

Drought over Southeast Asia and Its Association with Large-Scale Drivers

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ABSTRACT: In this study, the spatiotemporal variability of drought over the entire Southeast Asia (SEA) region and its associations with the large-scale climate drivers during the period 1960–2019 are investigated for the first time. The 12-month Standardized Precipitation Evapotranspiration Index (SPEI) was computed based on the monthly Global Precipitation Climatology Centre (GPCC) precipitation and the monthly Climate Research Unit (CRU) 2-m temperature. The relationships between drought and large-scale climate drivers were examined using the principal component analysis (PCA) and maximum covariance analysis (MCA) techniques. Results showed that the spatiotemporal variability of drought characteristics over SEA is significantly different between mainland Indochina and the Maritime Continent and the difference has been increased substantially in recent decades. Moreover, the entire SEA is divided into four homogeneous drought subregions. Drought over SEA is strongly associated with oceanic and atmospheric large-scale drivers, particularly El Niño–Southern Oscillation (ENSO), following by other remote factors such as the variability of sea surface temperature (SST) over the tropical Atlantic, the Pacific decadal oscillation (PDO), and the Indian Ocean dipole mode (IOD). In addition, there exists an SST anomaly dipole over the Pacific Ocean, which modulates the atmospheric circulations and consequently precipitation over SEA, affecting drought conditions in the study region.

KEYWORDS: Drought; ENSO; Asia; Teleconnections

1. Introduction

Drought is a recurrent, slow-onset, and extreme climate phenomenon over terrestrial land. It often originates from a temporary reduction in the regular precipitation regime. In addition, changes in other climatic factors such as high temperatures and low relative humidity can substantially aggravate the severity of the drought event (Naumann et al. 2018). Drought can last for several months or years over considerable spatial extents, and the intangible nature of drought impacts often result in devastating consequences on agriculture, ecosystems, and economics (WMO 2006). Drought is classified according to its impact (Wilhite and Glantz 1985; Mishra and Singh 2010), imposing an approximate time scale for each type. For instance, a meteorological drought occurs when precipitation is less than average over a period from weeks to months, whereas an agricultural drought is related to soil moisture deficits and may last for several months, causing crop losses (Mishra and Singh 2010; Fung et al. 2020). A hydrological drought develops from seasonal to interannual time scales by depleting streamflow or lake levels (Fung et al.

2020; Kuswanto et al. 2021). Socioeconomic drought arises from either a shortage of water supply or an excess of water demand for human applications (Ault 2020; Fung et al. 2020; Kuswanto et al. 2021). Among these four types, meteorological drought is the most prevalent and essential since it often acts as the starting point of the others (Mishra and Singh 2010).

Previous studies have documented the spatiotemporal variability and observed changes in drought characteristics across different scales (WMO 2006; Sheffield et al. 2009; Mishra and Singh 2010; Bonsal et al. 2011; Spinoni et al. 2013; Dai 2011, 2013; Trenberth et al. 2014; Ge et al. 2016; Haslinger and Blöschl 2017; Lima and AghaKouchak 2017; Hanel et al. 2018; Yao et al. 2019). On a global scale, past changes in drought characteristics remain uncertain. Sheffield et al. (2012) showed little change in global drought over the last 60 years while Dai (2013) found increasing drought under global warming in both observations and climate models. At the continental scale, in the United States for example, the Great Plains, western and eastern parts experienced large variations in the magnitudes of drought characteristics during 1900–2012 (Ge et al. 2016). The authors found that due to the influence of sea surface temperature (SST) in the tropical Pacific and Atlantic, the extreme drought events have frequently occurred. In another study by Spinoni et al. (2017), a large discrepancy in drought tendencies over Europe during the 1950–2015 period was indicated. More frequent and severe droughts have also been documented across regions in

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East Asia (Zhang and Zhou 2015) and India (Kumar et al. 2013; Mallya et al. 2016).

In the context of global warming, droughts in the twenty-first century are projected to increase in frequency, severity, and spatial extent over many regions, including southern Europe, the Middle East, and most regions of the Americas, Africa, Australia, and Southeast Asia (SEA) (e.g., Dai 2011; Collins et al. 2013; Guerreiro et al. 2018; Supharatid and Nafung 2021). Studies using the model outputs of different phases of the Coupled Model Intercomparison Project (CMIP) presented great challenges related to drought for socioeconomics and adaptation across the world. For instance, Cook et al. (2020) speculated that the projected patterns of wet and dry conditions obtained with CMIP6 models are consistent with those obtained with CMIP5 models for most regions, except for some areas such as the U.S. northern plains and Northeast Asia, where the differences between CMIP6 and CMIP5 could be spatially significant. For SEA, future drought is projected by CMIP6 models to have longer durations, higher peak intensities, and greater severity under the shared socioeconomic pathway SSP5–8.5; meanwhile, a higher number of drought events is projected under SSP2–4.5 (Supharatid and Nafung 2021).

Drought can be driven by large-scale atmospheric and oceanic processes (Sheffield et al. 2009; Dai 2013; Trenberth et al. 2014; Ge et al. 2016). According to Trenberth et al. (2014), major droughts over Australia, SEA, some parts of Africa, and northeastern Brazil were associated with the moving offshore of the main rainfall systems over the tropical Pacific during El Niño events. Dai (2013) found that on global scale the variations of leading maximum covariance analysis (MCA) modes between SST and drought index are induced by El Niño–Southern Oscillation (ENSO). At smaller scales, previous studies also showed the association between droughts and ENSO (D'Arrigo et al. 2006; Kumar et al. 2013; Räsänen et al. 2016; Lima and AghaKouchak 2017; Setiawan et al. 2017; Mursidi and Sari 2017; Yao et al. 2019). However, the influence of ENSO on drought varies in time and space, and the different ENSO events result in different precipitation anomalies (Capotondi et al. 2015; Räsänen et al. 2016; Lima and AghaKouchak 2017; Setiawan et al. 2017; Yao et al. 2019).

SEA, comprising Indochina, the Malay Peninsula, and the Maritime Continent, is mostly located within the tropical zone and strongly influenced by the Asian monsoons, which bring a substantial amount of rainfall to several parts of the region (Chang et al. 2004, 2005; D'Arrigo et al. 2006). Despite the abundance of rainfall, SEA has also been experiencing severe droughts (ESCAP 2020). Kang and Sridhar (2021) showed that the historic drought in 2015/16 caused the water levels in the Mekong River to drop to a record low in the last 100 years. Other studies have also revealed significant increases in drought severity in the mainland of SEA (Thilakaratne and Sridhar 2017; Le et al. 2019; Zhang et al. 2020). Moreover, the spatiotemporal characteristics of drought in different parts of the region such as Indonesia (Setiawan et al. 2017; Pratiwi et al. 2018; Suroso et al. 2021; Kuswanto et al. 2021), Malaysia (Salimun et al. 2014; Fung et al. 2020; Hasan et al. 2021), the Philippines (Warren 2013; Salvacion 2021),

and Vietnam (Le et al. 2019) are predominantly controlled by climate seasonality and partly influenced by large-scale climatic drivers. In Indonesia, El Niño impacts were explicitly pronounced during the dry seasons (from June to November) when anomalous dry conditions were experienced throughout the country for the period 1981–2012 (Supari et al. 2017; Kurniadi et al. 2021). In the regional scale, ENSO-related SSTs were shown to harmonize with SEA precipitation anomalies (Juneng and Tangang 2005). During El Niño events, Ummenhofer et al. (2013) found the coincidence between anomalous drought conditions over SEA and a weakened monsoon circulation over the Indian subcontinent and SEA, together with anomalous subsidence over monsoon Asia and reduced moisture flux. They also highlighted that when an Indian Ocean dipole (IOD) co-occurs with El Niño, SEA experiences severe drought conditions due to a weakened South Asian monsoon, as well as anomalous divergent flow and subsidence over Indonesia. Nguyen et al. (2020) studied the combined impacts of ENSO and the Pacific decadal oscillation (PDO) on drought and revealed that drought is intensified and expanded when ENSO is in phase with PDO—that is, when El Niño (La Niña) occurs at the same time with the warm (cold) phase of PDO. The in-phase PDO advances (delays) the onset (withdrawal) of El Niño (La Niña)-induced drought. Furthermore, Hernandez et al. (2015) showed that the drought patterns during the years with extremely weakened South Asian monsoon resemble those reconstructed for the “Strange Parallels” drought in the mid-eighteenth century. The authors also pointed out that these patterns arise during boreal spring over SEA with decreased precipitation and moisture flux. Several studies have also attributed the increased severity and longer durations of recent droughts in the SEA countries to global warming (Sam et al. 2019; ESCAP 2020).

Despite several existing studies on drought in SEA, these efforts only focused on a specific one or a few countries or sectors (e.g., Salimun et al. 2014; Setiawan et al. 2017; Uttarak and Laosuwan 2019; Fung et al. 2020; Kuswanto et al. 2021; Hasan et al. 2021; Salvacion 2021, etc.). To the best of our knowledge, no studies on drought over the whole SEA region have been conducted. The present study aims to comprehensively investigate and understand the key drought characteristics and relationships between drought and large-scale climate drivers over the entire SEA. The study domain (14.8°S–27°N, 89.5°–146.5°E; see Fig. S1 in the online supplemental material) coincides with that defined by the Coordinated Regional Climate Downscaling Experiment–Southeast Asia (CORDEX-SEA) project (Tangang et al. 2020). The rest of the paper is organized as follows. Section 2 describes the data and methods of analysis. Results and discussion are presented in section 3. Finally, conclusions are drawn in section 4. The overall framework of this study is illustrated in Fig. S2.

2. Data and methods

a. Data

The Global Precipitation Climatology Centre (GPCC; Schneider et al. 2020) and the Climatic Research Unit (CRU)

TABLE 1. Climate indices.

No.	Acronym	Index name	Variable used
1	Niño-3	Eastern tropical Pacific SST (5°N–5°S, 150°–90°W)	SST
2	Niño-3.4	East central tropical Pacific SST (5°N–5°S, 170°–120°W)	SST
3	Niño-4	Central tropical Pacific SST (5°N–5°S, 160°E–150°W)	SST
4	ONI	Oceanic Niño Index	SST
5	BEST	Bivariate ENSO time series	Niño-3.4, SOI
6	Rindo_slpa	Indonesia sea level pressure (SLP) (standardized anomalies)	SLP
7	SOI	Southern Oscillation index	SLP
8	ReqSOI	Equatorial SOI	SLP
9	Repac_slpa	Equatorial eastern Pacific SLP (standardized anomalies)	SLP
10	WHWP	Western Hemisphere warm pool	SST
11	AMMsst	Atlantic meridional mode (AMM) SST index	SST
12	NTA_SST	North tropical Atlantic SST Index	SST
13	TNA	Tropical North Atlantic Index	SST
14	AMONUS	AMO (Atlantic multidecadal oscillation) index	SST
15	PDO	Pacific decadal oscillation	SST
16	DMI	DMI HadISST1.1.	SST

2-m temperature (Harris et al. 2020) are used to calculate the drought index. Monthly precipitation is obtained from the GPCC version 2020 at the spatial resolution of 0.25°. Monthly temperature is obtained from the CRU version 4.04 and bilinearly interpolated from 0.5° to 0.25° resolution. Both the GPCC precipitation and CRU temperature are extracted for the SEA domain for the period January 1959 to December 2019, which are used to calculate the 12-month SPEI drought index (see section 2b) from January 1960 to December 2019 (720 months, 60 years). These time series are long enough for statistical analysis of variability and trends of drought in recent decades. The GPCC precipitation and CRU temperature were already used as reference products in some previous studies in the SEA region (e.g., Ali et al. 2015; Juneng et al. 2016; Thirumalai et al. 2017; Tangang et al. 2020; Miao et al. 2020).

To investigate the relationship between drought and large-scale climatic factors, additional climatic variables for the period from January 1960 to December 2019 are acquired. Specifically, 16 climate indices (CIs; see details in Table 1) at monthly time scale are obtained from <https://psl.noaa.gov/data/climateindices/list>. These CIs consist of two main groups: the indices based on SST and those based on variables describing atmospheric circulation. Monthly SST time series of the COBE-SST2 dataset at 1° × 1° resolution (Hirahara et al. 2014) are obtained from <https://www.esrl.noaa.gov/psd/data/gridded/data.cobe2.html>. Horizontal wind (u and v), specific humidity (q) at four different pressure levels (1000, 850, 700, and 500 hPa), and the mean sea level pressure (PMSL) and surface wind (us and vs) at 2.5° × 2.5° spatial resolution are obtained from the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis (Kalnay et al. 1996). Note that the data quality of different gridded datasets has been getting better in the recent decades thanks to the digitization of hand-written historical data and availability of advanced in situ and satellite-based observations (Kanamitsu et al. 2002; Poli et al. 2017; Kaspar et al. 2022).

b. The drought index

Drought can be evaluated by drought characteristics using drought indices calculated for different time scales. In general, drought time scales are arbitrary, but are selected based on the effects of precipitation deficits on usable water sources (McKee et al. 1993). In this study the 12-month Standardized Precipitation-Evapotranspiration Index (SPEI) is used as the drought index. It is determined based on a water balance, in which both precipitation and temperature data are considered. Therefore, the SPEI is expected to be comparable to the Palmer Drought Severity Index (PDSI; Vicente-Serrano et al. 2010) and to overcome the deficiencies of the Standardized Precipitation Index (SPI; Stojanovic et al. 2020). The calculation procedure of SPEI is similar to that of SPI, in which precipitation is replaced by the difference between precipitation and potential evapotranspiration (PET). PET is calculated using the Thornthwaite equation (Thornthwaite 1948), which considers only the effect of temperature (Wang et al. 2015). Therefore, the SPEI is an extension of SPI, with the advantage of being able to identify the impact of temperature on drought severity via PET.

c. Drought characteristics

Four drought characteristics are calculated based on the SPEI drought index: drought frequency (DF), drought duration (DD), drought severity (DS), and spatial extent of drought (SE). A drought month is identified as a month with the SPEI value falling below a specific threshold. A drought spell (or a drought event) is defined as the period of consecutive drought months. Here, DF is defined as the number of drought spells, DD is the total drought month, DS is the sum of SPEI values in all drought spells (Spinoni et al. 2014), and SE is the percentage of the grid points that drought occurs (Le et al. 2019). In this study, three categories of drought levels are examined: (i) moderate drought ($\text{SPEI} \leq -1.0$), (ii) severe drought ($\text{SPEI} \leq -1.5$), and (iii) extreme drought ($\text{SPEI} \leq -2.0$). The long-term (climatology) means of drought characteristics in each category is defined as the mean over the

whole period 1960–2019. The anomaly of drought characteristics for each of six decades (1960–69, 1970–79, 1980–89, 1990–99, 2000–09, and 2010–19) is derived by subtracting the mean of each period to the long-term mean.

d. Trend analysis

To determine the existence of trends for the variation of drought in the SEA, this study applies the nonparametric Mann–Kendall test (Mann 1945; Kendall 1970) at a 5% significance level for both the monthly SPEI and mean annual precipitation and temperature time series. To determine the magnitude of the trends, the nonparametric Sen's slope estimator (Sen 1968) is used. Compared to parametric methods, nonparametric ones have several advantages; for example, they do not require any assumption on the data distribution and can well handle missing data and outliers (Gocic and Trajkovic 2014).

e. Large-scale factors associated with drought

Numerous studies pointed out that drought in different regions is either directly or indirectly associated with different large-scale processes such as ENSO (Räsänen et al. 2016; Le et al. 2019), nonconventional El Niño (Zhang et al. 2013), moisture fluxes, moisture budgets (Wei et al. 2016; Qiu et al. 2017), and global warming (Dai 2013). To understand how large-scale processes are related to the evolution of drought over SEA, we examine the relationships between drought (via SPEI values) and CIs, SST, and atmospheric moisture fluxes.

To investigate the linkage between drought and large-scale factors, the principal component analysis (PCA) (Abdi and Williams 2010; Le et al. 2019) is first applied to the CIs and gridded SST to reduce data dimensionality and obtain their spatial patterns (PCs) and time series (EOFs). The method can be briefly shown as follows:

$$\mathbf{X}(s, t) = \sum_{i=1}^m \mathbf{PC}_i(s) \mathbf{EOF}_i(t) \approx \sum_{i=1}^k \mathbf{PC}_i(s) \mathbf{EOF}_i(t), \quad k \ll m, \quad (1)$$

where $\mathbf{X}(s, t)$ is the data matrix of either CIs or SST; $t = 1, 2, \dots, n$ is time steps to be considered as samples; $s = 1, 2, \dots, m$ is a list of variables (CIs) or grid points (SST); and k is the number of dominant modes of PCs to be retained. Mathematically, all vectors $\mathbf{EOF}_i$ are standardized orthogonal while vectors $\mathbf{PC}_i$ are orthogonal only—that is, $\mathbf{EOF}^T \cdot \mathbf{EOF} = \mathbf{I}$ ($\mathbf{I}$ is a unit matrix), and $\mathbf{PC}^T \cdot \mathbf{PC} = \mathbf{\Lambda}$ [$\mathbf{\Lambda} = \text{diag}(\lambda_1, \lambda_2, \dots)$], is a diagonal matrix with $\lambda_i > 0$ being the i th eigenvalue; the superscript T denotes transpose. On the physical aspect, each vector $\mathbf{EOF}_i$ is time series of the i th pattern $\mathbf{PC}_i$ of $\mathbf{X}(s, t)$; the elements of each vector $\mathbf{PC}_i$ can be explained as correlation coefficients between time series of $\mathbf{X}(s, t)$ and each $\mathbf{EOF}_i$ time series. Besides, the correlation maps between SPEI and $\mathbf{EOF}_i$ are conducted, which could be used to explain the relationship between drought and the patterns of CIs and SST.

The maximum covariance analysis (MCA) technique is then applied to the SPEI and both CIs and SST. The advantage

of the MCA is that it can capture the dominant patterns of the maximum covariance between two datasets (Bretherton et al. 1992; Mo 2003; Barreto et al. 2017). Let $\mathbf{X}(s, t)$ be a standardized data matrix of SPEI, and $\mathbf{Y}(r, t)$ be a standardized data matrix of either CIs or SST, where $s = 1, 2, \dots, p$ is the number of grid points of the SPEI data, $r = 1, 2, \dots, q$ is either the number of variables of CIs or the number of grid points of the SST data, and $t = 1, 2, \dots, n$ is the number of time steps to be considered as samples. Let $\mathbf{C}(s, r)$ be a covariance matrix between $\mathbf{X}$ and $\mathbf{Y}$, which can be represented as shown:

$$\mathbf{C}(s, r) = \frac{1}{n} \mathbf{X}(s, t) \mathbf{Y}^T(t, r). \quad (2)$$

Applying the singular value decomposition (SVD) technique to the matrix $\mathbf{C}$, we obtain

$$\mathbf{C}(s, r) = \mathbf{U}(s, r) \mathbf{\Gamma}(r, r) \mathbf{V}^T(r, r) \approx \mathbf{U}_k(s, k) \mathbf{\Gamma}_k(k, k) \mathbf{V}_k^T(k, r), \quad (3)$$

where $\mathbf{U}$ and $\mathbf{V}$ are singular matrices representing the patterns of $\mathbf{X}$ and $\mathbf{Y}$, respectively, and $\mathbf{\Gamma}$ is a diagonal matrix of singular values arranged in descending order with the number of nonnegative values being less than or equal to $\min\{p, q, n - 1\}$, where $k = 1, 2, \dots, K$ is the number of dominant modes to be retained. The first K pairs of the singular vectors ($\mathbf{U}_k, \mathbf{V}_k$) explain the largest contributions to the covariances between $\mathbf{X}$ and $\mathbf{Y}$. Here we note that $\mathbf{U}$ and $\mathbf{V}$ are the standardized orthogonal matrices (i.e., $\mathbf{U}^T \mathbf{U} = \mathbf{V}^T \mathbf{V} = \mathbf{I}$) and each of their columns is called a weight vector (Bretherton et al. 1992).

Following Mo (2003), from Eqs. (2) and (3), we have

$$\mathbf{X}(s, t) = \mathbf{U}(s, r) \mathbf{A}^T(r, t) \approx \mathbf{U}_k(s, k) \mathbf{A}_k^T(k, t), \quad (4)$$

$$\mathbf{A}(t, r) = \mathbf{X}^T(t, s) \mathbf{U}(s, r) \approx \mathbf{A}_k(t, k) = \mathbf{X}^T(t, s) \mathbf{U}_k(s, k), \quad (5)$$

$$\mathbf{Y}(r, t) = \mathbf{V}(r, r) \mathbf{B}^T(r, t) \approx \mathbf{V}_k(r, k) \mathbf{B}_k^T(k, t), \quad (6)$$

$$\mathbf{B}(t, r) = \mathbf{Y}^T(t, r) \mathbf{V}(r, r) \approx \mathbf{B}_k(t, k) = \mathbf{Y}^T(t, r) \mathbf{V}_k(r, k). \quad (7)$$

The matrices $\mathbf{A}$ and $\mathbf{B}$ are called the expansion coefficients, and each of their column vectors is a time series, and $\mathbf{A} \mathbf{B}^T = \mathbf{\Gamma}$. It can be seen from (5) and (7) that each element of the matrix $\mathbf{A}$ ($\mathbf{B}$) is the weight summation of all values in a column of the matrix $\mathbf{X}$ ($\mathbf{Y}$) with weight is a column vector of $\mathbf{U}$ ($\mathbf{V}$). The correlation between the column $\mathbf{A}(t, k)$ and $\mathbf{X}(s, t)$ is called the homogeneous correlation, an indicator of the geographic localization of the covarying part of $\mathbf{X}$ (SPEI in this study). Similarly, the correlation between the column $\mathbf{B}(t, k)$ and $\mathbf{X}(s, t)$ is called the heterogeneous correlation, which indicates how well the grid point of $\mathbf{X}$ (i.e., SPEI) can be predicted from the k th column vector of $\mathbf{B}$ (Bretherton et al. 1992).

To investigate the role of the atmospheric moisture transport and water vapor budgets on drought evolution, the vertically integrated moisture transport (VIMT; $\text{kg m}^{-1} \text{s}^{-1}$), moisture convergence (MCONV; $\text{kg m}^{-2} \text{s}^{-1}$) for each grid point, and water vapor budget (WBG; kg s^{-1}) for the whole

SEA domain are calculated as follows (Qiu et al. 2017; Schmitz and Mullen 1996):

$$\text{VIMT} = \mathbf{Q} = \frac{1}{g} \int_{P_{500}}^{P_{1000}} q \mathbf{V} dp, \quad (8)$$

$$\text{MCONV} = -\text{div } \mathbf{Q} = \nabla \cdot \mathbf{Q}, \quad (9)$$

$$\text{WBG} = \int_C \mathbf{Q} \cdot \mathbf{n} dC = \frac{1}{A} \int_A \nabla \cdot \mathbf{Q} dA, \quad (10)$$

where $g = 9.81 \text{ (m s}^{-2}\text{)}$ is the gravitational acceleration, q is specific humidity, $\mathbf{V} = (u; v)$ is horizontal wind vector, and P_{500} and P_{1000} are pressures at the top level (500 hPa) and bottom (1000 hPa or surface) levels of the lower troposphere, respectively (Cash et al. 2008). As about 90% of atmospheric water vapor content is in the layer of 1000–500 hPa (Hartmann 2016), the VIMT estimated with Eq. (8) is able to approximately describe the moisture transport in the atmosphere. In Eq. (10), C is the lateral boundary of the SEA domain, $\mathbf{n}$ is the normal vector of C , and A is the area of the SEA domain bounded by C .

f. Regionalization of drought

Drought over SEA is expected to be nonuniform due to the differences in spatiotemporal variability of precipitation and temperature caused by the predominant circulation patterns over the region. These differences are also modulated by other local factors such as orography, coastal proximity, or latitude. To regionalize drought in SEA, we use the K -means cluster analysis [hereafter referred to as K -means, an unsupervised learning approach demonstrated in Wilks (2006)] to classify SEA into different homogeneous subregions with relatively consistent drought characteristics. Note that there have been numerous extensions of K -means using different metrics or modifications of the original algorithm (Steinley 2006). The K -means can be used to identify unknown groups in complex datasets, which have been applied to climate regionalization (Fovell and Fovell 1993; Carvalho et al. 2016). The steps for regionalizing drought in SEA can be implemented as follows.

First, the PCA is applied to the drought index (SPEI) using Eq. (1) to obtain the $\text{PC}_i(s)$, where $\mathbf{X}(s, t) = \text{SPEI}(s, t)$, $s = 1, 2, \dots, m$ is the number of grid points, $t = 1, 2, \dots, n$ is time steps, and $i = 1, 2, \dots, p$ is the number of leading PCs. In this study, leading PCs are chosen to explain more than 70% of the total variance. Then, the K -means are applied to the $\text{PC}_i(s)$, which represent the spatial patterns of SPEI. The derived K data point groups are labeled by 1, 2, $\dots$, K and represented as a map of drought regionalization with K subregions. The optimum number of K groups is determined by using the silhouette criterion (Rousseeuw 1987), which shows how similar a data point is to its own group compared to other groups.

3. Results and discussion

a. Spatiotemporal variability of drought characteristics

Figure 1 exhibits the long-term (climatology) means of drought frequency (DF), duration (DD), and severity (DS)

for the period 1960–2019. For moderate drought (top row), DF has a large range of about 3 to 8 spells per decade (Fig. 1a) compared to severe drought (2–4 spells) and extreme drought (1–2 spells). In a similar manner, the DD of moderate drought ranges from 20 to 36 months per decade (Fig. 1b) over most of the SEA region and reduces to 10–16 (5–10) months for severe (extreme) drought. In the mainland (including a part of southern China, Indochina, and peninsular Malaysia), DF is 4–7 spells per decade and DD values are typically larger than 34 months per decade. In contrast, DF is only from 3 to 5 spells per decade over the Maritime Continent, while DD is from 20 to 36 months per decade. The most prolonged DD of more than 36 months per decade is observed in Thailand, north of Borneo and Sumatra. The result reveals a significant difference in drought features between the mainland and the Maritime Continent. Overall, drought over the mainland areas is more frequent, prolonged, and severe (Fig. 1c) than in the maritime areas. The DS values are largest over Thailand, Laos, the Red River Delta, the Mekong River Delta of Vietnam, and some parts of the Maritime Continent. The spatial patterns of severe and extreme drought (Fig. 1, middle and bottom rows) are very similar to moderate drought. However, the magnitude of drought characteristics in severe and extreme categories are smaller than the moderate category, especially for the extreme.

Figure 2 presents the anomaly of moderate drought characteristics for six decades. During the first three decades, 1960–89, minor changes in drought characteristics (DF, DD, and DS) were observed over SEA. In particular, intensified drought events occurred in south central Vietnam and the Maritime Continent during the 1960–69 period, in some parts of the Maritime Continent during 1970–79, and in the Philippines, Laos, and Myanmar during 1980–89. Remarkably, drought characteristics during the period 1990–99 were found to increase over the entire study domain (Figs. 2a4–c4), and this increase might be related to the strong El Niño event in 1997/98. During the 2000–09 period, most of the region recovered from the drought, except the northeastern domain, including northern Vietnam (Figs. 2a5–c5). In the subsequent period, 2010–19, DF, DD, and DS reached their peaks in most of the countries in the mainland and several parts of the Maritime Continent. Similar results were observed for the severe and extreme drought levels (see details in Figs. S3 and S4). The increase of drought in recent years in SEA has also been mentioned in previous studies (Thilakarathne and Sridhar 2017; Le et al. 2019; Uttarak and Laosuwan 2019; Fung et al. 2020; Zhang et al. 2020; Kang and Sridhar 2021; Salvacion 2021, etc.). The results indicate that DF, DD, and DS anomaly values reveal the complexity, volatility, and larger drought variability across the SEA region in the last three decades.

Figure 3 shows the Sen's slopes with corresponding Mann–Kendall statistical significance at 95% for the SPEI, the annual average of precipitation and temperature during the period 1960–2019. In brief, the spatial distribution of the SPEI slope agrees well with that of precipitation over SEA, except in some areas such as part of Thailand, Cambodia, southern Vietnam, the Malay Peninsula, and Sumatra Island. The decreasing (increasing) trends of SPEI, corresponding to the

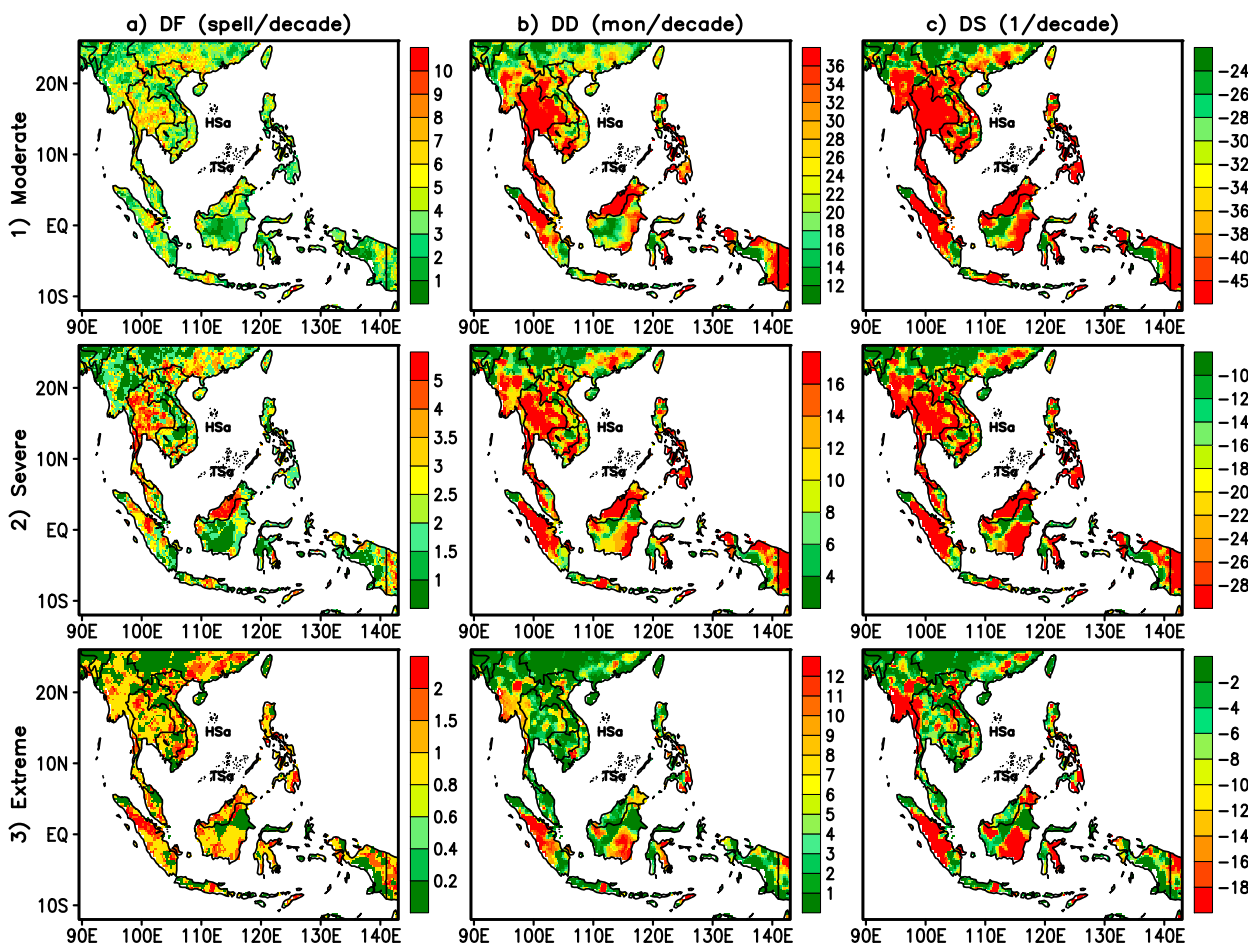


FIG. 1. Climatological drought characteristics over SEA (averaged over 1960–2019): (a) DF (spells decade⁻¹), (b) DD (month decade⁻¹), and (c) DS (decade⁻¹) for drought levels of 1) moderate, 2) severe, and 3) extreme.

increasing (decreasing) trends of drought, are generally observed in areas where precipitation decreases (increases). While drought increased significantly in the mainland areas (Myanmar, Thailand, Cambodia, and Vietnam), it decreased slightly or remained unchanged in other areas, such as the Philippines, and a part of the Maritime Continent. Note that the spatial distribution of changing trends of SPEI in some areas might not totally agree with that of precipitation (Fig. 3) because of the differences in evapotranspiration, which is related to the spatial variability of temperature trends. The result suggests that both precipitation and temperature played a vital role in the spatial and temporal distribution of drought over SEA, yet precipitation was a more dominant factor.

b. Regionalization-based drought characteristics

Figure 4 shows the results of the drought regionalization obtained from the *K*-means using the leading PCs of SPEI. The optimal number of clusters $K = 4$ is determined with the highest value of the silhouette width (Fig. 4, left panel). As a result, the SEA domain is clustered into four homogeneous subregions (denoted R1 to R4) (Fig. 4, right panel). Except

for the R4 subregion, which consists of a larger area of southern China and a small part of northern Vietnam, the majority of the SEA countries belong to the other three subregions. The R1 subregion covers most of the Maritime Continent, including Indonesia and Malaysia; the R2 subregion includes most of Vietnam, Laos, Cambodia, Thailand, the southern part of Myanmar, and the Philippines; and the R3 subregion covers the northwestern part of the SEA domain, comprising part of Kunming (China), part of eastern India, and the northern part of Myanmar. Because the SPEI's PCs are orthogonal, this regionalization could reflect the homogeneity in each subregion and the distinction among them in terms of drought characteristics.

Based on this regionalization, the values of the drought characteristics, including DF, DD, DS, and the monthly frequency of occurrence, are calculated for the whole period from 1960 to 2019 and each decade within it. Drought characteristics are also calculated for each subregion separately and over the entire SEA domain (Fig. 5). The drought characteristics shown in Fig. 5 are derived from the areal SPEI time series. Those time series are calculated based on the precipitation and

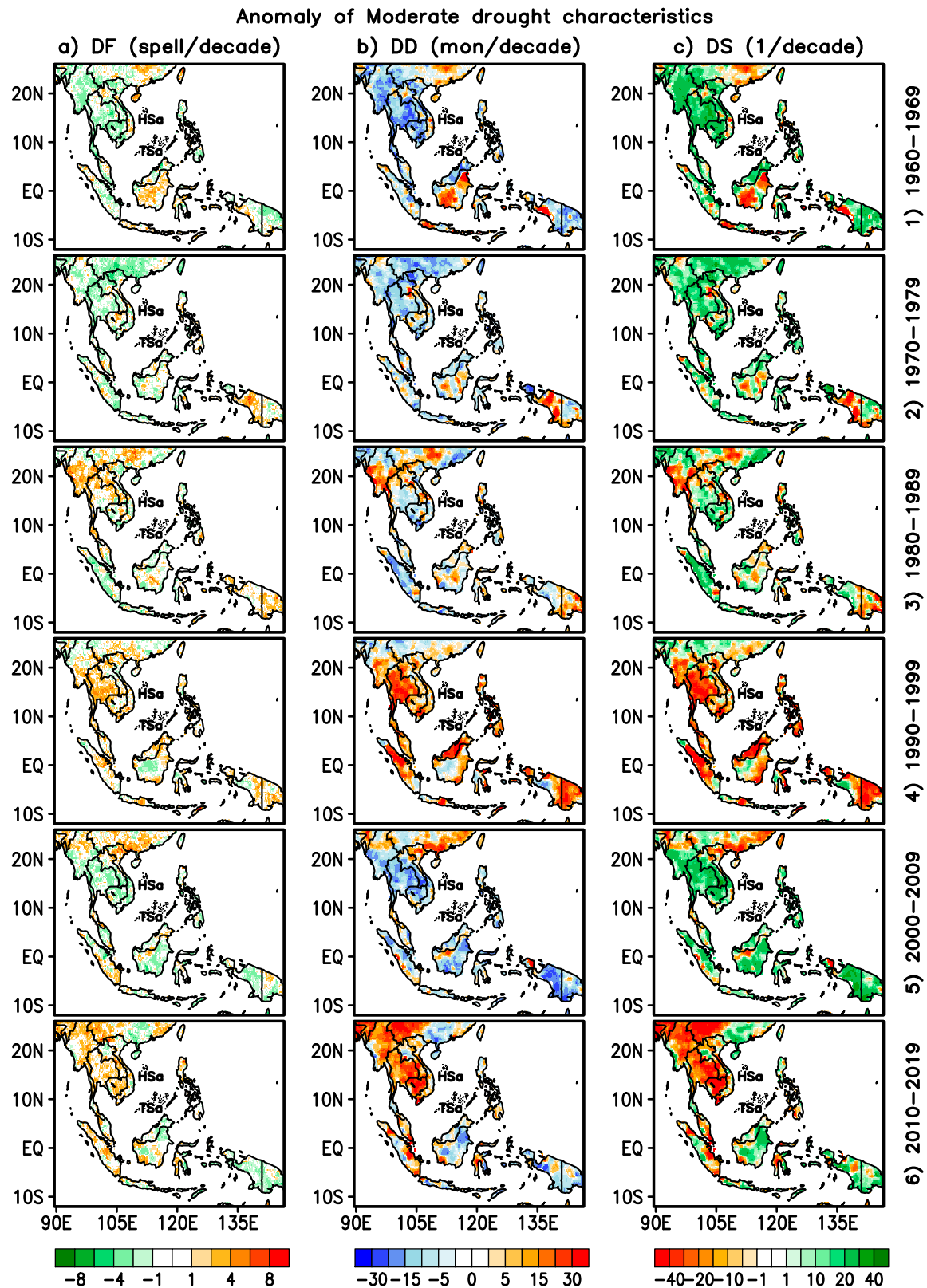


FIG. 2. Anomaly of the moderate drought characteristics of (a) DF (spells decade⁻¹), (b) DD (month decade⁻¹), and (c) DS (decade⁻¹) for the periods of 1) 1960–69, 2) 1970–79, 3) 1980–89, 4) 1990–99, 5) 2000–09, and 6) 2010–19 relative to the whole period 1960–2019.

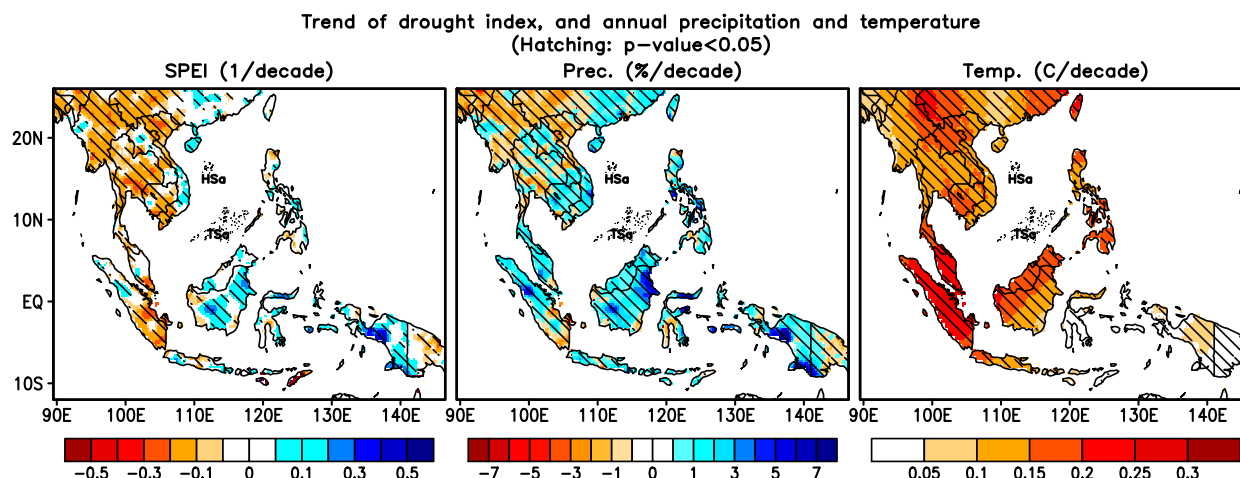


FIG. 3. Trend of (left) SPEI (decade^{-1}), (center) annual precipitation ($\% \text{decade}^{-1}$), and (bottom) annual temperature ($^{\circ}\text{C} \text{decade}^{-1}$) during the period 1960–2019.

potential evaporation (estimated using temperature) values averaged over all grid points within each subregion and the entire SEA. Figures 5a and 5b reveal that severe and extreme droughts were found in all subregions but different periods. In the periods 1990–99 and 2010–19 drought occurred in all subregions with significant increases in frequency, duration, and severity for all three drought levels. The frequent occurrences of extreme drought in these periods could be attributed to the strong El Niño events in 1997/98 (Setiawan et al. 2017) that caused forest fires and massive food shortages over many parts of Indonesia (Jim 1999; Hamid et al. 2001) and 2015/16 (Kang and Sridhar 2021). During 2000–09, drought decreased substantially over R1 and R2 but significantly increased in R3 and R4. The result implies that R1 and R2 appeared to have a tight connection with ENSO whereas R3 and R4 do not. Among four subregions, R2 was prone to drought with consistent behaviors over time.

Seasonal variability of drought frequency in all subregions is presented in Fig. 5d. Due to the geographical location, the dry season period varies between subregions. In particular, the dry season in subregions R2, R3, and R4 spans from December to April, which coincides with the boreal winter and spring seasons, whereas the dry season in R1 occurs during boreal summer (June–September). The R2 subregion experiences more moderate drought in the dry season than in the wet season. However, severe and extreme drought frequency in R2 during the dry season is lower than in other months. The deficit of water during the wet season may cause more severe droughts in this subregion. On the other hand, the R1 subregion shows the opposite pattern with more severe drought occurring in the dry season. Drought over SEA generally occurs in all months, with the monthly frequency in the range of 15%–20%, 6%–8%, and 0%–4% for moderate,

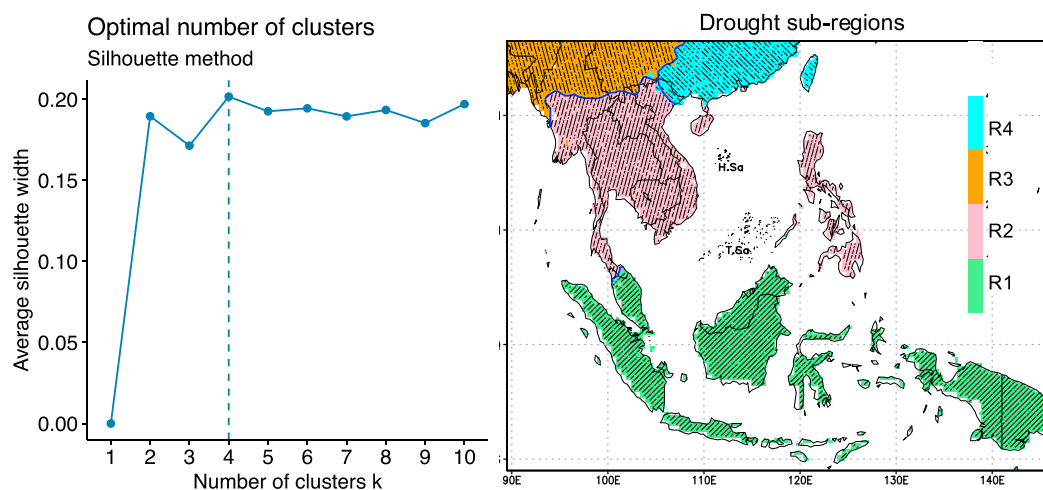


FIG. 4. (right) Four drought subregions of the SEA region classified using the K -means with (left) the optimal cluster number determined by the silhouette width.

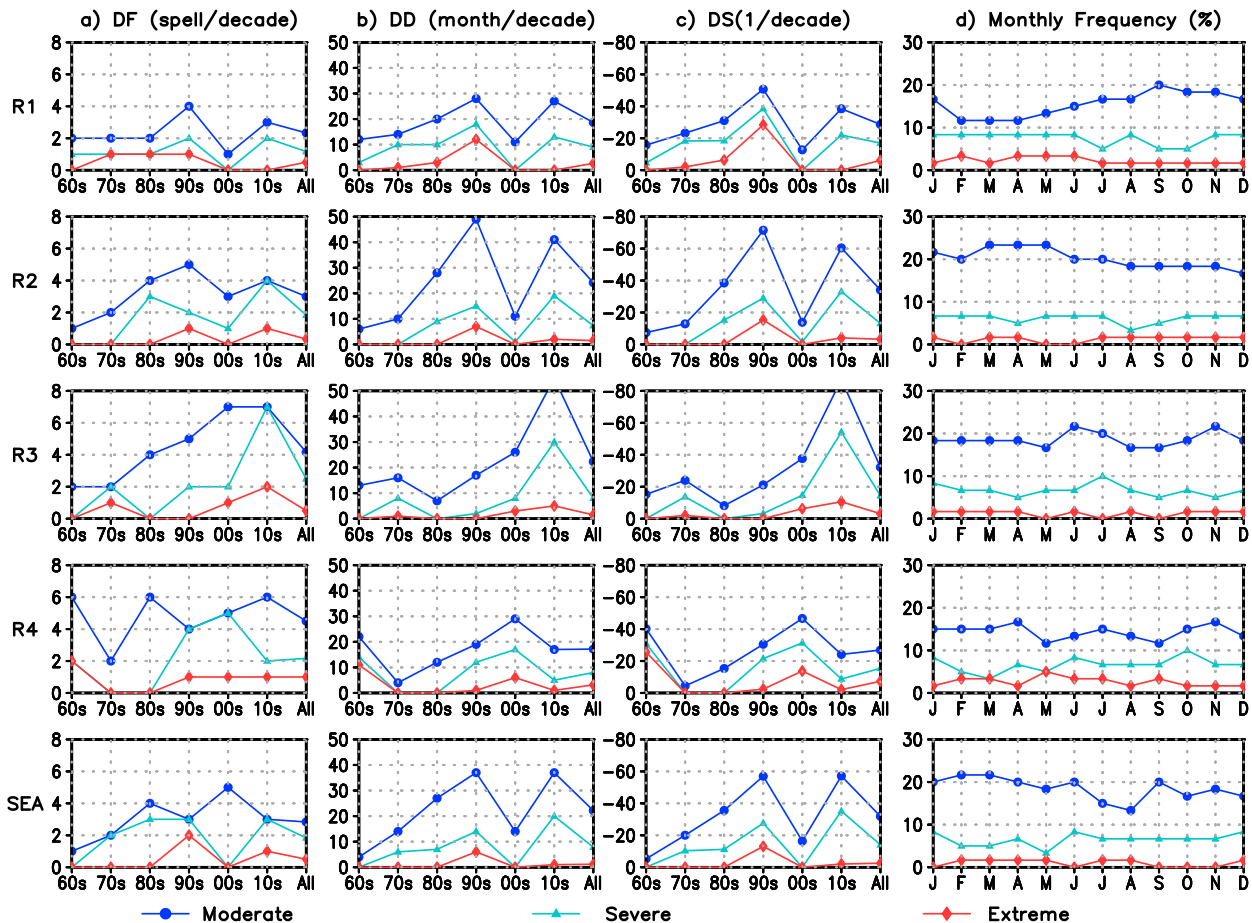


FIG. 5. (a) DF (spell decade⁻¹), (b) DD (month decade⁻¹), (c) DS (decade⁻¹) for the six decades and whole period from 1960 to 2019 (60s: 1960–69; 70s: 1970–79; 80s: 1980–89; 90s: 1990–99; 00s: 2000–09; 10s: 2010–19; All: 1960–2019) and (d) monthly frequency of occurrence (%) in the four subregions (R1–R4) and in the entire SEA.

severe drought, and extreme drought, respectively. The small seasonal variation of drought frequency over the entire SEA compared to those in the four subregions is due to the averaging of precipitation and temperature over all grid points within the domain.

The year-to-year variability of drought spatial extent (SE) is shown in Fig. 6 for four subregions and the entire SEA domain during the period 1960–2019 along with the Oceanic Niño Index (ONI) used as an ENSO indicator (e.g., Glantz and Ramirez 2020). There is an increasing tendency of SE in all subregions and the entire SEA, especially in R2 and R3. Among the subregions, drought is more widespread in R1 and R2, with SE values in the range of 15%–25%, 5%–15%, and 2%–5% for moderate, severe, and extreme drought levels, respectively. Note that drought might not happen concurrently in all subregions. For example, in the years of 1978–81, about 20%–50% of R2 and R3 experienced moderate drought, while other subregions experienced drought at much smaller SE values. Notably the SE values were significantly larger in the El Niño events than in the La Niña and normal conditions, indicating more widespread drought, especially in R1 and R2. For example, during the 1997/98 and

2015/16 strong El Niño events, drought occurred over much larger areas of R1 and R2 (60%–80%) than of R3 and R4 (10%–20%). Moreover, Figs. 5 and 6 show that stronger El Niño events could cause more severe and widespread drought. Drought characteristics in the R1 and R2 subregions tended to reach their peaks at the same phase of El Niño peaks, indicating the more pronounced impacts of ENSO in the lower-latitude bands.

c. Large-scale climate drivers and drought over SEA

1) CLIMATE INDICES

Figure 7 presents the patterns (Figs. 7a,b) and time series (Fig. 7c) of the first three MCA leading modes of SPEI and CIs corresponding to the percentage of variance of 45.4%, 21.8%, and 9.2%. The first two modes contribute more than 67% to the total variance, indicating that drought over most of SEA is linked with both oceanic and atmospheric teleconnections, including ENSO (Niño-3, Niño-3.4, Niño-4, ONI, BEST, Rindo_slp, SOI, ReqSOI, and Repac_slp) and other remote factors (WHWP, AMMsst, NTA_SST, TNA, and AMONUS) (Figs. 7b1–b2; see Table 1 for definitions). The

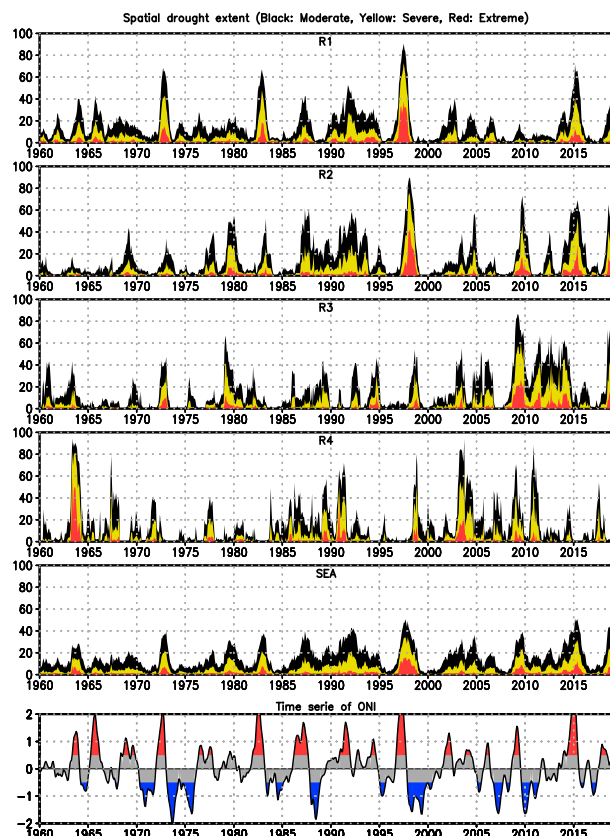


FIG. 6. Time series of SE (%) during the period 1960–2019 in four drought subregions (R1–R4) and the entire SEA domain for the moderate (black), severe (yellow), and extreme (red) drought levels. The ONI time series is used as an ENSO indicator.

first MCA pattern of SPEI demonstrates the important role of ENSO in modulating drought over the entire SEA (Figs. 7a1–b1), in which the ONI, BEST, and ReqSOI indices are the most significant. During the El Niño events, trade winds are weakened, leading to precipitation deficits and droughts over the region. The impact of El Niño on drought was depicted in the Philippines (Salinger et al. 2014), Indonesia, and the Maritime Continent (Lee and McBride 2016; Setiawan et al. 2017). In contrast, during the La Niña events, the Walker circulation is intensified with greater convection over the western Pacific, leading to stronger trade winds and increased precipitation in SEA (Juneng and Tangang 2005). The connections between ENSO and local interactions with prevailing winds from surrounding oceans, resulting in variation of drought conditions across Indonesia, have also been demonstrated by Chang et al. (2004) and Qian et al. (2010). ENSO-related precipitation variability over SEA has also been demonstrated by Lau and Nath (2003).

In the second MCA pattern, drought is more significantly controlled by the variability of SST over the tropical Atlantic (Figs. 7a2–b2). These indices are associated with the central Pacific-type ENSO through the Walker circulation and ocean dynamics (Wang 2019; Park et al. 2019), which might modulate precipitation and consequently drought over SEA. Notably,

these indices may be again related to ENSO (Chikamoto and Tanimoto 2005; Wang 2019). The correlations between time series of SPEI and CIs in both MCA1 and MCA2 are relatively high (0.695 and 0.625) indicating that the SPEI variability fairly resembles that of the CIs. The positive (negative) values of the MCAs of SPEI indicate the decreasing (increasing) rate of drought over the region (Fig. 7a) depending on the varying rate of the CIs (Fig. 7b). Among the CIs, some atmospheric indices have good connections with SPEI, such as RINDO_slp, SOI, ReqSOI, and REPAC_slp (Fig. 7b; see also Fig. S5).

Although the third mode of SPEI and CIs contributes only 9.2% to the total variance, it reveals the crucial roles of the PDO and DMI indices on the variation of SPEI in the R1 and R2 subregions. The PDO reflects SST variability of the North Pacific with warm and cold phases. During the warm phase, the SST cold anomalies occur over the western and central Pacific Ocean (Oñate-Valdivieso et al. 2020), associated with the weakening of trade winds and moisture divergence, resulting in negative precipitation anomalies over SEA and vice versa. The effect is especially enhanced when the PDO is in-phase with ENSO. The correlations between SPEI and the PDO (Fig. S5) indicate that the increased PDO could lead to increased drought over most of the R1 and R2 subregions. During the positive (negative) IOD phases, identified by the DMI, the cold (warm) SST anomaly in the eastern Indian Ocean occurs and the atmospheric convection is suppressed (enhanced), leading to precipitation deficiencies (excesses), hence the dry (wet) conditions in the Maritime Continent. In contrast, an increase (decrease) in the DMI will lead to a decrease (increase) in drought over the SEA mainland (Fig. S5).

The results suggest that drought variability over SEA is mainly associated with oceanic conditions and regional atmospheric processes (via the ReqSOI, Repac_slpa, and Rindo_slpa indices). Our findings motivate an in-depth investigation of the relationship between drought over SEA with SST and atmospheric moisture variability (described below). Regarding drought predictability, the MCA1 of the CIs generally has a good correlation with SPEI over most of SEA, except the R4 subregion, where the correlation coefficients are low [Fig. S6a(1)]. The correlations between the MCA2 and MCA3 of the CIs and SPEI are fairly high [Figs. S6a(2),(3)] which could also provide helpful information on the SPEI variability over the region.

2) SEA SURFACE TEMPERATURE

Figure 8 shows the spatial patterns (Figs. 8a,b) and time series (Fig. 8c) of the first three MCA leading modes of SPEI over SEA and SST over the domain from 30°S to 30°N and from 110° to 290°E, covering a major part of the Pacific Ocean. These three leading modes contribute 30.1%, 10.1%, and 6.0% to the total variance, respectively. The spatial pattern of the first mode of SST (Fig. 8b1) is remarkably similar to the ENSO pattern (Ashok et al. 2007; Dai 2013). This pattern represents the variations of ENSO-induced drought over SEA. During an El Niño event, a warm SST anomaly occurs over the tropical central and eastern Pacific Ocean,

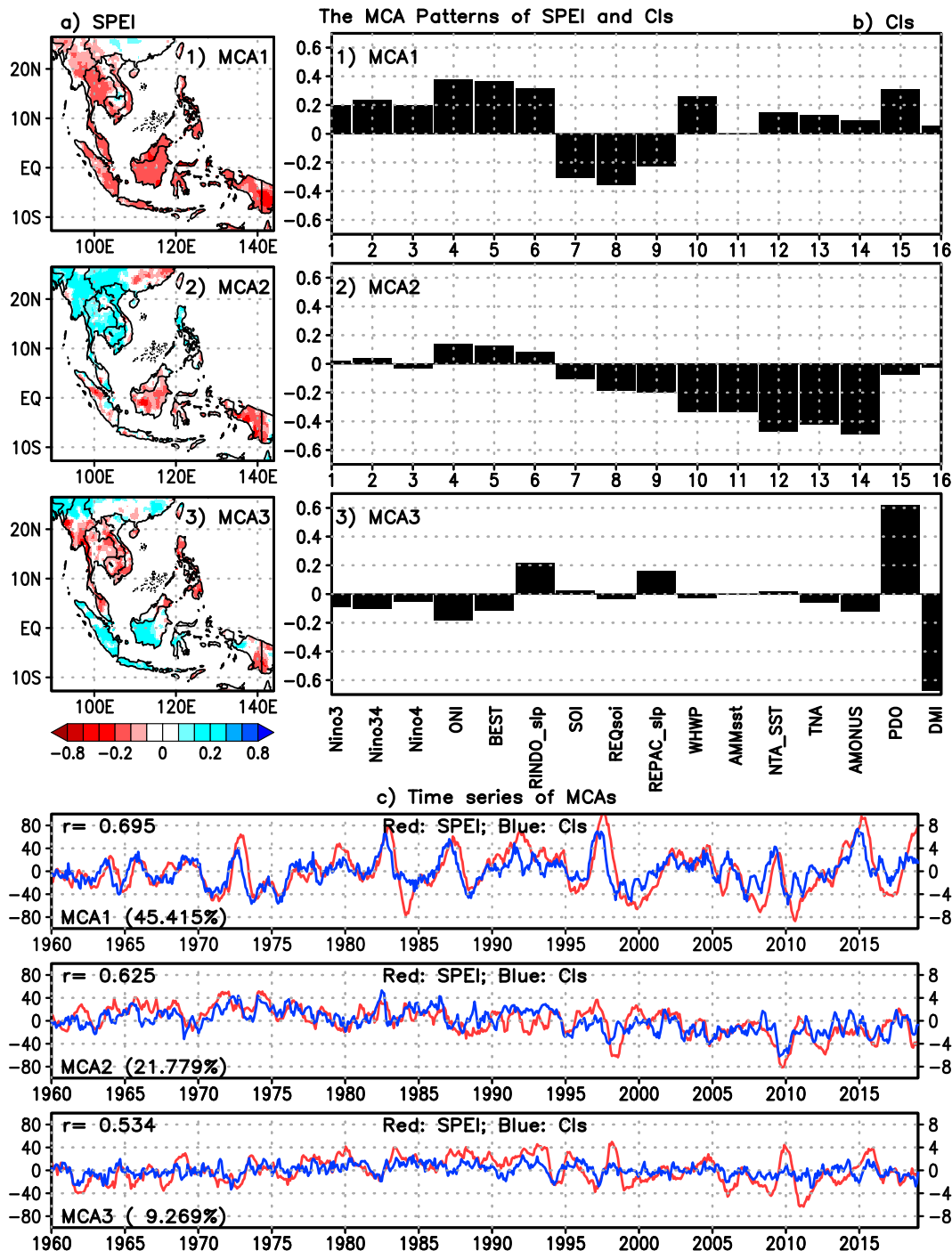


FIG. 7. Patterns of the first three leading modes of the MCA of (a) SPEI, (b) CIs, and (c) their time series (red for SPEI, blue for CIs).

atmospheric pressure increases in the western and decreases in the eastern Pacific, and trade winds weaken. Consequently, the tropical western Pacific convection migrates toward the central tropical Pacific Ocean, leading to precipitation deficits over SEA, and drought tends to occur over most of the domain. However, this pattern is reversed during the La Niña, and thus drought decreases or may not occur.

The second mode is associated with the SST variations over the tropical western and central Pacific, which resemble the central Pacific ENSO type (Capotondi et al. 2015). In this mode, drought tends to occur (not occur) in the mainland (Maritime Continent), depending on the increase (decrease) of SST over the tropical western (central) Pacific. The third mode of SST (Fig. 8b3) resembles the El Niño Modoki

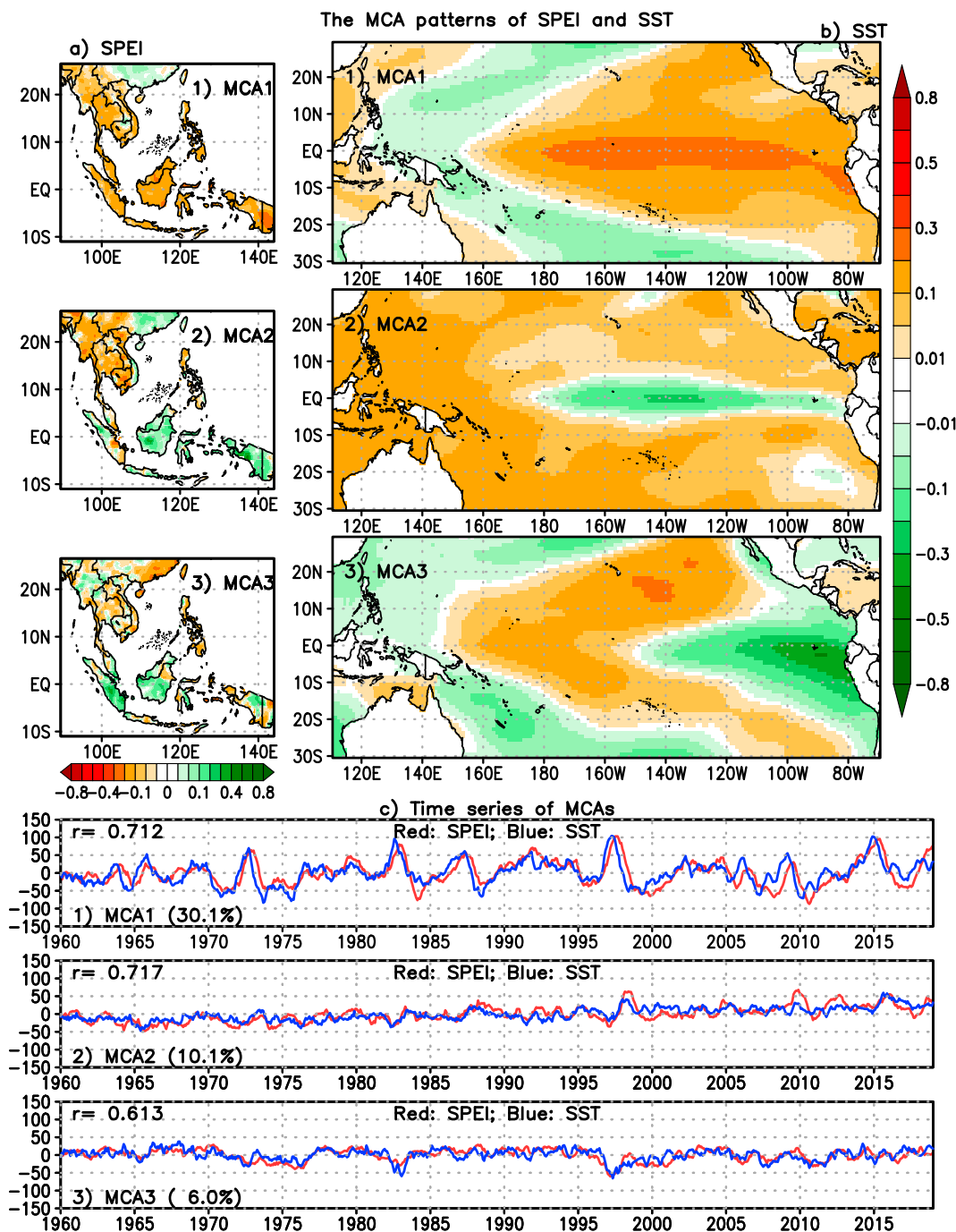


FIG. 8. As in Fig. 7, but for SPEI and SST.

pattern with the maximum warm anomalies occurring in the central equatorial Pacific and cooler conditions in the east and west (Ashok et al. 2007). According to Feng et al. (2010), precipitation anomalies over SEA are different in conventional El Niño and El Niño Modoki due to the different anomalous Walker circulation and low-level anticyclone around the Philippines. In El Niño Modoki, the Walker circulation over the western North Pacific occupies a smaller

domain and locates more northward. With this pattern, drought is reduced over the Maritime Continent (R1) and occurs over the mainland (R2). Because the MCA modes are obtained from the covariance matrix between the SPEI and SST (see section 2e), the SST patterns could be modulated by the SPEI values, which are influenced by the variations of both precipitation and temperature over the SEA domain. The correlations between the MCA time series of SPEI and

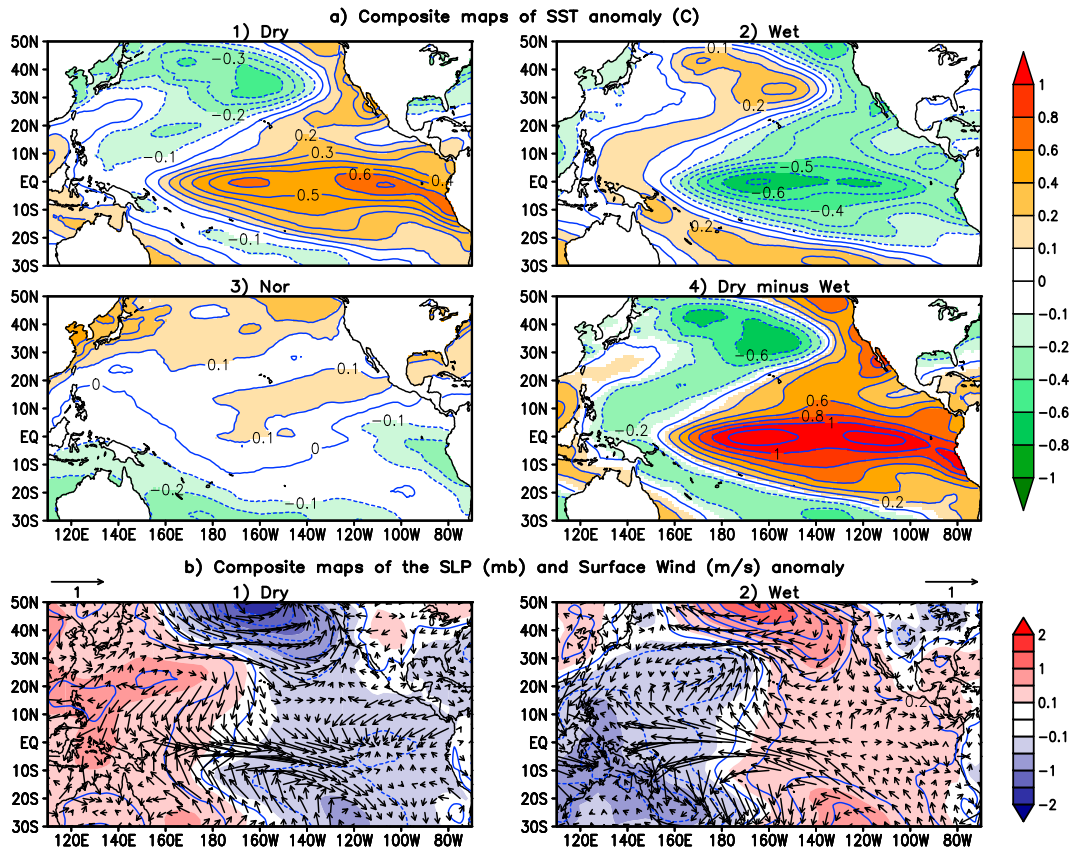


FIG. 9. Composite maps of the (a) SST anomaly for 1) dry, 2) wet, 3) normal, and 4) dry minus wet conditions, and (b) PMSL (shaded and contours) and SWind (vectors) anomalies for 1) dry and 2) wet conditions.

SST are relatively high (0.712, 0.717, and 0.600 for MCA1, MCA2, and MCA3, respectively), indicating that drought over SEA is strongly modulated by the variation of SST over the Pacific Ocean. Besides, the correlations of the MCA time series of SST and SPEI (Fig. S6b) are similar to those of the CIs (Fig. S6a), which show the ability to use SST over the Pacific to predict drought in the SEA region.

The linkage between drought over SEA and SST can be observed from Fig. 9a, which shows the composite maps of the SST anomaly for dry, wet, and normal conditions (defined as $\text{SPEI} \leq -0.5$, $\text{SPEI} \geq 0.5$, and $-0.5 < \text{SPEI} < 0.5$, respectively), and the differences between dry and wet. Interestingly, there exists an SST anomaly dipole over the central Pacific with contrasting patterns. During dry conditions, there is a large area of high positive SST anomaly over the tropical Pacific corresponding to an area of high negative SST anomaly over the midlatitudes of the north-central Pacific, producing the north–south gradient of SST (Fig. 9a1). In contrast, this dipole pattern is inverted during wet conditions, in which the negative SST anomaly area over the midlatitudes of the north-central Pacific is replaced by the high positive SST anomaly, while the positive SST anomaly area over the tropical Pacific is replaced by the high negative SST anomaly (Fig. 9a2). The contrast between these patterns can be seen clearly in Fig. 9a4. However, this SST anomaly dipole pattern

disappears in the normal condition (Fig. 9a3). Figure 9b shows the composite maps of the mean sea level pressure (MSLP) and surface wind (SWind) anomalies corresponding to the SST anomaly in Fig. 9a. During dry (wet) conditions, the MSLP anomaly is negative (positive) over the eastern (western) Pacific. Meanwhile, the North Pacific high (NPH) is significantly weakened (enhanced), leading to the strengthening of the equatorial western (eastern) flow over tropical Pacific (Figs. 9b1,2), causing the decrease (increase) of precipitation, and resulting in drought (wet) conditions over SEA.

3) ATMOSPHERIC MOISTURE

The composite maps of the vertically integrated moisture transport (VIMT) and MCONV are produced separately for the boreal winter monsoon season (November–April; Fig. 10a) and summer monsoon season (May–October; Fig. 10b) over the domain of 20°S – 50°N , 60°E – 180° , which is large enough to capture the monsoon influences on SEA. The differences of the VIMT and MCONV between wet and dry conditions (defined as $\text{SPEI} \geq 0.5$ and $\text{SPEI} \leq -0.5$, respectively) are also shown. Note that the patterns of VIMT and MCONV in the transition months of October–November and April–May are substantially similar to those of the boreal winter and summer monsoon seasons, respectively (not shown).

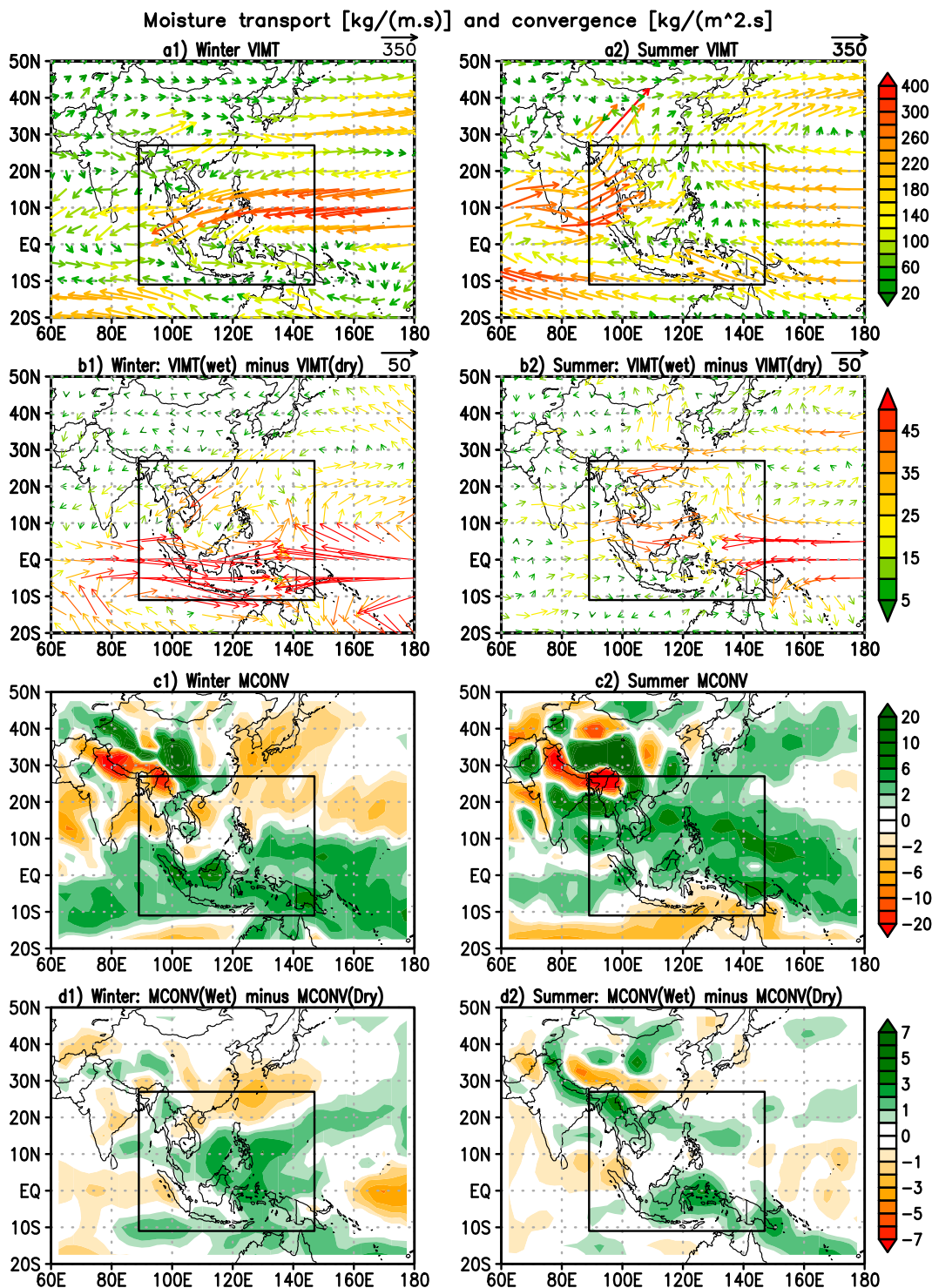


FIG. 10. Composite maps for the boreal (left) winter monsoon (November–April) and (right) summer monsoon (May–October) of (top) VMT ($\text{kg m}^{-1} \text{s}^{-1}$), (second row) the difference of VMT between wet and dry conditions, (third row) MCONV [$\times 10^{-5} \text{ kg (m}^2 \text{s}^{-1})^{-1}$], and (bottom) the difference of MCONV between wet and dry conditions. The black box denotes the SEA domain.

Figure 10 shows that the moisture flows are mainly easterly in the boreal winter monsoon season, bringing water vapor from the western Pacific crossing the eastern border into the SEA domain (Fig. 10a1). In this season the mainland SEA is primarily dominated by the Siberian high (Riaz et al. 2017) with dry cold weather in the early months and wet cold in the later months. Meanwhile, the Maritime Continent is in the wet season when weather conditions are characterized by the northeasterly cold surge and the low-level cyclonic system, known as the Borneo vortex (Chang et al. 2005; Juneng and Tangang 2010). The weak westerly and southeasterly flows toward the southern part of the domain are also observed. The positive MCONV seems to only occur over the Maritime Continent, where the rainy season is confined in between winter months (Fig. 10c1). In contrast, during the boreal summer monsoon season, strong southwesterly flows to the west, southeasterly flows to the southeast, and weaker easterly flows to the east of SEA are observed (Fig. 10a2), bringing moisture into the domain and leading to strong positive moisture convergences over the entire region, especially north of the equator (Fig. 10c2). Thus, boreal summer is a wet season in the mainland (Misra and DiNapoli 2013) but a dry season in the Maritime Continent (Chang et al. 2005). The differences of VIMT between wet and dry conditions in both winter and summer seasons are insignificant over the mainland but substantial over the Maritime Continent. The differences are especially remarkable in the winter when the westerly moisture transport in the wet condition is much stronger than that in the dry condition (Figs. 10b1,b2). The differences of MCONV between wet and dry conditions are also negligible with higher positive values in the winter (Figs. 10d1,d2).

Figure 11 shows the 1960–2019 time series of the areal SPEI, the monthly WBG in the SEA, and the ONI index. The WBG is interpreted as the net moisture transport across the SEA boundary, reflecting the monthly water vapor balance (Schmitz and Mullen 1996), that is, the monthly mean of moisture convergence over the region. Negative WBG results in drought at some times and subregions but not over the entire SEA domain (Figs. 11a,b). In particular, drought events were associated with the deficit of WBG in the periods of 1962–64 (R1 and R4), 1972/73 (R1–R3), 1983/84 (R1 and R2), 1997/98 (R1 and R2), and 2014–16 (R3 and R4). In contrast, drought could occur even if the WBG is positive for several consecutive months, such as in subregions R1 and R2 during 1998–2002. In general, the deficit of the WBG may have a connection with drought episodes in specific subregions at different times. Besides, the WBG over SEA is associated with ENSO, such that the WBG is negative in El Niño events and positive in La Niña events in most of the cases (Figs. 11b,c). During El Niño events, the surface cooling over the tropical western Pacific and warming over the tropical central/eastern Pacific Ocean generates an anomalous anticyclone over the western North Pacific. The positive thermodynamic feedback between the anticyclone and the sea surface cooling results in the reduction of moisture transport into SEA, leading to drought in the region (Wang et al. 2003; Lau and Nath 2003; Juneng and Tangang 2005).

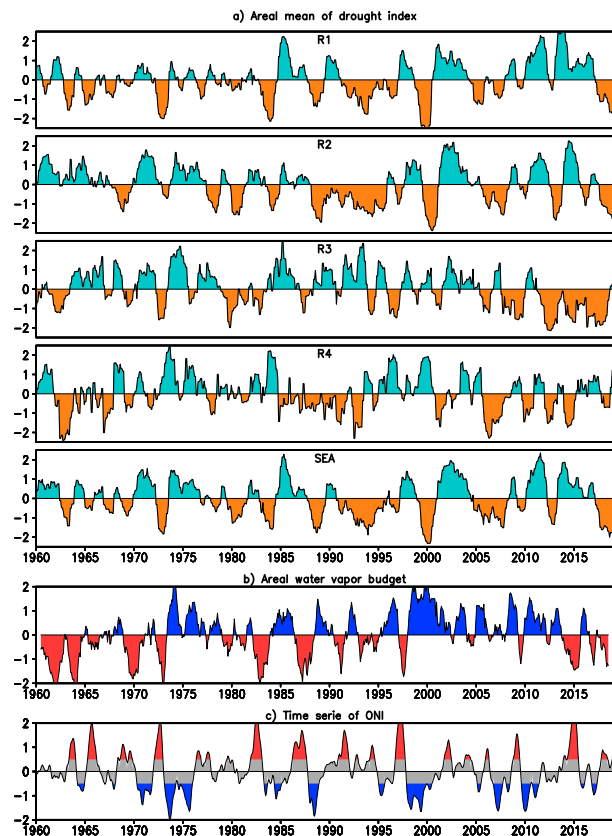


FIG. 11. Time series of (a) the areal SPEI drought index, (b) WBG ($\times 10^{11} \text{ kg s}^{-1}$) in the SEA domain, and (c) the ONI index ($^{\circ}\text{C}$).

4. Conclusions

In this study, an investigation on the spatiotemporal variability of drought and its associations with large-scale climate parameters was performed over SEA for the period 1960–2019. The drought characteristics were calculated based on the 12-month SPEI index. The links between drought with the CIs, SST and atmospheric moisture processes were examined. This is the first time drought conditions over SEA have been comprehensively assessed in relation to large-scale climate drivers. The main findings of this study are summarized as follows:

- 1) Drought characteristics in different levels strongly varied across the SEA region, identified by the differences of drought features between the mainland and the Maritime Continent. Drought in the mainland was more frequent and severe with a shorter duration than drought in the Maritime Continent. Among six recent decades, drought was more widespread and severe in two decades of 1990–99 and 2010–19, which were associated with the strong El Niño events of 1997/98 and 2015/16. The variability of the drought frequency, duration, severity, and geographic extent across the SEA region reveals the complexity, volatility, and variation of the spatial distribution of drought in the most recent two decades.

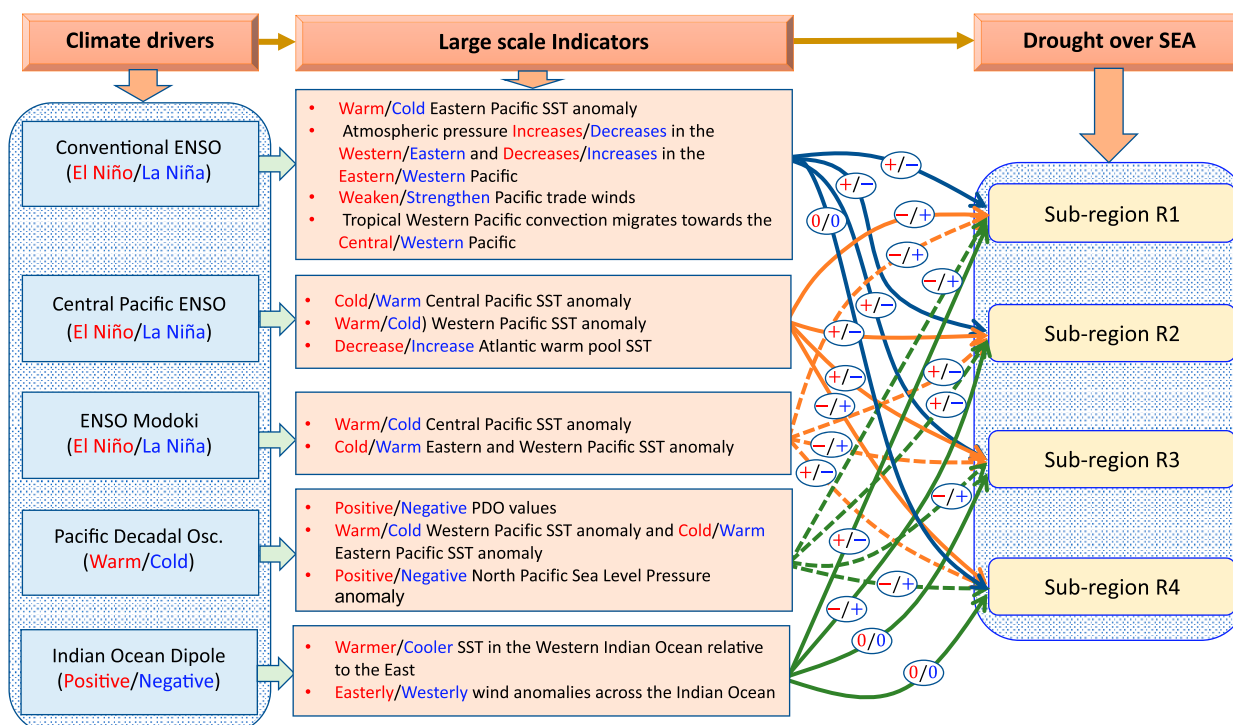


FIG. 12. Scheme illustrating the link between drought in the subregions of SEA and the large-scale climate drivers. Red (blue) indicates El Niño (La Niña), the warm (cold) phase of the PDO, the positive (negative) phase of the IOD, or their impacts. +/– (–/+) indicates increased/decreased (decreased/increased) drought. 0/0 indicates an unclear impact on drought.

- 2) Drought has increased more substantially in the mainland than in the Maritime Continent. The increasing trend of drought was also significant over Sumatra Island. However, drought slightly decreased or remained unchanged in most parts of the Maritime Continent and some other areas, such as the northern part of Laos, the southern part of Vietnam, and in the Philippines. The increasing (decreasing) drought trends were almost consistent with the decreasing (increasing) precipitation trends.
- 3) The entire SEA domain is partitioned into four drought subregions, in which three subregions, R1, R2, and R3, cover most areas of the SEA countries. This regionalization reflects the homogeneity of drought characteristics in each subregion and the heterogeneity of drought across subregions. Drought over the R2 and R3 was controlled by both boreal winter and summer monsoon. The boreal summer monsoon mainly modulated drought over R4. Meanwhile, drought over R1 was influenced by both monsoon and maritime climate. Among the four subregions, drought frequently occurred the most in R2. Drought was more prone to ENSO variation in the R1 and R2 subregions.
- 4) Drought over SEA is strongly associated with the both oceanic and atmospheric teleconnections, demonstrated by the strong relationships between the SPEI index and the CIs, including the ENSO-related, PDO, DMI, and the regional atmospheric indices (ReqSOI, Repac_slpa, Rindo_slpa). However, the SST variability over the tropical Atlantic

could also be well associated with the variability of drought over some parts of the region.

- 5) The drought variability over SEA was mostly dominated by the SST patterns over the Pacific Ocean. During the conventional ENSO, drought tended to occur over most of the domain. During the central Pacific ENSO drought tended to occur (not occur) in R2 (R1), depending on the increase (decrease) of SST over the tropical western (central) Pacific. During El Niño Modoki, drought may be reduced or not occur over R1 and a part of R3. There existed a dipole mode of the SST anomaly over the Pacific Ocean corresponding to dry and wet conditions in SEA. The changing sign of this dipole caused the alternation of the SST gradient's direction, modulating atmospheric circulation and consequently the precipitation over SEA, leading to the variation of drought in the region.

The abovementioned findings are finally schematized in Fig. 12, indicating the underlying processes that associate the variability of drought over SEA with the large-scale climate drivers, including ENSO, PDO, and IOD.

In the context of global warming, drought is expected to be increased in spatial extent, frequency, and severity in many regions worldwide, including SEA (Nguyen-Ngoc-Bich et al. 2021). To cope with these changes, a solid understanding of the spatial and temporal variability and trend of drought over SEA is required. This study, thus, provides a comprehensive view of drought over SEA and its associations with the large-

scale climate drivers. The good correlations between the drought index (SPEI) and the CIs and SST suggest the ability of the drought forecasting and early warning systems for the area, especially when some of the large-scale climate drivers could be predicted in advance such as ENSO. Based on that, drought prediction models can be developed to forecast drought characteristics, which are crucial information for various socioeconomic sectors, such as agriculture and water source management. Besides, there is a question of how land-atmosphere interactions may impact on drought conditions over some specific subregions of SEA, which would be an interesting topic to address in a future study.

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Data availability statement. All data used in this study are openly available and can be freely downloaded from:

- 1) The monthly Global Precipitation Climatology Centre (GPCC): https://opendata.dwd.de/climate_environment/GPCC/full_data_monthly_v2020/02/5/
- 2) The monthly Climatic Research Unit (CRU) 2-m temperature: https://data.ceda.ac.uk/badc/cru/data/cru_ts/cru_ts_4.04/data/tmp
- 3) Monthly climate indices (atmospheric and oceanic time series): <https://psl.noaa.gov/data/climateindices/list>
- 4) Monthly gridded sea surface temperature (COBE-SST2): <https://www.esrl.noaa.gov/psd/data/gridded/data.cobe2.html>
- 5) The National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) monthly gridded reanalysis data of horizontal wind (u and v), specific humidity (q), mean sea level pressure (PMSL), and surface wind (u_s and v_s): <https://psl.noaa.gov/data/gridded/data.ncep.reanalysis.derived.surface.html>

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