

Article

Multiscale Drought Assessment in Kien Giang Province, Vietnam: Comparing MSPI and MSPEI for Monitoring in a Coastal Mekong Delta Setting

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Abstract

Drought is a recurrent hazard in the Vietnamese Mekong Delta (VMD), with major implications for agriculture, water resources, and rural livelihoods. This study assesses drought variability in Kien Giang Province, Vietnam, from 1992 to 2024 using two multiscale indicators: the Multivariate Standardized Precipitation Index (MSPI) and the Multivariate Standardized Precipitation Evapotranspiration Index (MSPEI). Principal Component Analysis (PCA) was applied to Standardized Precipitation Index (SPI)- and Precipitation Evapotranspiration Index (SPEI)-based time series spanning multiple accumulation periods (3–48 months) to derive integrated drought signals and to reduce redundancy across timescales. The results show that the first principal component (PC1) captured a high proportion of total variance across stations, indicating strong coherence in drought dynamics across the province. Both MSPI and MSPEI successfully identified major historical drought episodes, particularly the severe events of 2004–2005 and 2015–2016. However, the two indices differed in their temporal behaviour: MSPI responded more directly to precipitation deficits, whereas MSPEI showed slower post-drought recovery in recent years, suggesting greater sensitivity to evaporative demand and climatic water-balance stress. These differences indicate that evapotranspiration-sensitive indices may provide added analytical value in warming coastal environments. Overall, the combined multiscale framework offers a robust basis for drought monitoring, comparative assessment, and water-resource planning in Kien Giang and other drought-prone coastal delta settings.



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Keywords: agricultural drought; drought monitoring; multiscale drought assessment; multivariate standardized precipitation index (MSPI); multivariate standardized precipitation evapotranspiration index (MSPEI); principal component analysis; The Vietnamese Mekong Delta

1. Introduction

Drought is among the most pervasive and economically damaging hydroclimatic hazards worldwide, with cascading effects on agricultural production, freshwater security, ecosystem stability, and rural livelihoods [1–6]. In delta regions, these pressures are especially acute because rainfall deficits often interact with salinity intrusion, rising temperatures, and increasingly stressed water-control systems. This is particularly evident in the VMD, where recent dry-season extremes have exposed the growing vulnerability of agriculture and water supply to compound drought–salinity dynamics [7–12]. Yet an important limitation remains in applied drought analysis: these indices are commonly interpreted at a single timescale, even though meteorological, agricultural, and hydrological droughts emerge and intensify across different temporal windows [9,12]. In practice, selecting one best timescale a priori may obscure relevant drought dynamics or create ambiguity for planners and water managers, particularly in climatically heterogeneous coastal provinces.

The development of drought indices initially focused on rainfall-based approaches, most notably the SPI, which has been widely adopted due to its simplicity and flexibility across multiple temporal scales [8,13]. To address the limitations of precipitation-only metrics under changing climatic conditions, the SPEI was introduced, incorporating temperature effects through potential evapotranspiration (PET) [8,14]. Together, these indices have been widely used to quantify precipitation deficits and the influence of evaporative demand on drought dynamics [15–18].

Beyond temporal considerations, the spatial dimension of drought has also received significant attention. Geostatistical techniques, such as Ordinary Kriging, have been widely applied to interpolate station-based drought indices and map spatial variability [19]. While such approaches are effective for identifying the spatial extent and distribution of drought, a key limitation remains in selecting an appropriate temporal scale. Drought is inherently multi-dimensional, shaped by the interaction of precipitation, temperature, humidity, and other hydroclimatic variables, and therefore cannot be fully captured by a single, fixed accumulation period [20,21].

Consequently, reliance on single-timescale indices may lead to ambiguity for decision-makers when selecting appropriate timeframes (e.g., 3, 6, or 12 months) for drought assessment in specific contexts [22]. Reflecting the growing recognition of drought as a multi-scalar and multi-sectoral phenomenon that affects meteorological, agricultural, hydrological, and socio-economic systems, research has increasingly shifted toward multi-variate approaches. These methods integrate multiple hydroclimatic variables and temporal scales, providing a more comprehensive and robust framework for drought assessment than conventional univariate indices [14,23]. To address this limitation, multiscale approaches have been developed to synthesise information across several correlated drought timescales rather than privileging a single one. The MSPI was proposed precisely for this purpose, using PCA to aggregate SPI series from multiple accumulation periods into a single standardized drought signal [22,24–26]. This offers a practical advantage when the dominant drought timescale is unknown in advance and when drought monitoring must address both short-term agricultural stress and longer-term hydrological conditions. A similar logic is increasingly relevant for evapotranspiration-sensitive drought assessment. In warming environments, precipitation-only and evapotranspiration-based indices do not always evolve in parallel, and recent comparative work suggests that their divergence may become more pronounced as evaporative demand intensifies [27]. For a coastal delta province such as Kien Giang, comparing a precipitation-based multiscale index with an evapotranspiration-sensitive multiscale index therefore offers a more robust framework for understanding drought severity, persistence, and post-drought recovery than reliance on a single SPI or SPEI series alone [28–30].

The Study of Javad Bazrafshan's (2014, 2015) [22,31] addressed the complexity of drought monitoring by proposing the MSPI based on PCA. Instead of confusing water resource managers with too many time-scaled single SPI indices, MSPI groups data series (from 3 to 48 months) into a single index, with the first PC1 explaining over 74% of the variation in the original data. Compared to other multivariate indices such as the Joint Deficit Index (JDI), MSPI demonstrates clear superiority in accurately identifying drought peaks and more accurately reflecting the frequency of drought levels from mild to extremely severe across various climatic conditions. Building on this theoretical foundation, studies by Pouya et al. (2021) [32] and Samira Rahnema (2025) [33] have expanded the application of MSPI to future forecasting and strategic planning. Specifically, artificial intelligence models such as GMDH have shown promising effectiveness in short-term forecasting of multivariate droughts (meteorological, agricultural, hydrological) through the MSPI, especially in dry, cold mountainous regions. Meanwhile, climate change scenarios CMIP6 predict that in sensitive areas such as Bandar Abbas, the MSPI will continue to trend downward, warning of more intense and prolonged droughts in the future. In summary, MSPI is not only an effective monitoring tool but also a crucial database for building sustainable adaptation and disaster risk management models.

Despite growing research on drought, salinity intrusion, and climate-related agricultural stress in the VMD, province-scale studies that compare multiscale precipitation-based and evapotranspiration-sensitive drought signals over a long station record remain limited, particularly for Kien Giang [7,12]. Much of the existing literature in the VMD has focused on salinity intrusion, sectoral impacts, or conventional univariate drought indicators. However, there remains a notable gap in understanding how multiscale aggregation influences the interpretation of drought dynamics across space and time. This limitation introduces uncertainty for decision-makers when selecting appropriate temporal scales for drought assessment, particularly in geographically diverse coastal provinces such as Kien Giang.

This study addresses these limitations by MSPI and the MSPEI to monthly hydro-climatic data from Kien Giang Province for the period 1992–2024. Using PCA, multiple accumulation timescales (3–48 months) are integrated into composite drought indices, enabling a systematic assessment of dominant variance structures and the spatial consistency of drought signals across the station network.

In doing so, the study advances beyond conventional univariate approaches by demonstrating how multiscale aggregation influences the interpretation of drought dynamics. By synthesising information across temporal scales, the framework reduces the need to pre-select a single drought timescale and instead captures the dominant drought signal across multiple temporal dimensions. The comparison between MSPI and MSPEI further allows for an assessment of how evapotranspiration-driven processes influence drought persistence and recovery in a coastal, warming environment.

Specifically, the study aims to: (i) develop multiscale drought indices from SPI- and SPEI-based timescale sets using PCA; (ii) evaluate the dominant variance structure and spatial consistency of drought signals across stations; (iii) compare the behaviour of MSPI and MSPEI with their underlying SPI and SPEI series; and (iv) assess the implications of these differences for drought monitoring and water resource planning in a coastal Mekong Delta setting.

By clarifying the role of multiscale aggregation and thermal stress in shaping drought dynamics, this study provides a more robust analytical basis for drought monitoring and interpretation. The findings are particularly relevant for improving drought assessment and supporting water resource planning in vulnerable coastal and agricultural systems under changing climatic conditions.

While the analysis provides a consistent regional assessment, it focuses on meteorological coherence across the station network and relies on provincial-scale temperature data. As such, the results prioritise regional drought signals over localised extremes and provide a foundation for future studies incorporating higher-resolution climatic and impact-based validation.

2. Methodology

2.1. Design, Data Collection and Study Area

The research process was carried out in systematic stages to build and compare multi-scale drought indices (Figure 1). Monthly rainfall and temperature data were collected as input. From the temperature data, the potential evapotranspiration index PET was calculated, then combined with rainfall P to determine the water balance. Next, standard drought indices, including SPI and SPEI, were established for timeframes from 3 to 48 months. To synthesise the multi-scale characteristics, PCA was applied to extract the PC1 for each specific combination group, including the 3–6, 6–12, 12–24, and 24–48 months intervals. The results of this process generated the corresponding MSPI and MSPEI sets.

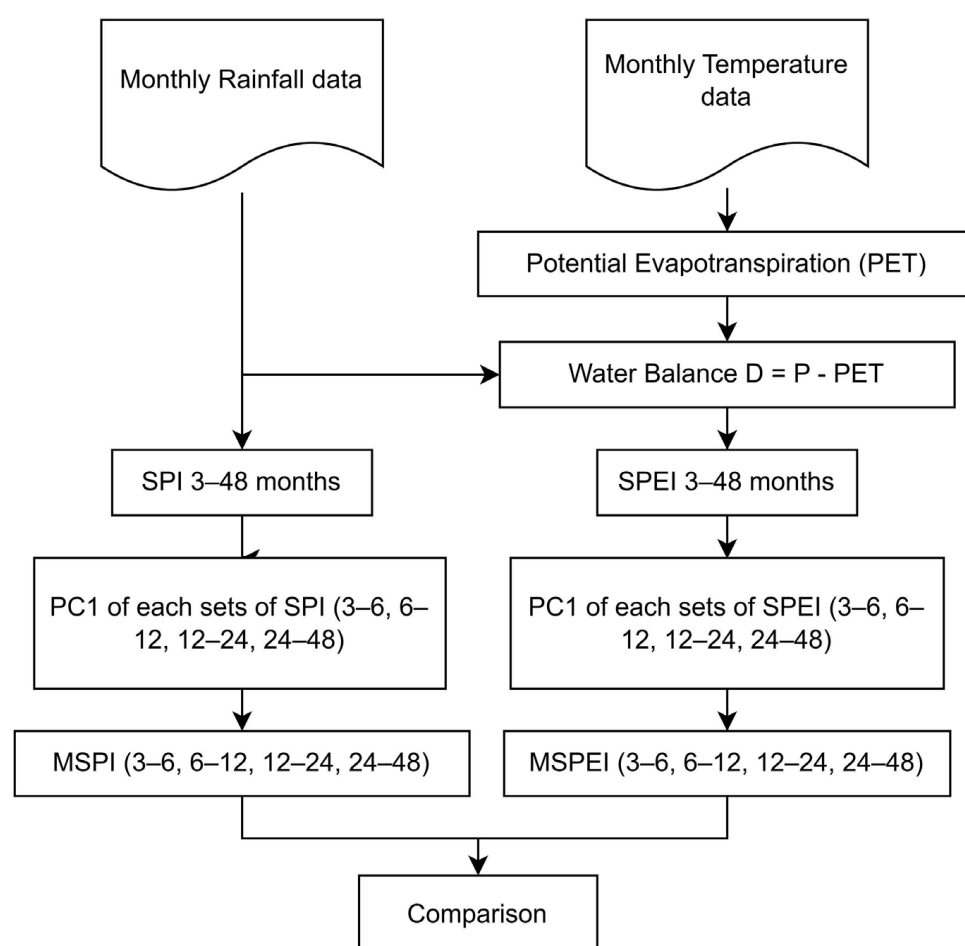


Figure 1. Methodological framework illustrating the workflow for computing and comparing MSPI and MSPEI.

Monthly rainfall data were collected from a network of 10 monitoring stations spread across the study area, while temperature data were only recorded at the Rach Gia station, as it is the only meteorological station in Kien Giang province that measures temperature. The entire data series was extracted for the period from 1992 to 2024. Secondary data sources were provided and guaranteed by the Southern Region Meteorological and Hydrological

Station. Using temperature data from the Rach Gia station as representative of the entire province for calculating the evapotranspiration index is a necessary approach given the limitations of the local temperature-monitoring station network. Due to the unavailability of long-term temperature records at other local stations, data from Rach Gia station were adopted as the provincial representative for PET calculation. Consequently, the spatial differentiation in MSPEI results across the network reflects the interaction between local precipitation and a uniform regional thermal signal.

The selection of An Bien station as a primary illustrative case is justified by its geographical position and its PCA profile, which closely mirrors the provincial mean. An Bien represents the coastal-interior transition zone of Kien Giang, making it highly sensitive to both rainfall failure and the thermal stress reflected in MSPEI. By focusing on this representative station, we can illustrate the fine-grained temporal divergence between precipitation-based and evapotranspiration-sensitive signals that are occurring throughout the wider network.

Kien Giang province is located in the western part of the VMD and borders the Gulf of Thailand, giving it a distinct coastal monsoonal setting (Figure 2). The province includes inland agricultural districts, coastal transition zones, and island areas, and is therefore exposed to pronounced seasonal hydroclimatic variability. This setting makes Kien Giang particularly relevant for drought assessment, because rainfall deficits may interact with high agricultural water demand and, in coastal areas, with saline intrusion during the dry season [7]. More broadly, recent severe dry seasons in the VMD have demonstrated how drought, salinity intrusion, and warming-related evaporative stress can jointly affect agriculture, water supply, and rural livelihoods, especially during the 2015–2016 and 2019–2020 events [34–37].

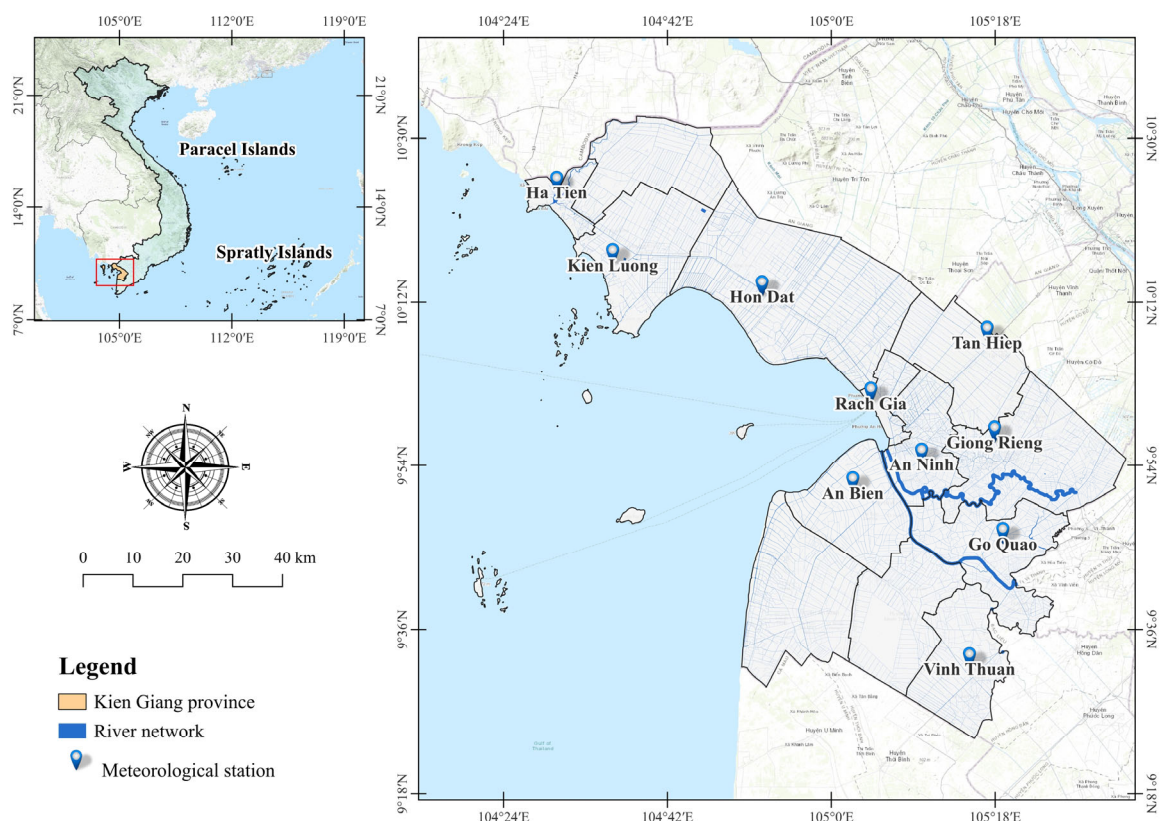


Figure 2. Locations of the ten rain-gauge stations in Kien Giang Province, Vietnam, used in this study for the period 1992–2024.

Recent climate analyses for Kien Giang indicate a warming trend, particularly an increase in minimum temperature, alongside shifts in rainfall seasonality. Station-based trend analysis has shown significant increases in dry-season rainfall, the number of dry-season rainy days, and annual rainy days, while wet-season rainfall exhibits a slight but statistically non-significant decline. January rainfall has also increased, indicating a tendency toward wetter dry-season conditions, whereas minimum temperature has risen more clearly than maximum temperature [7]. These findings are consistent with broader concerns about changing hydroclimatic regimes in the VMD and reinforce the need for robust drought-monitoring approaches at the provincial scale.

Monthly rainfall data for the period 1992–2024 were collected from ten rain-gauge stations in Kien Giang Province, including An Bien, An Ninh, Giong Rieng, Go Quao, Ha Tien, Hon Dat, Kien Luong, Rach Gia, Tan Hiep, and Vinh Thuan. Monthly maximum, minimum, and mean temperature data for the same period were obtained from the Rach Gia station and used as a provincial reference series for the evapotranspiration-sensitive drought analysis. Rainfall data were provided by the Southern Vietnam Regional Meteorological and Hydrological Station. The spatial distribution of the ten rain gauges is shown in Figure 3.

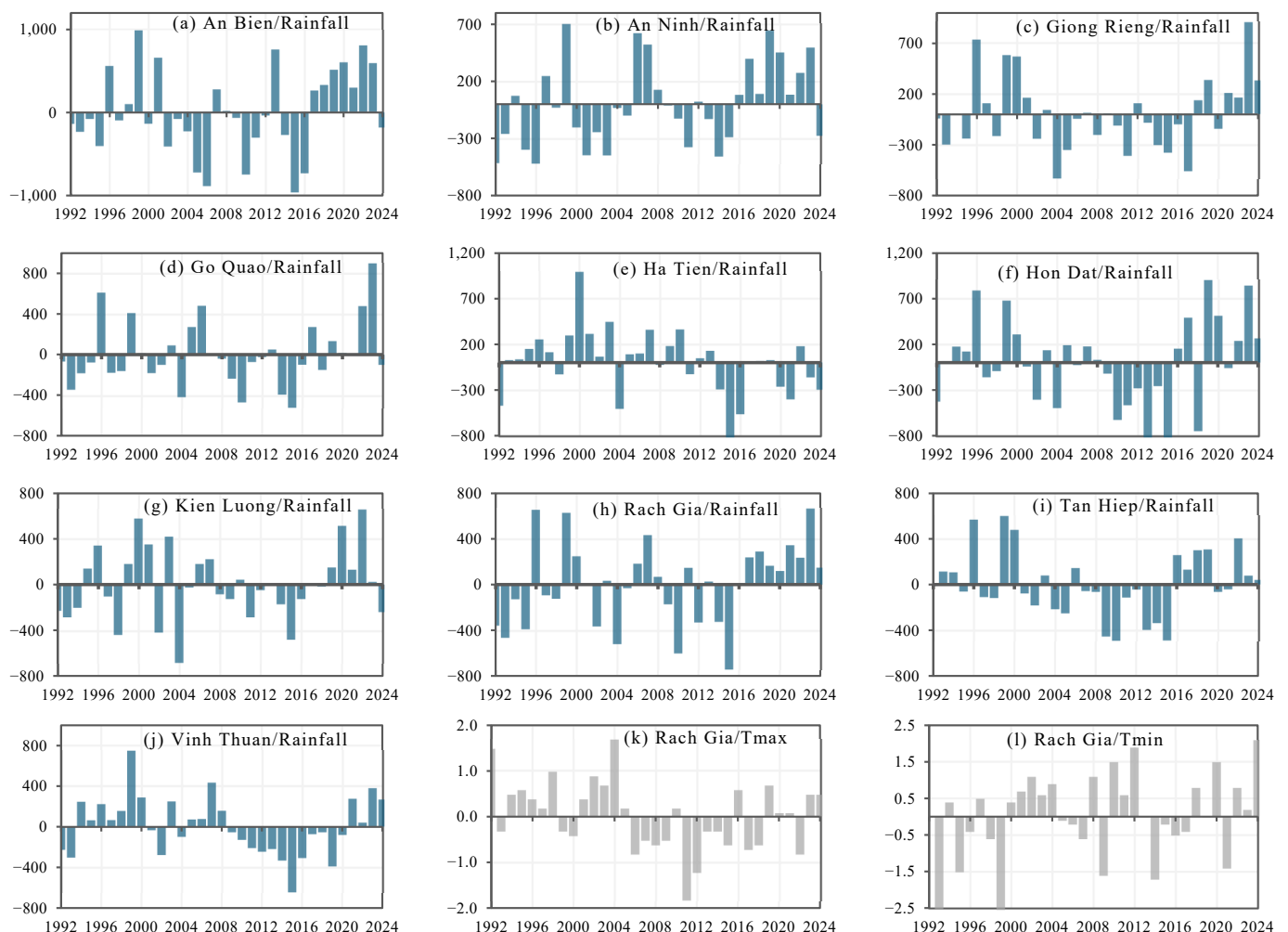


Figure 3. Annual rainfall anomalies at ten meteorological stations in Kien Giang Province (a–j) and annual Tmax and Tmin anomalies at Rach Gia station (k–l), 1992–2024. The x-axes show year; the y-axes show rainfall anomalies (mm) for panels (a–j) and temperature anomalies (°C) for panels (k–l).

To provide a hydroclimatic background for the drought analysis, annual rainfall anomalies for the ten stations and annual temperature anomalies for Rach Gia are presented

in Figure 2. These series indicate substantial interannual variability across the province and include major dry years that are consistent with well-documented regional drought–salinity episodes in the VMD [38,39]. However, the detailed interpretation of these anomaly patterns is presented in the Results section to clearly distinguish between data description and drought-index analysis. Because temperature data were represented by a single station, spatial interpretations of the MSPEI should be made with appropriate caution.

2.2. Multivariate Standardized Precipitation Index Calculation

1. SPI calculation and select a set of time scales

SPI was developed by [40] and is recommended by the World Meteorological Organization for monitoring and assessing meteorological drought. Based on the preceding j months, where j can be 1-, 3-, 6-, or 48-, a j -month moving average series can be calculated. The relationship between probability and precipitation is then determined by fitting the data to a gamma function. The probability density function of the gamma distribution is defined in Equation (1).

$$g(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \quad (1)$$

where $\alpha > 0$ is the shape parameter, $\beta > 0$ is the scale parameter, $x > 0$ is the precipitation and the gamma function $\Gamma(\alpha)$ can be represented in Equation (2).

$$\Gamma(\alpha) = \int_0^\infty y^{\alpha-1} e^{-y} dy \quad (2)$$

by using the Thom's approximation (Equation (3))

$$\hat{\alpha} = \frac{1}{4A} \left(1 + \sqrt{1 + \frac{4A}{3}} \right) \text{ and } \hat{\beta} = \frac{\bar{x}}{\hat{\alpha}} \quad (3)$$

where for n observations, $A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n}$

The cumulative probability $G(x)$ was obtained by integrating the density of the probability function $g(x)$ with respect to x (Equation (4)).

$$G(x) = \int_0^x g(x) dx = \frac{1}{\hat{\beta} \Gamma(\hat{\alpha})} \int_0^x x^{\hat{\alpha}-1} e^{-\frac{x}{\hat{\beta}}} dx \quad (4)$$

Considering the limitation of the gamma function that is not defined by $x = 0$, and the possibility of zero precipitation, the cumulative probability becomes as shown in Equation (5).

$$H(x) = q + (1 - q)G(x) \quad (5)$$

where q is the probability of zero precipitation. The SPI was then obtained by transforming the cumulative probability into a normal standardized distribution with null average and unit variance (Equations (6) and (7)).

$$Z = SPI = \begin{cases} -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), & \text{for } 0 < H(x) \leq 0.5, \\ +\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), & \text{for } 0.5 < H(x) \leq 1 \end{cases} \quad (6)$$

$$t = \begin{cases} \sqrt{\ln \left[\frac{1}{(H(x))^2} \right]}, & \text{for } 0 < H(x) \leq 0.5, \\ \sqrt{\ln \left[\frac{1}{(1-H(x))^2} \right]}, & \text{for } 0.5 < H(x) \leq 1 \end{cases} \quad (7)$$

where $c_0 = 2.515517$, $c_1 = 0.802853$, $c_2 = 0.010328$; $d_0 = 1.432788$, $d_1 = 0.189269$, $d_2 = 0.001308$.

MSPI is not constructed from a single SPI sequence but from a set of SPI sequences corresponding to multiple consecutive timescales at the same station or study area. According to Bazrafshan et al. (2014) [22], commonly used SPI timescale sets include: 3- to 6-month (MSPI 3–6), 6- to 12-month (MSPI 6–12), 3- to 12-month (MSPI 3–12), 12–24 months (MSPI 12–24), and 24- to 48-month (MSPI 24–48). Each timescale set represents a different level of aggregation of the drought signal, while ensuring flexibility in analysis for different climatic conditions.

The MSPI timescale 3–6 can monitor drought in terms of soil moisture and surface hydrology, or MSPI 6–12 can monitor both hydrological and agricultural drought simultaneously. MSPI 3–12 relates to three aspects of drought simultaneously: soil moisture, hydrology, and agriculture. Among the larger timeframes, MSPI 12–24 can simultaneously indicate drought in terms of agriculture and groundwater, and MSPI 24–48 theoretically relates to the socio-economic impacts of drought [22,31,41–43].

2. Principal Component Analysis of SPI scales

The calculation of the MSPI begins with the application of PCA to a set of K SPI time series, where K represents the corresponding time window. This process reduces data dimensionality and extracts the primary variation signal from highly correlated SPI time scales. Assuming there are K SPI series in a given set, the i th principal component is determined via Equation (1), with the PC1 used to describe the percentage of variance of the original K variables. However, unlike the standard SPI, which has a mean of 0 and a standard deviation of 1, PC1's characteristics render its values incomparable across months. Consequently, the PC1 time series must be normalized using the specific mean and standard deviation of each month to ensure consistency before further analysis (Equation (8)).

$$PC_i = \sum_{k=1}^K (e_{ki} \times SPI_k) \quad (8)$$

where

SPI_k denotes the SPI sequence at the k_{th} ;

e_{ki} denotes the k th element of the eigenvector corresponding to the i_{th} principal component;

PC_i denotes the i th principal component.

The resulting principal components are uncorrelated linear combinations of the original SPI sequences. Among them, the PC1 explains the largest proportion of variance in the SPI data set and is considered representative of the composite drought characteristics of the considered time-scale set. Research results by Bazrafshan (2014) [22] shows that PC1 can explain over 70% of the total variance of SPI series under many different climatic conditions.

3. Normalize the first principal component and determine the MSPI

Because PC1 is not standardized like SPI (does not have a mean of 0 and a standard deviation of 1), it is necessary to standardize PC1 on a monthly basis to ensure comparability over time. The MSPI is determined according to Equation (9).

$$MSPI_{y,m} = \frac{PC1_{y,m} - \overline{PC1}_m}{SD_{PC1_m}} \quad (9)$$

where

$MSPI_{y,m}$ denotes the MSPI value at year y , month m ;

$PC1_{y,m}$ denotes the value of the PC1 in year y , month m ;

$\overline{PC1}_m$, SD_{PC1_m} denote the mean value and standard deviation of PC1 in month m , respectively.

According to Bazrafshan et al. (2014) [32], the average value of PC1 by month is usually very small and approximately equal to 0, so it can be ignored during the normalization process without significantly affecting the MSPI results. Then Equation (2) becomes Equation (10).

$$MSPI_{y,m} = \frac{PC1_{y,m}}{SD_{PC1_m}} \quad (10)$$

After normalization, MSPI has a near-normal distribution and can be classified into drought and humidity levels similar to SPI. MSPI reflects long-term drought and wetness well while reducing the influence of short-term fluctuations in individual SPI series. The use of MSPI enables an integrated assessment of drought conditions, which is particularly useful in studies where the characteristic drought timescale has not been determined a priori, or where the impact of drought across multiple timescales needs to be analysed simultaneously.

2.3. Multivariate Standardized Precipitation Evapotranspiration Index Calculation

SPEI is a drought index calculated based on the difference between precipitation and potential evaporation [8]. The first step to calculate SPEI in this study is to estimate PET. Then, the water balance equation is used to calculate the deficit (D_i). At the same time, P_i and PET_i are precipitation and evaporation over time i , respectively, with the difference D_i being the difference between precipitation P_i and PET_i as in Equation (11).

$$D_i = P_i - PET_i \quad (11)$$

After calculating the D_i value series, the cumulative climate water balance series for different time scales was established, as shown in Equation (12).

$$D_n^k = \sum_{i=0}^{k-1} (P_{n-i} - PET_{n-i}), \quad n \geq k \quad (12)$$

where k is the time scale, usually in months and n is the number of calculations.

The FAO Penman–Monteith method was used to calculate PET. If x is the cumulative series of D in a given time window it was concluded that the log-logistic probability density function fits the series values x [8]. The formulas of the density function and the cumulative probability function of the three-parameter log-logistic probability distribution are expressed as Formulas (13) and (14) [44,45], respectively.

$$f(x) = \frac{\beta}{\alpha} \left(\frac{x - \gamma}{\alpha} \right)^{\beta-1} \left[1 + \left(\frac{x - \gamma}{\alpha} \right)^{\beta} \right]^{-2} \quad (13)$$

$$F(x) = \left[1 + \left(\frac{\alpha}{x - \gamma} \right)^{\beta} \right]^{-1} \quad (14)$$

In this case, the parameters α , β , and γ are equal to the parameters of scale, shape, and position for the D_i values in the range $\infty < D < \gamma$. They were determined using the L-moment method (Equations (15)–(18)).

$$\beta = \frac{2w_1 - w_0}{6w_1 - w_0 - 6w_2} \quad (15)$$

$$\alpha = \frac{(w_0 - 2w_1)\beta}{\Gamma\left(1 + \frac{1}{\beta}\right)\Gamma\left(1 - \frac{1}{\beta}\right)} \quad (16)$$

$$\gamma = w_0 - \alpha \Gamma \left(1 + \frac{1}{\beta} \right) \Gamma \left(1 - \frac{1}{\beta} \right) \quad (17)$$

In this case, Γ is the gamma function of β and w_i ($i = 0, 1, 2, \dots$); it is calculated by probability-weighted moments using the L-moment method [46].

$$w_1 = \frac{1}{n} \sum_{i=1}^n x_i \left(1 - \frac{i - 0.35}{n} \right)^i \quad (18)$$

where x_i is a sorted random sample ($x_1 < x_2 < \dots < x_n$) of D and n represents the sample size. The probability distribution function with three parameters is used as in Equation (19).

$$F(x) = \left[1 + \left(\frac{\alpha}{x - \gamma} \right)^\beta \right]^{-1} \quad (19)$$

The cumulative probability density was transformed into a normal distribution to obtain the corresponding SPEI time series as in Equation (20).

$$\text{SPEI} = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \quad (20)$$

where $W = (-2 \ln P)^{0.5}$, P is the probability of exceeding a defined increase/decrease in humidity, when $p \leq 0.5$, $p = 1 - F(x)$, khi $p \geq 0.5$.

The Multivariate Standardized Precipitation Evapotranspiration Index is calculated similarly to the MSPI.

2.4. Drought Severity Categorization Using Empirical Probability Distributions

To define the drought and wet severity classes, the MSPI time series is arranged in ascending order to construct an empirical probability distribution. Thresholds corresponding to the standard SPI probability classes (Table 1) are then extracted from this distribution. These derived thresholds are utilised to categorise the MSPI time series into their respective drought and wet severity levels. We developed empirical probability distributions for 10 stations across five SPI and SPEI timescales. Figure 4 shows the empirical probability distribution as an example for An Bien rain gauge for SPI 3-12 (a) and SPEI 3-12 (b).

Table 1. SPI probability classes and corresponding thresholds used to classify drought and wetness severity.

SPI Classes	Probability Limits (%)	Classes
$SPI \geq 2$	≥ 97.7	Extremely wet
$2 > SPI \geq 1.5$	93.3–97.7	Severely wet
$1.5 > SPI \geq 1$	84.1–93.3	Moderately wet
$1 > SPI \geq -1$	15.9–84.1	Normal
$-1 > SPI \geq -1.5$	6.7–15.9	Moderate drought
$-1.5 > SPI \geq -2$	2.3–6.7	Severe drought
$SPI \leq -2$	≤ 2.3	Extreme drought

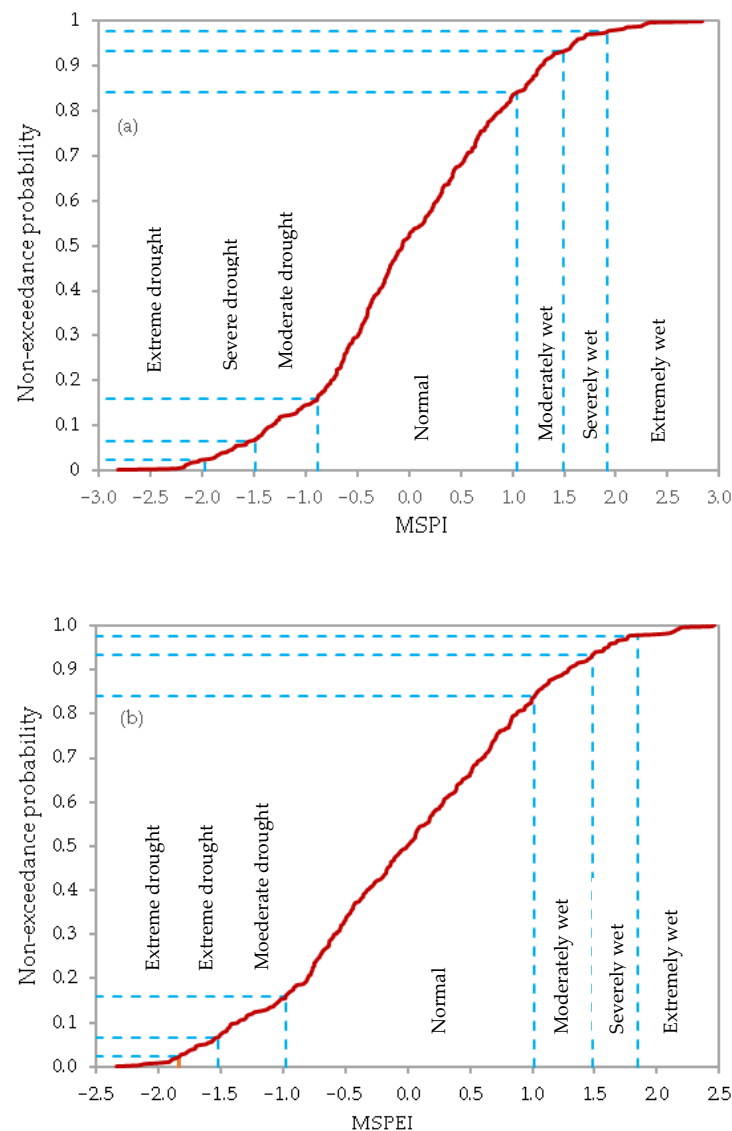


Figure 4. Empirical probability distributions of (a) MSPI and (b) MSPEI for An Bien station, derived from the SPI 3–12 and SPEI 3–12 timescale sets, respectively. Vertical thresholds indicate class boundaries from extreme drought to extremely wet conditions, and the y-axis shows cumulative probability.

3. Results

3.1. Principal Components Analysis of the SPI Time Series

Five SPI timescale sets (3–6, 6–12, 3–12, 12–24, and 24–48 months) were selected to examine the sensitivity of the MSPI. PCA was applied to these SPI timescale groups across the ten monitoring stations in Kien Giang Province to identify the dominant variability structure. As shown in Figure 5, the F1 (Principal Component 1—PC1) had a markedly larger eigenvalue than the remaining components at all stations, indicating that it captured the dominant multiscale precipitation signal.

For the SPI series spanning 3–12 months, F1 explained between 78.08% and 83.60% of the total variance across stations, whereas F2 explained only 8.56% to 14.12%. Tan Hiep showed the highest F1 contribution (83.60%), while Kien Luong showed the lowest (78.08%). In contrast, the contribution of F2 remained limited, with the highest value recorded at Go Quao (14.12%) and the lowest at Tan Hiep (8.56%). Higher-order components contributed only marginally.

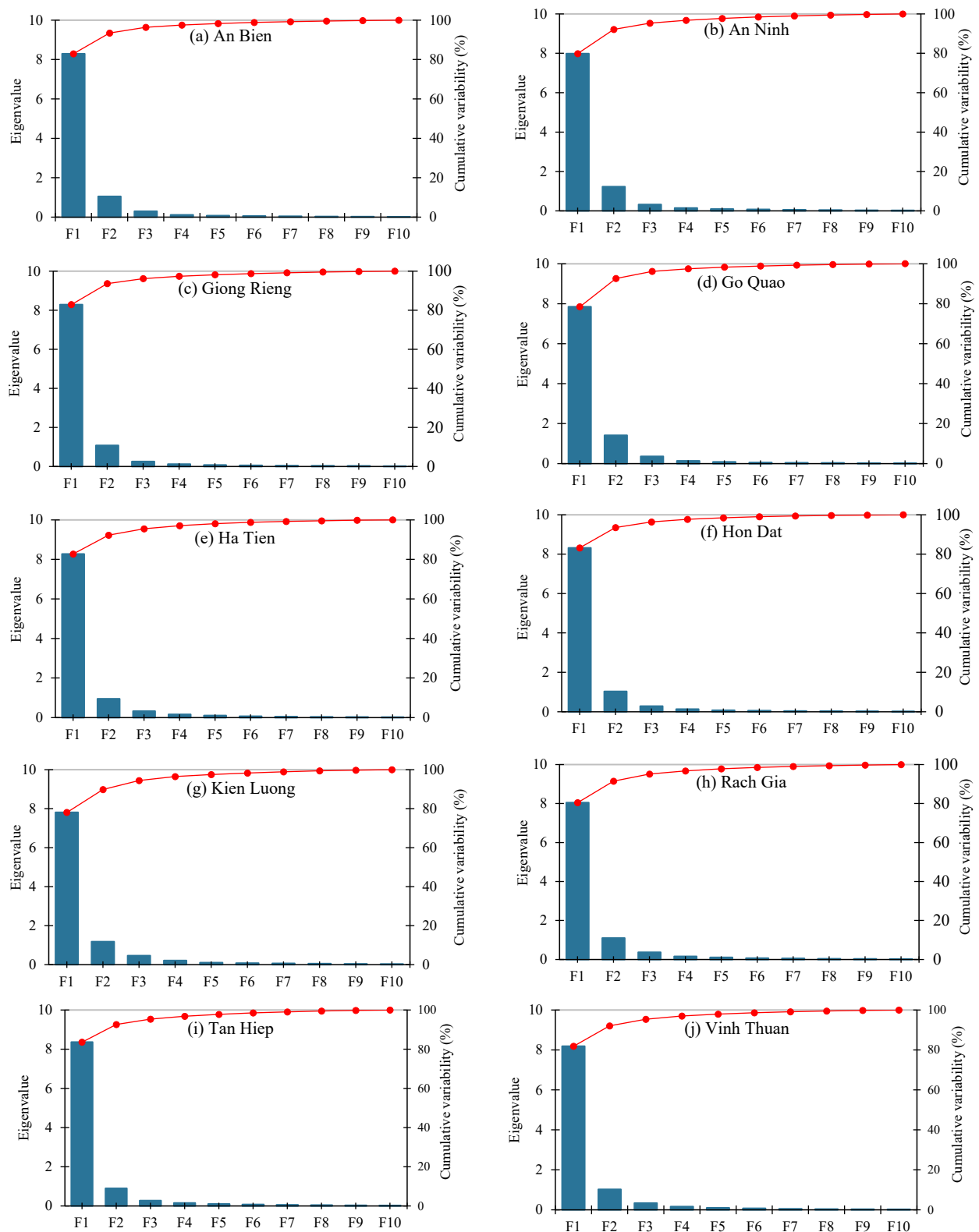


Figure 5. A Principal Component Analysis of SPI time series (3–12 months) recorded at ten monitoring stations in Kien Giang. The y-axis denotes the component number.

The F1–F2 ordination plots for the 3–12 month SPI series further clarify the structure of the PCA solution (Figure 6). All SPI variables loaded positively on F1, confirming that the first component represents a common drought signal across timescales. Along F2, however, the variables separate into two groups: shorter accumulation periods (<7 months) contribute positively, whereas longer accumulation periods (≥ 7 months) contribute negatively.

This indicates that F2 mainly captures the contrast between short-term and longer-duration drought behaviour rather than an independent drought process (Figure 6).

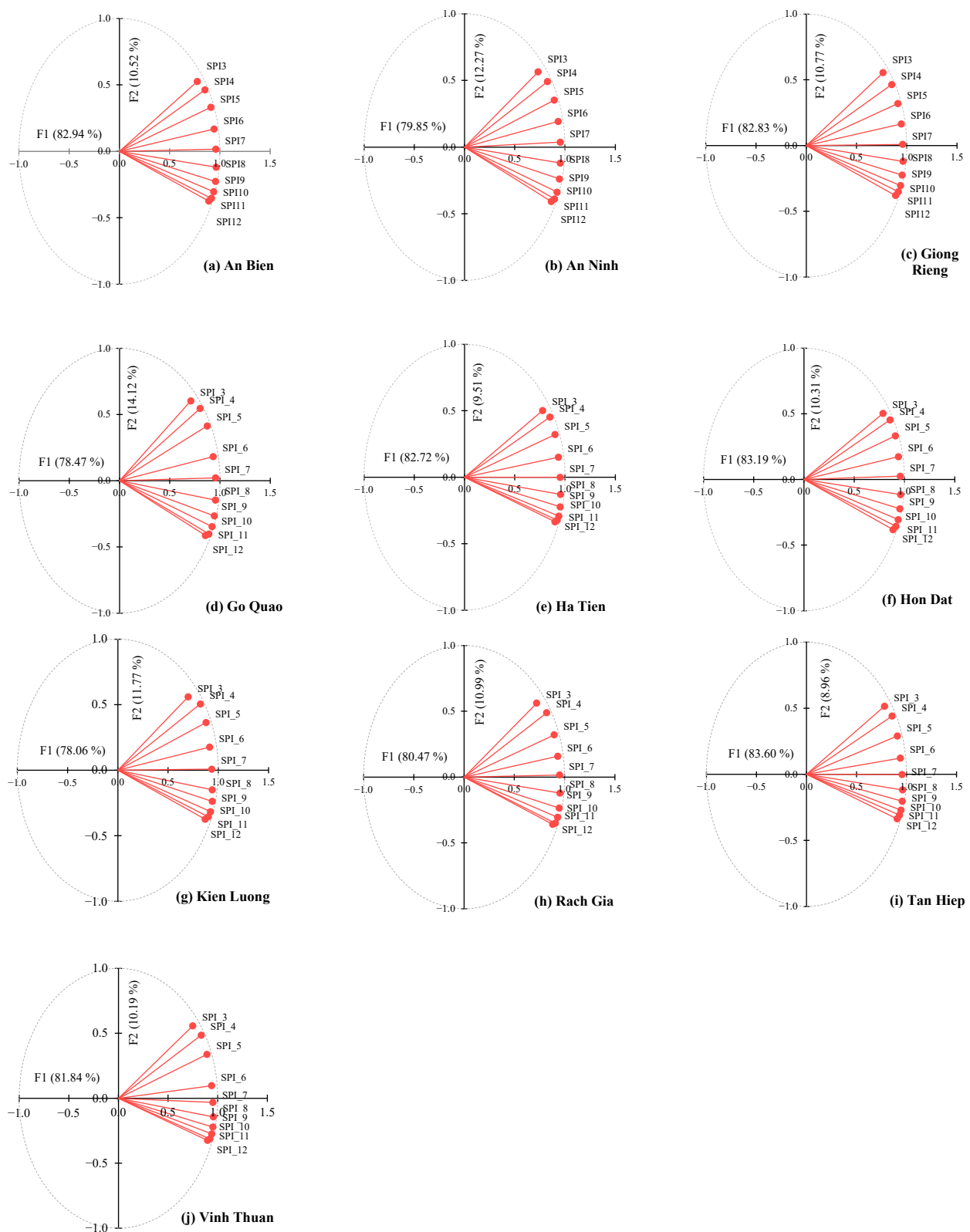


Figure 6. PCA ordination plots for the SPI 3–12 months time series at the ten monitoring stations in Kien Giang, showing the loadings of the original SPI series on the first (F1) and second (F2) principal components. Red labels indicate active variables.

Across the five selected SPI timescale sets, PC1 consistently explained more than 90% of the total variance at all stations (Figure 7). The highest values occurred for the long-term SPI 24–SPI 48 set, where PC1 approached 97–98%, indicating a highly coherent long-duration drought signal across the province. The lowest explained variance occurred for the SPI 3–SPI 12 set, which generally ranged from about 90% to 93%, with its minimum at Kien Luong. Overall, the PCA results indicate that drought variability in Kien Giang is strongly structured by a dominant common component, while shorter timescales retain somewhat greater local variability than longer timescales.

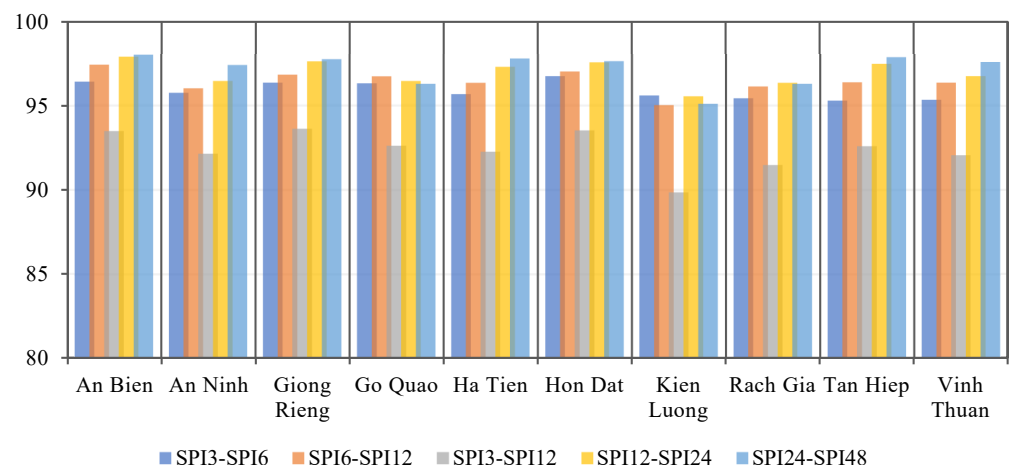


Figure 7. Percentage of variance explained by the first principal component for five selected SPI timescale sets (SPI3–SPI6, SPI6–SPI12, SPI3–SPI12, SPI12–SPI24, and SPI24–SPI48) across the ten monitoring stations in Kien Giang. The x-axis shows station, and the y-axis shows variance explained by PC1 (%).

3.2. Comparing MSPI with the SPI Time Series

The relationship between MSPI and the corresponding SPI timescale groups at An Bien station is shown in Figure 8. Across all five timescale sets (3–6, 6–12, 3–12, 12–24, and 24–48 months), the MSPI broadly tracked the temporal behaviour of the SPI series, with wet and dry periods occurring at similar times. Major drought episodes, especially those of 2004–2005 and 2015–2016, were consistently captured by both the multiscale index and the corresponding SPI series.

The principal distinction lies in the smoothing effect of the multiscale approach. Because the MSPI condenses information from several correlated SPI timescales into a single series, it reduces short-term oscillation and highlights the dominant drought trajectory within each timescale group. This becomes more evident as the accumulation window increases. At short timescales such as 3–6 months, the MSPI series shows relatively sharp fluctuations, reflecting the influence of short-lived rainfall anomalies. At longer timescales, particularly 24–48 months, the curves become progressively smoother and more persistent, allowing multi-year dry and wet phases to be identified more clearly.

An example is the 2015–2017 period, which appears as a highly variable sequence in the shorter-term series but as a more continuous and prolonged drought signal in the longer-term series. This suggests that long-term MSPI is better suited to identifying persistent drought conditions, whereas short-term MSPI is more sensitive to short-duration anomalies. The spatial consistency of these patterns across the full station network is shown in Appendix Figures A1–A5. These supplementary plots indicate broad consistency in drought timing across all ten monitoring stations, although some spatial differences in amplitude and persistence are evident. Coastal and island stations such as Ha Tien, Kien Luong, and Rach Gia show wider short-term SPI envelopes and sharper MSPI fluc-

tuations, indicating greater short-term rainfall variability. Inland stations such as An Ninh, Giong Rieng, and Tan Hiep display comparatively narrower short-term variation. Vinh Thuan shows a more prolonged low phase during 2015–2017, suggesting relatively persistent drought conditions during that episode.

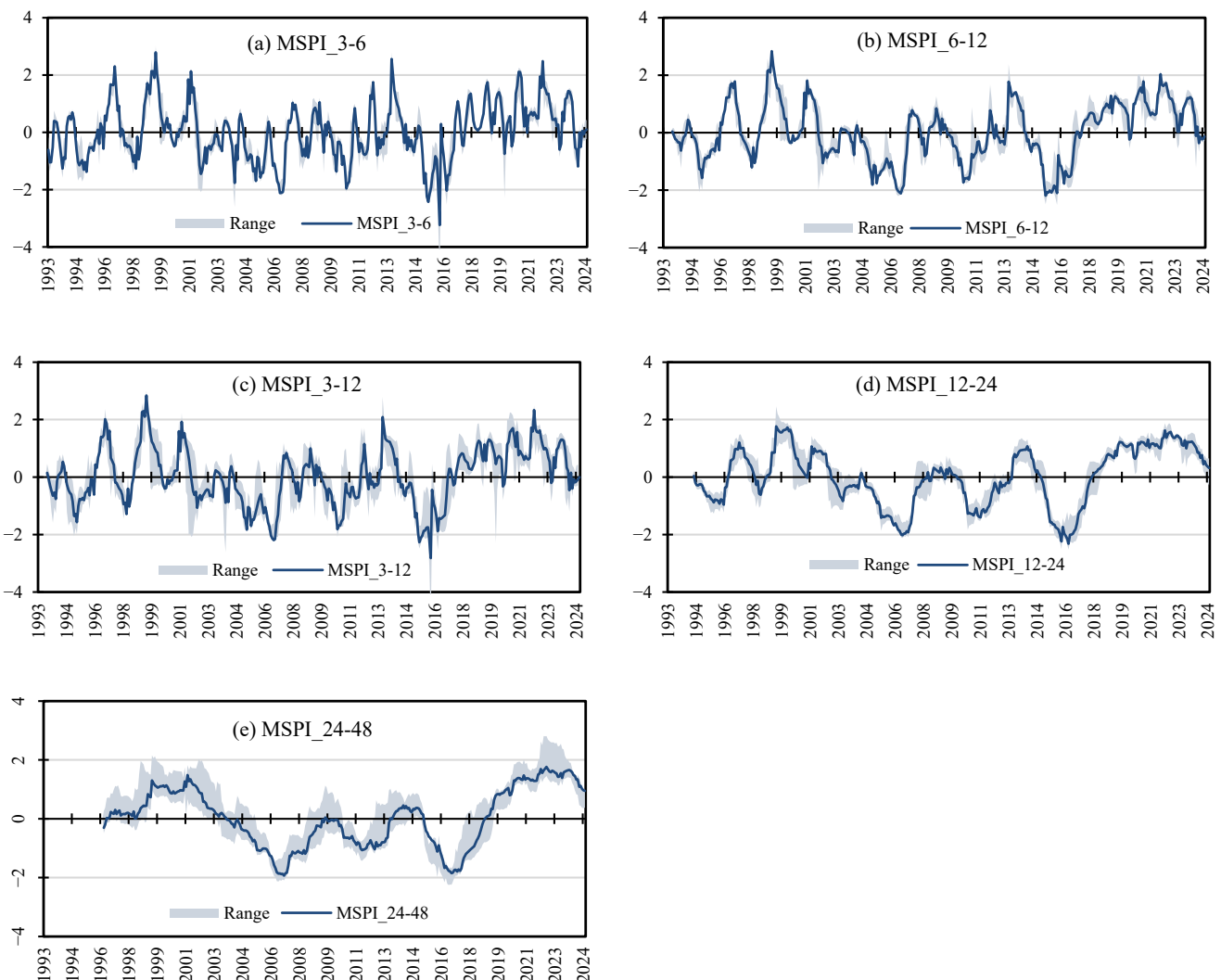


Figure 8. Comparison of MSPI with the corresponding SPI timescale groups (3–6, 6–12, 3–12, 12–24, and 24–48 months) at An Bien station, Kien Giang.

3.3. Principal Components Analysis of the SPEI Time Series

The PCA results for the SPEI time series show a structure very similar to that observed for SPI. As shown in Figure 9, the F1 dominated the variance structure across all ten monitoring stations, while F2 contributed only a small additional share, and the remaining components were negligible. For the 3–12 month SPEI series, F1 explained between 79.13% and 84.31% of the variance, whereas F2 explained 9.30% to 13.58%. Tan Hiep recorded the highest F1 contribution (84.31%) and the lowest F2 contribution (9.30%), while An Ninh recorded the lowest F1 contribution (79.13%) and Go Quao the highest F2 contribution (13.58%).

Across the five selected SPEI timescale sets, PC1 again explained more than 90% of the total variance at all stations (Figure 10). The highest explained variance was generally observed for the SPEI 24–SPEI 48 set, which approached 97–98% at several stations, while the SPEI 3–SPEI 12 set showed the lowest values, dropping to around 90% at Kien Luong. As with the SPI results, this indicates that long-term drought variability was highly co-

herent across the province, whereas shorter- and mixed-timescale sets retained somewhat more complexity.

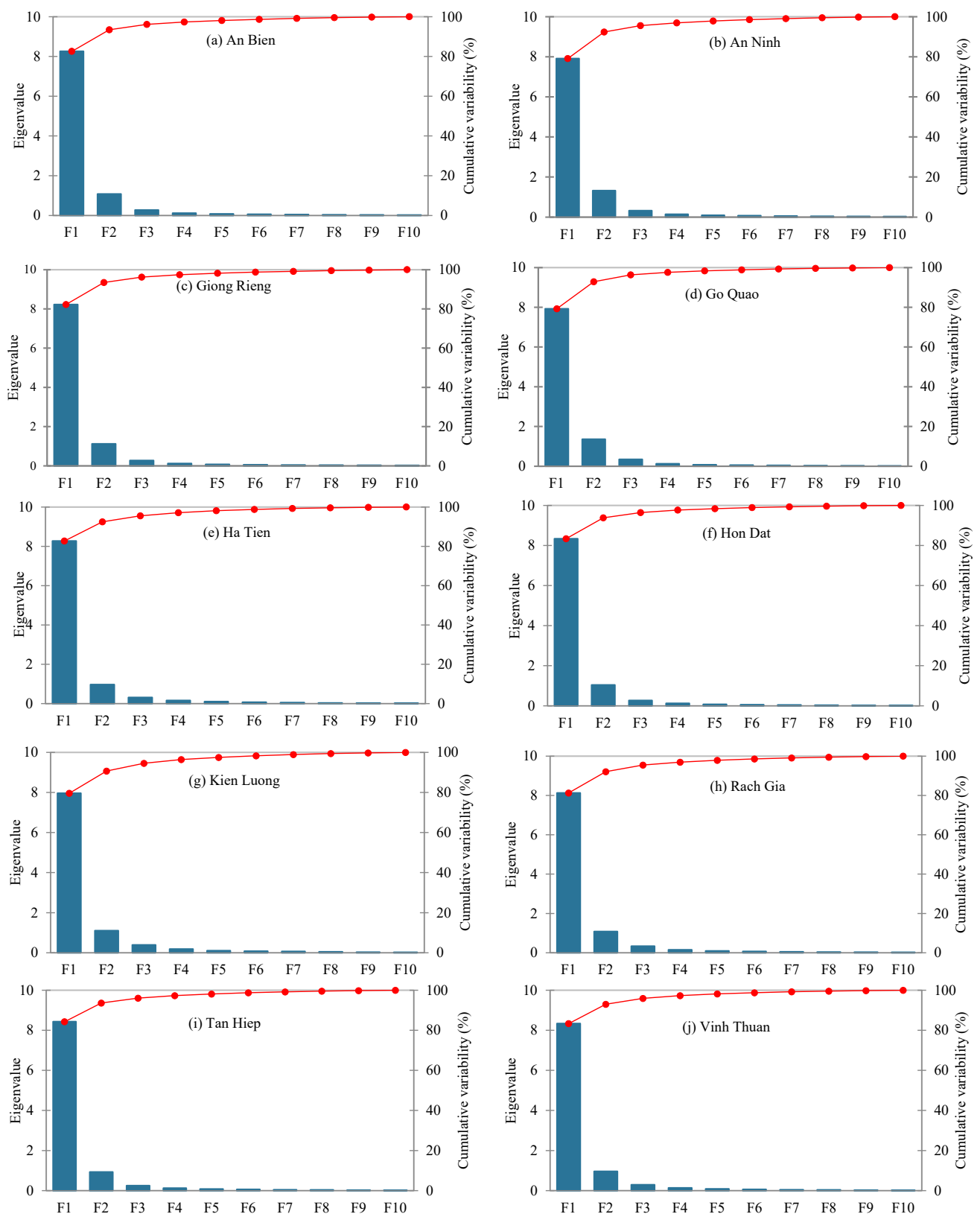


Figure 9. A Principal Component Analysis of SPEI time series (3–12 months) recorded at ten monitoring stations in Kien Giang.

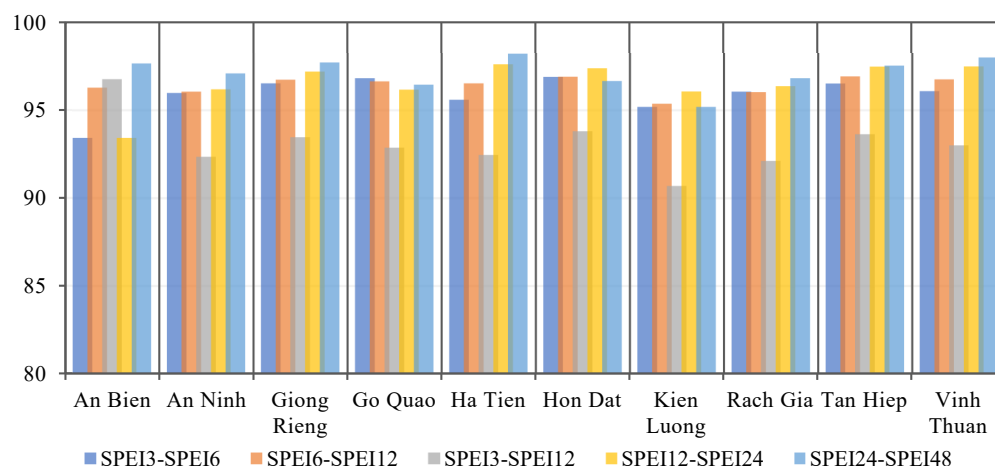


Figure 10. Percentage of variance explained by the first principal component for five selected SPEI timescale sets (SPEI3–SPEI6, SPEI6–SPEI12, SPEI3–SPEI12, SPEI12–SPEI24, and SPEI24–SPEI48) across the ten monitoring stations in Kien Giang. The x-axis shows station, and the y-axis shows variance explained by PC1 (%).

The F1–F2 plots for the 3–12 months SPEI series are presented in Figure 11. All SPEI variables loaded positively on F1, confirming that the first component captured the dominant common drought pattern. Separation along F2 again distinguished shorter from longer accumulation periods. Although both coastal and inland stations were strongly aligned with F1, stations such as Tan Hiep and Vinh Thuan exhibited particularly low F2 contributions, indicating a particularly strong dominance of the first component. Overall, the SPEI PCA results confirm a high degree of spatial consistency in evapotranspiration-sensitive drought behaviour across Kien Giang Province.

3.4. Comparing MSPEI with the SPEI Time Series

The relationship between MSPEI and the corresponding SPEI timescale groups at An Bien station is shown in Figure 12. As in the SPI-based analysis, the multiscale index closely follows the timing of dry and wet periods identified by the underlying SPEI series. Major drought episodes, particularly those of 2004–2005 and 2015–2016, are clearly detected in both representations. The main difference again lies in the smoothing effect across timescales. At short-term scales, such as 3–6 months, the MSPEI shows relatively sharp fluctuations, whereas at longer scales, especially 24–48 months, the series becomes smoother and more stable. The longer-term MSPEI therefore emphasises persistent drought and wet phases more clearly than the shorter-term series.

The station-level consistency of this behaviour is shown in Appendix Figures 8, A6, A7, A9 and A10. These supplementary plots indicate that the overall MSPEI pattern is broadly consistent across the ten stations. Coastal stations such as Ha Tien and Kien Luong tend to show somewhat stronger negative excursions than several inland stations, especially during major drought years. During the 2020–2024 period, most stations entered a mildly wet phase, but positive MSPEI values were generally more muted than the corresponding precipitation-based behaviour, indicating slower apparent recovery in the evapotranspiration-sensitive index. This contrast is particularly evident after 2015, when MSPEI often remained below zero for longer than the comparable MSPI series. Strong agreement was observed across all drought and moisture severity classes during the 1992–2024 period. This consistency was confirmed via correspondence analysis for the MSPI against various SPI scales and, similarly, the MSPEI against various SPEI scales. Overall, the MSPEI results confirm that the multiscale evapotranspiration-sensitive framework captured the

same major drought chronology as the SPEI series, while providing a more integrated representation of drought persistence across timescales.

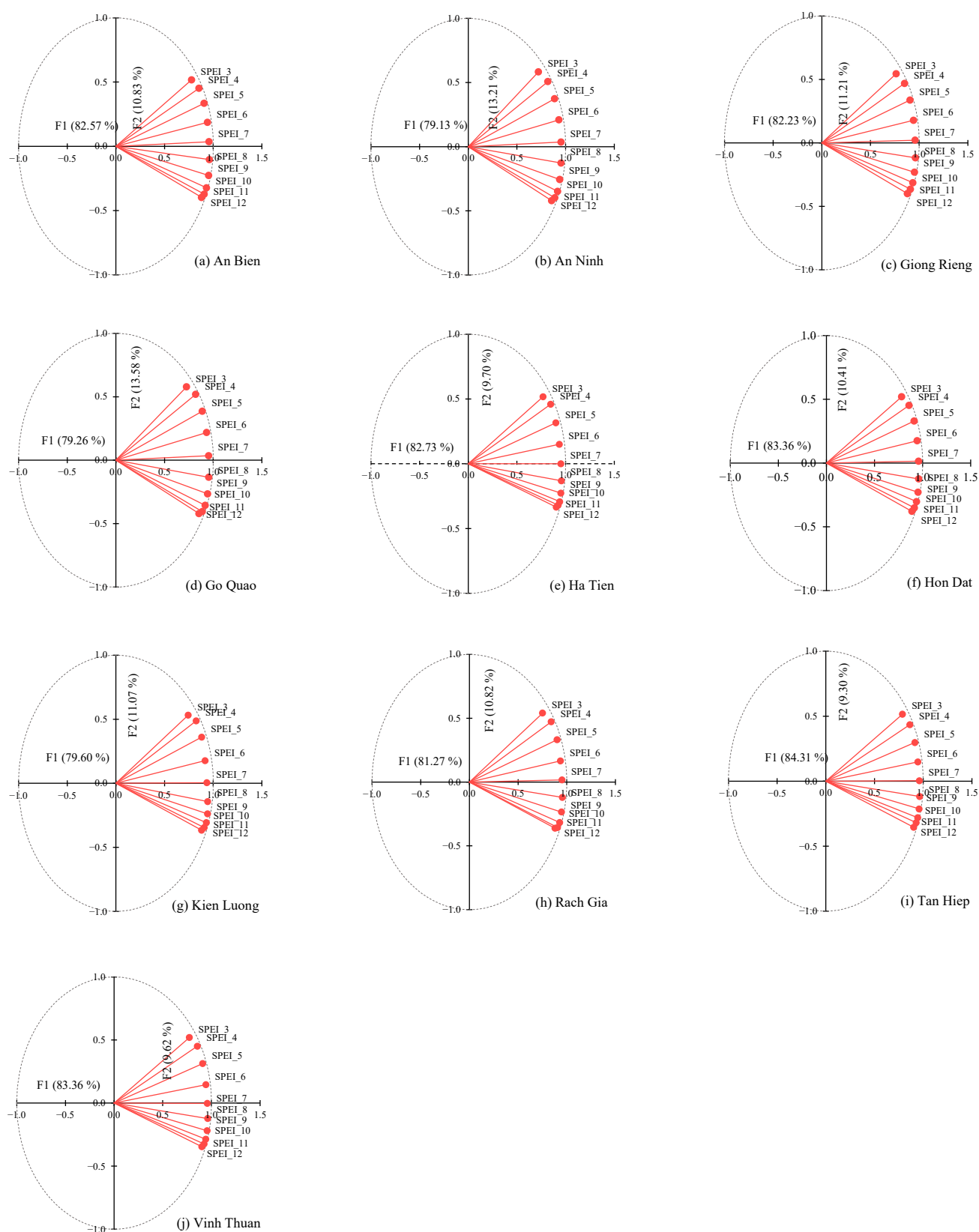


Figure 11. PCA ordination plots for the SPEI 3–12 month time series at the ten monitoring stations in Kien Giang, showing the loadings of the original SPEI series on the first (F1) and second (F2) principal components. Red labels indicate active variables.

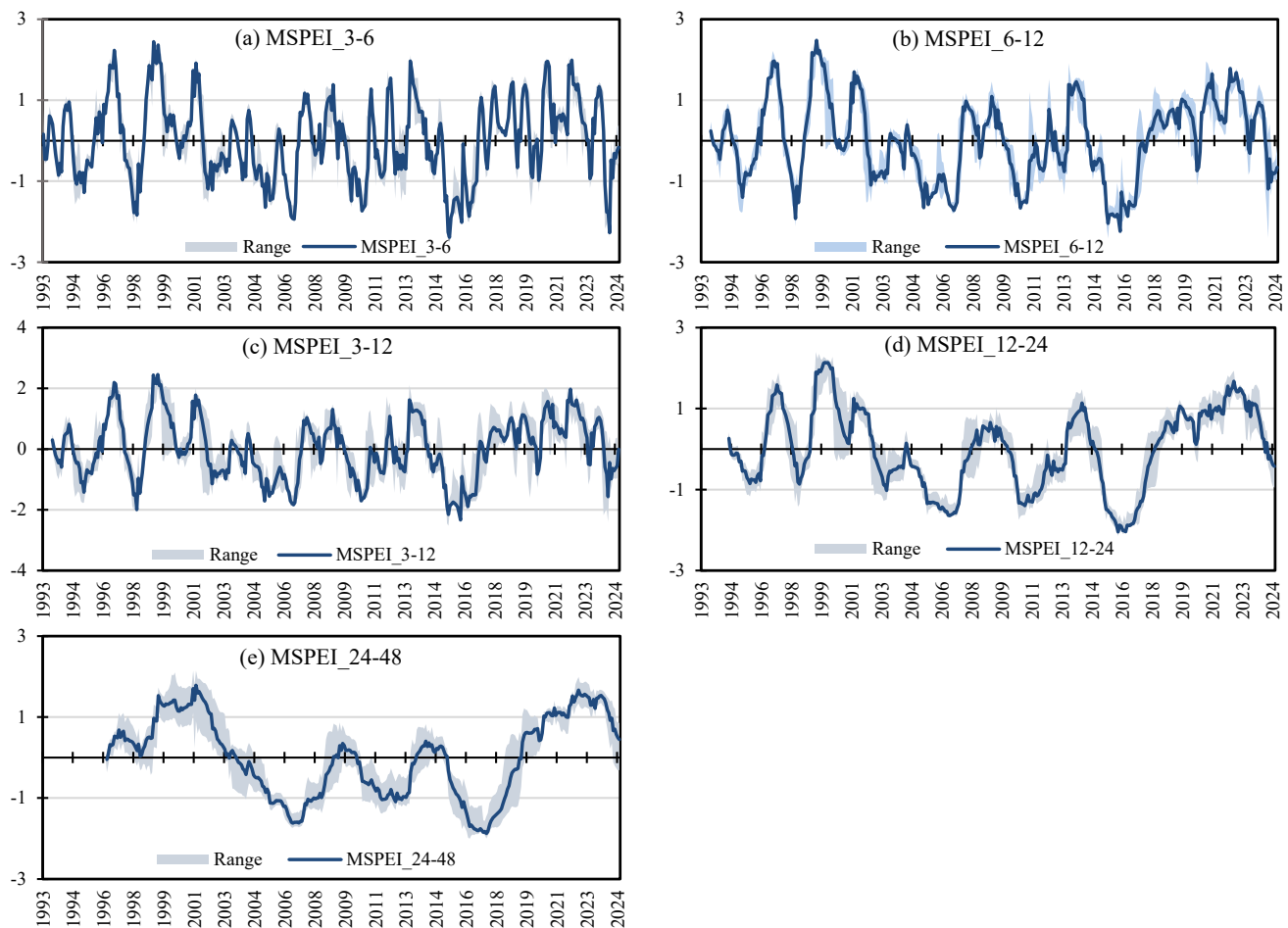


Figure 12. Comparison of MSPEI with the corresponding SPEI timescale groups (3–6, 6–12, 3–12, 12–24, and 24–48 months) at An Bien station, Kien Giang.

3.5. Comparative Performance of MSPI and MSPEI Against Standard Multiscale Indices

The comparative correspondence analysis is presented in Figure 13. Strong agreement was observed between the multiscale indices and the corresponding standard drought classes for the period 1992–2024. For MSPI, the lowest correspondence with the SPI series occurred for the 3–12 month set, ranging from 72.7% to 76.6% across stations, whereas the highest correspondence occurred for the 6–12 month set, ranging from 78.2% to 82.0%. Spatially, the lowest and highest MSPI correspondence values were recorded at Ha Tien and An Bien, respectively.

For MSPEI, the lowest correspondence with the SPEI series was also observed for the 3–12 month set, ranging from 70% to 77%, while the highest correspondence occurred for the 12–24 month set, ranging from 75% to 83%. The lowest and highest MSPEI correspondence values were recorded at An Ninh and Ha Tien, respectively.

Compared with MSPI, MSPEI showed a slightly broader spread of agreement values, with a lower minimum but a similar upper bound. This indicates that both multiscale indices reproduced the standard drought-class structure reasonably well, although their strongest correspondence occurred at different temporal windows. For MSPI, the consistency window was 6–12 months, whereas for MSPEI it was 12–24 months. This shift suggests that the evapotranspiration-sensitive index aligned most closely with the standard SPEI classification over a somewhat longer accumulation period. Given that temperature data were available only from the Rach Gia station, the spatial interpretation of the MSPEI correspondence patterns should be made with some caution.

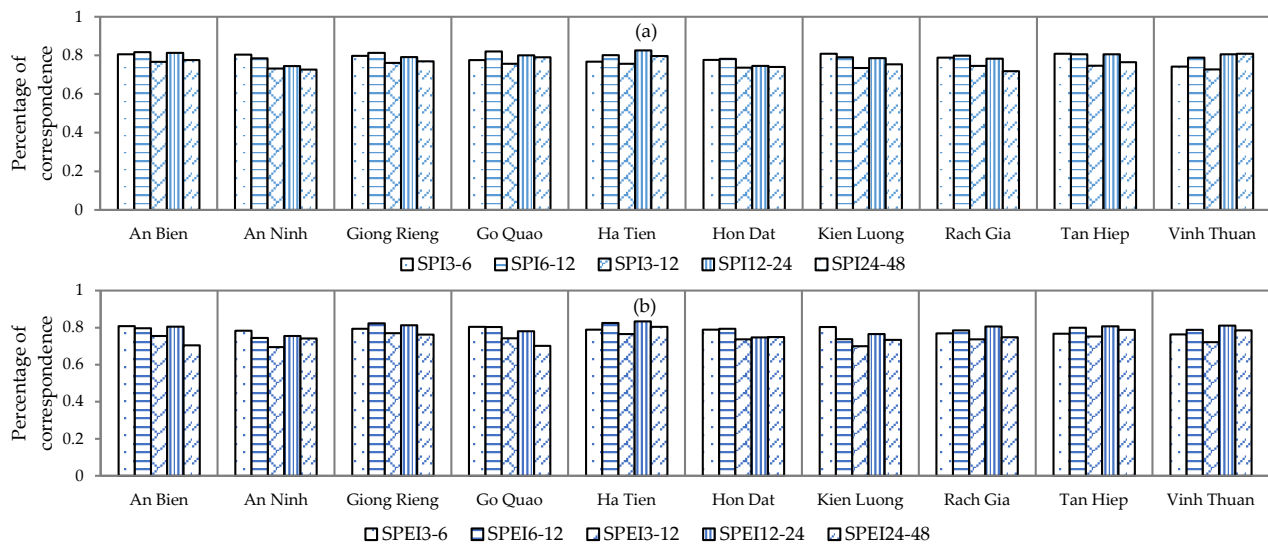


Figure 13. Percentage correspondence between drought and wetness severity classes derived from (a) MSPI and SPI, and (b) MSPEI and SPEI, for selected timescale sets across the monitoring stations during 1992–2024.

4. Discussion

4.1. Evaluating the Performance and Added Value of the Integrated Multiscale Drought Monitoring Framework

Study by Vicente-Serrano et al. (2010) [8] has established the conceptual foundation for the flexibility of multiscale drought indices in capturing diverse hydrological responses. However, a persistent challenge lies in the selection of an appropriate fixed time scale. The use of single scales (e.g., 3- or 6-month indices) introduces uncertainty, as no single temporal window can adequately represent the full spectrum of drought dynamics within a given region. This limitation is particularly pronounced in sensitive environments such as the coastal context of the VMD, where hydrological processes operate across multiple interacting temporal scales. In the absence of an integrated analytical framework, critical transition signals between short- and long-term drought conditions may remain undetected.

To address this limitation, this study applied MSPI and MSPEI derived through PCA. This approach enables the synthesis of correlated temporal scales into a single dominant signal, thereby reducing the subjectivity associated with scale selection. Results from Kien Giang province, particularly at the Rach Gia and An Bien stations, demonstrate that this integrated framework yields a more coherent and stable representation of drought conditions compared to discrete single-scale indices. PCA results indicate that the PC1 explains a substantial proportion of variance, typically ranging from 78% to over 90% for both SPI and SPEI datasets. The consistently positive loadings across all time scales (1–12 months) further confirm that PC1 effectively captures the full multi-temporal drought signal, integrating both short-term rainfall variability and longer-term hydrological accumulation processes.

The framework also provides clearer differentiation between key climatic drivers. The MSPI exhibits high sensitivity to short-term fluctuations, closely reflecting the temporal variability of precipitation events. In contrast, MSPEI displays a smoother and more persistent trajectory, particularly evident during prolonged drought phases following 2015. This divergence between MSPI and MSPEI, consistent with findings by Bhardwaj et al. (2025) [27] and Wei et al. (2024) [47], highlights that short-term rainfall recovery does not necessarily translate into broader hydroclimatic recovery. Under conditions of global warming, increased evaporative demand acts as a critical amplifying mechanism, extending drought duration even when precipitation deficits are temporarily alleviated.

From a water resources management perspective, these findings suggest that drought monitoring systems in the VMD would benefit from a dual-indicator approach. The parallel interpretation of precipitation-driven and evapotranspiration-sensitive signals enables a more nuanced assessment of drought severity, persistence, and recovery dynamics. Such an approach is particularly relevant for deltaic systems, where compound hydroclimatic stresses require monitoring frameworks capable of capturing both rapid fluctuations and longer-term system responses.

4.2. The Significance of Timescale in Drought Adaptation and Risk Mitigation Planning

The selection of an appropriate temporal scale plays a critical role in drought monitoring, as hydrological systems respond to water deficits at different rates. While studies by Vicente-Serrano et al. (2010) [8] and Beguería et al. (2014) [48] have demonstrated the effectiveness of multiscale indices, identifying a single fixed time scale that adequately represents regional drought characteristics remains challenging. Previous research shows that the most relevant time scale varies depending on environmental processes and management objectives; thus, reliance on a fixed scale can lead to misrepresentation of drought timing, severity, and persistence [22,49,50].

This study addresses this limitation by applying an integrated MSPI and MSPEI framework using PCA, which synthesizes correlated time scales into a single dominant signal. Results indicate that drought interpretation varies significantly across accumulation phases: short-term scales (3–12 months) respond strongly to seasonal rainfall variability, whereas longer-term scales (12–48 months) produce smoother, more persistent signals reflecting cumulative water deficits. Notably, the divergence between MSPI and MSPEI after 2015 in Kien Giang aligns with findings by Bhardwaj et al. (2025) [27], indicating that increased evaporative demand amplifies and prolongs drought conditions even when rainfall deficits are partially alleviated.

In the sensitive coastal context of Kien Giang, where livelihoods face combined pressures from climate change and saltwater intrusion [51], this integrated approach provides a stronger scientific basis for adaptation planning. Multiscale signals offer distinct value for risk management: (i) supporting short-term decisions such as adjusting cropping calendars, irrigation scheduling, and early warning during dry seasons; and (ii) informing medium- to long-term strategies by identifying cumulative water deficits affecting canal systems and regional water security. This aligns with contemporary drought management approaches that emphasise linking monitoring systems to sector-specific decision windows [43,52]. Moving from single indicators to a multi-tiered interpretive framework enhances the capacity for proactive drought management, shifting the focus from reactive response to anticipatory adaptation.

The need for more robust, integrated drought assessment frameworks is further underscored by global climate projections. As noted by Bhardwaj et al. (2025) [27], drought risks are projected to intensify significantly in the future across various regions, including central and southern parts of the Middle East, driven by changing climate patterns. Similar dynamics are increasingly evident in major Asian river deltas [53–55] where interactions between changing monsoon regimes and rising evaporative demand threaten regional water and food security. These parallels underscore the importance of monitoring tools such as MSPI and MSPEI in providing consistent, forward-looking signals for adaptation planning in the VMD and other vulnerable coastal systems.

4.3. Spatial Implications for Coastal Delta Planning

The dominance of PC1 indicates a highly structured hydroclimatic regime in Kien Giang province. From a physical perspective, the high proportion of explained variance

suggests that drought dynamics are primarily governed by large-scale synoptic climate forcing rather than localized or stochastic variability. The consistently strong loadings of PC1 across multiple accumulation periods point to a coherent water deficit signal that transcends individual time scales. Notably, the increasing coherence observed at longer accumulation periods (12–48 months), relative to shorter scales (3–6 months), reflects a form of cumulative hydrological memory. While shorter time scales remain sensitive to transient rainfall variability, longer scales filter out high-frequency fluctuations and reveal persistent drought conditions affecting groundwater reserves and canal storage systems.

Despite this strong province-wide coherence, station-level comparisons reveal important spatial differentiation in drought expression. Coastal and island stations such as Ha Tien, Kien Luong, and Rach Gia exhibit greater short-term variability and more pronounced negative anomalies during major drought periods, particularly in the MSPEI signal. In contrast, inland stations generally display more stable short-term variability, although locations such as Vinh Thuan show relatively persistent dry conditions during extended drought phases. While these differences are moderate rather than absolute, they remain significant for spatial interpretation and planning.

In the VMD, drought risk emerges from the interaction of multiple stressors, including reduced dry-season flows, salinity intrusion, land subsidence, groundwater depletion, and sea-level rise [10,11,51]. Previous studies have shown that severe drought and salinity events have substantial impacts on rice production and domestic water supply, while also prompting adaptive responses such as revised cropping calendars and improved irrigation practices. The slower recovery patterns observed in MSPEI in the later part of the Kien Giang record suggest that effective drought conditions may persist beyond the apparent recovery indicated by precipitation alone, reinforcing the importance of evapotranspiration-sensitive indicators.

From an adaptation planning perspective, these findings indicate that drought should not be treated as a spatially uniform hazard with a single response strategy. Coastal zones require closer integration of drought monitoring with salinity management and dry-season water allocation, while inland areas, despite relatively more stable rainfall regimes, remain vulnerable to cumulative multi-season water deficits affecting agricultural productivity. The principal policy contribution of this framework lies in demonstrating both the shared regional drought structure and the need for differentiated sub-regional responses within that structure. In doing so, it directly links climatic monitoring to the governance challenge of tailoring adaptation strategies to the spatial heterogeneity of coastal delta systems.

4.4. Limitations and Priorities for Future Research

Several methodological and data-related limitations warrant explicit consideration. The evapotranspiration-sensitive analysis relies exclusively on temperature records from a single meteorological station in Rach Gia. While this dataset provides a consistent provincial reference, it constrains the spatial resolution required to fully capture MSPEI variability across the wider station network. In addition, although multiscale drought signals are evaluated against standard SPI and SPEI classifications, the results lack independent validation against observed environmental impacts. The indices were not calibrated against variables such as soil moisture deficits, salinity intrusion, crop yield losses, or remotely sensed vegetation stress. As a result, the findings primarily demonstrate monitoring capability rather than fully validated impact representation.

The application of PCA effectively reduces dimensionality across correlated time scales, but inherently emphasises the dominant common signal. This may obscure short-duration or highly localised hydrological extremes, which remain critical in coastal delta systems where infrastructure and water management interventions can mediate drought

impacts independently of broader hydroclimatic forcing. More broadly, drought monitoring approaches often remain overly index-based and insufficiently aligned with operational water management realities.

Future refinements should address these constraints by strengthening the statistical robustness of the indices. As noted by Beguería et al. [48] the use of unbiased Probability Weighted Moments for estimating log-logistic distribution parameters is essential for accurate SPEI calculation, reducing systematic variance biases across time scales. Expanding the meteorological dataset to include a denser network of temperature observations would further improve the spatial reliability of evapotranspiration modelling.

Future research should prioritise integrating multiscale drought indices with direct impact indicators, including irrigation system stress, soil moisture conditions, and satellite-derived vegetation metrics. Establishing stronger linkages between multiscale monitoring outputs and operational early warning systems in the VMD is also critical. Recent evidence suggests that enhanced hydroclimatic monitoring can be effectively coupled with forecasting and preparedness frameworks to support proactive drought management.

5. Conclusions

This study assessed drought variability in Kien Giang province from 1992 to 2024 using two multiscale indices, MSPI and MSPEI. The results reveal a high degree of coherence in drought patterns across the station network, with the multiscale framework explaining over 90% of observed variability. Both indices successfully capture major historical drought events, including 2004–2005 and 2015–2016, confirming the robustness of the integrated approach for reconstructing drought dynamics in the coastal Mekong Delta.

A comparison between MSPI and MSPEI demonstrates that the indices are complementary rather than interchangeable. MSPI is highly responsive to precipitation deficits and enables early detection of drought onset, whereas MSPEI reflects more persistent and prolonged drought conditions, particularly evident after 2015. This divergence suggests that, under conditions of global warming, evapotranspiration-driven processes delay recovery relative to rainfall-based signals. This distinction is critical for water resource and agricultural management in Kien Giang, where climate variability interacts with the complexities of a coastal estuarine system.

The findings further highlight the importance of temporal scale in drought interpretation. Short-term indices are most relevant for seasonal agricultural monitoring, while medium- and long-term scales capture cumulative stress on water resources. Despite limitations related to evapotranspiration data and the spatial density of temperature observations, the study provides a robust foundation for integrated drought monitoring. Future research should focus on linking multiscale drought signals with direct impact indicators, including salinity intrusion, crop yield reduction, and soil moisture dynamics. Such integration is essential to enhance the efficacy of these signals within the context of operational climate risk planning and adaptive management strategies.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

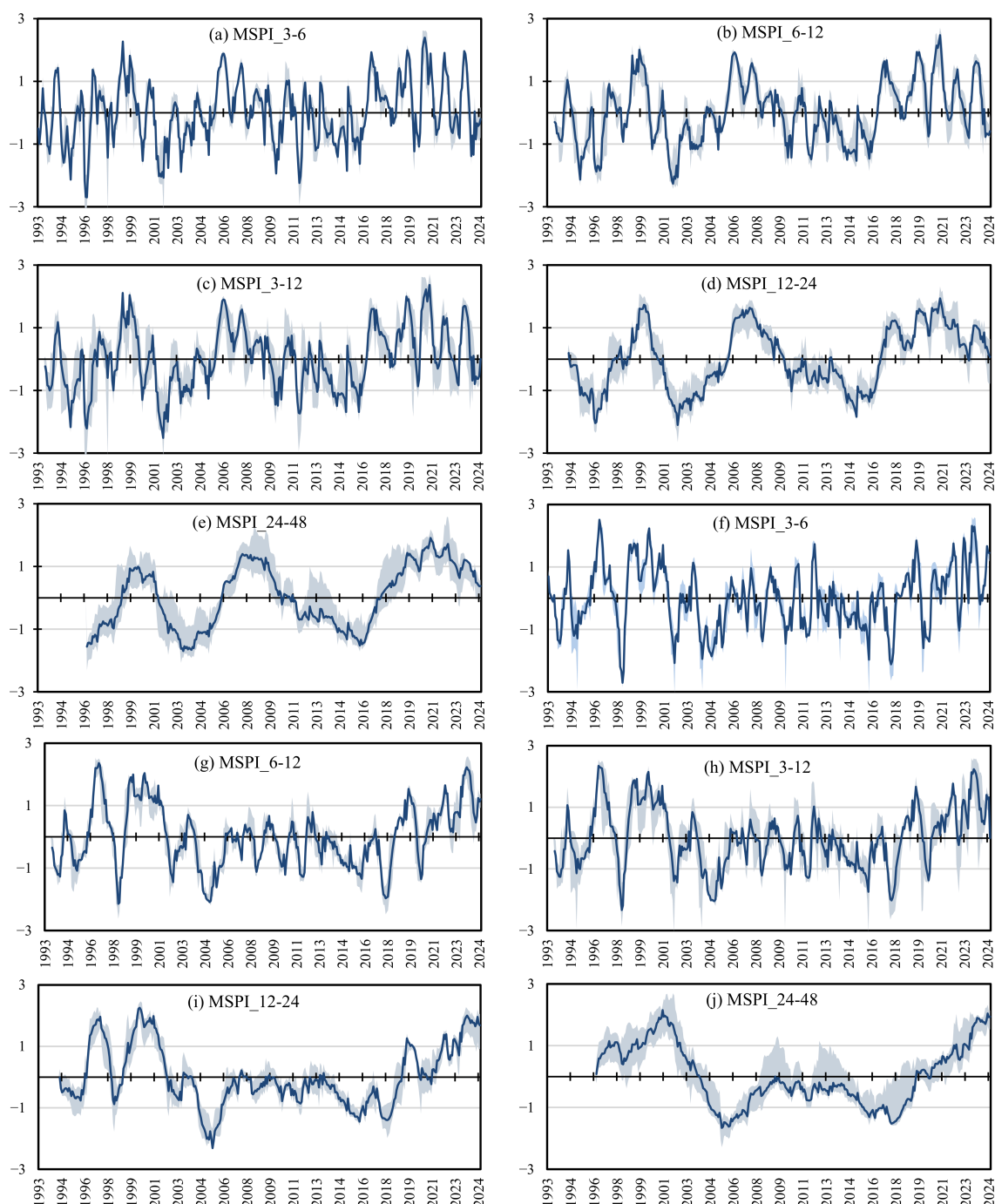


Figure A1. MSPI time series corresponding to each SPI time scale group (3–6, 6–12, 3–12, 12–24 and 24–48 months) at An Ninh and Giong Rieng stations, Kien Giang.

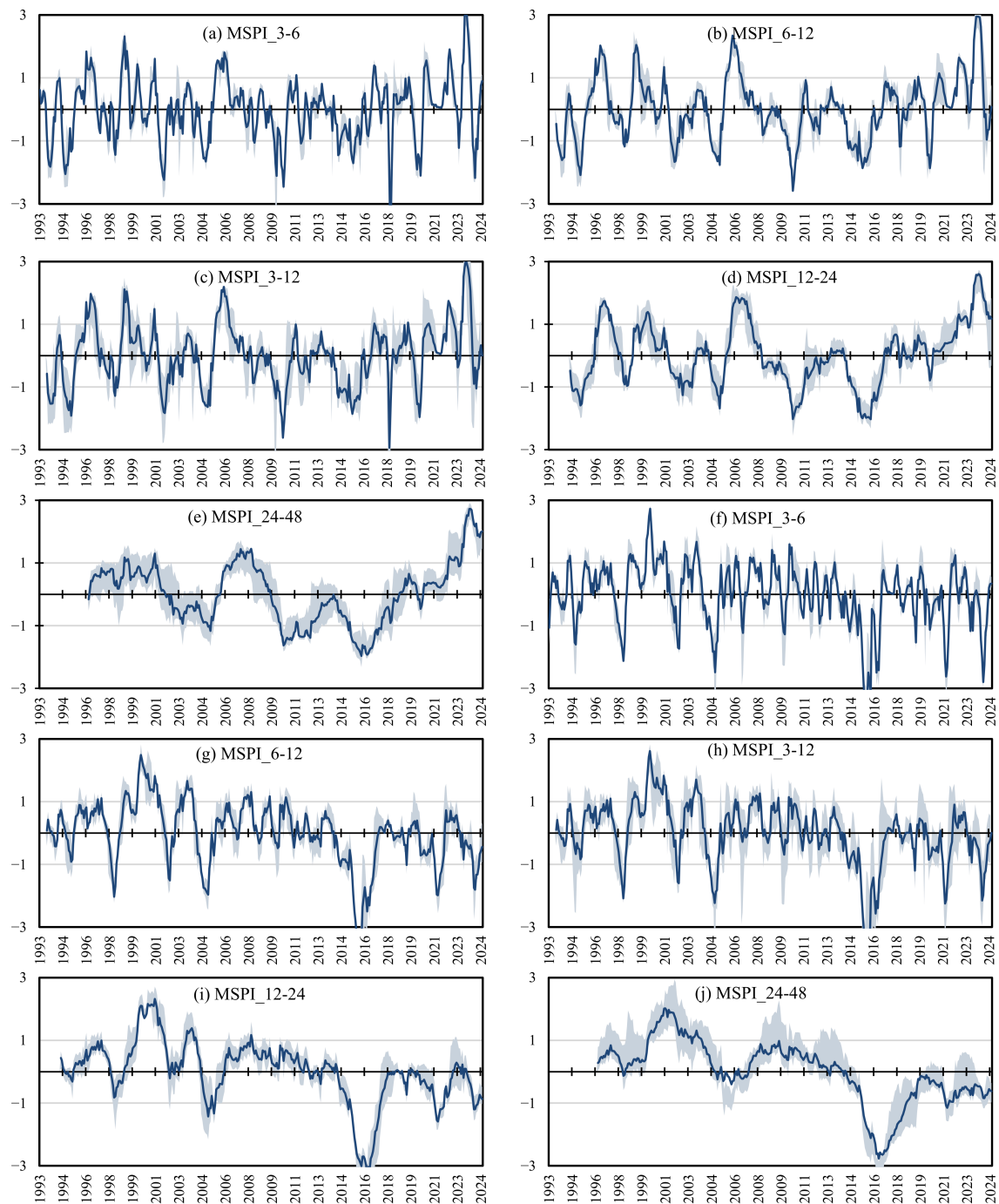


Figure A2. MSPI time series corresponding to each SPI time scale group (3–6, 6–12, 3–12, 12–24 and 24–48 months) at Go Quao and Ha Tien stations, Kien Giang.

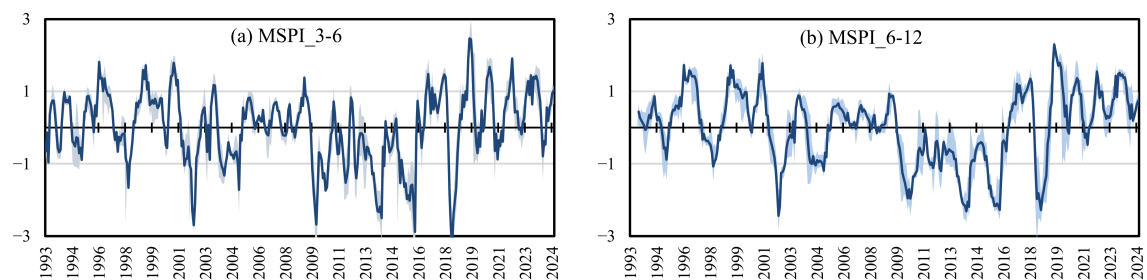


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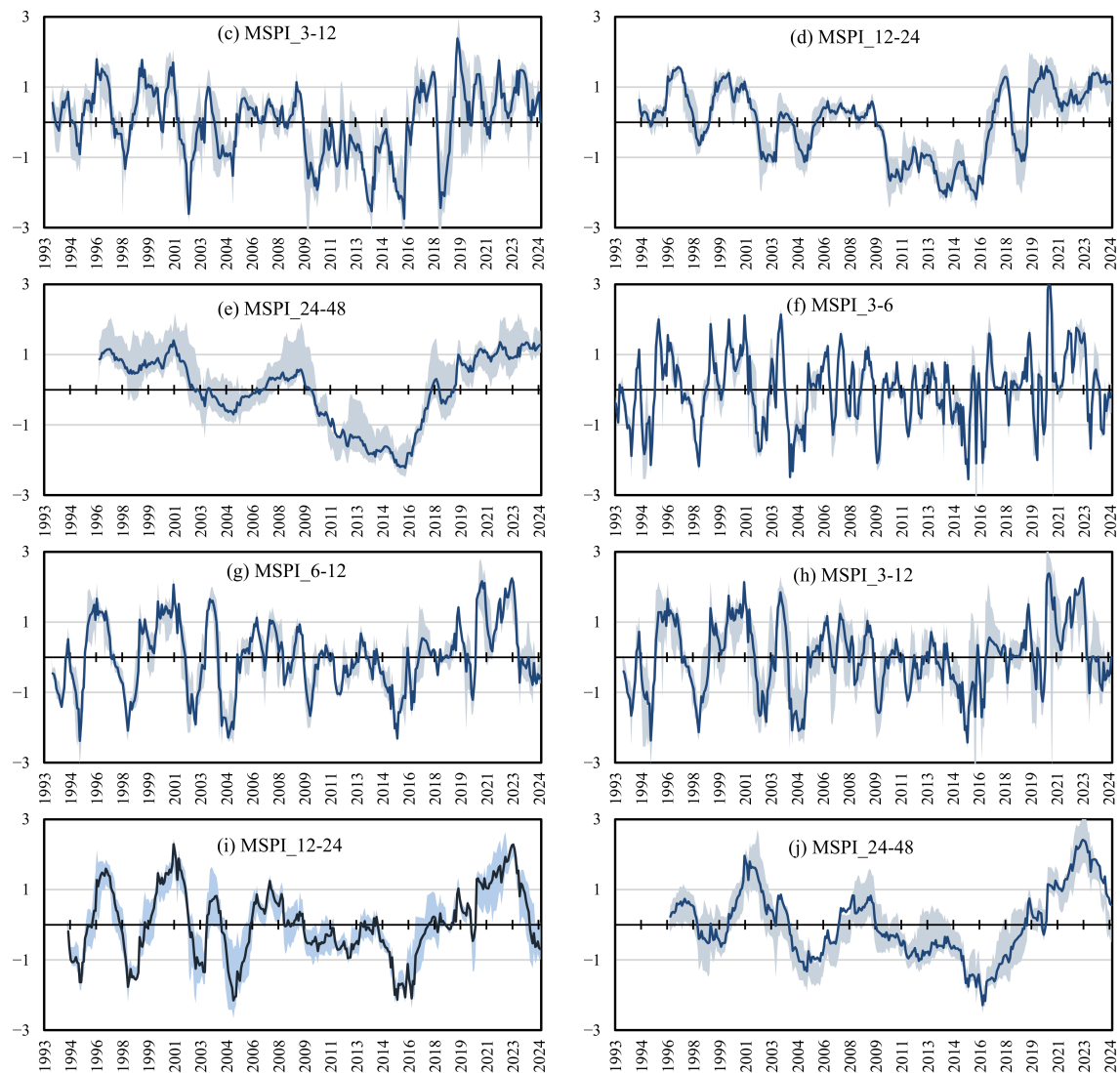


Figure A3. MSPI time series corresponding to each SPI time scale group (3–6, 6–12, 3–12, 12–24 and 24–48 months) at Hon Dat and Kien Luong stations, Kien Giang.

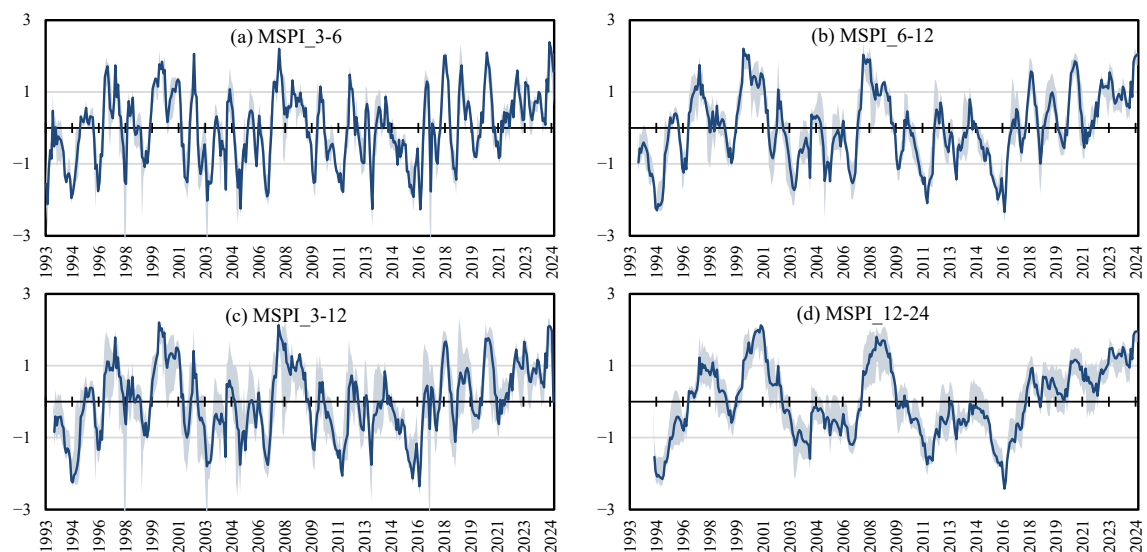


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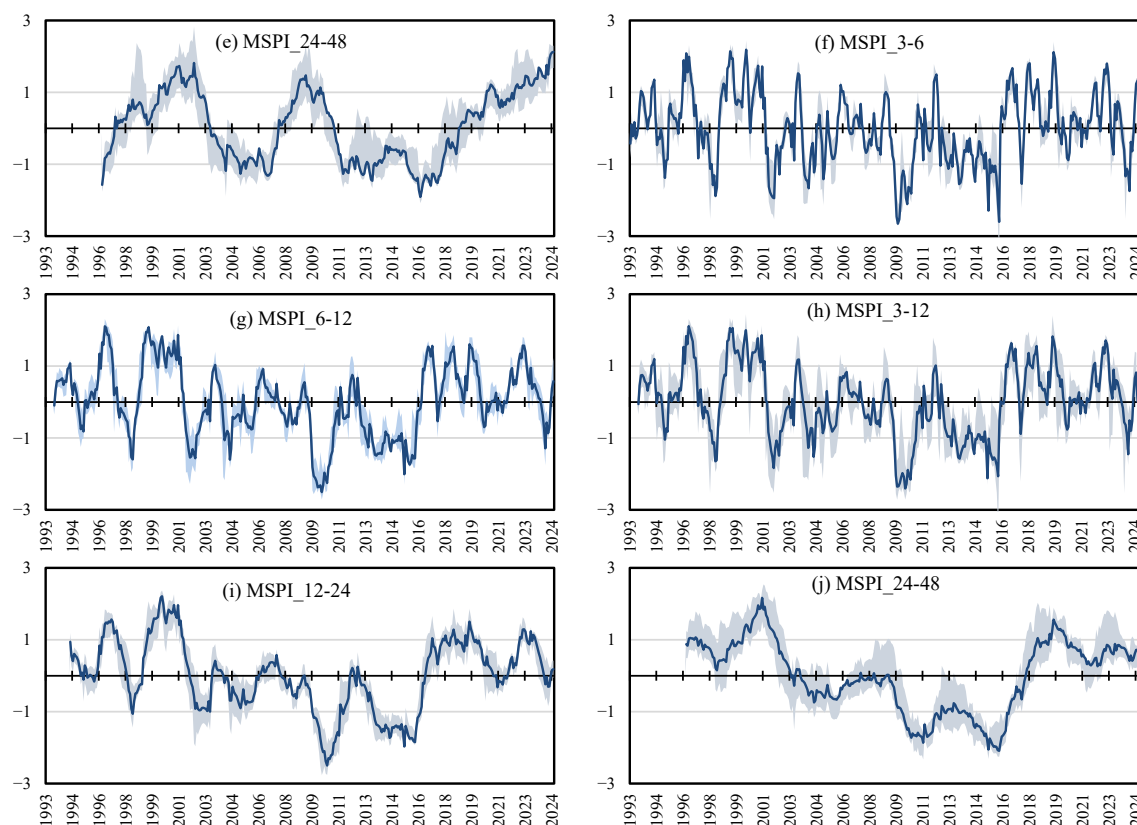


Figure A4. MSPI time series corresponding to each SPI time scale group (3–6, 6–12, 3–12, 12–24 and 24–48 months) at Rach Gia and Tan Hiep stations, Kien Giang.

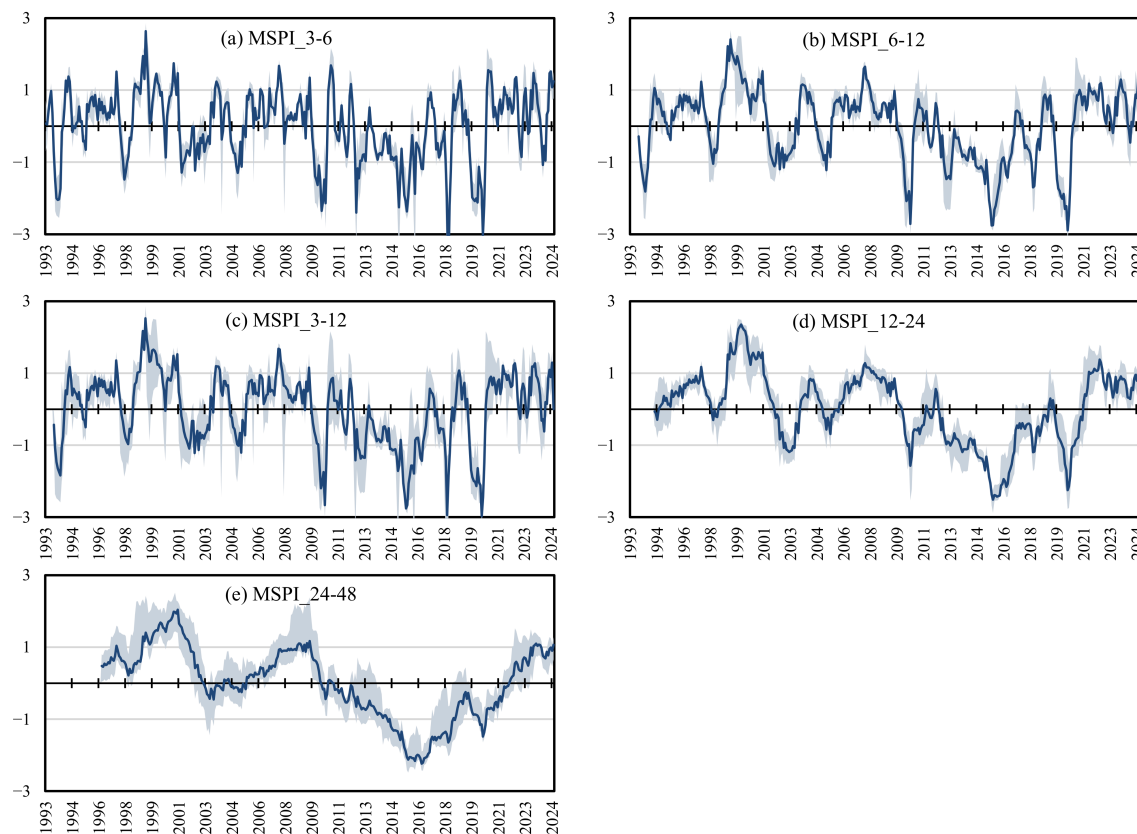


Figure A5. MSPI time series corresponding to each SPI time scale group (3–6, 6–12, 3–12, 12–24 and 24–48 months) at Vinh Thuan station, Kien Giang.

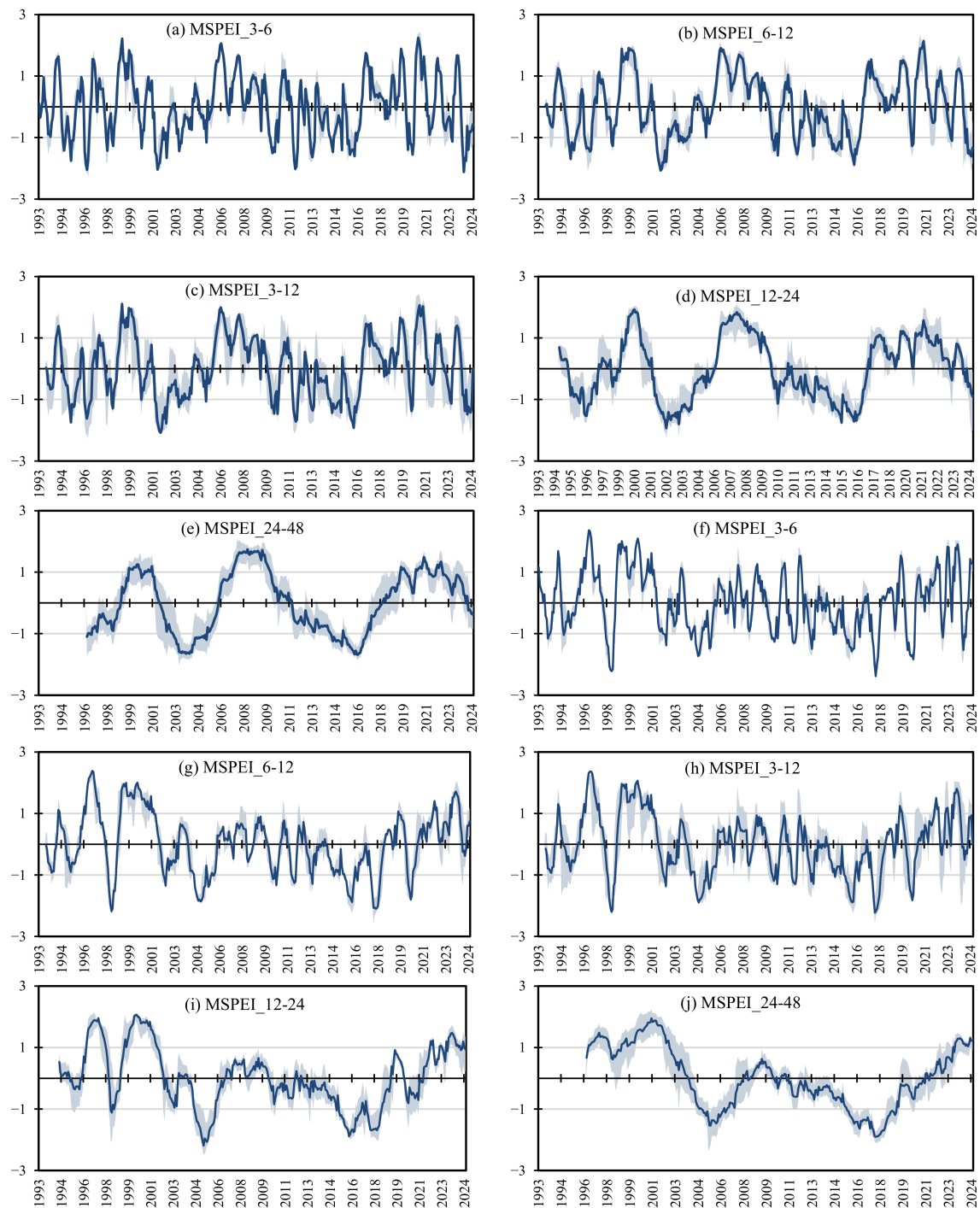


Figure A6. MSPEI time series corresponding to each SPEI time scale group (3–6, 6–12, 3–12, 12–24 and 24–48 months) at An Ninh and Giong Rieng stations, Kien Giang.

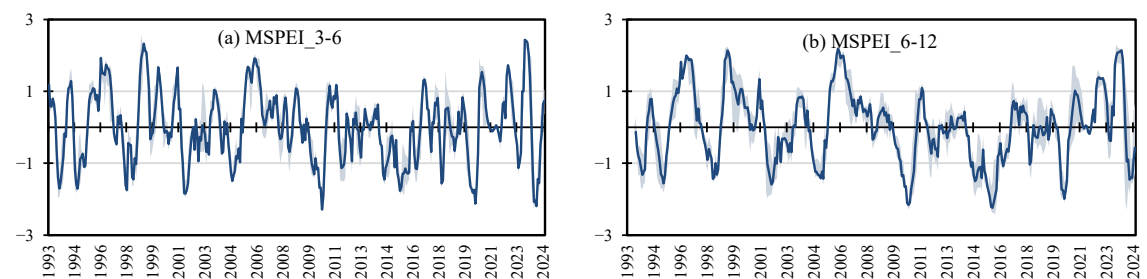


Figure A7. Cont.

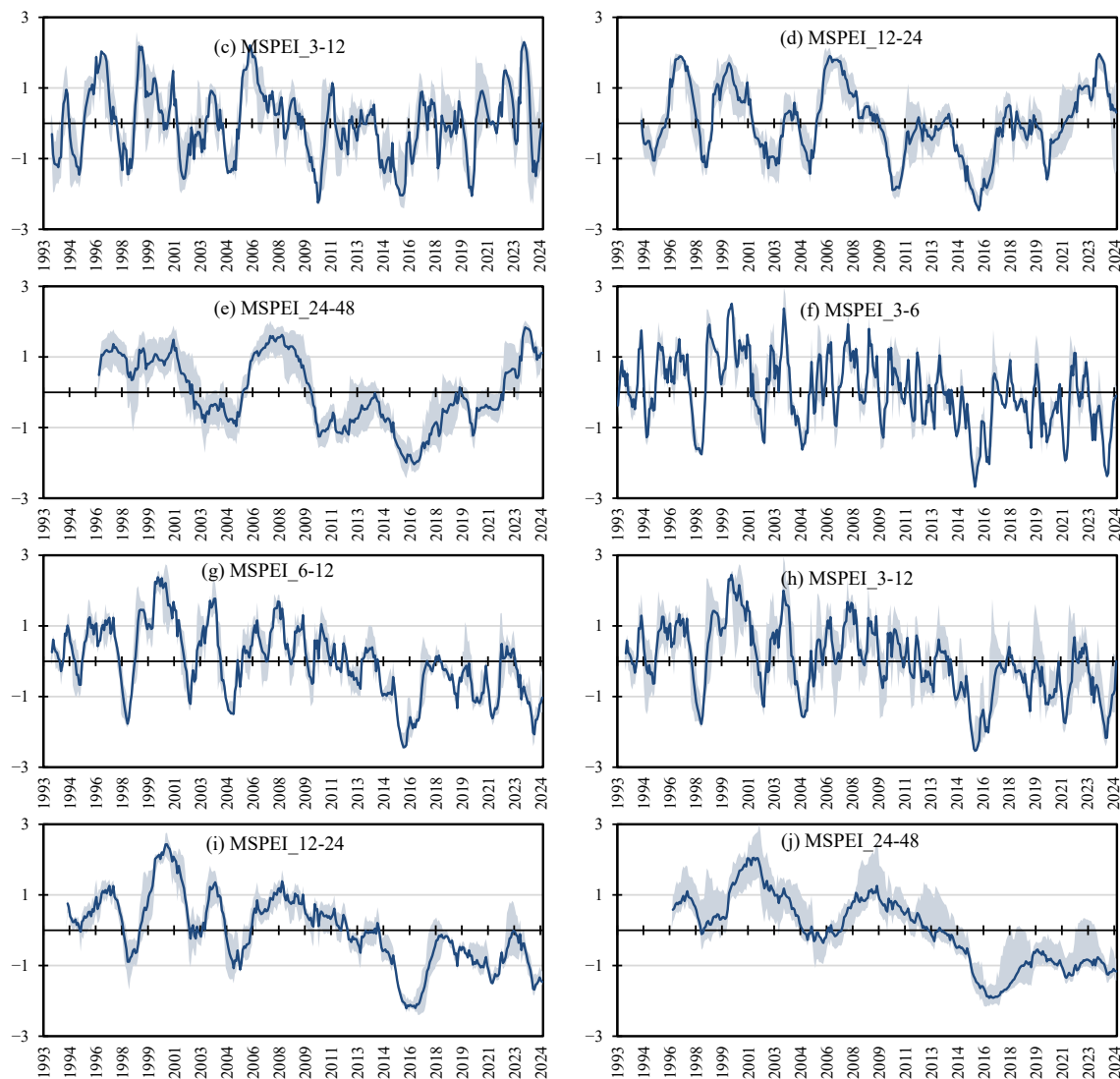


Figure A7. MSPEI time series corresponding to each SPEI time scale group (3–6, 6–12, 3–12, 12–24 and 24–48 months) at Go Quao and Ha Tien stations, Kien Giang.

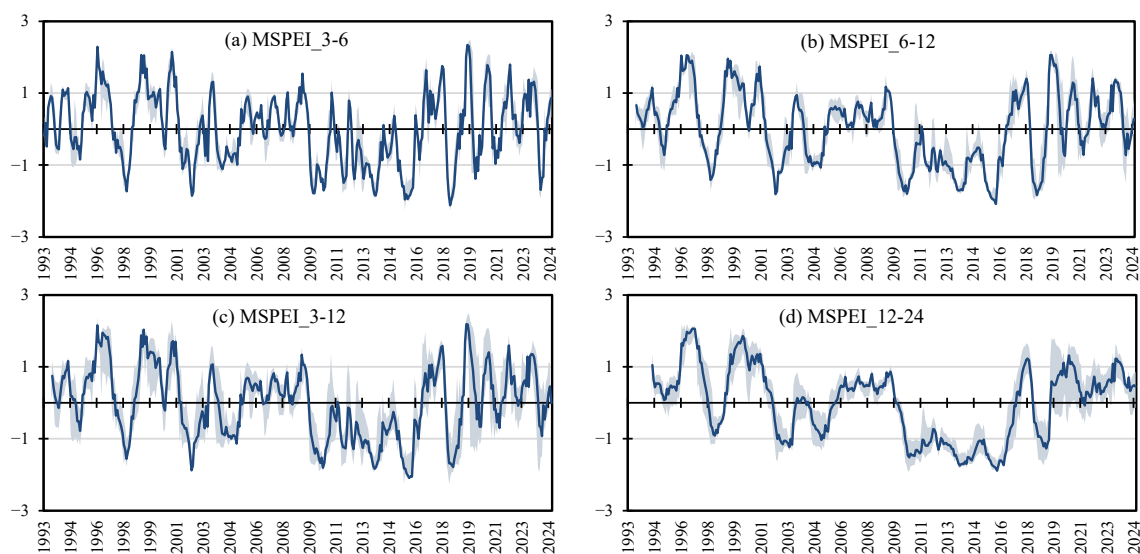


Figure A8. *Cont.*

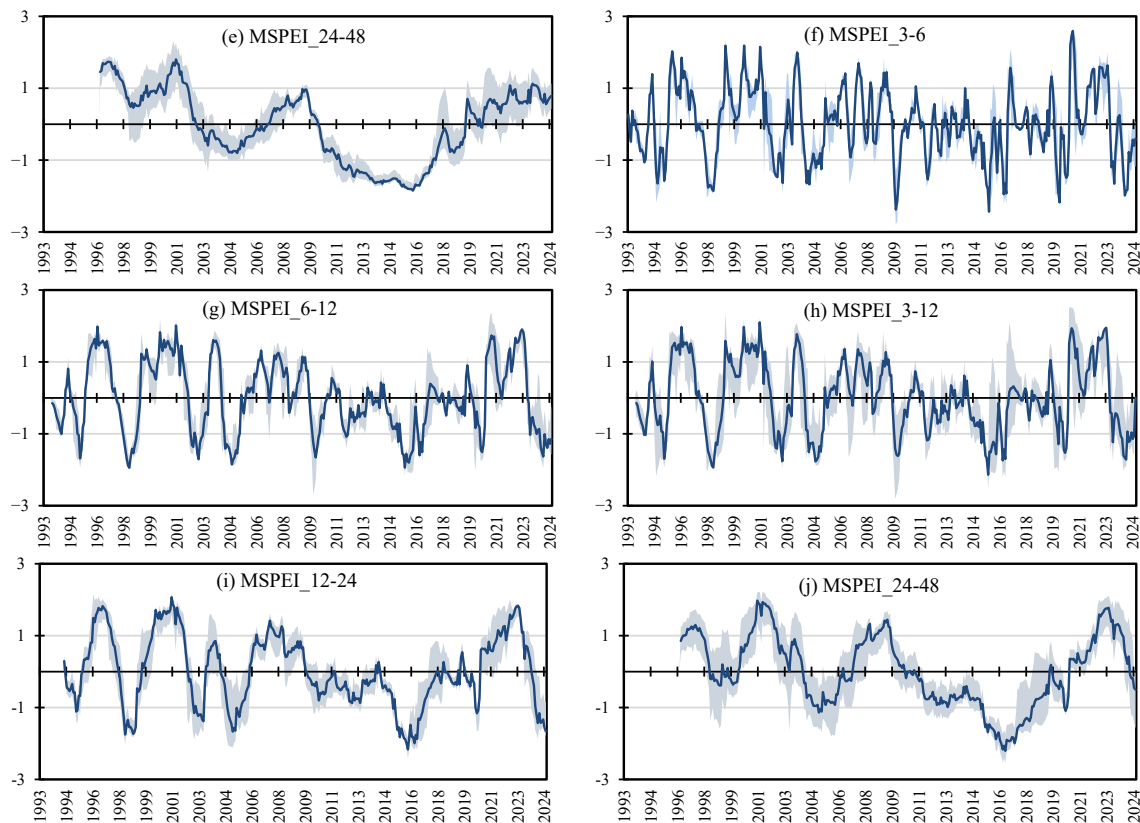


Figure A8. MSPEI time series corresponding to each SPEI time scale group (3–6, 6–12, 3–12, 12–24 and 24–48 months) at Hon Dat and Kien Luong stations, Kien Giang.

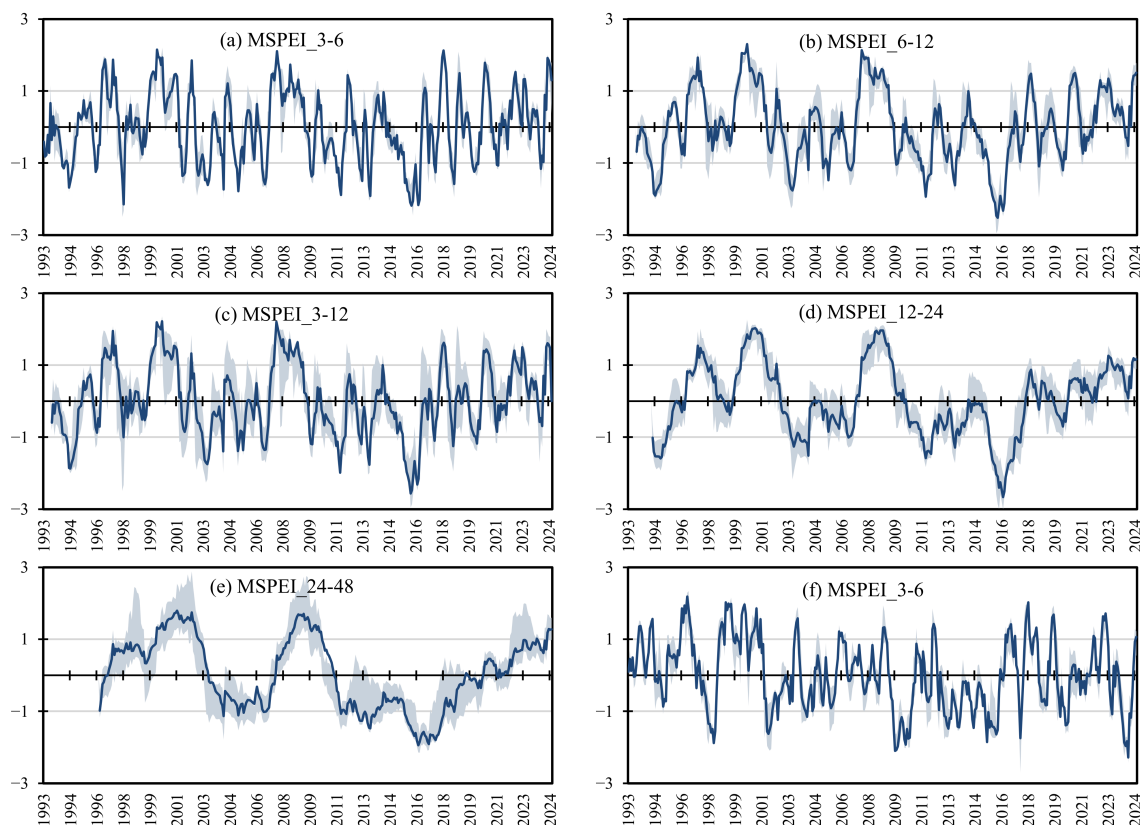


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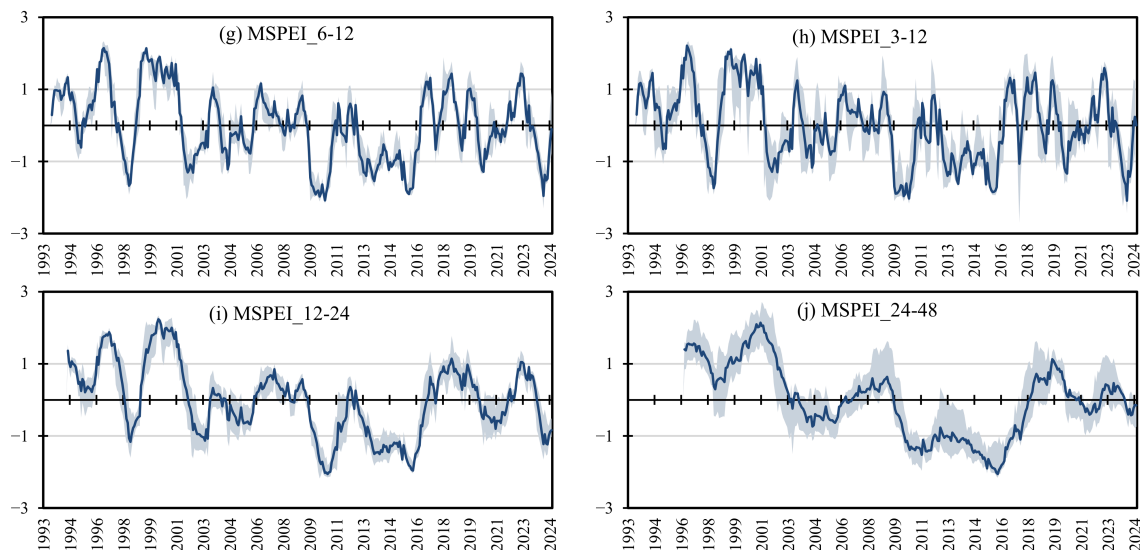


Figure A9. MSPEI time series corresponding to each SPEI time scale group (3–6, 6–12, 3–12, 12–24 and 24–48 months) at Rach Gia and Tan Hiep stations, Kien Giang.

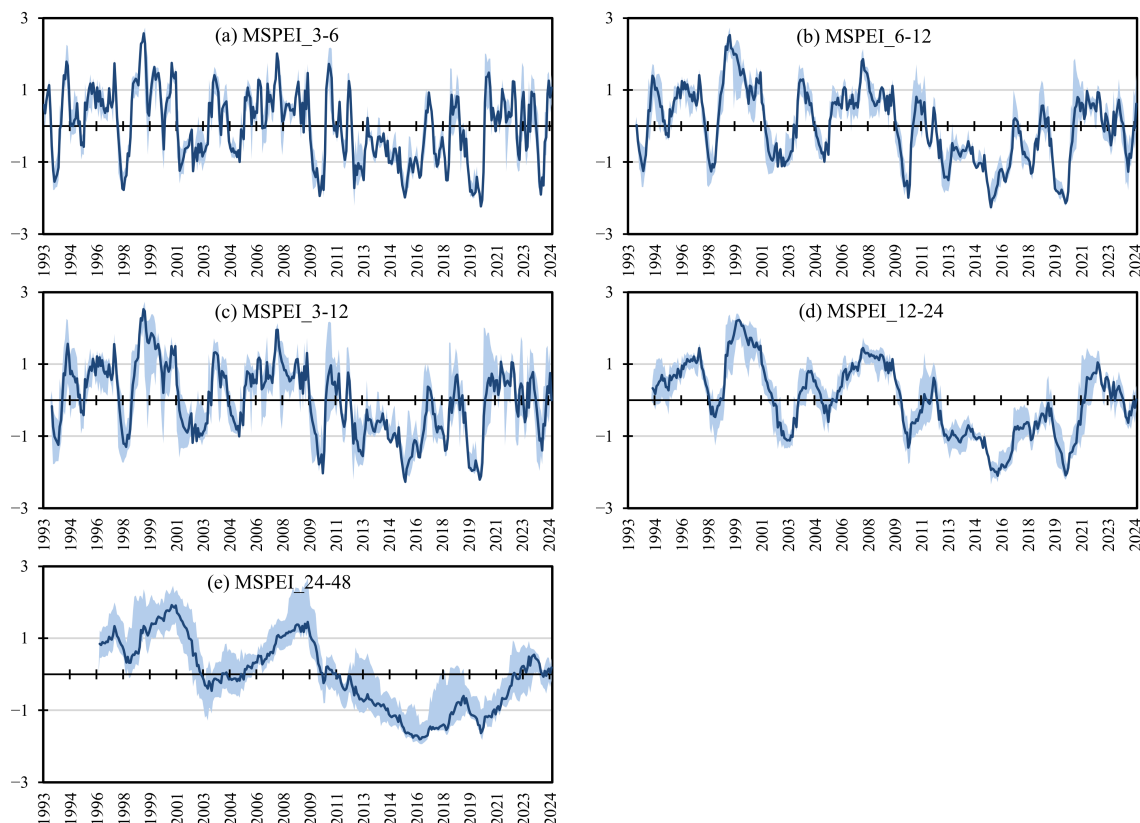


Figure A10. MSPEI time series corresponding to each SPEI time scale group (3–6, 6–12, 3–12, 12–24 and 24–48 months) at Vinh Thuan station, Kien Giang.

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