drought years. The variations could stem from differences in data sources, modeling techniques, or regional climate nuances. Overall, the comparison underscores the utility of ERA5 data but also highlights the importance of considering observed data for localized and accurate assessments of drought conditions. Further investigation into the specific factors contributing to these differences would enhance the understanding of the reliability of each dataset in capturing historical drought occurrences. The comparison between observed and ERA5 (European Reanalysis) data across various months and cumulative periods reveals some nuanced differences and similarities in reported drought occurrences. Generally, the observed and ERA5 data align closely in categories such as severe and extreme drought, with both datasets often reporting identical values. However, discrepancies emerge in milder drought categories, with ERA5 occasionally reporting more years with drought compared to observed data. This suggests that while both datasets capture severe drought events effectively, there might be variations in their representation of mild to moderate drought conditions. Overall, the comparison demonstrates that ERA5 can be effectively used for drought characterization, the development of operational drought monitoring systems, and applications such as crop yield prediction.

Conclusion

The comparison of SPEI values from observed data and ERA5 reanalysis data for four stations in Saurashtra—Amrlei, Junagadh, Jamnagar and Targhadia—across seven different time scales (monthly, three-monthly and seasonal) demonstrated the effectiveness of ERA5 data for drought characterization. Using three comparison methods—Pearson correlation, historical seasonal drought severity, and drought frequency analysis—it was found that ERA5 data aligns closely with observed data, providing reliable insights for drought monitoring. These findings suggest that ERA5 data can be effectively used for operational drought monitoring, crop yield prediction, and other similar applications, offering a valuable alternative, especially in regions with sparse ground-based data.

Acknowledgement

The authors would like to express their sincere gratitude to the National Agricultural Science Fund (NASF), Indian Council of Agricultural Research (ICAR), for providing the financial support and funding for this research project. We greatly appreciate Centres of Junagadh Agricultural University *i.e.* Department of Agrometeorology, and Research Stations at Amreli, Jamnagar and Targhdia for providing necessary data for the study.

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