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ARTICLE

Analyzing the impact of meteorological drought on crop yield of Kerala, India: a wavelet coherence approach

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Abstract
Drought is a natural phenomenon which is considered as an indicator of changing climatic conditions. The growth of crops is significantly affected by the lack of soil moisture caused by insufficient rainfall over a specific period. This study examines the occurrence of drought over seven districts in Kerala, India, by utilizing drought indices, namely the standardized precipitation index (SPI) and the agricultural standardized precipitation index (aSPI). The measured data pertaining to rainfall and computed data of crop yield of the seven districts have been gathered to analyze the teleconnections of crop yield. Modified standardized yield residual series (M-SYRS) of different crops are prepared by the proposed approach of empirical mode decomposition-based detrending. The correlation between aSPI and M-SYRS exhibits a higher magnitude compared to the correlation that SPI and M-SYRS, confirming the significance of aSPI in the analysis of agricultural yield. The wavelet coherence analysis yields the values of percentage of significant coherence (PoSC) and average wavelet coherence (AWC) for the time scales of 3, 6, and 12 months, with respect to the variables aSPI and crop yield. The crop with the greatest AWC value of 0.71 and PoSC value of 62 is banana, which holds a dominant position in the agricultural landscape of Kottayam district. It is further noted that the short to medium seasonal droughts have profound impact on the agricultural yield of the different districts.

Keywords Drought · Crop yield · Precipitation · Coherence · Correlation · Wavelet

Introduction

The shortfall of precipitation over its long term is often considered as drought, which is a persistent, widely dispersed phenomenon that can last for weeks, months, or even years (Sen 2015). As a result, the neighborhood's economy, environment, and vegetation may all suffer (Wilhite 2005). Drought is typically regarded as one of the most dangerous but unattended natural hazard due to the creeping characteristics (AghaKouchak et al. 2021; Staupe-Delgado and Rubin 2022). The drought conditions resulted from the reduction in the rainfall of any location can also affect soil moisture conditions, groundwater and streamflow, which may eventually affect the water balance of the entire region (Thomas et al. 2015; Karbassi et al. 2020; Maghrebi et al. 2020, 2023). Proper management of water resources is crucial in helping the growing population to deal more successfully with the extremes of climate including the preparedness against drought. In rain-fed regions, agricultural productivity has decreased by up to 40% as a result of severe droughts (Dietz et al. 2021). Drought conditions have an impact on plant growth by changing the relationships between water-soluble nutrients and the photosynthetic process, which ultimately leads to a significant drop in agricultural productivity. Climate change will have negative repercussions because drought periods will last longer and be more severe. Hence, the changing climate has direct and significant impact on the crop yield and food security (Kang et al. 2009; Ray et al. 2015; Leng and Huang 2017; Dixit et al. 2023). Several recent studies highlighted the detrimental impacts of the climate change in exacerbating drought, its environmental impacts and bringing changes in ecological and crop balance (Malekmohammadi et al. 2023; Noori et al. 2023; Mahdian et al. 2023; Kabeta et al. 2023). The cold/warm episodes have significant impact on crop production, and the proper

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impact assessment of the same is critical for assessing the sustainability of food systems (Chatrabgoun et al. 2020; Hasegawa et al. 2022). In short, understanding the drought has a significant influence on enhancing agricultural yield. Accurate forecasting of crop yield requires precise tracking of agricultural drought indicators (Dietz et al. 2021). Such teleconnections between drought and crop yield have been investigated by researchers for more than a decade (Li et al. 2009, 2020a; Hamal et al. 2020; Pena-Gallardo et al. 2019a, b; Santini et al. 2022). The scope of the investigation is future agricultural planning and management with better preparedness against drought disasters.

In order to quantify the drought conditions, many researchers presented the definition and method of estimation of a number of drought indices (Mishra and Singh 2010; Zargar et al. 2011; Yihdego et al. 2019). Moreover, they categorized the droughts to meteorological, agricultural, hydrological and socio-economic considering the variables involved in the estimation and their impacts. The indices aid in drought characterization and implementation of drought management strategies, while several drought indices, such as standardized precipitation index (SPI), standardized precipitation evapotranspiration index (SPEI), and normalized difference vegetation index (NDVI), have gained widespread attention and usage. Wang et al. (2015) studied the spatiotemporal evolution of drought in the Luanhe River Basin using SPI, SPEI, and sc-Palmer drought severity index (sc-PDSI). The results of this experiment showed that the SPEI is more precise than the SPI. Many of the reported drought indices are computed at monthly scale, while Li et al. (2020b) proposed a daily scale drought index, namely the standardized antecedent precipitation evapotranspiration index (SAPEI). It was proven that SAPEI is capable of revealing daily drought conditions, fairly consistent with soil moisture changes. It uses precipitation and potential evapotranspiration and also considers the effect of antecedent water balance on dry/wet conditions on the current day. The performance of SAPEI was compared with PDSI, SPEI, and soil moisture, by considering the data of Pearl River basin, China. SAPEI was found to be performing equally good SPEI and PDSI at the monthly scale but outperforms SPEI at the weekly scale. Mehr and Vaheddoost (2020) compared the trends of SPI and SPEI of Ankara Province Turkey at 3-, 6-, and 12-month time scales, using a number of graphical and nonparametric statistical methods. They have reported declining trends in SPEI series, while the pattern of trend was not similar for SPI.

Tigkas et al. (2014) presented detailed design and implementation of drought calculator software DrinC. Tigkas et al. (2018) improved the capacity of original index to characterize agricultural dryness by calculating the aSPI using the effective precipitation. aSPI is a better predictor of agricultural drought than the original index, according to an analysis of how well SPI and aSPI performed in four sites in Greece under Mediterranean conditions in terms of connecting crop output response to drought severity. Tigkas et al. (2020) revised reconnaissance drought index (RDI) by replacing the reference evapotranspiration component with crop evapotranspiration to aid in agricultural drought assessments by focusing on particular crops. An application in three locations in Greece, taking into account a variety of crops grown under Mediterranean conditions, illustrates the significance and benefits of CRDI. Two new drought indices were added to the Drought Indices Calculator (DrinC) program by Tigkas et al. (2022) for use in identifying agricultural droughts. Both of these indices, the effective reconnaissance drought index (eRDI) and the agricultural standardized precipitation index (aSPI), use the idea of effective precipitation, which consider the quantity of water that is required for plant growth. In short, DrinC can estimate SPI, RDI, streamflow drought index (SDI), aSPI, eRDI, and the Precipitation Deciles (PD).

Understanding the teleconnections between droughts and crop yield, large-scale climatic oscillations (COs) or local-scale meteorological variables is highly warranted for developing actionable plans for water and agricultural management for drought preparedness (Johny et al. 2020; Shamna et al. 2022). Moreover, such studies may help for accurate modeling of crop yield using advanced machine learning paradigms (Klompenburg et al. 2020; Ghose et al. 2021a, b). Numerous studies attempted to analyze the fluctuations of droughts and crop yield series across different parts of Globe including India, but mostly using conventional statistical and graphical approaches (Zhang et al. 2017; Dar and Dar 2021; Shi et al. 2022; Mokhtar et al. 2022; Hendrawan et al. 2022, 2023; Eze et al. 2022). The droughts are often quantified by drought indices, whereas crop yield is often represented by standardized yield residual series (SYRS) (Waseem et al. 2022; Qin et al. 2023). The SYRS series is normally obtained by a decomposition operation followed by the extraction of the residual by detrending. Empirical mode decomposition (EMD) propounded by Huang et al. (1998) is a popular decomposition tool, and the potential of EMD can be used for effective detrending (Wu et al. 2007). Ghose et al. (2021b) analyzed the rice yield of Bangladesh to large-scale atmospheric oscillation using machine learning and statistical techniques including ensemble EMD and wavelet coherence. Pena-Gallardo et al. (2019a, b) used different methods for capturing the trends if crop yield in their study pertaining to regions of USA and Spain. EMD is a data adaptive decomposition tool, which decomposes a time series into a specific number of modes, adapting to the data characteristics. Hence, EMD is more flexible in its implementation, whereas for applying the tools like WC, a mathematical function and the desired number of levels need to be specified a priori, which is often challenging task to the modeler. Thus, EMD is a preferable option for the trend detection and detrending involved in complex time series (Wu et al. 2007). However, its potential for the estimation of SYRS is not explored and utilized properly.

Based on SPI and SPEI, Mohammed et al. (2022) looked at the intensity, length, and severity of agricultural drought in Hungary from 1961 to 2010. Using the crop–drought resilient factor (CDRF) and standardized yield residual series (SYRS), the study examined the relationship between drought and crop yield for maize and wheat. The study using SPI and SPEI (of 3 and 6 months) revealed that Hungary's western region is substantially more susceptible to agricultural drought than its eastern region. The middle and western regions of the country generally had severely non-resilient maize and wheat yields (CDRF 0.8). The effect of meteorological dryness on wheat yields in South Africa from 1980 to 2017 is examined by Nxumalo et al. (2022) using SPEI and SPI as drought matrices. The effects of drought on wheat yields were found to vary based on the location of the wheat fields, the length and duration of the drought, and the growth stage of the crop. Using the SPI, Waseem et al. (2022) examined the effects of drought on wheat output in Pakistan's Punjab province. They evaluated the effects of the drought on the yield of the wheat crop in terms of the soil moisture deficit. The growth stage was shown to be the most crucial stage influenced by drought based on the association between the wheat yield and SPIs. According to the measurement of soil moisture, droughts can cause water stress throughout the growing season of wheat crops, which decreases yields. To assess the fluctuations in the wheat production brought on by the drought, they used the correlation between SYRS and SPI. They deduced from this study that drought occurrences during the growth stage had a greater impact on wheat yield than they did during the cropping stages. Even though effective precipitation, which consider as the quantity of water required for plant growth, computation of aSPI as the drought indicator over any of the regions is not reported.

Quantifying the teleconnections of droughts with simple statistical correlation alone may not provide the reliable results, because of the process nonlinearity. In this context, a time–frequency coherence measure like wavelet coherence (WC) rooted in wavelet transform (WT) may a more credible option for drought–crop yield teleconnections (Nourani et al. 2019, 2021; Sreedevi et al. 2022). Padakandla et al. (2022) used structural break and continuous WT methods on yearly data of seven crop yields and climate variables of 1956–2010 for the undivided Andhra Pradesh region in India. Change point evaluation showed a 1.0° rise in temperature with two prominent break points, while the fluctuations were reported to be random. CWT-based analysis exhibited significant association between the two variables (Araghi et al. 2017). The application of CWT was reported for rainfall and streamflow teleconnection studies in India (Rathinasamy et al. 2019; Das et al. 2020; Mohan et al. 2023), but its application for crop yield–drought teleconnection is limited.

The state of Kerala popularly known as Gateway of Indian Monsoon has experienced a severe over 100-year return period drought in 2016–2017 (Abhilash et al. 2019). In contrast, the same region has experienced a devastating 100-year flood in 2018 (Hunt and Menon 2020). In 2023, till at present about 90% reduction in monsoon rainfall was experienced in the State. These paradoxical climatic extreme makes severe threat to the agricultural sector of Kerala. Several studies has evaluated the rainfall trend of Kerala (Krishnakumar et al. 2009; Pal and Al-Tabbaa 2009; Adarsh and Janga Reddy 2015) which in general reported a reduction of monsoon and overall rainfall with an increase of post-monsoon rainfall. The precipitation-based drought estimator and its trend were evaluated in few studies (Joshi et al. 2016), while some of the research works performed rigorous studies on drought characteristics using advanced statistical tools like Copulas (Shiau and Modarres 2009; Adarsh et al. 2018). However, no studies considered the computation of aSPI and its teleconnection with crop yield in a time frequency perspective using the techniques like wavelet coherence for any of the region including Kerala.

This study presents the evaluation of aSPI for the state of Kerala, proposes an effective SYRS (modified SYRS or M-SYRS) computation using EMD-aided detrending and evaluates the coherence relationships by effective quantitative measures like average wavelet coherence (AWC) and percentage of significant coherence (PoSC). The specific objectives are (1) to estimate the agricultural standardized precipitation index (aSPI) and SPI of seven districts of Kerala; (2) to assess the correlation between aSPI and crop yield quantified by a newly proposed EMD based M-SYRS considering the dominant crops of different districts; (3) to evaluate the aSPI- M-SYRS associations of different crops using wavelet coherence approach.

Methodology

Drought indices

The extent of dryness in relation to a normal value and the length of the dry spell are used to define meteorological drought (MD). MD is often quantified by precipitation shortfall and its duration, while its definitions are region specific as it is often controlled by local-scale meteorology. The quantitative evaluation of all types of droughts including MDs and their characteristics (severity, location, timing and spell) are often depicted by drought indices. Among the drought indices, SPI is the simplest as it is based on precipitation as the only variable required for its estimation and provides flexibility to represent the droughts of different types (short, medium and long) by changing the evaluation time scale (Shiau and Modaress 2009; Mirabbasi et al. 2012; Adarsh et al. 2018; Esit and Yuce 2023), which made it as the most popular index. A modified version of the SPI known as the agricultural standardized precipitation index (aSPI) proposed by Tigkas et al. (2022) was developed specifically for agricultural purposes. Instead of total precipitation aSPI uses effective precipitation, which is the fraction of total precipitation that can be used effectively by plants. Using the aSPI, the effects of drought on agriculture are assessed. It is especially helpful for forecasting agricultural yields and pinpointing the areas where drought–related crop losses are likely to occur (Tigkas et al. 2022). It can also be used to direct decisions on agricultural management such as crop choice, planting seasons, and irrigation schedules. The computation of SPI and aSPI are very much popular in literature, whereas brief descriptions on them are given in the Supplementary File.

Proposed approach

The three variables required for this investigation are precipitation, effective precipitation, and crop yield data. SPI and aSPI computations are done in DrinC platform (https://drought-software.com/). Following that, EMD was used to decompose the crop yield data. After detrending using EMD, a modified SYRS series of each crops were obtained. The correlation between SPI versus M-SYRS and aSPI versus M-SYRS of all the crops were computed, for different time scales of drought. Based on the feedbacks, the coherence relationships between MSYRS and aSPI are evaluated to assess the effect of drought on agriculture and to get useful insights, which involves the use of wavelet transform. The overall methodology adopted for the study is given in the flowchart and is shown in Fig. 1.

Standardized yield residual series

The effect of external factors, such as weather patterns or changes in agricultural practices like fertilizers, better seed varieties, and irrigation operations that may have an impact on crop yields is removed from crop yield data using the SYRS. In the proposed modified approach, EMD is used to detrend crop yield data to get the residual series. Following that, the yield residual series is standardized by subtraction of mean and division by its standard deviation. SYRS is determined using the formula shown in Eq. (1).

$$\text{M - SYRS} = \frac{y_i - \mu}{\sigma} \tag{1}$$

where y_i is the residual of detrended crop yield by EMD and μ and σ indicate the mean standard deviation of residuals of the detrended yield.

Empirical mode decomposition

EMD is an efficient method for decomposing nonlinear and non-stationary signals without a priori assumptions on functional form and adapting closely with data characteristics. With the help of this technique, a complex and multiscale signal can be adaptively broken down into a collection of a limited number of zero mean oscillating parts known as intrinsic mode functions (IMF) and a final residue. The residue component represents the long-term inherent trend in the data. The end results are characterized by orthogonality of modes as shown in Eq. (2).

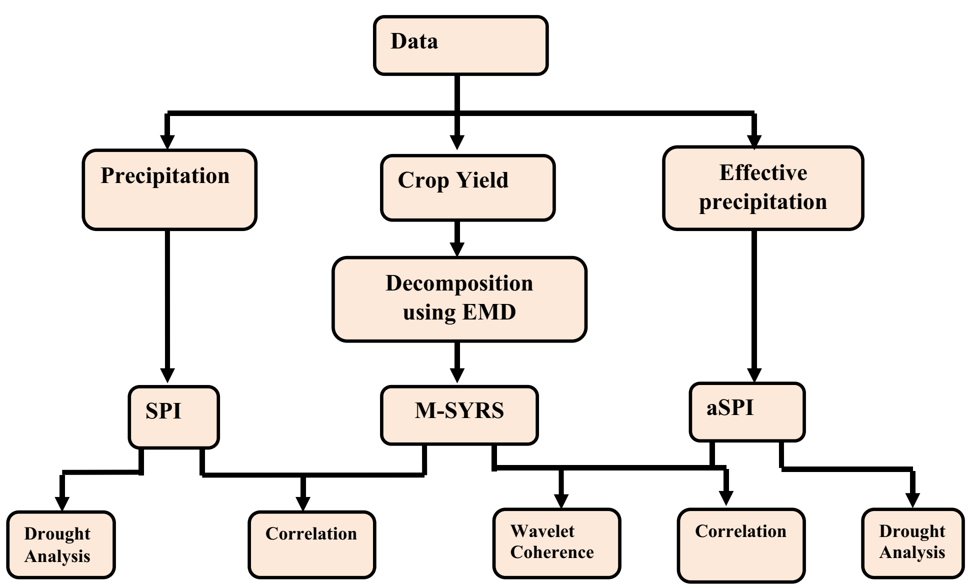

Fig. 1 Flowchart of proposed methodology

$$x(t) = \sum_{i=1}^{L} h_i(t) + r(t) \quad (2)$$

where $r(t)$ is a residual and $1 \leq i \leq L$ is the number of IMFs. The data adaptability feature helps for extraction of IMFs through the following steps:

1. Locate the peaks and troughs of $x(t)$.
2. Develop upper and lower envelopes $e_{u(t)}$ and $e_{1(t)}$ by spline interpolation through peaks and troughs
3. Find mean of envelope curves, $m_1(t) = \frac{e_{u(t)} + e_{1(t)}}{2}$
4. Let $d_1(t) = x(t) - m_1(t)$. If $d_1(t)$ is a zero mean function, stop the iteration and $d_1(t)$ is accepted as first IMF, i.e., $h_1(t) = d_1(t)$.
5. Else, use $d_1(t)$ as the new time series and repeat steps 1–4 until an IMF gets evolved.

Cauchy type stopping criterion (Huang and Wu 2008) is often used to control the number of iterations so that IMF preserve its physical meaning. Once the first IMF $h_1(t)$ is obtained, remaining IMFs are obtained by applying *sifting* process to the residual signal. Residual signal $r_1(t)$ can be defined in Eq. (3).

$$r_1(t) = x(t) - h_1(t) \quad (3)$$

The lower-frequency components of the residual signal can now be identified. The process will be carried out until the final residue is either a monotonic function, or a function with only one peak or trough, none of which may yield an IMF. The method is found to be effective tool for detrending as recommended in several literature (Wu et al. 2007), and detrending is one of the M-SYRS computations.

Wavelet transform

Wavelet transform is a popular mathematical technique that performs the transformation in a time–frequency space. It involves the passage of a short and definite wave form along the stretched and dilated time series to compute the correlation between the signal and wavelet (Araghi et al. 2017; Nourani et al. 2019, 2021; Sreedevi et al. 2022; Mohan et al. 2023). The resulting power spectrum and the global wavelet spectrum are useful to estimate the dominant periodicity of the series (Joshi et al. 2016). Subsequently, the strength of association between the two signals is computed using wavelet coherence. When WC is present, the cross-spectrum is normalized in relation to the wavelet power of M and N. WC calculates the coherence from 0 to 1, to assess the relationship between them inside the time–frequency space.

The wavelet coherence between two time series X and Y is given by Eq. (4).

$$R(M,N) = \frac{\in [W(M,N)]}{\sqrt{\in [W(N)] \in [W(N)]}} \quad (4)$$

$$R^2(M,N) = R(M,N).R(M,N) * \quad (5)$$

where $W(M, N)$ is the cross-wavelet transform, $W(\cdot)$ is the wavelet transform, $R(M, N)$ is the WC between N and M, $R^2(M, N)$ for the squared WC between N and M, and a smoothing operator $\in$ can be used to strike a balance between the required time–frequency resolution and statistical significance. The phase in a wavelet analysis represents the relative displacement between two signals and is often calculated as an angle over a particular point in the waveform. The two signals are said to be in-phase (anti-phase) when there is no phase difference between them. Other than graphical measures, a quantitative statistical measure is preferable to comment on the teleconnections between two nonlinear processes or variables. The utilization of average wavelet coherence (AWC) and the percentage of significant coherence (PoSC) matrices enables the assessment of the comparative influence exerted by individual or combined predictor variables (Nalley 2020; Song et al. 2020; Sreedevi et al. 2022; Mohan et al. 2023). The AWC can be determined by taking the average of the WC values obtained across all scales. The PoSC can be derived by determining the proportion of significant power values in relation to the total number of power values generated throughout the WC computation. Significant power is observed when the ratio of power to the significance threshold exceeds 1. Greater values of overall AWC and PoSC are indicative of increased dominance.

Study area and data collection

Study area

Kerala (between 74° 52′ to 77° 22′ E and 8° 18′ to 12° 48′ N) is the South Indian State located along the western Coast of the Indian subcontinent with a total area of 38,863 km^2. The region consists of 14 districts. Kerala is characterized by three distinct climatic regions: the eastern highlands, the middle midlands, and the western lowlands (Mathew et al. 2021). The climate of Kerala is tropical monsoon with seasonally excessive rainfall and hot summer except over Thiruvananthapuram district, as per Koppen's classification (Koppen 1936). For Thiruvananthapuram district located at the southern tip, the climate is tropical savanna with seasonally dry and hot summer weather. Both the northeast monsoon and the southwest summer monsoon exert influence on the tropical wet climate of the region. The southwest monsoon, which accounts for around 65% of the total annual precipitation, manifests itself throughout the period spanning from June to August. The northeast monsoon season is during the period from September to December. The mean annual precipitation of state of Kerala is approximately 3000 mm. The average daily temperature fluctuates between 19.8 and 36.7 °C. The research was carried out in seven districts of Kerala, namely Alappuzha, Ernakulam, Kannur, Kollam, Kottayam, Kozhikode, and Thiruvananthapuram, for which the dominant crop yield is available. The location of the state and the districts chosen is marked in Fig. 2.

Data collection

The precipitation data spanning from 1980 to 2020 for the seven selected districts were collected from the India Meteorological Department (IMD) (https://www.imdpune.gov.in/cmpg/Griddata/Rainfall_25_Bin.html). The data statistics are presented in Table 1. The crop yield data utilized in this study were obtained from the Kerala State Economics and Statistics Department (https://www.ecostat.kerala.gov.in/publication-list?sort=newest&tab=publications&category=3010&jurisdiction=&search=&scheme=3038&from=&to=&published_from=&published_to=). The selection of a dominating crop for each district is made from a range of available crops and the areas served. Accordingly, coconut is identified as dominant in Thiruvananthapuram district, cashew is identified as dominant in Kollam, banana is identified as dominant in the three mid-Kerala districts of Alappuzha, Kottayam and Ernakulam, and ginger is identified to be dominant in Kozhikode and Kannur districts. The annual rainfall and temperature (maximum and minimum) data of the locations are presented in Fig. 3, which often deciphers the drought characteristics and climate of the region. Moreover, many of the researchers computed the crop water requirement of crops in different parts of the world including Kerala and most of them followed FAO-CROPWAT-based approach (Lathika 2010; Surendran et al. 2015, 2017, 2019a; Solangi et al. 2022; Gabr 2022). Surendran et al. (2019a) proposed FAO-CROPWAT model-based irrigation requirements for coconut and reported that the quantity of water required per coconut palm varied between 115 and 200 L per day (LPD) per palm, which is lower than the existing recommendations of 175–300 LPD per palm. They made a comparison between the procedures followed by Kerala Agricultural University and CROPWAT for the estimation of water requirement. Surendran et al. (2015) made an effort has been made to calculate the water needs for various crops in different agro-ecological units (AEUs)

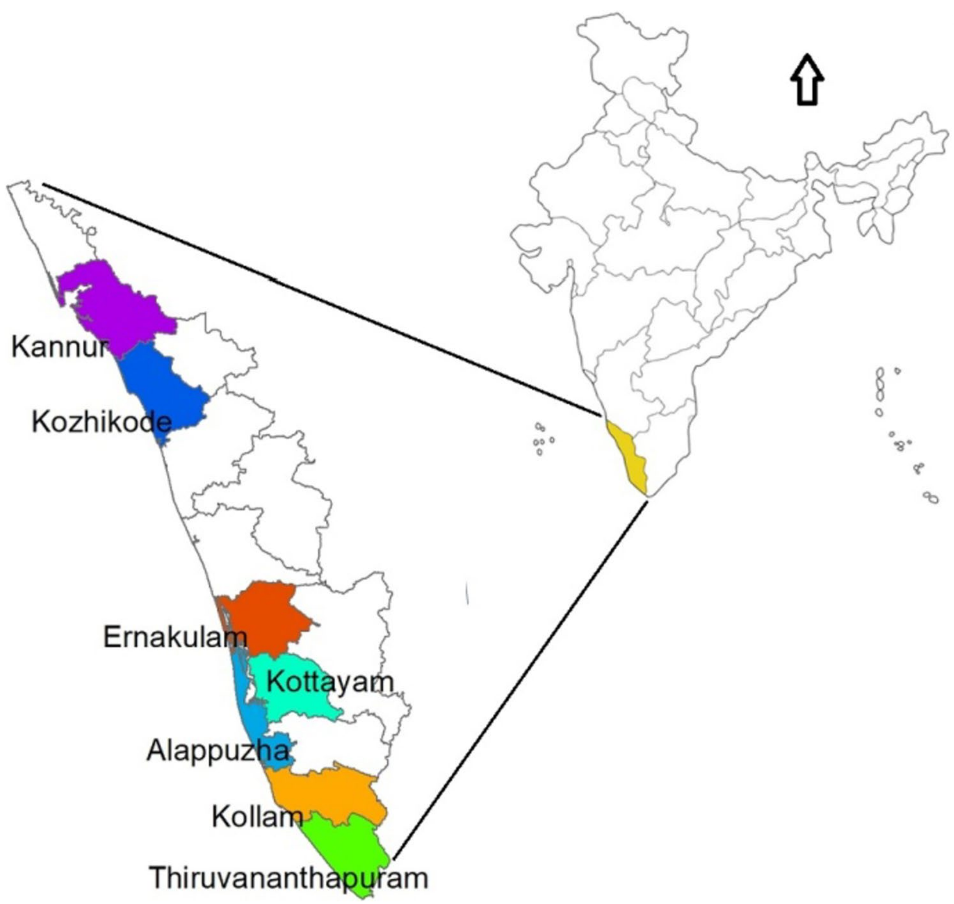

Fig. 2 Location of Kerala and the districts chosen for the study

Table 1 Descriptive statistics of meteorological data of different locations

Stations	Maximum	Minimum	Mean	Median	Standard deviation
Annual maximum temperature (1980–2020)					
Thiruvananthapuram	31.957	30.718	31.292	31.286	0.293
Kollam	34.079	31.906	33.143	33.114	0.470
Alappuzha	33.501	30.386	31.778	31.609	0.667
Kottayam	33.614	30.140	32.182	32.226	0.664
Ernakulam	32.248	30.811	31.425	31.347	0.384
Kozhikode	34.277	30.782	31.921	31.836	0.940
Kannur	33.828	30.238	32.177	32.325	0.800
Annual minimum temperature (1980–2020)					
Thiruvananthapuram	24.965	23.018	23.973	23.936	0.403
Kollam	23.453	20.821	22.424	22.431	0.509
Alappuzha	24.891	21.849	23.964	24.095	0.626
Kottayam	23.887	21.211	23.146	23.280	0.515
Ernakulam	24.924	23.334	24.333	24.313	0.350
Kozhikode	25.169	23.798	24.411	24.334	0.327
Kannur	24.912	22.558	23.614	23.511	0.588
Annual rainfall (1980–2020)					
Thiruvananthapuram	2422.300	1147.900	1732.929	1767.200	360.621
Kollam	3575.600	1774.600	2639.400	2621.800	408.767
Alappuzha	3490.100	1725.700	2798.456	2839.000	399.202
Kottayam	3616.500	1792.200	2899.144	2957.000	433.445
Ernakulam	3656.500	2138.800	2952.300	2953.500	367.387
Kozhikode	4343.700	1790.800	3034.741	2973.900	514.517
Kannur	4555.200	1148.900	3267.988	3314.100	671.335

of Kollam district (a humid tropical region of Kerala) using FAO-CROPWAT. Lathika (2010) computed the crop water needs of all the major crops of Kerala region. Ginger is cultivated as rain-fed crop in high rainfall areas (uniform distribution for 5–7 months) and irrigated crop in less rainfall areas where distribution is not uniform. Cashew requires 900–1200 mm of water during its crop cycle while Ginger requires water in the range of 500–700 mm (Lathika 2010). The critical stages for irrigation are during germination, rhizome initiation, and rhizome development stages. The first irrigation should be done immediately after planting and subsequent irrigations are given at intervals of 7–10 days in conventional irrigation (based on prevailing weather and soil type). The FAO-CROWAT based water requirements of Thiruvananthapuram, Ernakulam, and Kozhikode regions are presented in Supplementary file. The computation shows that mostly the necessity of irrigation for the crop is for non-monsoon season.

Results and discussion

In this research work, firstly the SPI of all the seven districts are computed.

Standardized precipitation index (SPI)

The meteorological drought index SPI for the years 1980 to 2020 for various time scales (12 months, 6 months, and 3 months) is measured using DrinC software data management environment for seven districts of Kerala. The data obtained from this analysis allow for the assessment of both immediate and prolonged moisture conditions, while also offering a means to estimate precipitation patterns throughout the course of a given season. The 3-month SPI provides the information on seasonal (quarterly) basis, while the 6-month SPI insights into historical precipitation trends for a mid-term period. SPI-12 provides information on long range drought conditions. The identification of drought years for each district from 1981 to 2020 conducted based on SPI is presented in Table 2. Severe or extreme drought conditions were noted in multiple districts for the years 1981, 1983, 1984, 1987, 2013 and 2017. The 2016–2017 drought condition is the worst drought hit the state during the past 115 years, which initiated a lot of debates on changing climatology of the State of Kerala (Abhilash et al. 2019).

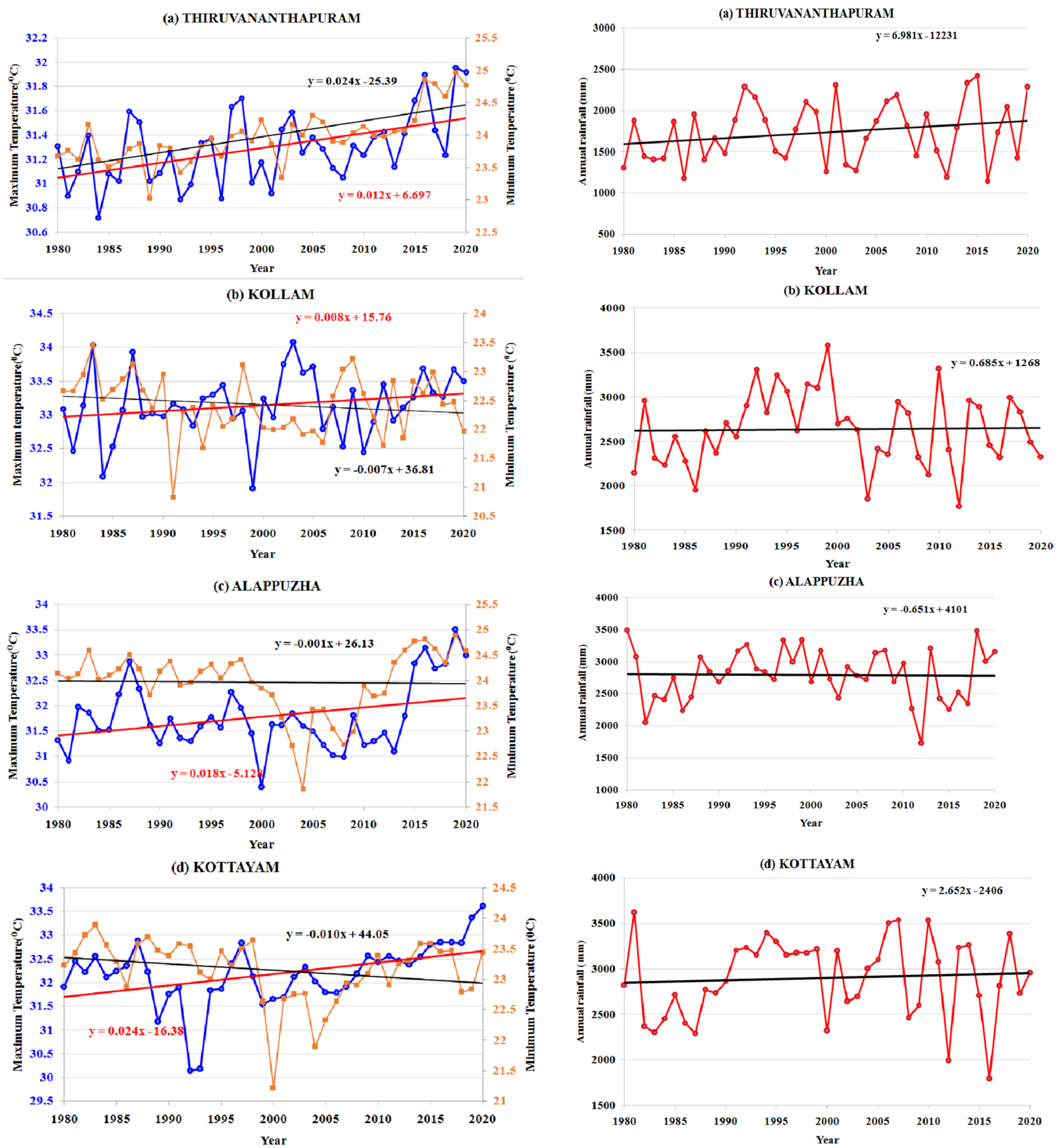

Fig. 3 Variation of annual data of temperature and rainfall data of different locations. Left column shows the variation of temperature data and right column shows the data of rainfall

Agricultural standardized precipitation index (aSPI)

The estimation of effective precipitation utilized in the computation of aSPI can be accomplished by three distinct approaches, namely USBR, USDA1, and USDA2 (Tigkas et al. 2022). The study identified a correlation between the SPI and the aforementioned approaches in order to choose the most appropriate method (Table 3).

According to the findings presented in Table 3, it is evident that the USDA1 and USDA2 methods exhibit a greater correlation value with the standardized precipitation index (SPI). This suggests that there is a somewhat

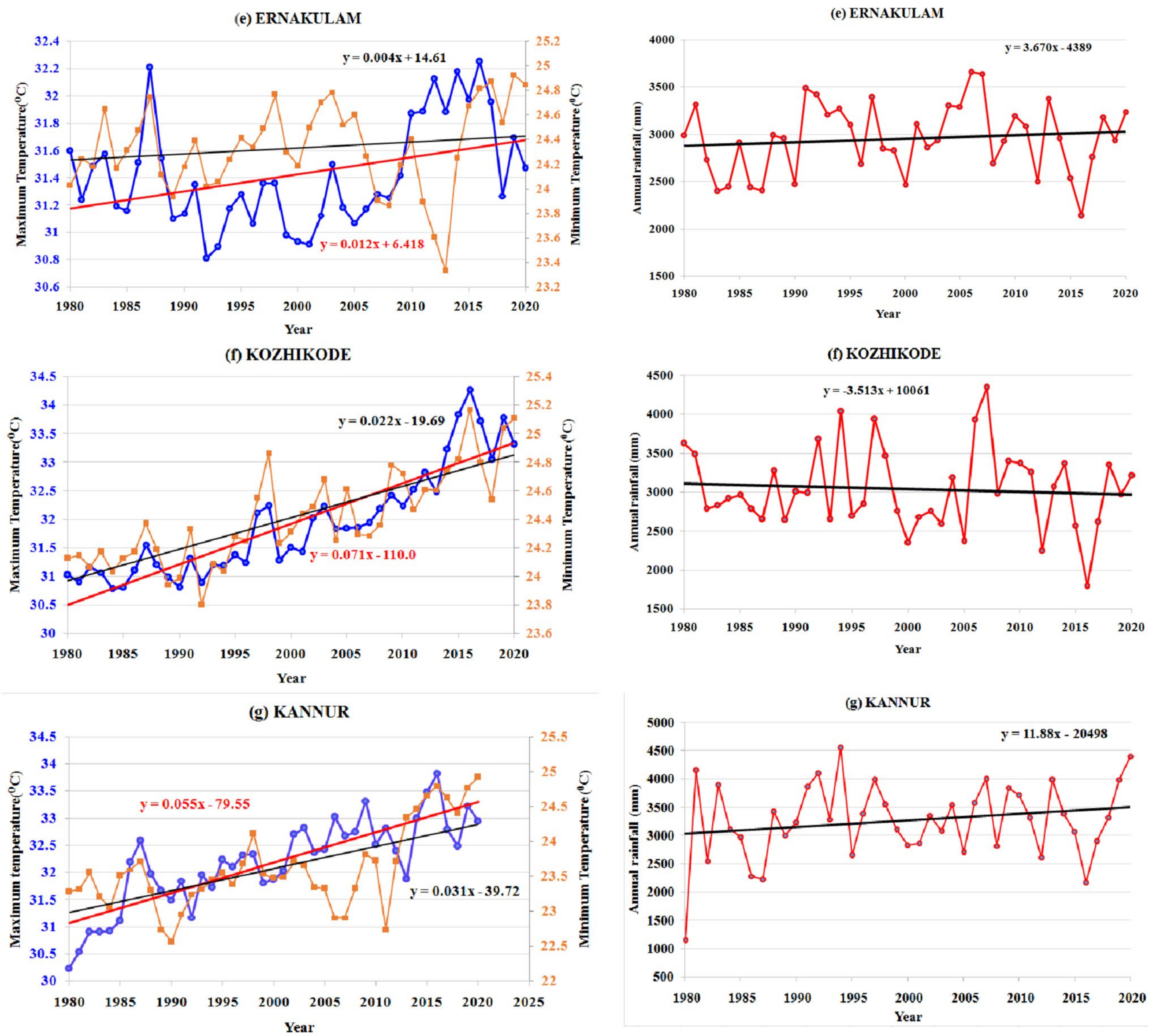

Fig. 3 (continued)

smaller degree of fluctuation between the SPI and aSPI values obtained through the use of these two methods. The USBR technique yields a lower correlation value with the SPI, suggesting a distinction between aSPI and SPI. Additionally, it is beneficial to differentiate between aSPI and SPI. Hence, the USBR approach is employed for subsequent investigations. The plot of aSPI for 12-month, 6-month, and 3-month time scales for all seven districts of Kerala is done for the years 1981–2020 and illustrated in Figs. 4, 5, and 6. Figure 4 represents aSPI derived in every 3 months of each year. The index is useful for short-term drought monitoring and assessing the potential impact on crops that have shorter growing season. The SPI-6, showing the trend of preceding 6-month period, is useful for medium-term drought monitoring is beneficial in evaluating the potential repercussions on crops that have extended growth seasons. Long-term drought monitoring is a valuable tool for determining the possible impact on perennial crops. The data collected revealed significant occurrences of severe dry and wet circumstances, surpassing the SPI drought values. The identification of drought years for each district from 1981 to 2020 was conducted using the aSPI values as presented in Table 4. The years 1983, 1984, 1990, 1992, and 2017 were characterized by drought conditions.

Table 2 Drought years based on SPI values. Identified drought years and corresponding drought states are marked in bold

Year	Thiruvananthapuram	Kollam	Alappuzha	Kottayam	Ernakulam	Kozhikode	Kannur
1981	**NN**	**NN**	**SD**	**SD**	**MD**	**NN**	**NN**
1982	VW	NN	NN	NN	NN	NN	MW
1983	**NN**	**ED**	**SD**	**ED**	**ED**	**NN**	**ED**
1984	**NN**	**SD**	**NN**	**SD**	**MD**	**SD**	**NN**
1985	NN	NN	NN	NN	NN	NN	VW
1986	NN	MD	NN	NN	NN	NN	NN
1987	**MD**	**SD**	**SD**	**SD**	**MD**	**MD**	**SD**
1988	NN	NN	MD	SD	NN	NN	NN
1989	NN	NN	NN	NN	NN	MW	NN
1990	NN	NN	NN	NN	NN	NN	NN
1991	NN	NN	NN	NN	NN	NN	MD
1992	MW	VW	NN	MD	MD	ED	NN
1993	MW	MW	NN	MD	MD	NN	NN
1994	NN	MW	NN	NN	NN	MD	NN
1995	NN	NN	NN	NN	MW	MW	NN
1996	NN	NN	NN	NN	NN	NN	NN
1997	NN	SD	NN	NN	NN	NN	NN
1998	NN	NN	MW	MW	VW	NN	NN
1999	NN	NN	NN	NN	NN	NN	NN
2000	NN	NN	MW	NN	NN	SD	MD
2001	MD	NN	NN	NN	NN	NN	NN
2002	NN	NN	NN	NN	MW	NN	NN
2003	ED	NN	NN	NN	NN	NN	NN
2004	ED	NN	NN	NN	NN	NN	MD
2005	NN	NN	NN	NN	NN	NN	NN
2006	MW	NN	MD	NN	NN	MD	NN
2007	VW	VW	MW	NN	MW	NN	NN
2008	NN	MD	NN	NN	NN	MW	NN
2009	NN	NN	NN	NN	NN	NN	NN
2010	NN	NN	NN	MW	NN	NN	VW
2011	VW	MW	MW	VW	VW	VW	MW
2012	NN	NN	NN	VW	EW	NN	NN
2013	**NN**	**SD**	**ED**	**NN**	**NN**	**NN**	**MD**
2014	NN	NN	NN	MW	NN	NN	NN
2015	NN	NN	NN	MW	MW	NN	NN
2016	VW	NN	NN	VW	MW	VW	NN
2017	**SD**	**MD**	**SD**	**NN**	**NN**	**ED**	**ED**
2018	ED	NN	MD	NN	NN	NN	NN
2019	NN	NN	NN	NN	SD	NN	SD
2020	NN	NN	NN	NN	NN	NN	NN

MD moderate drought, *MLD* mild drought, *ED* Extreme Drought; *VW* very wet; *SD* severe drought, *MW* moderately wet, *MLW* mildly wet, *SW* severely wet, *EW* extremely wet, *NN* near normal

M-SYRS and its correlation with drought

The decomposition of the agricultural yield series for several crops into IMFs and a residual series is done utilizing the EMD methodology. The modes of decomposition of the yield series of dominant crops of different districts are presented in Fig. 7. It is evident that lower order modes exhibit a high frequency component compared to higher-order IMFs. The trend component is separated and aggregated to get the detrended series. Subsequently the modified SYRS (M-SYRS) is computed from the basic statistics of the resulting residual series. Now the Pearson correlation coefficient (R) between the SPI values at different time scales (3 months, 6 months, and 12 months) and the corresponding

Table 3 Correlation between SPI and three methods of aSPI

Districts	USBR	USDA1	USDA2
Thiruvananthapuram	0.6999	0.8998	0.9742
Kollam	0.6047	0.7859	0.9936
Alappuzha	0.5076	0.6744	0.9902
Kottayam	0.3583	0.6216	0.9868
Ernakulam	0.4433	0.6817	0.9888
Kozhikode	0.6787	0.8146	0.9929
Kannur	0.6972	0.8359	0.9938

SYRS of crops in each area are computed. The results are presented in Table 5. Based on the values in Table 5, it its very evident that the correlation between SPI and SYRS is very weak (< 0.2 in most of the cases). Therefore, it is hypothesized that SPI alone may not able to decipher the crop yield behavior and aSPI is to be considered. The correlation values between the aSPI values of different time scales (3 months, 6 months, and 12 months) and the corresponding M-SYRS of dominant crops in each area are computed and presented in Table 5.

From the table, it can be seen that the aSPI values and SYRS have a stronger link than the SPI values do (correlation ranges between 0.17 and 0.6). As hypothesized, it is concluded that effective precipitation has a role on crop yield and SPI alone may be insufficient to depict the crop yield variability. It is clear from Table 5 that 3-month aSPI and SYRS have a higher and positive correlation value than the other time frames. It is obvious because crop timings are more closely tied to a 3-month time frame. The fluctuations of aSPI-3 and M-SYRS for the period from 1998 to 2020 are illustrated in Fig. 8. The evidence of close similarity in the evolution of profiles also indicates the correlation between aSPI and SYRS series. In short, the agricultural crop production exhibits a significant degree of responsiveness to variations drought conditions quantified by aSPI-3. Moreover, overall similarity between the M-SYRS and aSPI is noted irrespective of the type of crops and districts. Similar plots for the associations of aSPI-6 and aSPI-12 are presented in Figs. 9 and 10.

Wavelet coherence analysis

The analysis of the correlation values between aSPI and SYRS revealed a stronger association between the two variables. However, these numbers represent a general linear correlation and in order to conduct a more effective and realistic estimate the WC method is employed to determine the influence within each specific time range. The wavelet coherence analysis between M-SYRS and aSPI for three different time scales (3-month, 6-month, and 12-month) was conducted for all the seven pairs. The results of this analysis are presented and visually depicted in Figs. 11, 12 and 13.

Figure 11 illustrates the wavelet coherence plots of 3-month aSPI and M-SYRS. The phase difference between the aSPI and yield of dominating crop in seven districts of Kerala is noted from the plot. Figures 12 and 13 show similar plots for 6-month aSPI and 12 month aSPI, respectively. As a quantitative measure of these coherence plots, AWC and PoSC were deduced as coherence strength for each pair of aSPI and crop yield, which are presented in Table 6.

Coconut is the dominant crop of the Thiruvananthapuram district. The AWC value found for this crop is 0.56, indicating a moderate level of agreement with aSPI-3 of the district. For the same case, the coherence score measured in percentage found to be 35. Cashew is the predominant crop cultivated in the region of Kollam. The coherence value of the observed case is found to be 49%. A distinct temporal pattern, spanning from 2002 to 2007, is noted with the occurrence of a recurring event lasting for the duration of 1 month. Alappuzha exhibits a notable coherence value of 0.6 for banana cultivation over the years 2002 and 2007 with the drought. The obtained AWC value is 0.71. The agricultural produce cultivated in the region of Kottayam primarily consists of bananas. The coherence value of the given data with aSPI-3 is 0.62. A distinct band emerged between the years 2002 and 2017, persisting for duration of 2 months. The crop banana in Ernakulam exhibits a coherence value of 53% and AWC value of 0.66 with the short-term drought series. The period from 2010 to 2012 exhibits a high level of coherence. The coherence value measured for the crop ginger in Kozhikode is 0.45. A musical ensemble was established between the years 2003 and 2005, with duration of 2 months. The major crop cultivated in the region of Kannur is ginger. The coherence value of the considered case is noted to be 0.53. Notably, a distinct pattern emerges within the temporal span of 2010–2012, specifically for duration of 3 months.

For the coconut yield of Thiruvananthapuram district, AWC value in this study is found to be 0.57 for the association with aSPI-6 series. A strong positive association is observed between the years 2005 and 2008, as shown by a coherence score of 0.9. In Kollam, a significant link is observed between aSPI-6 and the crop cashew with a coherence value of 0.85. This strong coherence is observed during the period spanning from 2001 to 2007, specifically between the first 2 months of each year. A coherence value of 0.85 was observed in Alappuzha for the cultivation of banana between the years 2002 and 2010, for the initial 2 months and the sixth month. Between the years 2017 and 2020 revealed a high level of coherence around 0.9 in the period of up to 4 months for the banana crop in Kottayam district. A distinct pattern is observed in the cultivation of bananas in the Ernakulam region, wherein a visible band is consistently

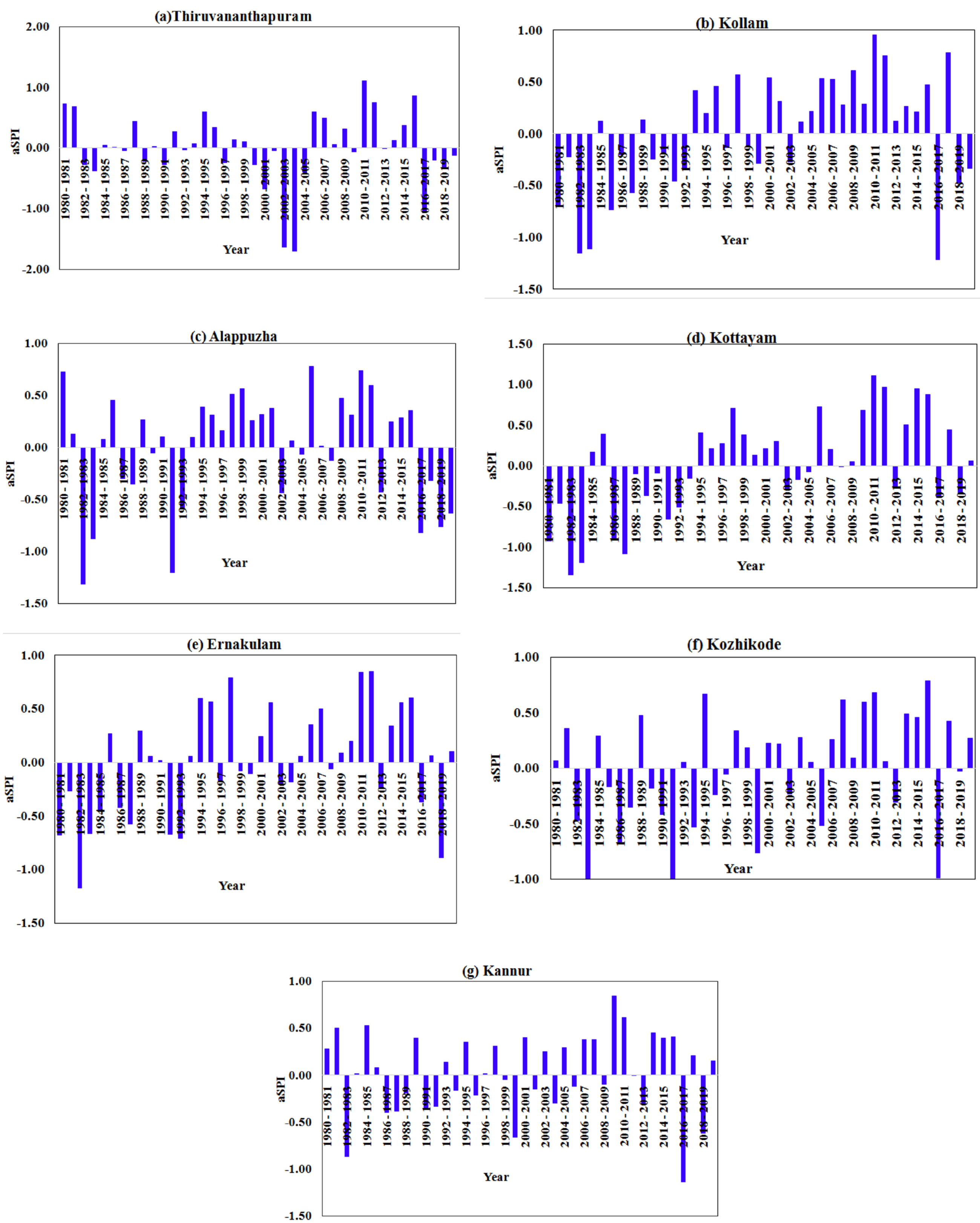

Fig. 4 Three month aSPI plot of seven districts

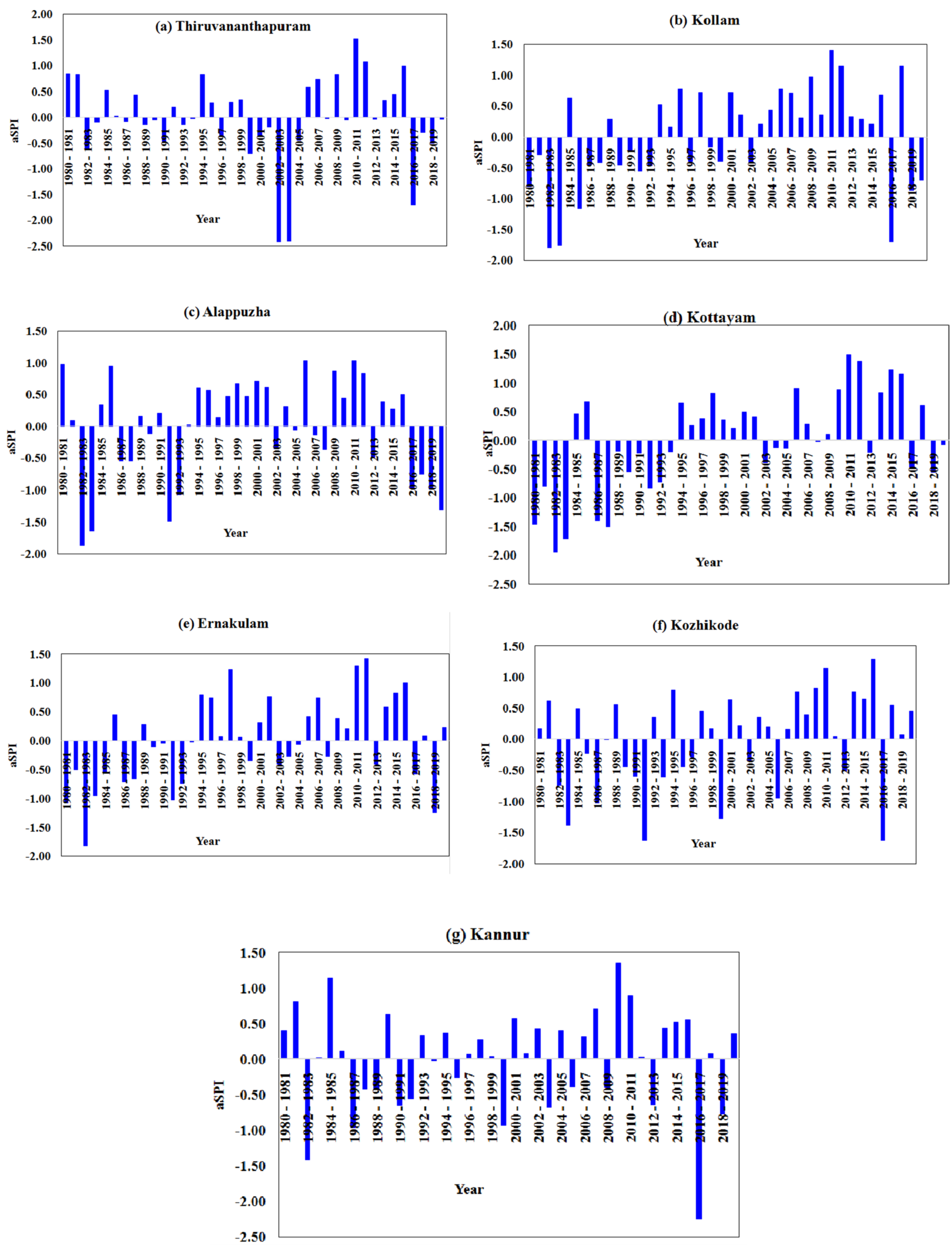

Fig. 5 Six-month aSPI plot of seven districts

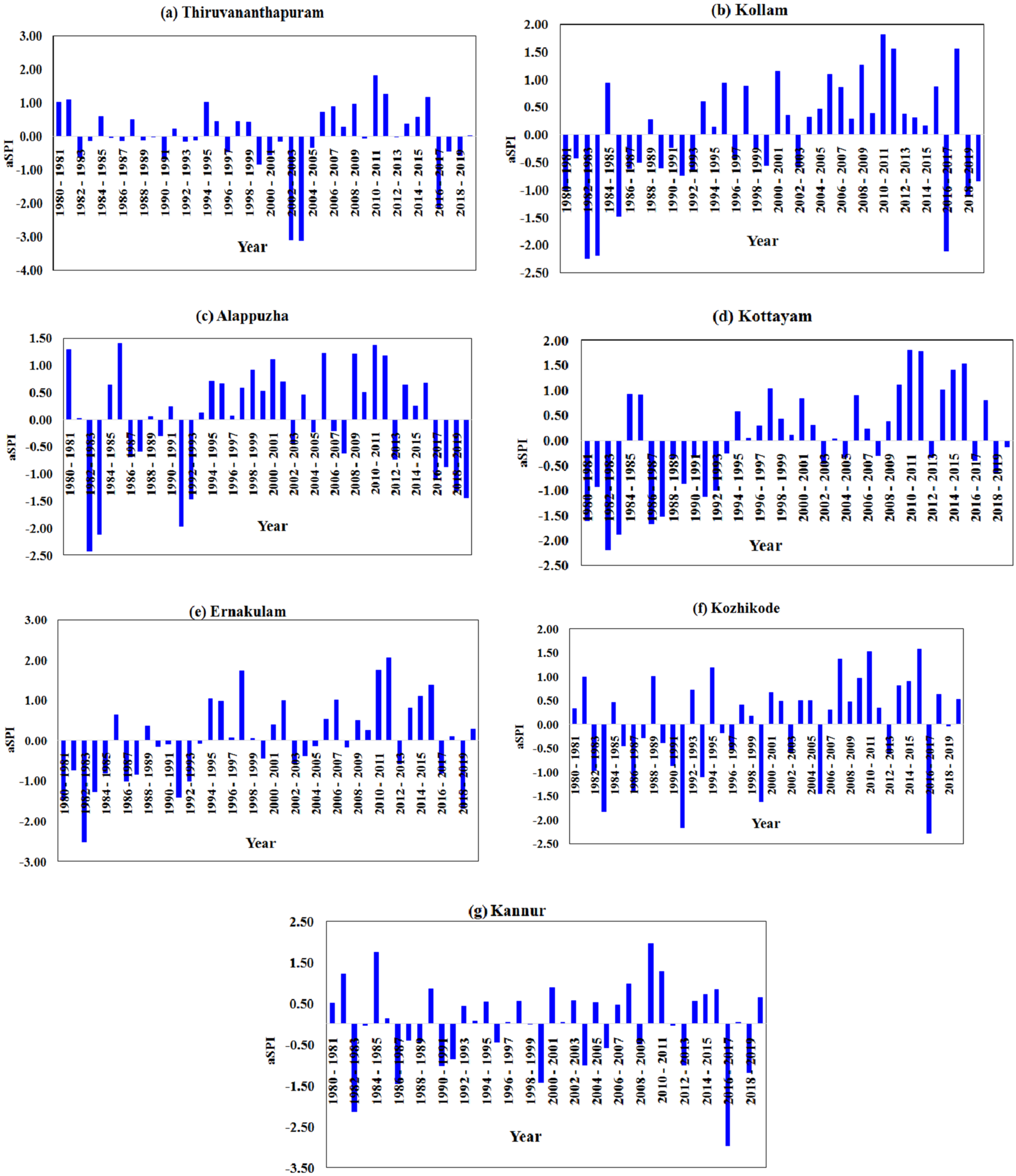

Fig. 6 Twelve month aSPI plot of seven districts

formed over a span of around 2 months between the years ranging from 2002 to 2012. The ginger crop cultivated in Kozhikode exhibits a distinct pattern characterized by a band formation spanning from 2007 to 2020, persisting for duration around 6–7 months. This pattern is quantified by a coherence value of 0.75. In the region of Kannur, the coherence value pertaining to ginger cultivation is approximately 0.8. This value is seen within the time frame spanning from

Table 4 Drought years based on aSPI values. Identified drought years and corresponding drought states are marked in bold

Year	Thiruvananthapuram	Kollam	Alappuzha	Kottayam	Ernakulam	Kozhikode	Kannur
1981	MW	MD	MW	SD	MD	Normal	MLW
1982	MW	Normal	Normal	MLD	MLD	MLW	MW
1983	**MLD**	**ED**	**ED**	**ED**	**ED**	**MLD**	**ED**
1984	**Normal**	**ED**	**ED**	**SD**	**MD**	**SD**	**Normal**
1985	MLW	MLW	MLD	MLW	MLD	Normal	SW
1986	Normal	MD	MW	MLW	MLW	Normal	Normal
1987	Normal	MLD	MLD	SD	MD	MD	MD
1988	Normal	MLD	MLD	SD	MLD	Normal	Normal
1989	Normal	Normal	Normal	Normal	Normal	MW	Normal
1990	Normal	MLD	Normal	MLD	Normal	Normal	MLW
1991	MLD	Normal	Normal	Normal	Normal	MLD	MD
1992	**Normal**	**MLD**	**SD**	**MD**	**MD**	**ED**	**MLD**
1993	Normal	MLD	MD	MD	MD	MLW	Normal
1994	Normal	MLW	Normal	Normal	Normal	MD	Normal
1995	MW	Normal	MLW	MLW	MW	MW	MLW
1996	Normal	MLW	MLW	Normal	MLW	Normal	Normal
1997	Normal	Normal	Normal	Normal	Normal	MLD	Normal
1998	Normal	MLW	MLD	MW	SW	Normal	MLW
1999	Normal	Normal	MLW	Normal	Normal	Normal	Normal
2000	MLD	MLD	MLW	Normal	Normal	SD	MD
2001	MLD	MW	MW	MLW	Normal	MLW	MLW
2002	Normal	Normal	MLW	Normal	MW	Normal	Normal
2003	**ED**	MLD	Normal	Normal	MLD	MLD	MLW
2004	**ED**	Normal	Normal	Normal	Normal	Normal	MD
2005	Normal	Normal	Normal	Normal	Normal	Normal	MLW
2006	MLW	MW	MW	MLW	MLW	MD	MLD
2007	MLW	MLW	Normal	Normal	MW	Normal	Normal
2008	Normal	Normal	MLD	Normal	Normal	MW	MLW
2009	MLW	MW	MW	Normal	Normal	Normal	MLD
2010	Normal	Normal	MLW	MW	Normal	MLW	SW
2011	SW	SW	MW	SW	SW	SW	MW
2012	MW	SW	MW	SW	EW	Normal	Normal
2013	Normal	Normal	MLD	Normal	MLD	MLD	MD
2014	Normal	Normal	MLW	MW	MLW	MLW	MLW
2015	MLW	Normal	Normal	MW	MW	MLW	MLW
2016	MW	MLW	MLW	SW	MW	SW	MLW
2017	**ED**	**ED**	**MD**	**Normal**	**MLD**	**ED**	**ED**
2018	Normal	SW	MLD	MLW	Normal	MLW	Normal
2019	MLD	MD	MD	MLD	SD	Normal	MD
2020	Normal	MLD	MD	Normal	Normal	MLW	MLW

MD moderate drought, *MLD* mild drought, *ED* Extreme Drought; *VW* very wet, *SD* severe drought, *MW* moderately wet, *MLW* mildly wet, *SW* severely wet, *EW* extremely wet, *NN* near normal

2002 to 2007, specifically during the initial 3 months of each year. Arrows to the right (left) indicates positive (negative) correlations with in-phase (anti-phase) relationships. Arrows pointing up indicates that the aSPI series leads the M-SYRS by 90°, while arrows pointing down indicate that the yield series leads the drought series by 90°. The arrow pointing to the northeast indicates that the series are positively correlated with phase relationships are partially dependent and vice versa.

The calculated AWC value in this study is found to be 0.56 for aSPI-12 with coconut yield of Thiruvananthapuram. A strong positive association is observed between the time periods spanning from 2005 to 2008, as shown by a coherence value of 0.65. The duration is limited to a period of

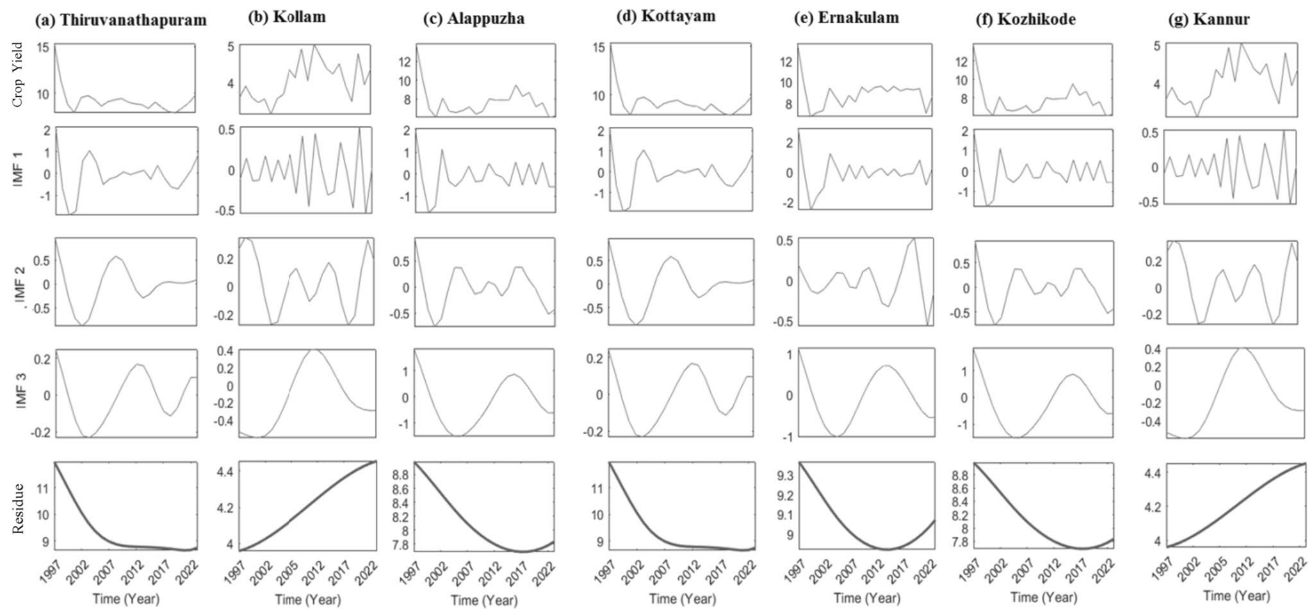

Fig. 7 Decomposition of the crop yield series

Table 5 Correlation values between drought index and SYRS for different time scale. Highest correlation values of drought index of different scales are marked in bold

District and crop	SPI			aSPI		
	3 Months	6 Months	12 Months	3 Months	6 Months	12 Months
Thiruvananthapuram (coconut)	0.19	0.17	0.02	0.40	0.47	0.26
Kollam (cashew)	0.19	0.16	0.09	0.32	0.49	0.32
Alappuzha (banana)	0.13	0.09	0.06	0.47	**0.58**	0.47
Kottayam (banana)	0.21	0.12	0.08	**0.60**	0.56	0.50
Ernakulam (banana)	0.20	0.15	0.10	0.50	0.54	**0.52**
Kozhikode (ginger)	0.16	0.11	0.08	0.54	0.17	0.20
Kannur (ginger)	0.11	0.09	0.03	0.52	0.45	0.29

1 month. A coherence value of 0.85 was observed in the region of Kollam for the cashew crop during the years 2002 and 2010, specifically during the initial 2 months of the growing season. Between the years 2002 and 2008, a coherence value of approximately 0.8 was observed over the periods of 2 months and 6–7 months in relation to banana crop of Kottayam district. A distinct pattern emerges over a span of approximately 2 months during the years 2002 to 2012, specifically pertaining to the banana harvest in the region of Ernakulam. In the region of Kozhikode, the coherence value pertaining to ginger cultivation ranges about at 0.75. This value is seen over the temporal span of 2005 to 2008, specifically during the duration of 5–7 months. The ginger crop cultivated in Kannur exhibits a distinct band structure from 2003 to 2007, during the initial 3 months of each year. This band formation is characterized by a coherence value of 0.8.

For Kottayam district, strong in-phase relationship between the two series is noted, which might be partially controlled by other meteorological factors particularly after 2010. The down and southeast arrows are noted for ginger in northern Kerala districts, irrespective of the scales. For southern Kerala districts, the behavior of drought series leads by crop yield (fully or partially) in lower scales. But at higher time scales, the behavior got reversed. For ginger yield of Kannur, such a behavior was noted between aSPI-6 and M-SYRS even at the intra-annual scales. In general, a strong coherence relationship was noted at intra-annual/seasonal scales in the yield-short term drought relations at all the districts. The relationship is weaker lasting for few months in ginger crop of Kannur district. For banana yield of Kottayam, there exists strong coherence ranging even at inter annual time scales. On considering the relationship between yield and moderate drought, similar behavior (coherence lasting for few months) was noted in most of the cases. The relationship is very weak for coconut crop of Thiruvananthapuram and ginger crop of Kozhikode. However, localized coherences lasting for maximum of couple of years were noted at larger time scales, indicating that the

Fig. 8 aSPI of 3-month and modified SYRS of the selected crops of the seven districts

Fig. 9 aSPI of 6-month and modified SYRS of the selected crops of the seven districts

Fig. 10 aSPI of 12-month and modified SYRS of the selected crops of the seven district

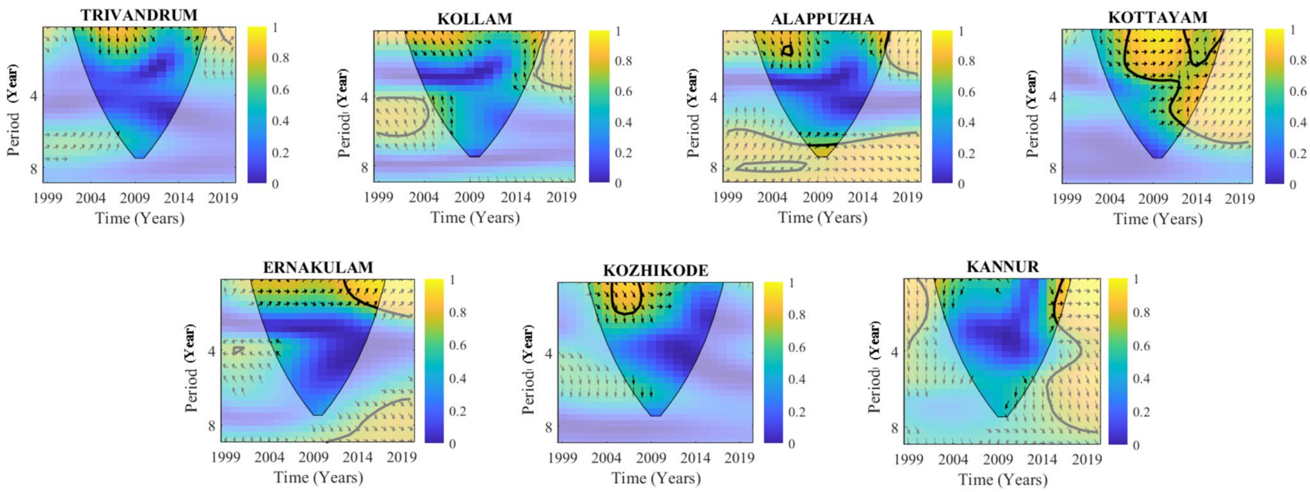

Fig. 11 Wavelet coherence between 3-month aSPI and M-SYRS of dominant crops of seven districts

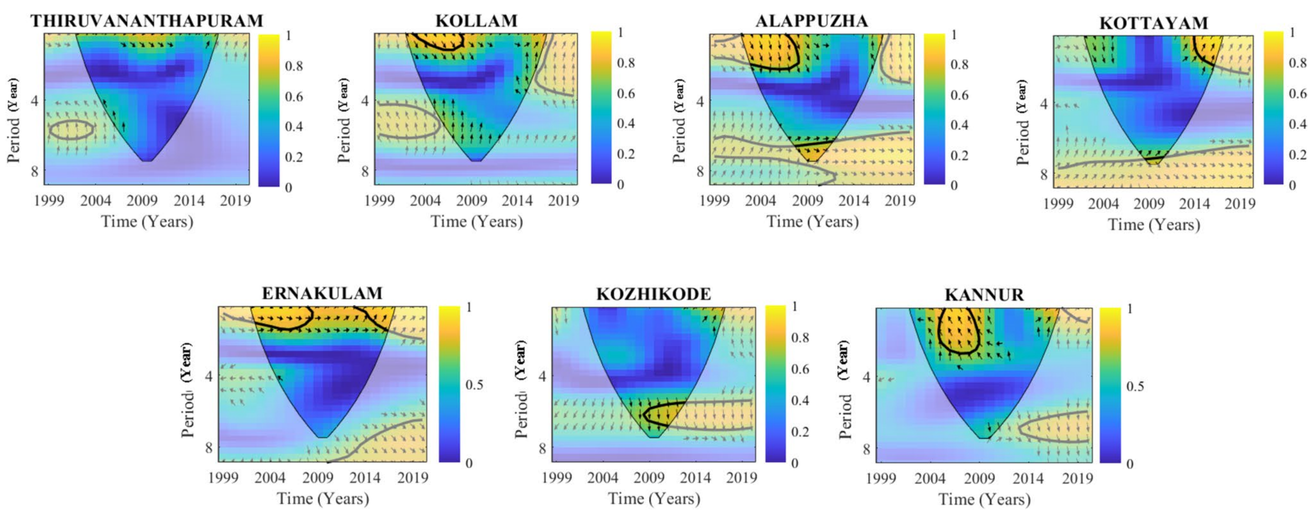

Fig. 12 Wavelet coherence between 6-month aSPI and M-SYRS of dominant crop of seven districts

phase relationships are controlled by local meteorological or global climatic oscillations, which are unaccounted in our analysis. On comparing the coherence of yield with aSPI-12 and aSPI-6, a good amount of similarity is noted. This is obvious as beyond the crop season lasting few months time, a drought lasting for an annual period is extremely rare in the scenario of Kerala.

Discussion

The teleconnections of crop yield with the local- and global-scale climatic variables have been performed by many researchers (Dietz et al. 2021). Many of the studies considered the local-scale variables like rainfall, temperature, soil moisture, global-scale climatic oscillations and drought indices in different forms (like SPI, SPEI, NDVI). The dominant crops are often considered for analysis, and the standardized yield was estimated using different approaches. The findings of some of the very recent studies (after 2020) reported in literature are summarized in Table 7. On examining the results of the past studies, it is evident that most of the studies followed simple correlation analysis and many of them have not considered the study in a time–frequency perspective. Also in most of the studies, SPI or SPEI is used and none of the studies used the aSPI for the analysis, even though it is more appropriate to use aSPI in an agricultural perspective, as it considers the effective precipitation which plays key role on crop yield variability. Our study presents the first results of the teleconnection between a detrended SYRS and aSPI-based meteorological drought of different scales using wavelet coherence. Moreover, we have used two wavelet coherence measures of AWC and PoSC in order to

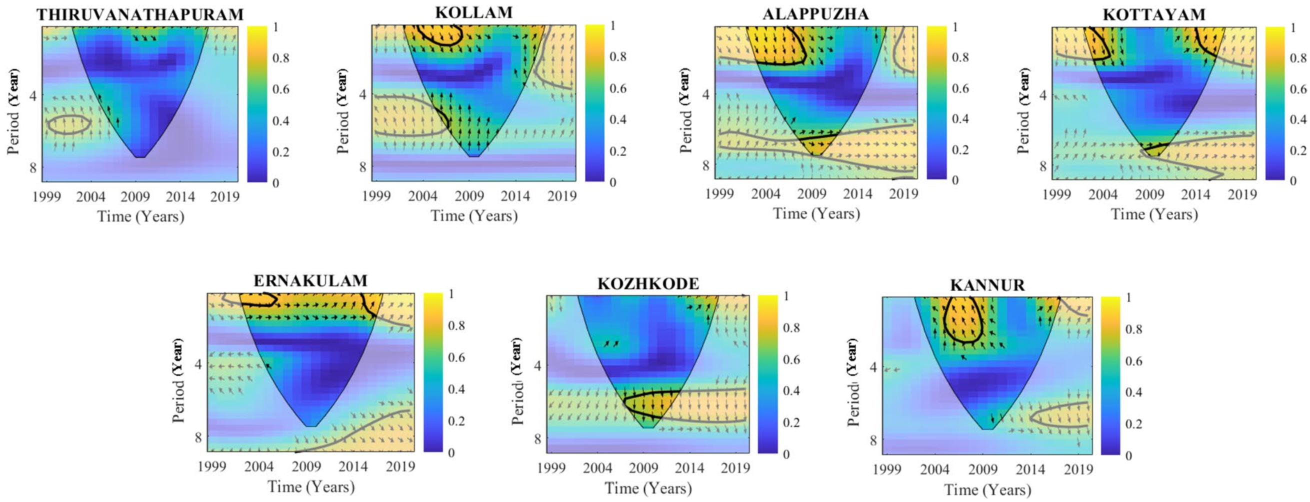

Fig. 13 Wavelet coherence between 12-month aSPI and SYRS of dominant crop of seven districts

Table 6 AWC and PoSC values for wavelet coherence between 3-month aSPI and SYRS for all districts. Highest AWC and PoSC values for aSPI of different scales are marked in bold

District	Crop	aSPI-3		aSPI-6		aSPI-12	
		AWC	PoSC	AWC	PoSC	AWC	PoSC
Thiruvananthapuram	Coconut	0.561	35.47	0.577	38.23	0.567	54.81
Kollam	Cashew	0.661	49.11	0.678	49.91	0.680	50.81
Alappuzha	Banana	0.710	60.07	0.704	60.34	0.697	54.19
Kottayam	Banana	**0.718**	**62.30**	**0.716**	**62.21**	**0.712**	**58.11**
Ernakulam	Banana	0.663	53.29	0.677	56.33	0.675	54.81
Kozhikode	Ginger	0.633	45.36	0.612	43.05	0.636	56.79
Kannur	Ginger	0.658	51.96	0.660	49.02	0.646	48.04

quantitatively decipher the crop yield-drought relationships. We have followed a modified SYRS computation employing EMD, which works in a data adaptive environment and not biased by non-stationarity features of yield series from climatic changes or anthropogenic factors.

Even though our study provide some new insights on the crop-yield teleconnections, the study is not free from limitations. It is worth mentioning that the wavelet analysis was performed under the constraints of limited data length due to lack of availability of long term crop yield data. The shorter data length further constrains us from performing the analysis by considering stages of crop growth and water demanding months (Hamal et al. 2020). Even though many modified and advanced forms of drought indices involving variables like evapotranspiration, temperature and soil moisture were proposed (Yang et al. 2023), this study considered rainfall as the sole variable for performing drought analysis. It is worth noting that in an agricultural perspective, the factors like soil moisture have a greater influence on crop yield and sufficient soil moisture in the root zone by way of irrigation/rainfall can augment crop production (Surendran et al. 2019b). This can be monitored continuously or periodically, using several soil moisture sensors installed at various depths in the root zone. Moreover, the rate of change in soil moisture is an indicator of the atmospheric water demand. When it is hot and dry, rapid depletion of soil moisture occurs through evaporation from the soil surface and uptake by plants. As a result, the root zone moisture declines much faster in comparison with cold and wet periods. Hence accounting soil moisture component is definitely a better choice for crop yield teleconnection studies. But long term long term and real time data products including soil moisture for the study region is not available to perform such a more precise analysis. Therefore we used aSPI which considers effective rainfall as proxy to quantify the agricultural drought. Therefore, such factors need to be considered in future studies on crop yield–drought relationships, by circumventing the limitations through real time monitoring of soil moisture and related data acquired through rigorous field measurements. The propagation of drought from one form to other (like meteorological to hydrological) is a well-attended problem in water resources studies (Ding et al. 2021; Saleem et al. 2022; Hooshyaripor et al. 2022; Raposo et al. 2023). Accordingly, the impact of different types of

Table 7 Findings of few recent (reported after 2020) studies on crop yield–climate teleconnections

R	Crop variable/index	Climate variable/drought index	Area	Method	Key findings
Ghose et al. (2021b)	Rice yield	Climatic oscillation	Bangladesh	Ensemble EMD	South-central and northern zones had the most notable yield-climate associations, while PET of March and multivariate ENSO indices (MEI) of January were identified as the best yield prediction indicator
Mohammed et al. (2022)	Crop-drought resilient factor (CDRF) and standardized yield residual series (SYRS)	SPI and SPEI	Hungary	Pearson correlation	Hungary's western region is substantially more susceptible to agricultural drought than its eastern region
Hamal et al. (2020)	SYRS	SPEI	Nepal	Spearman's rho	The most correlated crop growth period for summer maize and winter wheat was the sowing and growing period drought impacts increased in the western and central regions
Maghrebi et al. (2020)	Crop yield and area	SPI	Iran	Mann–Kendall, Pearson correlation	Despite decreasing water availability during this period, irrigated agricultural production and area continuously increased
Waseem et al. (2022)	Wheat, SYRS	SPI	Punjab, Pakistan	Spearman's rho	Drought occurrences during the growth stage had a greater impact on wheat yield than they did during the cropping stages
Padakandla et al. (2022)	SYRS	Rainfall and Temperature	Andhra Pradesh India	Wavelet	Significant co-movement between climatic and crop variables at varying time horizon up to 8 years
Hendrawan et al. (2022)	Crop yield	Rainfall	Global	Correlation	Drought index based on the ensemble precipitation dataset correlates better with the crop yield anomaly than a single dataset
Zhou et al. (2022a, b)	Normalized difference vegetation index (NDVI) and Solar-induced chlorophyll fluorescence (SIF)	Climatic oscillation and solars	Pearl river basin, China	Partial wavelet coherence, cross-wavelet	The relationship between the SIF and drought was more significant than that between the NDVI and drought; significant positive correlation between meteorological drought and vegetation in the period of 8–20 year

Table 7 (continued)

R	Crop variable/index	Climate variable/drought index	Area	Method	Key findings
Prodhan et al. (2022)	Future Crop yield	Future SPEI	South Asia	Machine learning	The SW regions of India and Afghanistan, NE India, are expected to have the highest drought intensity in the future. Rice is projected to have the highest risk of yield loss, followed by maize and wheat in South Asia
Hendrawan et al. (2023)	Crop yield	SPI	Global	Machine learning	The results indicate that the spatial variations of the crop-drought sensitivity were mainly explained by environmental factors (i.e., annual precipitation, soil water-holding capacity, soil acidity, annual PET) and crop management factors (i.e., fertilizer rate, growing season)
Thomas and Nair (2023)	Crop yield	SPI	Kerala, India	Probabilistic convolution neighborhood technique (PCNT)	Meteorological variables and crop yield relations show special variability in coherence

drought have adverse effects on crop yield, especially on considering the base period of crop and the water requirement during different stages of crop growth. In a more in-depth and accurate teleconnections studies on crop yield, the effects of drought transitions on yield needs to be considered as another promising domain of research. In this study we could consider only the aSPI for the analysis and how the transitions will impact crop yield is left unattended in this study, as the competing datasets (say streamflow) of other forms of droughts for the same period of crop yield are not available.

Some of the recent studies reported that agriculturally dominated reservoirs increase the water losses through strong evaporation and frequent infiltration (Sang et al. 2023), which in turn influence water balance and may lead to drought. Such cyclic process and its interplay with yield need worth investigating in future. The use of different forms of drought indices and SYRS brings uncertainty in the results on crop yield–drought relationships. Therefore more experiments need to be solicited using data of longer period, alternatives of SYRS and drought index formulations, concepts of seasonal variations of water requirements, propagation of drought, etc. The study can also be extended considering the concurrent role of multiple meteorological factors and large-scale climatic oscillations by invoking the potential of multiple and partial WC variants (Mohan et al. 2023). Moreover, the study needs to be extended to improved predictability crop yield and food production from the drought projections for the preparedness against famine disasters.

Conclusion

The impact of drought on crop yield is significant for the better preparedness against disasters. The traditional SPI and recently proposed agricultural SPI (aSPI) values for the time scales of 3, 6, and 12 months were estimated for the seven districts of Kerala. The more intense drought years are captured by aSPI than SPI on drought classifications. The detrending of agricultural yield series of dominant crops is performed using a proposed empirical mode decomposition (EMD) and afterward standardized to get modified standardized yield residual series (M-SYRS). The major conclusions drawn from the study include:

- The correlation between aSPI and M-SYRS is found to be stronger than SPI and M-SYRS, irrespective of crop type and time scale, which indicated the role of effective precipitation on the crop yield variability. This advocated the use of aSPI for agricultural crop-yield analysis and applications.

- The yield of primary crop of Kottayam, namely banana, exhibits the highest correlation value of 0.6 with aSPI. The analysis of wavelet coherence is performed to examine the relationship between M-SYRS and aSPI at various temporal scales. The average wavelet coherence (AWC) and the percentage of significant coherence (PoSC) measures revealed the highest values for banana, of Kottayam district (0.71 and PoSC value of 62). Among all the districts and crops, banana of Kottayam district has greater correlation and coherence values with aSPI.
- The study reveals that there is a significant correlation and coherence exists between drought indices and crop yield value, particularly on a 6-month time period. This association consistently remains same across different crops and districts. It is further noted that the short to medium seasonal droughts have profound impact on the agricultural yield of the different districts of Kerala.

This study considered rainfall as the only variable for the investigation of drought, because of the lack of availability of real time data. It is worth noting that other factors such as temperature and soil moisture have a greater influence on crop yield. In short, future research endeavors may encompass a broader range of indicators and comprehensive analysis of drought conditions utilizing alternative drought indices, SYRS measures, concepts of seasonal water requirements and drought propagation in crop yield teleconnection studies pertaining to the region.

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Data availability The data used in this research are available in public. The compiled data will be made available on reasonable request to the corresponding author.

Declarations

Conflict of interest Authors declare no conflict of interest.

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