Projected drought conditions by CMIP6 multimodel ensemble over Southeast Asia

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ABSTRACT

Southeast Asia (SEA) is vulnerable to climate extremes due to its large and growing population, long coastlines with low-lying areas, reliance on agricultural sector developments. Here, the latest Coupled Model Intercomparison Project Phase 6 (CMIP6) was employed to examine future climate change and drought in this region under two SSP–RCP (shared socioeconomic pathway–representative concentration pathway) scenarios (SSP2-4.5 and SSP5-8.5). The CMIP6 multimodel ensemble mean projects a warming (wetting) of 1.99–4.29 °C (9.62–18.43%) in the 21st century. The Standardized Precipitation Evapotranspiration Index at 12-month time scales (SPEI-12) displays moderate-to-severe dry conditions over all countries during the near-future period, then the wet condition is projected from mid-future to far-future periods. The projected drought characteristics show relatively longer durations, higher peak intensities, and more severities under SSP5-8.5, while the higher number of events are projected under SSP2-4.5. Overall, the SPEI-12 over SEA displays significant regional differences with decreasing dryness trend toward the 21st century. All these findings have important implications for policy intervention to water resource management under a changing climate over SEA.

Key words: CMIP6, precipitation, shared socioeconomic pathway, SPEI-12, temperature

HIGHLIGHTS

• Climate change impact on Southeast Asia is significant due to its ‘Kitchen of the world’ vision.
• The newly launched CMIP6 model is the latest findings for scientific community.
• The assessment of climate change impact by CMIP6 over SEA is never done.
• Key findings for drought characteristics are found.
• These findings are very beneficial for policymakers.

1. INTRODUCTION

With a 0.85 °C increase in the global annual-mean temperature during 1880–2012, the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) (IPCC 2018) revealed directly increased meteorological disasters, e.g., droughts, floods, and typhoons. In present-day climate simulations, general circulation models (GCMs) are the major tools used to project future climate based on well-established physical principles (Randall et al. 2007). Both GCMs and observations on global and regional scales (Ghosh et al. 2012) have confirmed that rising extreme precipitation events are linked to climate warming, which leads to increased atmospheric moisture content and specific humidity (Willett et al. 2007). Extreme precipitation is projected to intensify in the future under a warming climate (Ali & Mishra 2017). To better understand past, present, and future climate change, the Working Group on Coupled Modeling under the framework of the World Climate Research Programme (WCRP) established the Coupled Model Intercomparison Project (CMIP3, CMIP5, and now CMIP6). This serves as a fundamental basis for international climate research with a remarkable technical and scientific coordination effort among climate modeling centers (Meehl et al. 2007; Taylor et al. 2012; Eyring et al. 2015). The near-surface air temperature has increased by approximately 0.78 °C (0.72–0.85 °C) on a global scale since 1900, with most of the increase occurring in recent decades (IPCC 2013). The United Nations Framework Convention on Climate Change 2015 (UNFCCC 2015) Paris agreement agreed to limit global mean surface temperature to well
below 2.0 °C, with the ambition to keep temperature change below 1.5 °C compared to the preindustrial levels. Therefore, a more detailed analysis of the potential regional and local changes in climate extremes is essential, especially in the most vulnerable regions.

Projections of potential changes in climate extremes are now being investigated by global climate models (GCMs) in many regions. Under IPCC AR4 (CMIP3), changes in temperature indices tend to agree for all seasons, but changes in precipitation are uncertain (Orlowsky & Seneviratne 2012). Projected changes in temperature and precipitation extremes are generally more pronounced in CMIP5 than in CMIP3 (Sillmann et al. 2013a, 2013b). Overall, comparisons between model results and observations indicated uncertainty in their projections (Alexander & Arblaster 2017). Most GCMs represent climatic variation at gross spatial resolutions (typically 100–500 km), which are not capable in impact assessments that require relatively fine spatial resolutions of just a few kilometers.

Drought is generally defined as a ‘prolonged absence or marked deficiency of precipitation, that results in water shortage for a community or group of people’ or a ‘period of abnormally dry weather, prolonged enough as a result of lack of precipitation to cause an extreme hydrological imbalance’ (IPCC-Special Report Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (SREX) 2012). Drought can lead to aridity, which is a permanent climatic feature (low precipitation and usually high temperature) of a region (World Meteorological Organization (WMO) 2006; Araghi et al. 2018) and to a persistent lack of water resources (Zhang et al. 2015), resulting in dying crops and shortage of other agricultural products (Al-Kaisi et al. 2013) becoming an economic problem (see Ding et al. 2011; He et al. 2014; Sternberg 2018). Droughts are very complex events and difficult to define, as a result of the multiple mechanisms causing them (Kiern et al. 2016). It can be considered as a creeping phenomenon (Tannehill 1947) or climatic phenomena such as monsoons and El Nino–Southern Oscillation (ENSO) (Hilario et al. 2009), hence need to be carefully monitored. In real practice, droughts are not only defined based on absolute thresholds, but also meteorological anomalies (precipitation, temperature, wind speed, radiation, and land-surface physical process) and human activities (van Loon et al. 2016; Zhang et al. 2017). In general, the time scales over which precipitation deficits accumulate become very crucial and classify droughts into different types (meteorological, agricultural, and hydrological droughts) (IPCC-SREX 2012). Changes in droughts and assessments of their trends depend on the type of drought, the model assumptions, and datasets (Sippel et al. 2018).

Recently, several studies found an increase in drought frequency and severity due to global climate change (Dai 2013; Sheffield et al. 2012). With increasing temperature and more variations in precipitation regimes together with the increasing water demand due to population growth, it is expected that drought events will become more frequent and more severe in future (Martin 2018). However, quantitative differences exist when different indices are used to identify and project droughts (Mishra & Singh 2010). Four major sources of uncertainty are climate model, future scenario, drought index, and drought threshold uncertainties (Taylor et al. 2013).

Over the past decades, several drought indices were used quantitatively for detecting droughts at global and regional scales (Dai 2011; Liu et al. 2016), e.g., the Palmer Drought Severity Index (PDSI; Palmer 1965), the Standardized Precipitation Index (SPI; Svoboda et al. 2012), the Standardized Streamflow Index (SSI; Shamshirband et al. 2020), and the Standardized Precipitation Evapotranspiration Index (SPEI; Vicente-Serrano et al. 2010). Until recently, great efforts have been devoted to develop and characterize multiple drought indices for drought monitoring (WMO and Global Water Partnership (GWP) 2016). Considering both, the sensitivity of droughts to temperature and precipitation with their variabilities across multiple timescales, the SPEI has been widely used in drought monitoring and projections at global and regional scales (Mallya et al. 2015; Gao et al. 2017; Su et al. 2018; Zhai et al. 2020).

The challenge of climate change in SEA is real and is likely to amplify some of the existing low-lying urban areas and environmental stresses (floods, droughts, fires, and haze). This region lies in the tropics and consists of various climates between Mainland Southeast Asia (SEA) and the Maritime Continent. The majority of SEA is influenced by the Asian–Australian monsoon, and several regions within it are affected by extreme weather events, particularly tropical cyclones, droughts, and floods (Wang et al. 2003; Chang et al. 2005). In addition, climate variability, such as ENSO and Madden–Julian Oscillation (MJO), directly impacts the SEA climate (Tangang et al. 2017; Xavier et al. 2020). Most studies of the projected changes in SEA climate are embedded in the global-scale domain carried out using GCMs (e.g., Caesar et al. 2011; Kharin et al. 2013; Chadwick et al. 2016). The complexity of land–sea structures and long coastlines of SEA necessitate the quantification of climate changes at a higher resolution than a typical GCM resolution. A number of studies, which
assessed future changes in SEA climate at higher resolution, have performed so far (e.g., Mandapaka & Lo 2018; Ge et al. 2019; Tangang et al. 2020).

Recently, new simulations from the latest, state-of-the-art climate models participating in Phase 6 of the CMIP (CMIP6) have become available (Eyring et al. 2015). Using a multimodel ensemble (MME) drawn from CMIP6, we investigate changes in temperature, precipitation, potential evapotranspiration (PET), and SPEI across a range of 21st-century development and radiative forcing scenarios (shared socioeconomic pathways, SSPs) developed for ScenariosMIP (Model Intercomparison Project; O’Neill et al. 2016). Some recent researches have been performed globally (Cook et al. 2020) and regionally (Almazroui et al. 2020; Grose et al. 2020; Jiang et al. 2020; Ukkola et al. 2020; Zhu et al. 2020; Mondal et al. 2021). However, it is still not well understood how model simulations from CMIP6, considering both socioeconomic and climate change factors, could be regarded as a reasonable source for future climate projections over SEA compared to CMIP5 and CMIP3.

In this study, we focus our analyses on three primary research questions: (1) What are the long-term observed trends of the climate parameters (temperature, precipitation, PET, and SPEI) over each SEA country? (2) How they are likely to change under new scenarios? (3) How does SPEI imply changes in drought characteristics compare across different CMIP6 forcing scenarios? This is an initial step required for formulating evidence-based strategies to enhance water resource management and food security against drought impact across the SEA.

2. STUDY REGION AND DATA METHODOLOGY

2.1. Study region

Our region of interest is the SEA domain (see Figure 1) similar to the Coordinated Regional Climate Downscaling Experiment-SEA (CORDEX-SEA) domain (14.8°S–27°N, 89.5–146.5°E). Two geographic regions are separated by the Mainland SEA or Indochina Peninsula (Cambodia, Laos, Myanmar, Vietnam, and Thailand) and the Maritime Continent (Malaysia, Singapore, Indonesia, Philippines, Brunei, and East Timor). It is home to densely populated megacities (Bangkok, Jakarta, and Manila) and rapidly urbanized cities (Hanoi and Ho Chi Minh).

SEA experiences two distinct sub-monsoon seasons: wet and dry. The same weather system that delivers rain during India’s monsoon season also affects SEA, but at different times (Kripalani et al. 2007). The southwest monsoon causes the maximum rainfall during the boreal summer over the Mainland SEA, while the northeast monsoon causes the maximum rainfall during the boreal winter over most areas in the Maritime Continent (Chang et al. 2005). The influencing meteorological factors that determine to decrease/increase droughts in SEA are changes in seasonal and regional precipitation (due to increasing temperature), changes in prevailing winds (monsoon system), and evaporation. Therefore, drought features differ due to monsoon climate with seasonal precipitation variability between wet and dry seasons. Furthermore, the complex terrain with several islands of different sizes causes significant regional variations in precipitation along the annual cycle (Chang et al. 2005).

Figure 1 | Study area of SEA.
2.2. Datasets

2.2.1. Observational datasets

In this study, we examined several observational datasets (SA-OBS, APHRODITE, CPC-UNI, CRU, GPCP1DD, TRMM, ERA-Interim, JRA55, GPCC, CHIRPS, and CMORPH) over SEA. They are briefly described in Table 1. All observational datasets differ due to varying original observations, different resolutions, and different methods employed. Comparisons among these observational datasets reveal that SA-OBS is a station-based dataset that represents the median values and is suitable for use as a reference. Recently, van den Besselaar et al. (2017) concluded that SA-OBS is currently the best available daily gridded observational dataset for SEA. Owing to the different horizontal resolutions (0.25°–1.0°) of the observations, we decided to regrid to 0.25° × 0.25° common resolution using the bilinear interpolation technique.

2.2.2. Model datasets

We examined 18 CMIP6 models (available since February 2020 when we started this work) from the CMIP6 database website (https://esgf-node.llnl.gov/search/cmip6), as given in Table 2. The new generation of CMIP6 models differs from the CMIP5 in having a new set of specifications for concentration, emission, and land-use scenarios (Gidden et al. 2019) as well as a new start year (CMIP6: 2015 and CMIP5: 2006) for future scenarios. In this phase, SSPs are combined with the Representative Concentration Pathways (RCPs) of CMIP5. The SSPs are based on five narratives that describe different levels of socio-economic development (Riahi et al. 2017): sustainable development (SSP1), middle-of-the-road development (SSP2), regional rivalry (SSP3), inequality (SSP4), and fossil fuel-driven development (SSP5). Detailed descriptions of the SSPs are available in O’Neill et al. (2016).

To evaluate model performance and to set a baseline for assessing future changes, we used the historical runs for the period 1998–2014 (due to the common period availability of observational dataset in Section 2.2.1) to determine the present-day climate. To assess future climate change, we analyzed the data for three periods (near-future: 2015–2039, mid-future: 2040–2069, and far-future: 2070–2099) derived from the climate projections under two SSPs of medium-emission (SSP2-4.5) and high-emission (SSP5-8.5) scenarios. For a fair comparison, all models are regridded to 0.25° × 0.25° resolution using a bilinear interpolation technique similar to the observational datasets.

2.3. Data preprocessing

2.3.1. Bias correction

Bias correction is widely used in climate impact modeling. The aim is to adjust selected statistics (mean, variance, and/or quantile) in a climate model simulation to better match observed statistics during a reference period. Many bias correction methods have been employed in previous studies (Teutschbein & Seibert 2012; Supharatid 2016; Araghi et al. 2019; Homsi et al. 2020) with a critical review by Maraun (2016). In this study, we employed a ‘variance scaling’ method (similar to Supharatid et al. 2021) to correct the historical and projected temperature over SEA from CMIP6 models. This approach can guarantee that the adjusted model simulation in the reference period has the same mean and standard deviation (SD) as the observations.

The first step we used is the ‘delta change’ approach to adjust the temperature at each grid point \((T_{ij} (d))\) as Equation (1).

\[
T_{ij} (d) = T_{\text{model}, ij} + (T_{\text{obs}, ij} - T_{\text{model}, ij})
\] (1)

The second step is to find the corresponding anomalies \((T'_{ij})\) in reference and projection periods by the following equations:

\[
T'_{\text{ref}, ij} = T_{\text{ref}, ij} (d) - T_{\text{ref}, ij} (d)
\] (2)

\[
T'_{\text{proj}, ij} = T_{\text{proj}, ij} (d) - T_{\text{proj}, ij} (d)
\] (3)

\[
T_{ij} (d) = T_{\text{model}, ij} + (T_{\text{obs}, ij} - T_{\text{model}, ij})
\]
<table>
<thead>
<tr>
<th>Data Version (Refs.)</th>
<th>Resolution</th>
<th>Data source</th>
<th>Brief description</th>
</tr>
</thead>
<tbody>
<tr>
<td>SA-OBS</td>
<td>0.25° × 0.25°</td>
<td>Rain gauge</td>
<td>SA-OBS is a new daily high-resolution land-only observational gridded dataset of precipitation and minimum, mean, and maximum temperatures covering SEA. Improvements upon existing observational products are in terms of the number of contributing stations, the use of an interpolation technique appropriate for daily climate observations, and the estimation of the uncertainty of the gridded data. The underlying daily station time series are collected in cooperation among meteorological services in the region (Southeast Asian Climate Assessment and Dataset, SACA&amp;D).</td>
</tr>
<tr>
<td>SA-OBS v. 2 (van den Besselaar et al. 2017)</td>
<td></td>
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</tr>
<tr>
<td>APHRODITE APHRO_MA V1808 APHRO_MA V1901 (Yatagai et al. 2012)</td>
<td>0.25° × 0.25°</td>
<td>Rain gauge</td>
<td>A daily gridded precipitation dataset covering a period of more than 57 years was created by collecting and analyzing rain gauge observational data across Asia through Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation (APHRODITE) project. This dataset is generated primarily with ground-based data obtained from an in situ rain gauge observational network (between 5000 and 12,000 stations) over Asia by international collaborations with local meteorological/hydrological agencies and researchers. APHRO_MA V1808 is daily mean temperature product as 0.5 and 0.25° gridded daily product. Topographical effect scheme is introduced to the interpolation algorithm. APHRO MA V1901 is 24-h accumulated precipitation product during 1998–2015 for monsoon Asia.</td>
</tr>
<tr>
<td>CPC-UNI CPC-UNI v1.0 (Xie et al. 2007)</td>
<td>0.5° × 0.5°</td>
<td>Rain gauge</td>
<td>This dataset is part of the products suite from the CPC Unified Precipitation Project that is underway at NOAA Climate Prediction Center (CPC). A gauge-based analysis of daily precipitation has been constructed over the global land areas. Gauge reports from over 30,000 stations are collected from multiple sources including GTS, COOP, and other national and international agencies. The daily analysis is constructed on a 0.125° lat./lon. grid over the entire global land areas and released on a 0.5° lat./lon. grid over the global domain for a period from 1979 to the present. In this study, we used the CPC-UNI, version 1.0 (v1.0), global land data at a 0.5° lat./lon. grid.</td>
</tr>
<tr>
<td>CRU CRU-TS-4.04 (Harris et al. 2020)</td>
<td>0.5° × 0.5°</td>
<td>Rain gauge</td>
<td>The CRU-TS dataset was developed and has been subsequently updated, improved, and maintained with support from a number of funders, principally the UK's Natural Environment Research Council (NERC) and the US Department of Energy. CRU-TS (Climatic Research Unit gridded Time Series) is a widely used climate dataset on a 0.5° lat./lon. grid over all land domains of the world except Antarctica. It is derived by the interpolation of monthly climate anomalies from extensive networks of weather station observations. CRU TS v4 is annually updated to span 1901–2018 by the inclusion of additional station observations.</td>
</tr>
<tr>
<td>GPCP1DD GPCP1DD v1.2 (Huffman et al. 2001)</td>
<td>1.0° × 1.0°</td>
<td>Satellite</td>
<td>The 1DD product provides precipitation estimates on a 1° grid over the entire globe at 1 day (daily) for the period October 1996–2015. The Global Precipitation Climatology Project (GPCP) sponsored by the World Climate Research Program and Global Energy and Water Cycle Experiment provides global precipitation products based on satellite and rain gauge information. The GPCP 1-Degree Daily (GPCP1DD) version 1.2 dataset is produced by optimally merging estimates computed from microwave, infrared, and sounder data observed by the international constellation of precipitation-related satellites and precipitation gauge analyses.</td>
</tr>
<tr>
<td>GPCP1DD GPCP1DD v1.2 (Huffman et al. 2001)</td>
<td>0.25° × 0.25°</td>
<td>Satellite</td>
<td>This daily accumulated precipitation product is generated from the research-quality 3-hourly TRMM Multi-Satellite Precipitation Analysis T6V4 (3B42). It is produced at</td>
</tr>
<tr>
<td>Dataset</td>
<td>Resolution</td>
<td>Type</td>
<td>Description</td>
</tr>
<tr>
<td>--------------------</td>
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<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>TRMM_3B42 Daily</td>
<td>0.25° × 0.25°</td>
<td>Reanalysis</td>
<td>TRMM 3B42 Daily TRMM (TMPA) Precipitation L3 day V7 (Huffman et al. 2007) is a product from NASA GES DISC, as a value-added product. In this study, we employ the TMPA Level 3 (L3) 3B42 V7 estimator produced as the 0.25° × 0.25° quasi-global (50°N-S) gridded databases during 1998–present.</td>
</tr>
<tr>
<td>ERA-Interim (Dec et al. 2011)</td>
<td>0.5° × 0.5°</td>
<td>Reanalysis</td>
<td>The European Centre for Medium-Range Weather Forecasts (ECMWF) Interim reanalysis (ERA-Interim) is the most recent global atmospheric reanalysis produced by ECMWF covering the period from 1979 until the present. ERA-Interim uses four-dimensional variational data assimilation (4D-Var) with a 12-hourly cycle, a revised humidity analysis, variational bias correction for satellite data, and other improvements in data handling. These data are available at a daily resolution on a 0.5° lat./lon. grid.</td>
</tr>
<tr>
<td>JRA55 (Kobayashi et al. 2015)</td>
<td>0.563° × 0.563°</td>
<td>Reanalysis</td>
<td>JRA55 is the longest third-generation reanalysis (performed by JMA) that uses the full observing system with more advanced data assimilation scheme (4D-var), increased model resolution (T319L60 with a reduced Gaussian grid system). The datasets cover the 55 years from 1958 when regular radiosonde observation began on a global basis. Many of the deficiencies of JRA25 are alleviated in JRA55 because the DA system used for the project featured a variety of improvements introduced after JRA25. As a result, the JRA55 project produced a high-quality homogeneous climate dataset covering the last half-century. JRA55 has a resolution of 0.563° lat./lon. grid.</td>
</tr>
<tr>
<td>GPCC GPCC/FD_D_V2018 (Ziese et al. 2018)</td>
<td>1.0° × 1.0°</td>
<td>Rain gauge</td>
<td>The GPCC Full Data Daily Product V.2018 of daily global land-surface precipitation totals is based on precipitation data provided by national meteorological and hydrological services, regional and global data collections, as well as WMO GTS data. It is provided at a regular latitude/longitude grid with a spatial resolution of 1.0° × 1.0° and covers the time period from January 1982 to December 2016.</td>
</tr>
<tr>
<td>CHIRPS CHIRPS-2.0 (Funk et al. 2014)</td>
<td>0.25° × 0.25°</td>
<td>Satellite</td>
<td>Climate Hazards Group Infrared Precipitation with Station data (CHIRPS) was created in collaboration with scientists at the USGS Earth Resources Observation and Science (EROS) Center in order to deliver complete, reliable, up-to-date datasets. CHIRPS is a dataset of daily, pentadal, and monthly precipitation climatology (CHPclin) blended from multiple sources including rain gauge data of various sources, such as the Cold Cloud Duration (CCD)-based precipitation on thermal infrared (IR) data archived in the NOAA National Climate Data Center (NCDC), Version 7 TRMM 3B42 data, and the Version 2 atmospheric model rainfall field of the NOAA Climate Forecast System (CFS). CHIRPS products are available in 0.05 and 0.25 horizontal resolutions covering a period spanning from 1981 until present.</td>
</tr>
<tr>
<td>CMORPH CMORPH025 (Joyce et al. 2004)</td>
<td>0.25° × 0.25°</td>
<td>Satellite</td>
<td>CMORPH (CPC MORPHing technique) produces global precipitation analyses at very high spatial and temporal resolutions. This technique uses precipitation estimates that have been derived from low orbiter satellite microwave observations exclusively, and whose features are transported via spatial propagation information that is obtained entirely from geostationary satellite IR data.</td>
</tr>
</tbody>
</table>
Then, the anomalies from Equations (2) and (3) are scaled by the ratio of their observed \((s_{\text{obs}, i, j})\) and reference \((s_{\text{ref}, i, j}(d))\) SD:

\[
T_{\text{rel}, i, j}^\omega = T_{\text{rel}, i, j} / s_{\text{ref}, i, j}(d) \\
T_{\text{pro}, j, i}^\omega = T_{\text{pro}, j, i} / s_{\text{ref}, i, j}(d)
\]  

(4)  

(5)

Finally, the corrected-adjust values during the reference and projection periods can be found:

\[
T_{\text{rel}, i, j}(\text{cor}, d) = T_{\text{rel}, i, j}^\omega + T_{\text{rel}, i, j}(d) \\
T_{\text{pro}, j, i}(\text{cor}, d) = T_{\text{pro}, j, i}^\omega + T_{\text{pro}, j, i}(d)
\]  

(6)  

(7)

For precipitation, we implement the ‘Empirical quantile mapping (EQM)’ method to remove the systematic biases in the GCMs simulation. The EQM, which corrects the distribution shape of the monthly precipitation based on cumulative density functions (CDFs), is constructed for both the observed and the GCM simulation (1998–2014) for all months. For a given monthly precipitation, the CDF of a control simulation is first matched with the CDF of the observations, generating a correction function depending on the quantile. Then, this correction function is used to unbias them from the climate simulation quantile by quantile. Finally, the monthly precipitation for reference and future periods are obtained by the following

<table>
<thead>
<tr>
<th>GCM</th>
<th>Research center</th>
<th>Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACCESS-CM2</td>
<td>Australian Community Climate and Earth System Simulator</td>
<td>1.88 × 1.25</td>
</tr>
<tr>
<td>ACCESS-ESM1-5</td>
<td>Australian Community Climate and Earth System Simulator</td>
<td>1.88 × 1.25</td>
</tr>
<tr>
<td>BCC-CSM2-MR</td>
<td>Beijing Climate Center, China Meteorological Administration, Beijing, China</td>
<td>1.12 × 1.11</td>
</tr>
<tr>
<td>CanESM5</td>
<td>Canadian Centre for Climate Modelling and Analysis, Environment and Climate Change Canada, Canada</td>
<td>2.81 × 2.77</td>
</tr>
<tr>
<td>CNRM-CM6-1</td>
<td>National Center for Meteorological Research, France</td>
<td>1.41 × 1.39</td>
</tr>
<tr>
<td>CNRM-ESM2-1</td>
<td>National Center for Meteorological Research, France</td>
<td>1.41 × 1.39</td>
</tr>
<tr>
<td>EC-Earth3</td>
<td>EC-Earth Consortium (EC-Earth)</td>
<td>0.70 × 0.70</td>
</tr>
<tr>
<td>FGOALS-g3</td>
<td>LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing, 100029, China</td>
<td>0.70 × 0.70</td>
</tr>
<tr>
<td>GFDL-ESM4</td>
<td>NOAA Geophysical Fluid Dynamics Laboratory, USA</td>
<td>1.25 × 1.00</td>
</tr>
<tr>
<td>INM-CM4-8</td>
<td>Institute for Numerical Mathematics, Russia</td>
<td>2.00 × 1.50</td>
</tr>
<tr>
<td>INM-CM5-0</td>
<td>Institute for Numerical Mathematics, Russia</td>
<td>2.00 × 1.50</td>
</tr>
<tr>
<td>IPSL-CM6A-LR</td>
<td>The Institut Pierre Simon Laplace, France</td>
<td>2.50 × 1.27</td>
</tr>
<tr>
<td>MIROC6</td>
<td>JAMSTEC (Japan Agency for Marine-Earth Science and Technology, Japan), AORI (Atmosphere and Ocean Research Institute, The University of Tokyo), NIES (National Institute for Environmental Studies), and R-CCS (RIKEN Center for Computational Science), Japan</td>
<td>1.41 × 1.39</td>
</tr>
<tr>
<td>MIROC-ES2 L</td>
<td>JAMSTEC, AORI, NIES, and R-CCS, Japan</td>
<td>2.81 × 2.77</td>
</tr>
<tr>
<td>MPI-ESM1-2-LR</td>
<td>Max Planck Institute for Meteorology, Germany</td>
<td>1.88 × 1.85</td>
</tr>
<tr>
<td>MRI-ESM2-0</td>
<td>Meteorological Research Institute, Japan</td>
<td>1.12 × 1.11</td>
</tr>
<tr>
<td>NESM3</td>
<td>Nanjing University of Information Science and Technology, China</td>
<td>1.88 × 1.85</td>
</tr>
<tr>
<td>NorESM2-LM</td>
<td>NorESM Climate modeling Consortium consisting of CICERO (Center for International Climate and Environmental Research), MET-Norway (Norwegian Meteorological Institute), NERSC (Nansen Environmental and Remote Sensing Center, Bergen), NILU (Norwegian Institute for Air Research), UiB (University of Bergen, Bergen), UiO (University of Oslo), and UNI (Uni Research), Norway</td>
<td>2.50 × 1.89</td>
</tr>
</tbody>
</table>
equations:

\[ P_{\text{ref},i,j}(\text{cor},d) = F_{\text{obs},i,j}^{-1}(F_{\text{ref},i,j}(P_{\text{ref},i,j})) \]  
\[ (8) \]

\[ P_{\text{proj},i,j}(\text{cor},d) = F_{\text{obs},i,j}^{-1}(F_{\text{proj},i,j}(P_{\text{proj},i,j})) \]  
\[ (9) \]

where \( F \) is the cumulative distribution function (CDFs) and \( F^{-1} \) is its inverse.

### 2.3.2. PET and SPEI calculations

There are many methods to calculate the PET. In this article, PET is calculated based on three equations: Thornthwaite (Thornthwaite 1948), Penman–Monteith (Allen et al. 1998), and Hargreaves (Hargreaves & Allen 2003) equations. We estimate the PET from these equations by using input variables from bias-corrected CMIP6 models that do not provide internal PET variables. To compare and select the best approximation PET equations, two CMIP6 models (CNRM-CM6-1 and CNRM-ESM2-1) that provided the simulated PET (evspsblpot) as a model output variable are examined in this study.

There are several drought indices available from WMO (2016). We, in this article, identify drought events using a widely used drought index, namely SPEI. It was selected because it combines the sensitivity of PDSI, evaporation demand changes, and the multitemporal nature of SPI (Vicente-Serrano et al. 2010; Zhao et al. 2018). In addition, it is suggested that PET-based drought indices, such as the SPEI, are preferable for measuring future droughts. Previous drought index performance evaluation-based studies (Adnan et al. 2018; Gupta & Jain 2018) indicated that the SPEI is the best-suited index for assessing drought across South Asian countries.

SPEI is a normalized index so that the mean SPEI is 0 and the SD is 1 for the location and desired period. The SPEI describes to what extent dry and wet conditions deviated from the long-term average by standardizing the difference between precipitation and PET. The meteorological condition can be classified into nine categories based on SPEI (see Table 3). In general, the different types of drought can represent different time scales, e.g., meteorological drought (1 month), agricultural drought (3–6 months), and hydrological drought (12 months) (WMO 2012). The 12-month scale (SPEI-12) is selected to fit the study purpose, since this time scale is well suited for describing hydrological as well as long-term meteorological droughts. It is recognized as a vigorous representation of drought dynamics (Chen & Sun 2015). This indicates that drought indicator at longer time scale like SPEI-12 is substantially more suitable than that at shorter time scale. However, other time scales of SPEI (SPEI-3 and SPEI-6) are also calculated for comparisons.

### 3. RESULTS AND DISCUSSION

#### 3.1. Model simulation of key climate variables in the reference period

The spatial distribution in the annual mean daily temperature \((T_{\text{mean}})\) of CMIP6 models and SA-OBS is displayed in Figure 2. The CMIP6 models generally give a similar distributing pattern to SA-OBS with higher (lower) \(T_{\text{mean}}\) over the Maritime Continent (Northern Mainland SEA). Models ACCESS-CM2, ACCESS-ESM1-5, BCC-CSM2-MR, CANESMS, FGOALS-G3, and NORESM2-LM (CNRM-CM6-1, CNRM-ESM2-1, EC-EARTH3, GFDL-ESM4, INM-CM4-8, INM-CM5-0, IPSL-CM6A-LR,

<table>
<thead>
<tr>
<th>SPEI</th>
<th>Categories</th>
<th>Frequency (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(2.0 \leq \text{SPEI})</td>
<td>Extreme wetness</td>
<td>2.2</td>
</tr>
<tr>
<td>(1.5 \leq \text{SPEI} &lt; 2.0)</td>
<td>Severe wetness</td>
<td>4.4</td>
</tr>
<tr>
<td>(1.0 \leq \text{SPEI} &lt; 1.5)</td>
<td>Moderate wetness</td>
<td>9.2</td>
</tr>
<tr>
<td>(0.5 \leq \text{SPEI} &lt; 1.0)</td>
<td>Slight wetness</td>
<td>15.0</td>
</tr>
<tr>
<td>(-0.5 &lt; \text{SPEI} &lt; 0.5)</td>
<td>Normal</td>
<td>38.4</td>
</tr>
<tr>
<td>(-1.0 &lt; \text{SPEI} &lt; -0.5)</td>
<td>Slight dryness</td>
<td>15.0</td>
</tr>
<tr>
<td>(-1.5 &lt; \text{SPEI} &lt; -1.0)</td>
<td>Moderate dryness</td>
<td>9.2</td>
</tr>
<tr>
<td>(-2.0 &lt; \text{SPEI} &lt; -1.5)</td>
<td>Severe dryness</td>
<td>4.4</td>
</tr>
<tr>
<td>(\text{SPEI} \leq -2.0)</td>
<td>Extreme dryness</td>
<td>2.2</td>
</tr>
</tbody>
</table>
MPI-ESM1-2-LR, and NESM3) overestimate (underestimate) $T_{\text{mean}}$, especially over the Maritime Continent (Indochina Peninsula).

Figure 3 displays the spatial distribution in annual mean precipitation ($P_{\text{mean}}$) of CMIP6 models and SA-OBS. Overall, CMIP6 models agree well in their distribution patterns with observations. Higher $P_{\text{mean}}$ are observed over the Maritime Continent (especially, over high elevation area) than the Mainland SEA. Models ACCESS-CM2, ACCESS-ESM1-5, BCC-CSM2-MR, CANESM5, CNRM-CM6-1, CNRM-ESM2-1, FGOALS-G3, INM-CM4-8, INM-CM5-0, IPSL-CM6A-LR, and MRI-ESM2-0 overestimate results over the Maritime Continent, while models INM-CM4-8 and INM-CM5-0 also overestimate results over the Mainland SEA. In general, areas of overestimation (Kalimantan and east Papua) by most models were found to be similar areas (low station density) of observational uncertainty (van den Besselaar et al. 2017).
3.2. Model performance evaluation

In general, there are uncertainties in both $T_{\text{mean}}$ and $P_{\text{mean}}$ among various observational datasets. The precipitation datasets are very different, making it difficult to assess how much it actually rains, similar findings by Herold et al. (2016). We intend to use the rain gauge-based datasets such as SA-OBS, APHRODITE, CPC, CRU, and GPCC as reference. However, there are shortcomings, as the rain gauges do not cover the whole region. Finally, we decide to use SA-OBS as a reference and do a detailed intercomparison of all observational datasets and also CMIP6 models in terms of correlation coefficient ($R$), center root-mean-square difference (RMSD), and SD by the Taylor diagram (Taylor 2001) (see Figure 4). The Taylor analysis is broadly recognized to evaluate the performance of GCMs against reference data (Mondal et al. 2021). The center RMSD

Figure 3 | Spatial distribution in $P_{\text{mean}}$ of CMIP6 models and SA-OBS during the present climate (1998–2014).
and the SD are normalized by their corresponding observations of SA-OBS. The observational datasets are represented by the black symbol, and the CMIP6 models are represented by other colors.

Most temperature datasets show high $R (>0.9)$ to SA-OBS (see also Figure 2) with the lowest value for ERA-Interim. Other groups of temperature datasets (JRA55, CRU, and APHRODITE) show similar ranges of $R (0.96–0.98)$ but different magnitudes of RMSD and SD. Most CMIP6 models give $R$ in a range of 0.8–0.9 and more spread SD are found than $R$ and RMSD. For $P_{\text{mean}}$, all datasets are found to give also high $R (>0.8)$ but lower than ones of $T_{\text{mean}}$. The CMIP6 models display more widespread with lower $R$ compared to $T_{\text{mean}}$. The $R$ in most CMIP6 models lies between 0.4 and 0.7 by which MIROC-ES2 L gives the highest $R$ and smallest RMSD, while NorESM2 shows the highest SD and also RMSD. The MME model is found to give the best results (highest $R$ and lowest RMSD) among CMIP6 models.

To assess the performance of individual CMIP6 models in reproducing the climatological spatial pattern, we perform bias correction by using the ‘Variance scaling’ for $T_{\text{mean}}$ and EQM for $P_{\text{mean}}$ (Section 2.3). Figure 5 displays the spatial distribution of statistical parameters ($R$, RMSD, and SD) in $T_{\text{mean}}$ and $P_{\text{mean}}$ of the MME model before and after bias corrections during the reference period. As expected, the bias-corrected MME model gives higher $R$ and lower RMSD and SD than the raw CMIP6 models over the majority of SEA. However, there are no significant improvements over the Maritime Continent, especially over high topography such as Kalimantan, Sulawesi, and east Papua islands. Most regions characterized by high topography give profound differences between the observation and the model (see Figures 2 and 3). Higher RMSD in $P_{\text{mean}}$ is also found over northern and central Vietnam (similar areas of high observed rainfall in Figure 3). For the spatial distribution of SD, the MME model gives higher values over northern Mainland SEA (in $T_{\text{mean}}$) and Arakan coast (in $P_{\text{mean}}$).

### 3.3. Projection of drought index

#### 3.3.1. PET calculation

Figure 6 displays the spatial distribution of monthly PET over SEA. In this study, we calculate PET by three methods (Thornthwaite, PET-TH; Hargreaves, PET-HS; and Penman–Monteith, PET-PM) and compare with the internal PET (evspsblpot) provided by two GCMs (CNRM-CM6-1 and CNRM-ESM2-1), which are only available during this study. The evspsblpot shows significantly higher values compared to other PET calculation methods. There are large uncertainties in PET from these two GCMs. Biases in the estimation of PET can lead to drought or drying trend uncertainties (Milly & Dunne 2016, 2017). Overall, the PET-TH gives the highest PET, while the PET-HS gives the lowest value. The PET-PM displays values between PET-TH and PET-HS. We use PET-PM to compute SPEI in this research due to its improved physical calculation process. The Penman–Monteith method is recommended by the Food and Agriculture Organization (FAO) for calculating the PET to apply for the SPEI calculation (Allen et al. 1998). The PET-PM combines mass transfer and energy balance with temperature and vegetation conductance and requires observed maximum temperature, minimum temperature, air temperature, wind speed, relative humidity, and solar radiation (or solar duration) as input variables. In addition, the PET-PM is widely accepted as the most accurate method to calculate PET (Kite & Droogers 2000; Chen & Sun 2015; Gao et al. 2017).
3.3.2. Projected changes in key climate variables and SPEI

Figure 7 shows the temporal evaluation of monthly SPEI at different timescales (1–12 months) from 1998 to 2100 under SSP2-4.5 and SSP5-8.5. The SPEI can represent similar behavior of the drought occurrence in all time scales with longer durations for longer time scales. It is also found that most drought events do not prolong across the 12-month timescale. The magnitude of drought decreases from the reference period to the near and mid-future periods and then shows higher wet conditions, especially during the far-future period under SSP5-8.5.

Figure 8 displays the time series of historical and projected $T_{\text{mean}}$, $P_{\text{mean}}$, PET, and SPEI-12. The SPEI-12 for December is used in the annual analysis. The projected $T_{\text{mean}}$ shows a continuous increase over SEA with larger magnitudes and trends under SSP5-8.5 rather than SSP2-4.5 scenarios. Both scenarios display distinct differences from 2035. The 5-year running means of annual mean temperature is projected to increase by 1.1 °C (1.41 °C) in 2050 and 1.99 °C (4.29 °C) in 2100 under SSP2-4.5 (SSP5-8.5). The climate stabilization is shown to flatten the curve of SSP2-4.5 later in the century.

Figure 5 | Spatial distribution of $R$, RMSD, and SD in $T_{\text{mean}}$ and $P_{\text{mean}}$ of the MME model.
The projected $P_{\text{mean}}$ under both SSP2-4.5 and SSP5-8.5 scenarios do not display any distinct difference until 2050. The increasing trend in annual mean precipitation is also depicted under the SPS5-8.5 scenario through the 21st century, but the curves show flattening for the SSP2-4.5 scenario as the climate stabilizes later in the century. The 5-year running means of the annual mean precipitation is projected to increase by 6.21% (8.11%) in 2050 and 9.62% (18.43%) in 2100.
under SSP2-4.5 (SSP5-8.5). Mandapaka & Lo (2018) also found that the mean precipitation increases 29% by the end of the 21st century under the CMIP5-RCP8.5 scenario using the NEX-GDDP dataset.

The projected PET displays a similar pattern to change temperature (Figure 8(a)). All $T_{\text{mean}}$, $P_{\text{mean}}$, and PET are projected to increase under all scenarios from the historical to the 21st century. The 5-year running means of the annual mean PET is projected to increase by 3.44% (4.39) in 2050 and 6.0% (13.18) in 2100 under SSP2-4.5 (SSP5-8.5). In general, SPEI-12 over SEA displays decreasing dryness trend toward the 21st century. This indicates less drought risk during the future climate than the present climate (see also Figure 7). The complex terrain with several islands of different sizes over the Maritime Continent may cause significant regional variations in SPEI along the annual cycle.

The spatial distribution of the projected change in $T_{\text{mean}}$, $P_{\text{mean}}$, PET, and SPEI-12 over SEA under two different SSPs is shown in Figure 9. The projected annual mean temperature (Figure 9(a)) under two scenarios increases with time and shows little local difference in its pattern. However, it shows a larger increase over northern SEA with the largest increase in east Papua under the SSP5-8.5 scenario. The projected $T_{\text{mean}}$ shows increase of 0.34 °C (0.40), 1.20 °C (1.68), and 1.82 °C (3.48) under SSP2-4.5 (SSP5-8.5) for the near-future, mid-future, and far-future periods, respectively.

In contrast to $T_{\text{mean}}$, the annual mean precipitation changes show significant regional differences. Overall, the projected $P_{\text{mean}}$ shows small reductions (<10%) over northern SEA and Indonesia (Java) for the near-future period and then increases toward the far-future periods. The projected $P_{\text{mean}}$ shows increase of 3.40% (3.64), 7.10% (8.51), and 9.62% (15.19) under SSP2-4.5 (SSP5-8.5) for the near-future, mid-future, and far-future periods, respectively. Under the high-emission SSP5-8.5 scenario, most areas in SEA exhibit a significant and robust increase in $P_{\text{mean}}$ (except in Java) relative to the present climate. The larger increases in precipitation are projected over northern and central Vietnam, northern Thailand, northern Myanmar, northern Laos, Cambodia, Kalimantan, Sulawesi, and east Papua. These findings are generally consistent with Tangang et al. (2020) who used seven RCMs over the CORDEX-SEA domain and 11 driving CMIP5 GCMs and found robust increases over northern Vietnam, Cambodia, Laos, and northern Thailand in the 21st century.

The spatial distribution changes in PET display also significant regional differences. The projected PET shows small reductions (<10%) over east Papua for the near-future period and then increases toward the far-future periods. The projected PET shows increase of 1.40% (1.51), 3.75% (5.20), and 5.61% (10.66) under SSP2-4.5 (SSP5-8.5) for the near-future, mid-future, and far-future periods, respectively. The SPEI-12 distributions over SEA, in general, display also significant regional differences with increasing (decreasing) dryness trend from historical to the near-future periods (near-future to mid-future and far-future periods) under both SSP2-4.5 and SSP5-8.5 scenarios. These results are consistent with Spinoni et al. (2020) who investigated global meteorological drought hotspots by employing several high-resolution simulations from CORDEX based on CMIP5 scenarios. However, there are some parts (central and southern parts of Thailand, southern Philippines) that still show increasing dryness trend. Although the MME can reduce uncertainties, some individual GCMs may have large biases or some uncertainties may remain for extreme values.
Figure 9 | Spatial distribution of projected changes in $T_{\text{mean}}$, $P_{\text{mean}}$, PET, and SPEI-12 under (a) SSP2-4.5 and (b) SSP5-8.5 scenarios.
The time evolution of projected changes in $T_{\text{mean}}$ for individual months over Mainland SEA country under SSP2-4.5 and SSP5-8.5 is shown in Figure 10. We do not include countries in the Maritime Continent due to their complex terrain, land-water contrasts with several islands. Overall, the increased temperature is pronounced from March to October and is more pronounced under SSP5-8.5. All countries display robust increases in temperature toward the 21st century. The maximum increased temperature is found in April (for Cambodia, Myanmar, and Thailand) and in June (for Laos and Vietnam), while Cambodia gives the smallest increase. The monthly increase in precipitation is shown in Figure 11. The increased precipitation for all Mainland SEA is pronounced from May to October and is more pronounced under SSP5-8.5. The precipitation decreases from January to April and November to December. The smallest increase (decrease) in precipitation is found in May and October (April and November). The monthly precipitation changes show robust increases under SSP5-8.5 and display more fluctuations than monthly temperature changes along the timeline to the 21st century. However, the climate stabilization under SSP2-4.5 is shown to slow down the increase in monthly precipitation after 2050 to the 21st century (see also Figure 8).

Figure 10 | Time evolution of projected changes in $T_{\text{mean}}$ under (a) SSP2-4.5 and (b) SSP5-8.5 scenarios.
Figure 12 displays the evolution of projected SPEI-12 for each country under SSP2-4.5 and SSP5-8.5 scenarios. Overall, the Mainland SEA shows drought risk during the near-future period and then shows flood risk toward the 21st century with larger SPEI-12 for SSP5-8.5 than for SSP2-4.5. The moderate-to-severe dry conditions are projected over all countries during the near-future, and then the wet condition is projected from mid-future to far-future periods, especially under SSP5-8.5.

### 3.3.3. Projected changes in drought characteristics

In the present paper, we use the run theory (Yevjevich 1967) to investigate the drought characteristics (number of event, duration, severity, and peak) over SEA. The drought event is counted when SPEI is less than the truncation level (−1.0 in this study). Figure 13 shows the spatial distribution of drought characteristics during the historical, near-future, mid-future, and far-future periods under SSP2-4.5 (see also Table 4). The number of events increases from 4.6 (1–11) (for the historical period) to 8.7 (1–22) (for the near-future period) but decreases from 7.3 (1–16) (for the mid-future period) and to 6.3 (1–17) (for the far-future period). The drought duration increases from 7.1 (2–29) (for the historical period) to 7.8 (2–27)
(for the near-future period) but decreases from 6.6 (2–16) (for the mid-future period) and to 6.2 (2–22) (for the far-future period). The peak intensity does not change significantly from the historical to the far-future periods (–1.66 to –1.62).

The drought severity increases from 10.6 (3–49) (for the historical period) to 12.1 (2–47) (for the near-future period) but decreases from 9.8 (2–27) (for the mid-future period) and to 9.3 (2–36) (for the far-future period).

Figure 14 shows the spatial distribution of drought characteristics during the historical, near-future, mid-future, and far-future periods under SSP5-8.5 (see also Table 4). The number of events increases from 6.4 (1–19) (for the near-future period) and to 6.5 (1–19) (for the mid-future period) and to 7.0 (1–20) (for the far-future period). The drought duration increases to 8.0 (2–36) (for the near-future period) but decreases from 7.5 (2–24) (for the mid-future period) and to 7.4 (2–20) (for the far-future period). The peak intensity also does not change significantly from the historical to the far-future periods (–1.66 to –1.72). The drought severity increases to 11.6 (2–58) (for the near-future period) and does not change significantly from the mid-future period to the far-future period.

Overall, the mean drought characteristics show significant regional differences, where the maximum values are found over northern Mainland SEA and Kalimantan during the near-future period. Relatively longer durations, higher peak intensities,
and more severities are projected under SSP5-8.5, while a higher number of events are projected under SSP2-4.5. This indicates that the drought condition increases during the near-future period and decreases toward the far-future period.

It has to be mentioned that various uncertainties are inherent in almost all projected future scenarios in GCMs. Uncertainties may arise from internal variability, parameterization, and emission scenarios, which imply uncertainties in the PET and drought index calculations, particularly drought characteristics.
4. CONCLUSIONS

This study applies the statistical bias correction to analyze the changes in mean climate (temperature, precipitation, and drought) of the latest CMIP6 model simulation over SEA. The CMIP6 is based on community scenarios known as SSPs, which differ from CMIP3 and CMIP5 in a different start year of the future scenarios, as well as a new set of specifications on emission and land-use scenarios. Here, 18 CMIP6 models are employed under two SSP-RCP scenarios (SSP2-4.5 and SSP5-8.5) to assess future changes for three periods (near-future: 2015–2039, mid-future: 2040–2069, and far-future: 2070–2099). The SA-OBS is used as a reference dataset for model performance evaluation. Significant conclusions can be drawn from this study:

1. The spatial distributions in annual mean temperature and precipitation of CMIP6 models generally produce a similar pattern to SA-OBS. The time evolution of projected change in mean temperature and precipitation for individual months displays increases from March to October and is more pronounced under SSP5-8.5. All countries display robust increases in temperature toward the 21st century. The climate stabilization under SSP2-4.5 is shown to slow down the increase in monthly precipitation after 2050 to the 21st century.

2. The internal PET (evpsb1p2) provided by two GCMs (CNRM-CM6-1 and CNRM-ESM2-1) are significantly larger than values computed based on Thornthwaite (PET-TH), Penman–Monteith (PET-PM), and Hargreaves (PET-HS) equations. Therefore, large uncertainties from internal PET can lead to drought or drying trend uncertainties.

3. The temporal evaluation of monthly SPEI based on PET-PM displays similar behavior of the drought occurrence in all time scales with longer durations for longer time scales. Most drought events do not prolong across the 12-month timescale. The magnitude of drought decreases from the reference period to the near and mid-future periods and then shows higher wet conditions during the far-future period. The SPEI-12 over SEA, in general, displays significant regional differences with decreasing dryness trend toward the 21st century.

4. The mean drought characteristics (number of event, duration, peak intensity, and severity) display relatively longer durations, higher peak intensities, and more severities under SSP5-8.5, while a higher number of events are projected
under SSP2-4.5. The complex terrain with several islands of different sizes over the Maritime Continent may cause significant regional variations in SPEI along the annual cycle.

Due to the temporarily limited number of available CMIP6 models which will be gradually released by the Scenario Model Intercomparison Project (Scenario MIP) (O’Neill et al. 2016), the evaluation of more CMIP6 models still needs to be carried out in the future. Although the MME can reduce uncertainties, some individual GCMs may have large biases or some uncertainties may remain for extreme values. In addition, uncertainties may arise from internal variability, parameterization, and emission scenarios, which imply uncertainties in the PET and drought index calculations, particularly drought characteristics. However, based on the findings of the 18 CMIP6 models in this research, projection in temperature, precipitation, and drought have been improved significantly and are benefit to SEA countries. Therefore, the corresponding policymakers need to prepare for the appropriate level of adaptation measures in response to the projected changing climate.

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**DATA AVAILABILITY STATEMENT**

All relevant data are available from an online repository or repositories. (https://esgf-node.llnl.gov/search/cmip6/)

**REFERENCES**


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