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RESEARCH ARTICLE

Drought monitoring over the Indian state of Tamil Nadu using multitudinous standardized precipitation evapotranspiration index

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Abstract

Droughts significantly impact agriculture and water resources in Tamil Nadu, India, making precise monitoring essential for effective response and mitigation. Traditional drought indices, like the Standardized Precipitation Index (SPI), rely solely on precipitation data and may overlook other critical factors. The Standardized Precipitation Evapotranspiration Index (SPEI) addresses this by incorporating temperature and precipitation data, offering a more comprehensive assessment of drought conditions, especially under changing climate scenarios. This study utilized daily temperature and precipitation records from NASA's Prediction of Worldwide Energy Resources (POWER) project, covering 1991 to 2024. Potential evapotranspiration (PET) was calculated using the Thornthwaite method, and the water balance was derived by aggregating monthly precipitation and PET data, which was then fitted to a log-logistic probability distribution (1). SPEI values were standardized to create a drought severity index, validated through comparisons with SPI and the Enhanced Vegetation Index (EVI) from MODIS data. Temporal analysis revealed significant year-to-year variability in drought conditions, with 2021 experiencing the most severe drought. The extreme droughts of 2019, 2020 and 2021 highlighted the need for adaptive drought management strategies due to their substantial impacts on agriculture and water resources. Spatial analysis identified the north-western and southern regions of Tamil Nadu as more vulnerable to drought. Strong correlations between SPEI, SPI and EVI validated SPEI's effectiveness as a drought monitoring tool. The study emphasizes the importance of advanced indices like SPEI for precise drought monitoring and recommends integrating SPEI with real-time data and remote sensing technologies for improved drought prediction.

Keywords

SPEI; SPI; agricultural drought; evapotranspiration

Introduction

Drought is a complex natural hazard that significantly impacts the environment, society and economy. It is particularly detrimental to agriculture, heavily dependent on water availability (2). In regions like Tamil Nadu, India, where agriculture forms a significant part of the economy and livelihood, understanding and monitoring drought is crucial. Drought in

Tamil Nadu can lead to severe water scarcity, crop failure and economic loss, affecting millions of people. Several indices have been developed over the past few decades to monitor and assess drought conditions. Among these, the Standardized Precipitation Evapotranspiration Index (SPEI) has gained prominence due to its comprehensive approach to precipitation and evapotranspiration (3). Based on the soil-water balance equation, the Palmer Drought Severity Index (PDSI) has been traditionally used for drought analysis. However, the PDSI has limitations, particularly in accounting for the varying significance of temperature and evapotranspiration over time (4). The Standardized Precipitation Index (SPI) is another widely used metric focusing on precipitation but not considering temperature variations, leading to potential inaccuracies in drought assessment. Drought indices like the SPI depend solely on rainfall, ignoring other critical factors such as temperature and potential evapotranspiration (PET), which play vital roles in the hydrological cycle (5).

The development of the SPEI addresses these limitations by integrating precipitation and temperature variables. This dual consideration provides a more accurate representation of drought conditions, especially in the context of climate change, where rising temperatures significantly influence drought severity. The SPEI's ability to incorporate the effects of temperature changes makes it a superior tool for drought monitoring compared to traditional indices. Determining the total amount of vegetation in a given area becomes easy due to vegetation indices derived from satellite data. Vegetation Indices are calculated using the proportion of different band combinations (6). The EVI and NDVI are the most typically used. Hute et al. (7) observed that NDVI is susceptible to air disturbances, particularly in regions with high aerosol concentrations, which hinders its ability to differentiate between areas with substantial biomass reliably. Where EVI produces better results. EVI's vegetation monitoring is further enhanced by its capacity to distinguish between the background signal and the plant canopy. These justifications illustrate that the vegetation indices in this investigation lined up with the EVI.

Furthermore, depending on the computation of cloud coverage at the time of image acquisition, a pixel reliability layer is added. The data layer enlarges this layer to recognize the pixels with the most significant degree of certainty. The SPEI is a multiscalar drought index that calculates drought severity at different temporal scales by considering the probability of precipitation and potential evapotranspiration (P-PET) (8). This feature allows the SPEI to effectively represent hydrological, meteorological, and agricultural droughts. The index's multi-temporal nature is crucial for understanding droughts' onset, duration and intensity, providing valuable insights for mitigation and preparedness. The state's agriculture is highly vulnerable to variations in monsoon rainfall, and understanding these variations is essential for effective drought management. This study focuses on applying the SPEI for drought monitoring in the Indian state of Tamil Nadu. Tamil Nadu, located at the southernmost tip of India, experiences diverse climatic conditions, making it a suitable region for detailed drought analysis. The study evaluated the SPEI's effectiveness in identifying drought-prone areas and its correlation with other indices like the SPI and the Enhanced Vegetation Index (EVI). Using data from the NASAPOWER, including temperature and precipitation records from 1990 to 2024, the SPEI was computed for Tamil Nadu. The significance of the SPEI becomes even more pronounced in the context of climate change (9).Rising temperatures and changing precipitation patterns are expected to alter drought dynamics globally. In India, several regions are projected to experience significant temperature increases in the twenty-first century, exacerbating drought conditions. The SPEI's consideration of temperature variations makes it a critical tool for understanding and addressing these future challenges (10). By providing a comprehensive assessment of drought severity, the SPEI can aid in developing more effective drought mitigation and adaptation strategies, ensuring sustainable agricultural practices and water resource management in Tamil Nadu and beyond. The SPEI offers a robust and comprehensive approach to drought monitoring by integrating precipitation and temperature variables. Its application in Tamil Nadu demonstrates its effectiveness in identifying and assessing drought conditions, providing valuable insights for mitigation and preparedness. As climate change continues to influence drought dynamics, the SPEI will play a crucial role in enhancing our understanding and management of droughts, contributing to the resilience and sustainability of agricultural and water resources. This study underscores the importance of adopting advanced drought indices like the SPEI for accurate and reliable monitoring. By leveraging the capabilities of the SPEI, policymakers, researchers, and stakeholders can develop more informed and practical strategies to combat the adverse effects of drought, ensuring a sustainable future for regions like Tamil Nadu that are highly dependent on agricultural productivity and water availability.

Materials and Methods

2.1 Study Area

The study was conducted in Tamil Nadu (Fig. 1), located at the southernmost point of the Indian subcontinent, encompassing an area of approximately 130,058 square kilometres. Tamil Nadu experiences a tropical climate with distinct seasons: summer (March to May), monsoon (June to September), post-monsoon (October to December) and winter (January to February). The state's economy heavily relies on agriculture, which is highly susceptible to variations in monsoon rainfall, making drought monitoring essential for agricultural planning and water resource management.

2.2 Data Collection

Daily rainfall and temperature data from 1991 to 2024 were sourced from NASA's Prediction of Worldwide Energy Resources (POWER) project. This dataset provides consistent and high-resolution meteorological data critical

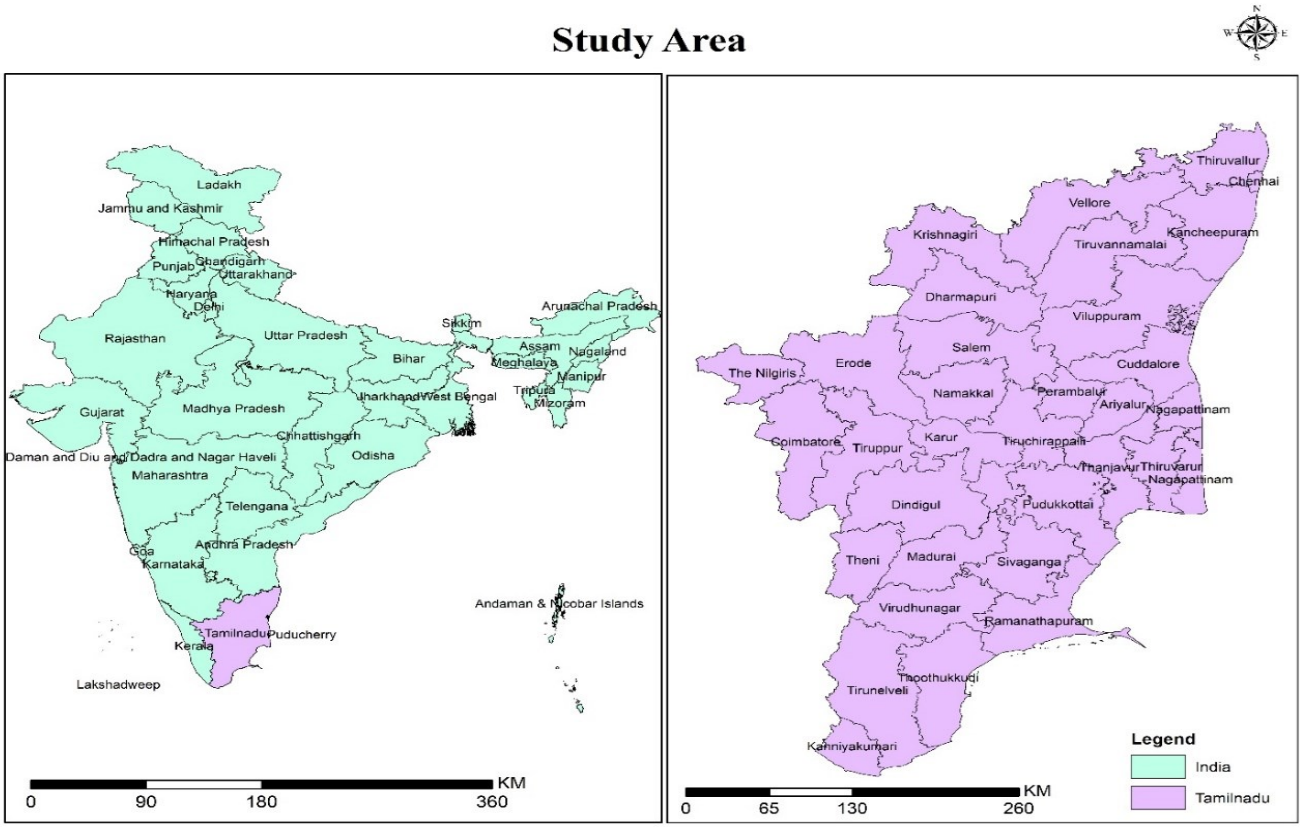


Fig. 1. Map showing the study area

for accurate drought assessment. The data were processed to obtain monthly averages for both rainfall and temperature.

2.3 Calculation of Potential Evapotranspiration (PET)

Potential Evapotranspiration (PET) was calculated using the Thornthwaite method, which estimates PET based on temperature and the length of daylight (11). The formula used is:

$$\mathbf{PET}=16\,(10\cdot Tm/I)^{a} \qquad \text{(Eqn. 1)}$$

Where:

T_m is the monthly mean temperature in degrees Celsius.

I is a heat index calculated as the sum of 12 monthly index values:

$$\sum_{i+1}^{12}\left(\frac{tmi}{5}\right)1.514 \qquad \text{(Eqn. 2)}$$

a is an empirical exponent derived from I:

$$a=6.75*10^{-7}I^{3}-7.71*10^{-5}I^{2}+1.792*10^{-2}I+0.49239B \qquad \text{(Eqn. 3)}$$

The calculated PET values were used to derive the water balance (12).

2.4 Standardized Precipitation Evapotranspiration Index (SPEI) Calculation

The SPEI was computed through the following steps:

1. **Data Preparation**: Monthly precipitation and PET values were aggregated from daily data.
2. **Water Balance Calculation**: The water balance was calculated by subtracting PET from precipitation for each month (2):

$$D=P-PET \qquad \text{(Eqn. 4)}$$

Where D= Water Deficit or water balance P is precipitation, and PET is potential evapotranspiration.

3. **Accumulation Periods**: The monthly water balance values (DDD) were aggregated over different timescales (e.g., 1, 3, 6 and 12 months) to assess short-term and long-term drought conditions.
4. **Probability Distribution**: The accumulated water balance values were fitted to a log-logistic probability distribution, which is suitable for hydrological data:

$$F(x) = 1/1 +(\ \alpha\frac{1}{\alpha} -\ \beta)\gamma \qquad \text{(Eqn. 5)}$$

Where α, β and γ are parameters of the log-logistic distribution.

5. **Standardization**: The standardized SPEI was calculated by transforming the cumulative probability F(x) into a standard normal distribution, yielding values typically ranging from -3 to +3, indicating varying degrees of drought and wet conditions.

2.5 Validation

The SPEI was validated using two complementary approaches:

1. **Comparison with SPI**: The correlation between SPEI and the Standardized Precipitation Index (SPI) was calculated to assess the consistency between these indices (13). The SPI was computed using the same precipitation data, excluding PET. The correlation coefficients (Pearson's r) were calculated for different

timescales to evaluate the temporal agreement between SPEI and SPI.

2. **Comparison with EVI**: The Enhanced Vegetation Index (EVI) from MODIS (Moderate Resolution Imaging Spectroradiometer) was used to validate the SPEI. EVI, which measures vegetation health and is sensitive to drought conditions, was used to conduct a spatial correlation analysis with SPEI (14). Monthly EVI data were averaged to match the timescale of SPEI and the spatial correlation was calculated to verify the spatial accuracy of SPEI in identifying drought-affected areas.

2.6 MODIS Image Processing

The processing of MODIS (Moderate Resolution Imaging Spectroradiometer) images for EVI involved the following steps:

1. **Data Acquisition**: MODIS EVI data were acquired from the NASA Earth Observing System Data and Information System (EOSDIS). The data was downloaded for the study period from 2019 to 2023.
2. **Pre-processing**: The downloaded MODIS images were pre-processed to remove atmospheric disturbances and correct geometric distortions. This included:

- **Radiometric Correction**: Correcting the images for sensor noise and atmospheric interference.
- **Geometric Correction**: Aligning the images to a standard map projection to ensure spatial accuracy.

3. **Temporal Aggregation**: Monthly EVI composites were created by averaging the daily EVI values for each month. This step helps reduce noise and provide a consistent temporal dataset.
4. **Cloud Masking**: A cloud masking algorithm was applied to remove cloud-contaminated pixels. The MODIS quality assurance (QA) flags were used to identify and mask out cloudy areas.
5. **Reprojection and Resampling**: The images were reprojected to an ordinary spatial resolution and coordinate system to ensure consistency with other datasets used in the study.
6. **EVI Calculation**: The Enhanced Vegetation Index was calculated using the standard MODIS EVI algorithm:

$$EVI=2.5x(NIR-RED)/(NIR+6*RED-7.5*BLUE+1) \quad \text{(Eqn. 6)}$$

7. NIR, RED and BLUE reflectance values in the near-infrared, red and blue bands, respectively.
8. **Validation and Quality Control**: The processed EVI data were validated against ground-based observations and other remote sensing products to ensure accuracy and reliability.

2.7 Data Analysis

MATLAB software was used for all numerical computations, including the calculation of PET, SPEI and statistical analyses (15). The following steps were taken in MATLAB:

1. **Data Import and Pre-processing**: Rainfall and temperature data were imported and processed to calculate monthly averages.
2. **PET Calculation**: The Thornthwaite method calculated PET values from the monthly temperature data.
3. **SPEI Calculation**: The water balance (D) was computed, accumulated over various timescales and fitted to the log-logistic distribution to derive SPEI values.
4. **Correlation Analysis**: Pearson's correlation coefficients between SPEI and SPI and SPEI and EVI were computed to assess the validity and reliability of SPEI as a drought monitoring tool.

2.8 Spatial Analysis and Mapping

Geographic Information System (GIS) software was used to map the spatial distribution of drought conditions across Tamil Nadu over the study period. The steps involved were:

1. **Data Preparation**: The GIS software imported SPEI values for different timescales.
2. **Spatial Interpolation**: SPEI values were interpolated to create continuous spatial surfaces representing drought severity across the study area.
3. **Visualization**: The spatial distribution of SPEI was visualized using color-coded maps to highlight areas with varying drought intensities.

2.9 Interpretation

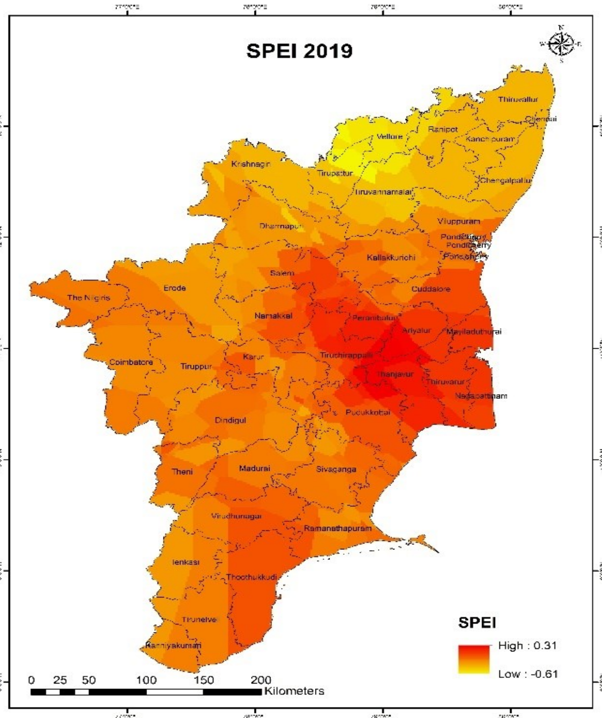
The resulting SPEI maps were analyzed to identify temporal and spatial patterns of drought. The high correlation coefficients between SPEI, SPI and EVI confirmed the reliability of SPEI in monitoring drought. The findings were discussed in the context of historical drought events, their impact on agriculture and the potential applications of SPEI in agricultural advisory services.

Results

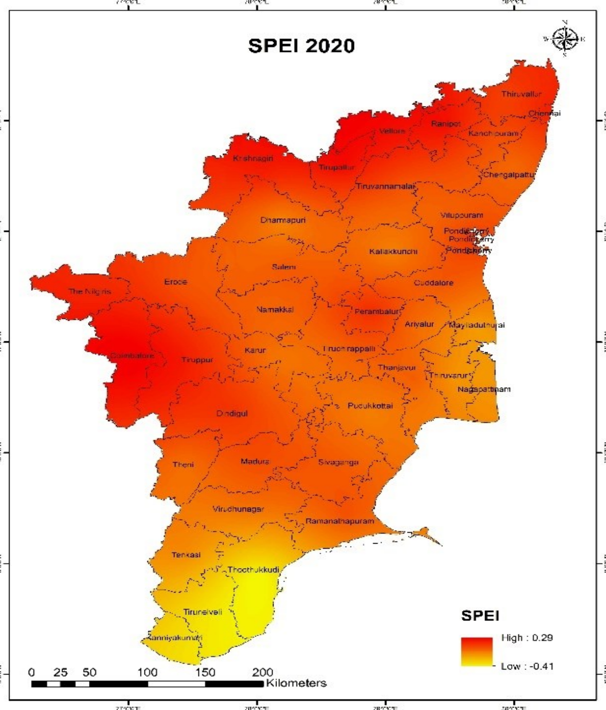
3.1 Drought Assessment using SPEI

Year 2019: The SPEI values for 2019 indicated that the north-western regions of Tamil Nadu experienced varying degrees of drought. The SPEI values ranged from -0.61 to 0.31, signifying mild to moderate drought conditions. The monsoon season saw insufficient rainfall, contributing to the negative SPEI values. This year marked the beginning of a significant drought that impacted agricultural productivity, particularly in Coimbatore, Salem and Dharmapuri districts. Similar trends of reduced monsoon rainfall and consequent drought conditions have been documented in other studies focusing on the Indian subcontinent (Fig. 2a).

Year 2020: In 2020, the southern districts of Tamil Nadu, including Madurai, Sivaganga and Ramanathapuram, experienced moderate to severe drought conditions. SPEI values in these areas reached as low as -0.41. The reduced precipitation and higher temperatures exacerbated the water deficit, leading to severe agricultural stress. The drought severity in 2020 was more pronounced than in 2019, affecting crop yield and water resources significantly. Studies have shown that temperature anomalies and reduced rainfall during this period led to



2a) SPEI map of the year 2019

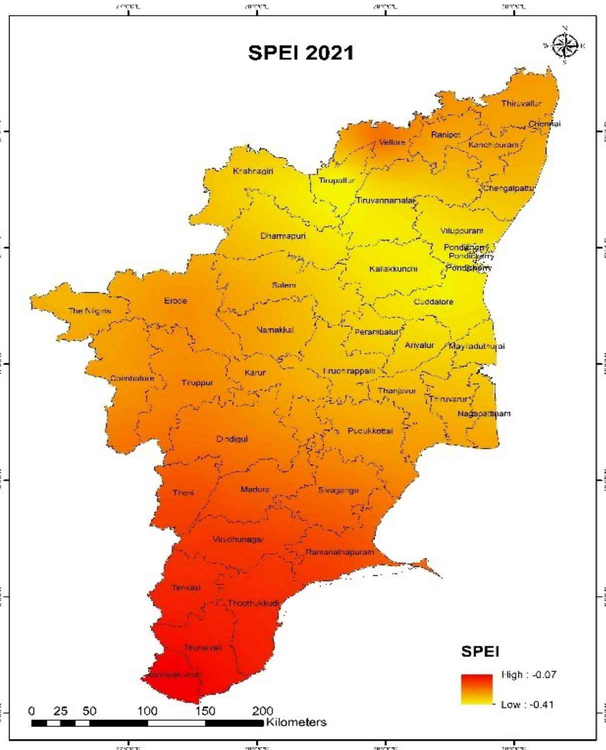


2b) SPEI map of the year 2020

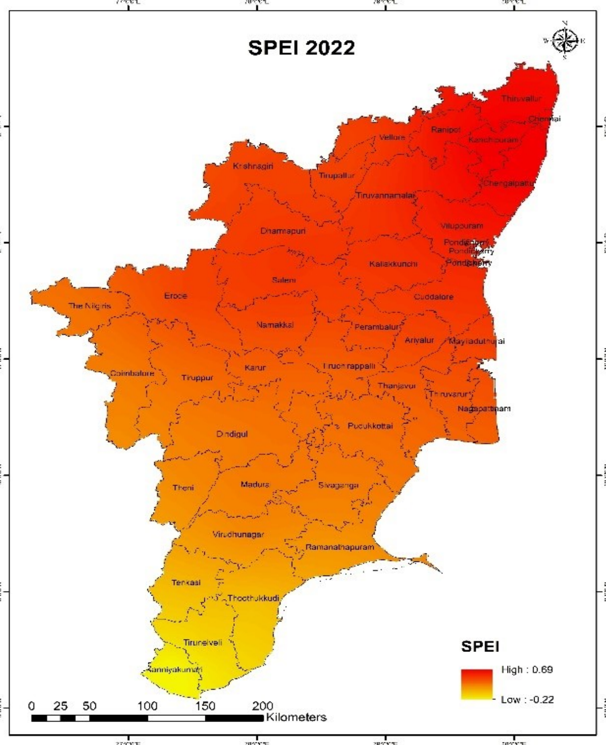
increased drought severity across various regions in India (SPEI) (Fig. 2b).

Year 2021: The entire state of Tamil Nadu suffered from moderate to severe drought in 2021. SPEI values ranged from -0.07 to -0.41, indicating widespread water deficits. The combined effect of lower-than-average rainfall and high temperatures across the state resulted in severe drought conditions. Agricultural sectors, particularly rain-fed crops, faced substantial challenges. The state government had to implement extensive drought relief measures to mitigate the impact on farmers and rural communities. Similar extensive drought conditions were reported across South Asia during this period, reflecting more significant climatic anomalies (Fig. 2c).

Year 2022: By 2022, the drought intensity slightly reduced in the southern districts, but moderate drought conditions persisted. In some regions, SPEI values ranged from 0.41 to 1.13, indicating slight improvements due to occasional rainfall events. However, the overall water availability remained below average, affecting groundwater recharge and reservoir levels. The districts of Thoothukudi and Tirunelveli showed some recovery, but agricultural stress



2c) SPEI map of the year 2021



2d) SPEI map of the year 2022

continued. The partial recovery aligns with findings from other regions experiencing sporadic rainfall during otherwise dry periods (Fig. 2d).

Year 2023: In 2023, the drought intensity varied across Tamil Nadu, with some areas showing significant improvement. SPEI values ranged from 0.41 to 1.13, indicating mild to moderate wet conditions in certain regions. The north-eastern districts, including Chennai and Kanchipuram, received better monsoon rainfall, improving water availability. However, central and western parts of Tamil Nadu still faced moderate drought conditions, highlighting the need for continued drought management efforts. Such spatial variability in drought conditions has been documented in other tropical regions, emphasizing the importance of localized drought assessment and management (Fig. 2e).

Year 2024: Up to April 2024, SPEI were predicted to know the drought intensity in Tamil Nadu, India, whose value ranged from 0.026 to 0.56. From the value, we can understand that the drought until April 2024 is moderate in almost all regions except the western and northern areas (Fig. 2f).

3.2 Validation of SPEI with SPI

The correlation between SPEI and SPI was calculated to assess the consistency between these indices. The results showed a strong positive correlation, with Pearson's correlation coefficients (r) ranging from 0.65 to 0.79 across different years (Table 1 and Fig. 4). This high correlation indicates that SPEI, which incorporates both precipitation and evapotranspiration, aligns well with SPI, a precipitation-only index. The integration of PET in SPEI provides a more comprehensive assessment of drought conditions, capturing the impact of temperature variations (13).

The high correlation between SPEI and SPI is consistent with findings from other studies that have validated SPEI as an effective tool for drought monitoring globally.

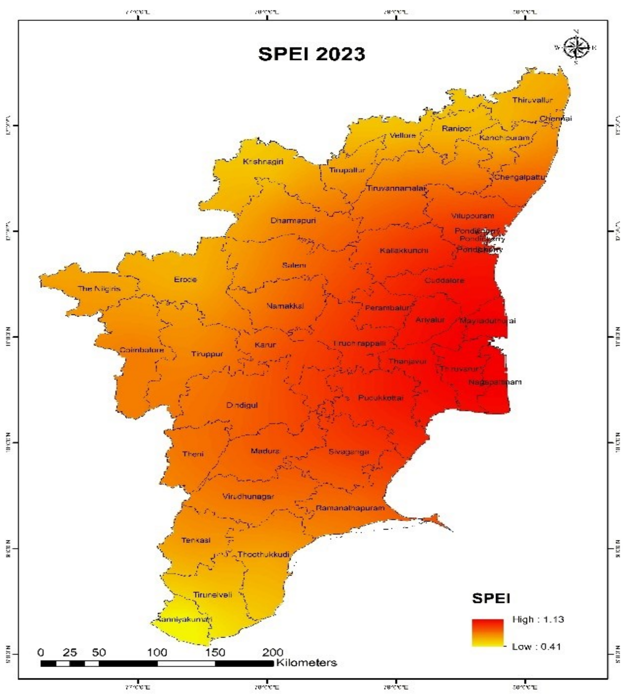
Table 1: Year-wise Correlation between SPI and SPEI

Year	Correlation Coefficient (r)
2019	0.70
2020	0.68
2021	0.75
2022	0.65
2023	0.79

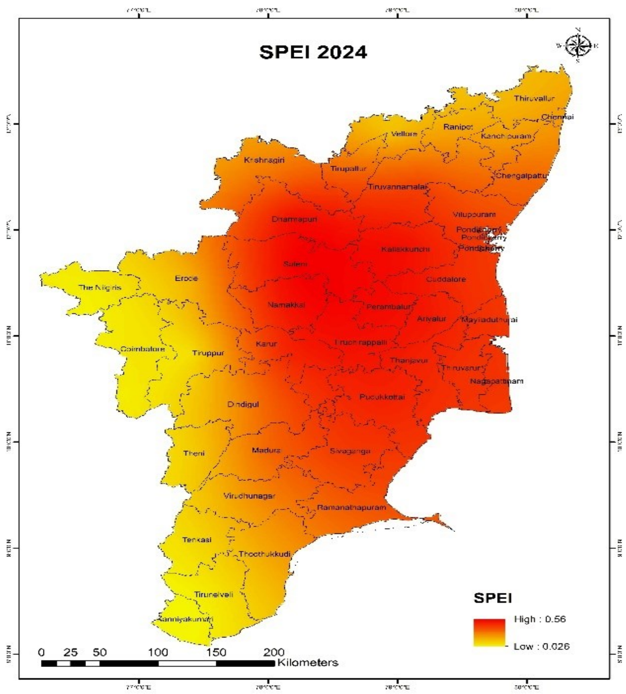
3.3 Spatial Validation with EVI

To further validate the effectiveness of SPEI, spatial correlation analysis was conducted with the Enhanced Vegetation Index (EVI) from MODIS (Fig. 3 a,b,c,d,e). EVI is a satellite-derived index sensitive to vegetation health and indirectly indicates drought conditions. The spatial correlation analysis revealed significant alignment between SPEI and EVI, particularly in areas experiencing severe drought. The correlation coefficients between SPEI and EVI across different years are shown in Table 2 and Fig. 5.

The higher correlation between SPEI and EVI compared to SPI and EVI demonstrates SPEI's superior capability in monitoring drought conditions. Including PET in SPEI enhances its sensitivity to precipitation deficits and increased evapotranspiration, which are critical under changing climate conditions. This observation is in line with (16), which has highlighted the benefits of including

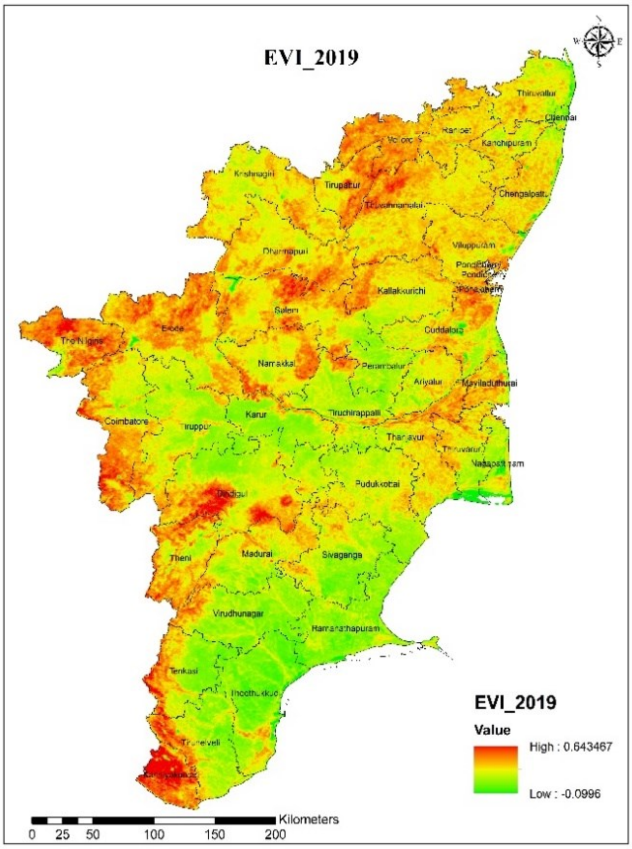


2e) SPEI map of the year 2023

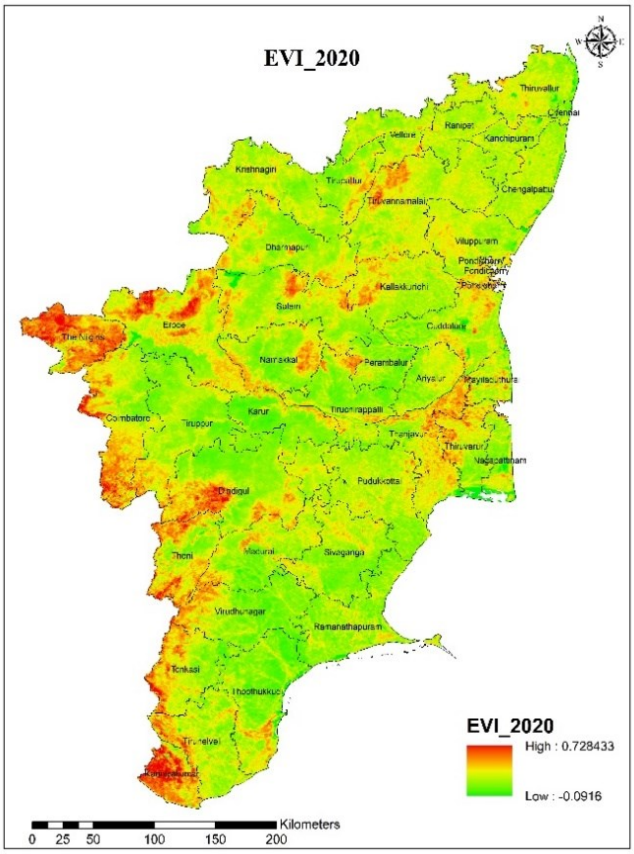


2f) SPEI map of the year 2024

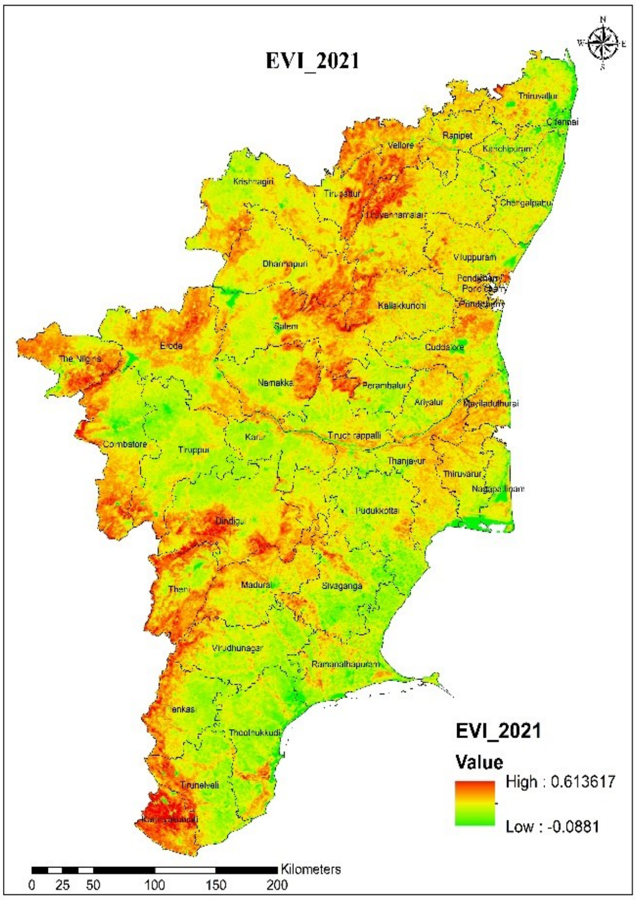
Fig. 2. Standard Precipitation Evapotranspiration map of Tamil Nadu for the year 2019 - 2024



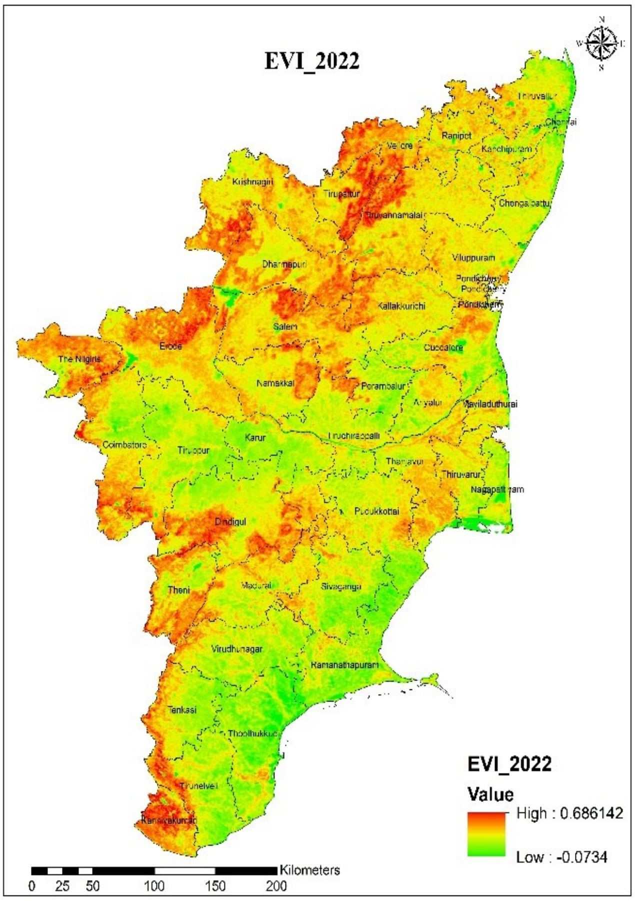
3a) EVI map of the year 2019



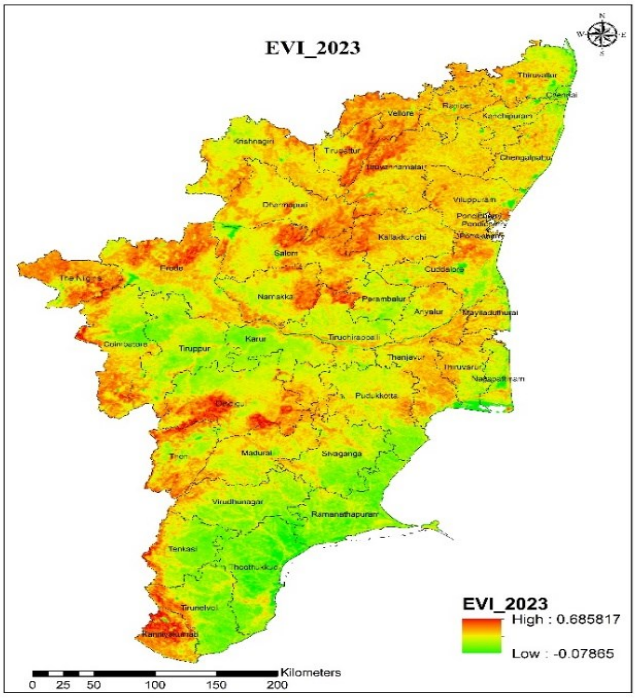
3b) EVI map of the year 2020



3c) EVI map of the year 2021



3d) EVI map of the year 2022



3e) EVI map of the year 2023

Fig. 3. Enhanced Vegetation Index map of Tamil Nadu for the year 2019 - 2023

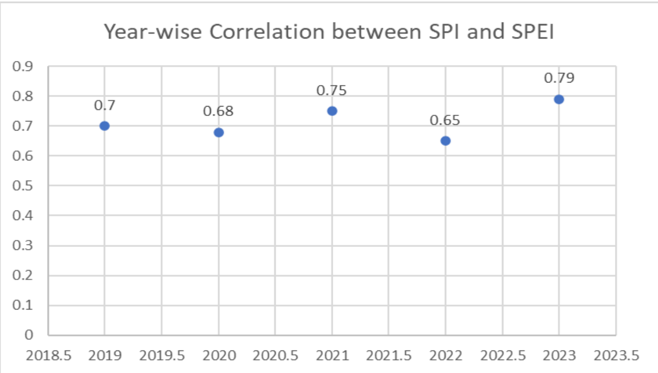


Fig. 4. Year-wise Correlation between SPI and SPEI

evapotranspiration in drought indices like NDVI instead of EVI in their study

Discussion

4.1 Effectiveness of SPEI in Drought Monitoring

The study's findings underscore the effectiveness of SPEI in drought monitoring across Tamil Nadu. The index's ability to integrate precipitation and temperature data provides a more nuanced understanding of drought conditions compared to precipitation-only indices like SPI. (17) used the Standardized Precipitation Evapotranspiration Index (SPEI) and a categorization method based on daily rainfall to investigate the exposure of the Tamil Nadu area, India, to droughts and extreme rainfall events. SPEI's strong correlation with SPI and EVI validates its reliability as a drought monitoring tool. These results are consistent with studies highlighting the robustness of SPEI in various climatic regions.

4.2 Temporal and Spatial Patterns

Table 2: Year-wise Correlation between SPI-EVI and SPEI-EVI

Year	SPI-EVI Correlation	SPEI-EVI Correlation
2019	0.63	0.71
2020	0.60	0.69
2021	0.66	0.74
2022	0.59	0.68
2023	0.70	0.77

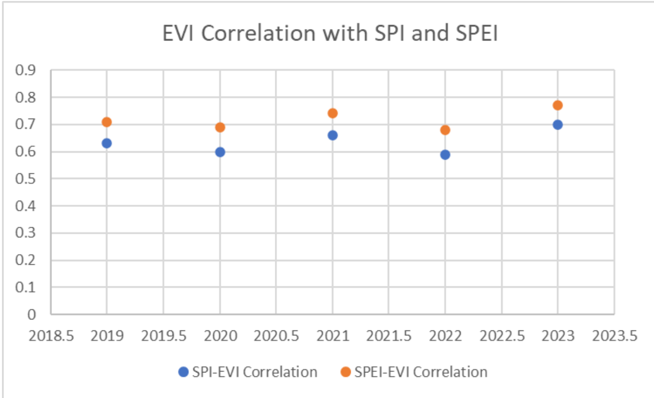


Fig. 5. EVI Correlation with SPI and SPEI

The temporal analysis revealed that drought conditions varied significantly across the years, with 2021 being the most severe in drought intensity and spatial coverage. The spatial analysis highlighted that particular regions, particularly in the north-western and southern parts of Tamil Nadu, are more prone to drought. This information is crucial for targeted drought mitigation strategies and resource allocation. Spatial variability in drought conditions has been a significant focus in drought research, emphasizing the need for localized drought management practices.

4.3 Impact on Agriculture and Water Resources

The severe drought conditions observed in 2019, 2020 and 2021 substantially impacted agriculture and water resources in Tamil Nadu. Reduced rainfall and increased temperatures led to significant water deficits, affecting crop yields and water availability for irrigation. The moderate recovery in 2022 and 2023, particularly in north-eastern districts, underscores the variability of monsoon patterns and the need for adaptive drought management strategies. The agricultural impacts observed align with broader studies on the socio-economic implications of drought in India and other regions (18).

4.4 Validation

The validation of the Standardized Precipitation Evapotranspiration Index (SPEI) was conducted using correlation analysis with the Standardized Precipitation Index (SPI) and spatial correlation with the Enhanced Vegetation Index (EVI). The SPI provided a benchmark for assessing SPEI's consistency, revealing strong positive correlations (Pearson's coefficients ranging from 0.65 to 0.79) across different years, indicating SPEI's robustness despite its additional complexity from incorporating potential evapotranspiration (PET). Spatial correlation with the EVI, derived from MODIS satellite data, further validated SPEI's spatial accuracy in identifying drought-affected areas. The significant spatial alignment between SPEI and EVI, especially in severe drought regions (19), highlighted SPEI's superior capability in monitoring drought conditions due to its sensitivity to precipitation deficits and increased evapotranspiration. These results underscore SPEI's reliability and enhanced sensitivity, making it a valuable tool for agricultural planning and water resource management in Tamil Nadu, with future studies needed to refine validation methods and integrate real-time data and advanced remote sensing technologies to enhance its predictive capabilities (20).

Conclusion

The study on drought monitoring in Tamil Nadu using the Multitudinous Standardized Precipitation Evapotranspiration Index (SPEI) offers an in-depth analysis of drought conditions by combining precipitation and temperature data. This integrated approach provides a clearer understanding of drought dynamics, especially in the context of climate change. The results highlight significant temporal and spatial variations in drought across Tamil Nadu from 1991 to 2024, with notable drought years in 2019, 2020 and 2021 significantly impacting agriculture and water resources. The validation of SPEI against the Standardized Precipitation Index (SPI) and the Enhanced Vegetation Index (EVI) affirms its reliability and effectiveness as a comprehensive drought monitoring tool, demonstrating strong correlations with these indices and confirming its capability to reflect the complex interplay between precipitation deficits and increased evapotranspiration. This study highlights the need to adopt advanced drought indices like SPEI for precise and dependable drought assessment. The potential of integrating SPEI with real-time data and cutting-edge remote sensing technologies suggests improved drought prediction and monitoring. Policymakers and stakeholders are advised to incorporate SPEI-based assessments into their drought preparedness strategies to enhance resilience against future droughts. Ultimately, the application of SPEI in Tamil Nadu proves its significant value in establishing a robust framework for drought monitoring, supporting the development of effective mitigation strategies and contributing to the sustainability of agricultural and water resources amid evolving climatic conditions.

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Authors' contributions

SJ carried out the experiment observation and drafted the manuscript. RJ guided the research by formulating the concept and approved the final manuscript. SP guided the research by formulating the research concept. BK participated in the data analysis and performed the statistical analysis. RK conceived of the study and participated in its design and coordination. NKS participated in the data analysis and revised manuscript. All authors reviewed the results and approved the final version of the manuscript.

Compliance with ethical standards

Conflict of interest: The authors declare no conflict of interest.

Ethical issues: None.

References

1. Pereira AR, De Camargo ÂP. An analysis of the criticism of Thornthwaite's equation for estimating potential evapotranspiration. Agric For Meteorol. 1989; 46(1-2):149-57. https://doi.org/10.1016/0168-1923(89)90118-4
2. Wells N, Goddard S, Hayes MJ. A self-calibrating Palmer drought severity index. J Clim. 2004; 17(12):2335-51. https://doi.org/10.1175/1520-0442(2004)017<2335:ASPDSI>2.0.CO;2
3. Vicente-Serrano SM, Beguería S, López-Moreno JI. A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. J Clim. 2010; 23(7):1696-718. https://doi.org/10.1175/2009JCLI2909.1
4. Sheffield J, Wood EF. Global trends and variability in soil moisture and drought characteristics 1950-2000 from observation-driven simulations of the terrestrial hydrologic cycle. J Clim. 2008; 21(3):432-58. https://doi.org/10.1175/2007JCLI1822.1
5. Hamon WR. Estimating potential evapotranspiration. Trans Am Soc Civ Eng. 1963; 128(1):324-38. https://doi.org/10.1061/TACEAT.0008673
6. Xue J, Su B. Significant remote sensing vegetation indices: a review of developments and applications. J Sens. 2017.https://doi.org/10.1155/2017/1353691
7. Huete A, Didan K, Miura T, Rodriguez EP, Gao X, Ferreira LG. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sens Environ. 2002; 83(1-2):195-213. Available from: https://doi.org/10.1016/S0034-4257(02)00096-2
8. Vyas SS, Bhattacharya BK, Nigam R, Guhathakurta P, Ghosh K, Chattopadhyay N, et al. A combined deficit index for regional agricultural drought assessment over semi-arid tract of India using geostationary meteorological satellite data. Int J Appl Earth Obs Geoinf. 2015; 39:28-39. https://doi.org/10.1016/j.jag.2015.02.009
9. Tsakiris G, Pangalou D, Vangelis H. Regional drought assessment based on the Reconnaissance Drought Index (RDI). Water Resour Manage. 2007; 21:821-33. https://doi.org/10.1007/s11269-006-9105-4
10. Jain VK, Pandey RP, Jain MK, Byun HR. Comparison of drought indices for appraisal of drought characteristics in the Ken River Basin. Weather Clim Extremes. 2015; 8:1-11. https://doi.org/10.1016/j.wace.2015.05.002
11. McKee TB, Doesken NJ, Kleist J. The relationship of drought frequency and duration to time scales. Proceedings of the 8th Conference on Applied Climatology.
12. Das PK, Dutta D, Sharma J, Dadhwal V. Trends and behaviour of meteorological drought (1901-2008) over Indian region using standardized precipitation-evapotranspiration index. Int J Climatol. 2016; 36(2):909-16. https://doi.org/10.1002/joc.4392
13. Gumus V. Evaluating the effect of the SPI and SPEI methods on drought monitoring over Turkey. J Hydrol. 2023; 626:130386.

https://doi.org/10.1016/j.jhydrol.2023.130386

14. Janarth S, Jagadeeswaran R, Pazhanivelan S, Kannan B, Ragunath KP, Sathiyamoorthy NK. Assessment of Agricultural Drought in Tamil Nadu using Remote Sensing Techniques. Agric Sci Dig. 2024. https://doi.org/10.18805/ag.D-6007
15. Abramowitz M, Stegun I. Handbook of Mathematical Functions US Government Printing Office Washington DC (1964) Sec. 17.8 (Examples 16 and 18). In: Reprinted by Dover New York. 1965.
16. Nejadrekabi M, Eslamian S, Zareian MJ. Spatial statistics techniques for SPEI and NDVI drought indices: a case study of Khuzestan Province. Int J Environ Sci Technol. 2022; 19:6573-94. https://doi.org/10.1007/s13762-021-03852-8
17. Tirivarombo S, Osupile D, Eliasson P. Drought monitoring and analysis: Standardized Precipitation Evapotranspiration Index (SPEI) and Standardised Precipitation Index (SPI). Phys Chem Earth. 2018; 106:1-10. https://doi.org/10.1016/j.pce.2018.07.001
18. Ward FA. Economic impacts on irrigated agriculture of water conservation programs in drought. J Hydrol. 2014; 508:114-27. https://doi.org/10.1016/j.jhydrol.2013.10.024
19. Bezdan J, Bezdan A, Blagojević B, Mesaroš M, Pejić B, et al. SPEI -based approach to agricultural drought monitoring in Vojvodina region. Water. 2019; 11(7):1481. https://doi.org/10.3390/w11071481
20. Vicente-Serrano SM, Domínguez-Castro F, Reig F, Beguería S, Tomas-Burguera M, Latorre B, et al. A near real-time drought monitoring system for Spain using automatic weather station network. Atmos Res. 2022; 271:106095. https://doi.org/10.1016/j.atmosres.2022.106095.