Projected changes in temperature and precipitation over mainland Southeast Asia by CMIP6 models
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ABSTRACT

Five mainland SEA countries (Cambodia, Laos, Myanmar, Vietnam, and Thailand) are threatened by climate change. Here, the latest 18 Coupled Model Intercomparison Project Phase 6 (CMIP6) is employed to examine future climate change in this region under two SSP-RCP (shared socioeconomic pathway-representative concentration pathway) scenarios (SSP2-4.5 and SSP5-8.5). The bias-corrected multi-model ensemble (MME) projects a warming (wetting) over Cambodia, Laos, Myanmar, Vietnam, and Thailand by 1.88–3.89, 2.04–4.22, 1.88–4.09, 2.03–4.25, and 1.90–3.96/C (8.76–20.47, 12.69–21.10, 9.54–21.10, 13.47–22.12, and 7.03–15.17%) in the 21st century with larger values found under SSP5-8.5 than SSP2-4.5. The MME model displays approximately triple the current rainfall during the boreal summer. Overall, there are robust increases in rainfall during the Southwest Monsoon (3.41–3.44, 8.44–9.53, and 10.89–17.59%) and the Northeast Monsoon (–2.58 to 0.78, –0.43 to 2.81, and 2.32 to 5.45%). The effectiveness of anticipated climate change mitigation and adaptation strategies under SSP2-4.5 results in slowing down the warming trends and decreasing precipitation trends after 2050. All these findings imply that member countries of mainland SEA need to prepare for appropriate adaptation measures in response to the changing climate.

Key words | climate change, CLMVT, CMIP6, precipitation, temperature

HIGHLIGHTS

- There is a robust increase in SWMR rainfall while the NEMR displays smaller increases.
- The temperature changes among CLMVT countries do not show any significant differences.
  However, there are significant precipitation changes.

INTRODUCTION

A large number of climate extremes (e.g., floods, droughts, heat waves, and extreme precipitation) have been recently observed across the globe in conjunction with global warming. Several studies reveal that continued greenhouse gas emissions will lead to long-term changes in the climate system and increasing the likelihood of widespread climate-extreme impacts on social and ecological systems (IPCC 2014; Easterling et al. 2016; Fischer & Knutti 2016; Giorgi et al. 2018; Oppenheimer et al. 2019; Cook et al. 2020). 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). Impacts on natural and human systems from global warming have already been observed with high confidence (IPCC SR5).

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 the global (Pall et al. 2007) 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 (CMIP, 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 (Eyring et al. 2015). 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). Previous studies of climate model comparison revealed that CMIP5 models perform better than CMIP3 models, particularly over North and Central America including the Caribbean (Bukovsky et al. 2015; Hidalgo & Alfaro 2015; Koutoulis et al. 2016). 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 100–300 km) which are not capable in impact assessments that require relatively fine spatial resolutions of just a few kilometers.

The latest CMIP6 models use the combination of shared socioeconomic pathways (SSPs) and representative concentration pathways (RCPs) that make more reasonable for future scenarios (Eyring et al. 2016). As CMIP6 has been improved in several aspects (e.g., higher horizontal resolution, better representation of synoptic processes, and better agreement with the estimation of global energy balance), more reasonable results can be obtained from climate-extreme studies (e.g., Di Luca et al. 2020; Kim et al. 2020; Laurie & Mathew 2020; Nie et al. 2020; Srivastava et al. 2020; Wild 2020).

Studies investigating the consequences of climate change over SEA are limited. Manton et al. (2001) analyzed extreme climate indices for the historical period over SEA and the South Pacific. 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 (Chang et al. 2005). The warm extremes increased while the cold extremes decreased over the Indo-Pacific region during 1971–2005 (Caesar et al. 2011). Most studies of the projected changes in SEA climate are embedded in global-scale domain carried out using GCMs (Chadwick et al. 2016). The projected changes in mean and extreme precipitation (using the NASA Earth Exchange Global Daily Downscaled Projection, NEX-GDDP dataset) over several parts of SEA show substantial increases in the 21st century (Mandapaka & Lo 2018). Suppari et al. (2019) found significant changes in consecutive dry day (CDD) and a decrease in total wet day precipitation (PRCPTOT) over most regions in SEA by using eight ensemble members of CORDEX-SEA simulations for RCP4.5 and RCP8.5 scenarios. A marked amplification in extreme precipitation over the Indochina Peninsula and the Maritime Continent were found under 1.5 and 2 °C global warming levels (Ge et al. 2019). Recently, Tangang et al. (2020) examined the projected rainfall changes in Southeast Asia in the 21st century based on seven regional climate models (RCMs) members of archived CORDEX-SEA simulations.

To our knowledge, few studies have analyzed the CMIP6 datasets to examine the future climate, especially in SEA. Grose et al. (2020) evaluated CMIP6 models and their future climate projects over Australia and compared the results to those obtained using CMIP5 models. Almazroui et al. (2020) examined the projected changes in temperature and precipitation over six South Asian countries during the 21st century using the latest CMIP6 dataset. Ukkola et al. (2020) revealed larger projected drought changes, which were more consistent in CMIP6 compared to CMIP5 models. Very recently, Almazroui et al. (2021) used CMIP6 models to examine the projected changes in temperature and precipitation over the United States, Central America, and the Caribbean. Su et al. (2020) analyzed the future drought characteristics over China using CMIP6 models. Mondal et al. (2021) examined the changing population exposure to drought across South Asia using 20 CMIP6 multi-model ensembles (MMEs).
In this study, we analyze the changes in mean temperature and precipitation using the latest Couple Model Intercomparison Project Phase 6 (CMIP6) model simulation dataset over mainland SEA. It is still not well understood how the new CMIP6 models can effectively simulate the climate response to anthropogenic forcing in this region. The overall aim of this study is to reveal the ability of the CMIP6 model to simulate the climate response to anthropogenic forcing over five mainland Southeast Asian countries. The specific questions to address are: what are the long-term observed trends in temperature and precipitation over each country and how are they likely to change in the seasonal monsoon for the near-, mid-, and far-future periods? This is an initial step required for a decision on what appropriate level of adaptation measures to the impacts of projected climate-extreme events.

**STUDY REGION AND DATA METHODOLOGY**

**Study region**

Our region of interest consists of the five mainland SEA countries: Cambodia, Laos, Myanmar, Vietnam, and Thailand (CLMVT), as displayed in Figure 1. We first examined the historical climate over the full domain of SEA similar to CORDEX-SEA (14.8°S–27.5°N, 89.5°E–146.5°E). Then, we projected the change in climate and seasonal monsoon precipitation over each country. SEA experiences two distinct sub-monsoon seasons: wet and dry. The same weather system that delivers rain during India’s monsoon season also affects Southeast Asia, but at different times (Kripalani et al. 2007). The southwest monsoon (SWM) causes the maximum rainfall during the boreal summer over the mainland SEA, while the northeast monsoon (NEM) causes maximum rainfall during the boreal winter over most areas in the Maritime Continent (Waliser & Gautier 1993; Chang et al. 2005). Furthermore, the complex terrain with several islands of different sizes causes significant regional variations in precipitation along the annual cycle (Chang et al. 2005).

**Observation datasets**

To estimate observational uncertainty, we examined several observation datasets (SA-OBS, APHRODITE, CPC-UNI, CRU, GPCP1DD, TRMM, ERA-Interim, JRA55, GPCCC, CHIRPS, and CMORPH) over CLMVT. The observation datasets used in this study are the daily maximum and minimum temperature and daily precipitation. All observation datasets differ due to varying original observations, different
resolutions, and different methods employed. The common period of 1998–2014 was used for intercomparison due to data availability. Comparisons among these observation datasets (see Figure 2) revealed that SA-OBS is a station-based dataset that represents the median values and is suitable for use as a reference. Recently, Else et al. (2017) have 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.

**Model data**

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 1. The new generation of CMIP6 models differs from the CMIP5 in having a new set of specifications for concentration, emission, and land-use scenarios as well as a new start year (CMIP6: 2015 and CMIP5: 2006) for future scenarios. In this phase, SSPs are combined with the RCPs of CMIP5. The SSPs are based on five narratives that describe different levels of socioeconomic 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). The 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 of the same common period (1998–2014) of observations 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
SSP-RCP scenarios, i.e., medium-emission (SSP2-4.5) and high-emission (SSP5-8.5). For a fair comparison, all models were regridded to $0.25^\circ \times 0.25^\circ$ resolution using a bilinear interpolation technique similar to the observation datasets.

**Bias correction method**

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). In this study, we employed a ‘variance scaling’ method 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 as the observations.

The first step we used ‘Delta change’ approach to adjust the temperature at each grid point ($T_{ij}(d)$) as given in Equation (1). Where $T_{obs, ij}$ and $T_{model, ij}$ are the climatological mean daily temperature of the observations and model in the reference period (1998–2014), respectively.

$$T_{ij}(d) = T_{model, ij} + (T_{obs, ij} - T_{model, ij})$$  \hspace{1cm} (1)

The second step is to find the corresponding anomalies ($T_{ij}'$) in the reference and projection periods by

$$T_{ref, ij}' = T_{ref, ij}(d) - T_{ref, ij}(d)$$  \hspace{1cm} (2)

$$T_{proj, ij}' = T_{proj, ij}(d) - T_{proj, ij}(d)$$  \hspace{1cm} (3)

### Table 1 | List of CMIP6 models used in this study

| GCM                  | Research Center                                                                 | Resolution       |
|----------------------|---------------------------------------------------------------------------------|------------------|
| ACCESS-CM2           | Australian Community Climate and Earth System Simulator                          | 1.88 × 1.25      |
| ACCESS-ESM1-5        | Australian Community Climate and Earth System Simulator                          | 1.88 × 1.25      |
| BCC-CSM2-MR          | Beijing Climate Center, China Meteorological Administration, Beijing, China     | 1.12 × 1.11      |
| CanESM5              | Canadian Centre for Climate Modelling and Analysis, Environment and Climate Change Canada | 2.81 × 2.77      |
| CNRM-CM6-1           | National Center for Meteorological Research, France                             | 1.41 × 1.39      |
| CNRM-ESM2-1          | National Center for Meteorological Research, France                             | 1.41 × 1.39      |
| EC-Earth3            | EC-Earth Consortium (EC-Earth)                                                   | 0.70 × 0.70      |
| FGOALS-g3            | LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 100029, China | 0.70 × 0.70      |
| GFDL-ESM4            | NOAA Geophysical Fluid Dynamics Laboratory, USA                                   | 1.25 × 1.00      |
| INM-CM4-8            | Institute for Numerical Mathematics, Russia                                     | 2.00 × 1.50      |
| INM-CM5-0            | Institute for Numerical Mathematics, Russia                                     | 2.00 × 1.50      |
| IPSL-CM6A-LR         | The Institut Pierre Simon Laplace, France                                       | 2.50 × 1.27      |
| MIROC6               | JAMSTEC (Japan Agency for Marine-Earth Science and Technology, Japan), AORI (Atmospheric and Ocean Research Institute, The University of Tokyo), NIES (National Institute for Environmental Studies), and R-CCS (RIKEN Center for Computational Science), Japan | 1.41 × 1.39      |
| MIROC-ES2-L          | JAMSTEC, AORI, NIES, and R-CCS, Japan                                           | 2.81 × 2.77      |
| MPI-ESM1-2-LR        | Max Planck Institute for Meteorology, Germany                                   | 1.88 × 1.85      |
| MRI-ESM2-0           | Meteorological Research Institute, Japan                                         | 1.12 × 1.11      |
| NESM3                | Nanjing University of Information Science and Technology, China                 | 1.88 × 1.85      |
| NorESM2-LM           | NorESM Climate Modeling Consortium consisting of CICERO (Center for International Climate and Environmental Research), MET-Norway (Norwegian Meteorological Institute), NERC (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 | 2.50 × 1.89      |
Then, the anomalies from Equations (2) and (3) are scaled by the ratio of their observed ($\sigma_{\text{obs},ij}$) and reference ($\sigma_{\text{ref},ij} (d)$) standard deviations (SDs).

$$T^+_{\text{ref},ij} = T^+_{\text{ref},ij} \times \frac{\sigma(T_{\text{obs},ij})}{\sigma(T_{\text{ref},ij} (d))}$$  \quad (4)$$

$$T^+_{\text{proj},ij} = T^+_{\text{proj},ij} \times \frac{\sigma(T_{\text{obs},ij})}{\sigma(T_{\text{ref},ij} (d))}$$  \quad (5)$$

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

$$T_{\text{ref},ij} (\text{cor}, d) = T^+_{\text{ref},ij} + T_{\text{ref},ij} (d)$$  \quad (6)$$

$$T_{\text{proj},ij} (\text{cor}, d) = T^+_{\text{proj},ij} + T_{\text{proj},ij} (d)$$  \quad (7)$$

In addition, we implement the ‘Empirical quantile mapping (EQM)’ method to remove the systematic precipitation biases in the GCMs simulation. The EQM, 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 cumulative density function 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 un-bias them from the climate simulation quantile by quantile. Finally, the monthly precipitation for the reference and future periods are obtained by Equations (8) and (9).

$$P_{\text{ref},ij} (\text{cor}, d) = F^{-1}_{\text{obs},ij} [F_{\text{ref},ij} (P_{\text{ref},ij})]$$  \quad (8)$$

$$P_{\text{proj},ij} (\text{cor}, d) = F^{-1}_{\text{obs},ij} [F_{\text{proj},ij} (P_{\text{proj},ij})]$$  \quad (9)$$

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

**ANALYSIS OF THE PRESENT CLIMATE**

Model simulation in the reference period

We first examined the CMIP6 models performance over CLMVT in the present climate (1998–2014) against SA-OBS. The spatial distributions of model bias (°C) in annual-mean daily temperature ($T_{\text{mean}}$) during 1998–2014 is displayed in Figure 3. The observed $T_{\text{mean}}$ is computed from the mean of the maximum and minimum daily temperature. The CMIP6 models in qualitative behavior generally can capture climatological temperature distribution pattern over CLMVT. Most models commonly underestimate the temperature over Myanmar, Thailand (above lat 13°), and Cambodia by more than 3 °C except ACCESS-ESM1-5 and Miroc6. These cold biases are most pronounced in the simulation by CNRM-CM6-1, CNRM-ESM2-1, GFDL-ESM4, INM-CM4-8, INM-CM5-0, IPSL-CM6A-LR, MPI-ESM-2-LR, and NESM3. However, most models show warm biases over Laos and Vietnam, especially the simulation by ACCESS-ESM1-5. The MME shows better agreement (with bias within 2.5 °C) than any single model. A similar distribution pattern of bias is also evident in the MME. These may be linked to the uncertainties from low density of the observed stations (over northern CLMVT and central Vietnam) from SA-OBS (see Else et al. 2017).

The spatial distribution of bias (%) in annual-mean precipitation ($P_{\text{mean}}$) are displayed in Figure 4. In general, there are regional variations in $P_{\text{mean}}$ among CMIP6 models and observations. Most CMIP6 models display wet biases along the coastline of Myanmar, Thailand, and southern Vietnam, especially BCC-CSM2-MR, CanESM5, INM-CM4-8, and INM-CM5-0. However, CNRM-CM6-1 and CNRM-ESM2-1 show significant dry biases over Thailand, Laos, Cambodia, and Vietnam. The dry biases are most pronounced over northern Laos and northern Vietnam except INM-CM4-8 and INM-CM5-0. The wet bias over northern CLMVT and central Vietnam may be linked to the uncertainties from low density of the observed rainfall stations. In general, most regions characterized by high topography give profound differences between the observation and the model.

Figure 5 displays the annual cycle and box plot of monthly mean temperature and precipitation of CMIP6 models during the reference period. The models of both temperature and
Figure 3 | Spatial distribution of model bias (°C) in $T_{mean}$ during the reference period.
Figure 4 | Spatial distribution of model bias in $P_{\text{mean}}$ (%) during the reference period.
precipitation show similarities on interannual variations with the observations. Most models show the highest mean temperature in April or May. ACCESS-ESM1-5 gives the largest warm bias (>30 °C) in May. Most models including the MME underestimate the mean temperature in months NDJF. For precipitation, most models display wet (Dry) biases in months JJAS (ONDJ). BCC-CSM2-MR gives the highest peak in June (>400 mm), while the observation peak is in August. The model median temperature is close to the observed values in months AMJ, but they underestimate in the rest season. The observed temperature is above the median and the 75th quantile of the box plots in months NDJF (Figure 5(a)). Larger spreads are found for the mean precipitation than the temperature during the peak season.

**Evaluation of observation datasets and CMIP6 models in the present climate**

From Figures 2–5, there are uncertainties in both \( T_{\text{mean}} \) and \( P_{\text{mean}} \) among the various observation datasets and CMIP6 models. Observation datasets give very different in precipitation, making it difficult to assess accurately, as previously reported by Herold et al. (2016). To assess the performance of individual CMIP6 models in reproducing the climatological spatial pattern, we performed bias correction by using ‘Variance scaling’ for \( T_{\text{mean}} \) and EQM for \( P_{\text{mean}} \) (Section ‘Bias correction method’). We selected SA-OBS as a reference and performed a detailed intercomparison of all observation datasets and CMIP6 models (both \( T_{\text{mean}} \) and \( P_{\text{mean}} \)) in terms of correlation coefficient \( R \), center root-mean-square difference (RMSD), and SDs using the Taylor Diagram (Taylor 2001) during the reference period (see Figure 6). The center RMSD and the SD are normalized by their corresponding observations of SA-OBS. The observation datasets are represented by black symbols, and the CMIP6 models (both before and after bias corrections) are represented by other colors.

Most temperature observation datasets (Figure 6(a)) show high \( R \) (>0.9), with the lowest values for ERA-Interim and different magnitudes of RMSD and SD. The Era-Interim also displayed the highest RMSD. Most CMIP6 models before bias correction (red and blue symbols) give \( R \) in the
range 0.8–0.9, and show larger spread in SD than R and RMSD. After bias correction (green and pink symbols), $R$ increases (>0.9) and RMSD and SD are significantly lower than their values before bias correction. Overall, the CMIP6 model has reliable capabilities in simulating the annual-mean temperature. For precipitation (Figure 6(b)), all observation datasets were found to give high $R$ (>0.9) but lower than those of temperature. We observe distinctly different magnitudes of SD but similar RMSD values. The CMIP6 models before bias correction display more widespread in RMSD and SD with lower $R$ compared with temperature. After bias correction, individual CMIP6 models do not show distinct improvement in $R$ but significant improvement in RMSD and SD. The MME model yields the best results (highest $R$ and lowest RMSD) among individual CMIP6 GCMs.

**PROJECTED CHANGES IN ANNUAL-MEAN TEMPERATURE AND PRECIPITATION**

The spatial distribution of the projected change in $T_{\text{mean}}$ and $P_{\text{mean}}$ under two different SSP-RCP scenarios is shown in Figure 7. The projected annual-mean temperature (Figure 7(a)) under two scenarios increases with time and shows little local difference in its pattern. However, it shows a larger increase over northern CLMVT, with the largest increase over northern Vietnam, Laos, and Myanmar. In the near-future, the annual-mean temperature averaged over CLMVT is projected to increase by 0.63 and 0.77 °C under SSP2-4.5 and SSP5-8.5, respectively. In the mid-future, it is projected to increase by 1.28 and 1.88 °C, respectively, and in the far-future, it is projected to increase by 1.80 and 3.36 °C, respectively.
Figure 7 | Spatial distribution of future changes in $T_{\text{mean}}$ and $P_{\text{mean}}$. 
In contrast to $T_{\text{mean}}$, the changes in annual-mean precipitation show significant regional differences (Figure 7(b)).

Overall, the projected annual-mean precipitation shows small reductions (<10%) over central Vietnam and Laos for the near-future and then increases in the far-future. In the near-future, the projected $P_{\text{mean}}$ shows an increase of 2.36 and 2.88% under SSP2-4.5 and SSP5-8.5, respectively. For the mid-future period, it shows an increase of 6.76 and 8.09%, respectively, and in the far-future, it is projected to increase by 9.29 and 15.58%, respectively. Under the high-emission SSP5-8.5 scenario, most areas in CLMVT exhibit a significant increase in $P_{\text{mean}}$ relative to the present climate.

Overall, the temperature changes among CLMVT countries do not show any significant differences. However, there are significant precipitation changes with are minimum and maximum over Thailand and Vietnam, respectively. Mandapaka & Lo (2018) found similar results from the NEX-GDDP dataset under the RCP4.5 and RCP8.5 scenarios. Larger increases in precipitation are projected over northern and central Vietnam, northern Thailand, northern Myanmar, northern Laos, and Cambodia. These findings are generally consistent with those of Tangang et al. (2020), who used seven RCMs in the CORDEX-SEA domain and 11 driving CMIP5 GCMs and found robust increases in the 21st century over northern Vietnam, Cambodia, Laos, and northern Thailand.

Figures 8 and 9 display the temporal changes in projected $T_{\text{mean}}$ and $P_{\text{mean}}$ over CLMVT countries. The solid thick lines represent MME, and shaded regions denote the minimum and maximum changes from individual models. The change in $T_{\text{mean}}$ was computed from the difference between the projected $T_{\text{mean}}$ and the observed means during the reference period (1998–2014). The change in $P_{\text{mean}}$ was computed using the normalized index between the projected $P_{\text{mean}}$ and the mean observation during the reference period (1998–2014). Normalization was performed for each model at every grid to minimize the effect of large spatial variations on regional averages. The projected changes in $T_{\text{mean}}$ over CLMVT countries show larger magnitudes and trends under SSP5-8.5 rather than SSP2-4.5 scenarios. The projected changes in 5-year running mean of temperature and precipitation over each country are summarized in Table 2. Under SSP2-4.5 (SSP5-8.5), the temperature over Cambodia, Laos, Myanmar, Vietnam, and Thailand is projected to increase by 1.21, 1.31, 1.19, 1.23, and 1.27 °C, respectively (1.58, 1.71, 1.70, 1.59, and 1.66 °C, respectively) in 2050 and 1.88, 2.04, 1.88, 2.03, 1.88, 2.04, and 1.88, 2.04, 1.88, 2.03,
and 1.90 °C, respectively (3.89, 4.22, 4.09, 4.25, and 3.96 °C, respectively) in 2100. The warming trends start to slow down with decreasing trends overall countries after 2050 under SSP2-4.5. This reveals the effectiveness of anticipated climate mitigation and adaptation strategies under the combination of socioeconomic development and radiative forcing projection (SSP2-4.5: peak in 2040 and then decrease in magnitude).

The increasing trend in annual-mean precipitation is also seen for the SPS5-8.5 scenario, but the curves flatten under the SSP2-4.5 scenario as the climate stabilizes later in the century. Under SSP2-4.5 (SSP5-8.5), the precipitation over Cambodia, Laos, Myanmar, Vietnam, and Thailand is projected to increase by 8.12, 8.35, 5.03, 11.17, and 4.17%, respectively (10.52, 10.41, 7.03, 12.90, and 7.91%, respectively) in 2050 and 8.76, 12.69, 9.54, 13.47, and 7.03%, respectively (20.47, 21.10, 21.57, 22.12, and 15.17%, respectively) in 2100. Major differences are apparent between the lowest and the highest values of the individual models due to their projection uncertainties. Various sources of uncertainties (Almazroui et al. 2020) may arise from (1) internal variability of the climate system, (2) inter-model variability, and (3) variability among different emission scenarios. Uncertainties from (2) and (3) in this study are found to increase over time by the inter-modal spreads under both scenarios.

### PROJECTED CHANGES IN SEASONAL MONSOON PRECIPITATION

Because CLMVT is located in the Asian-monsoon-dominated region, a large proportion of annual rainfall and its variability in the present and future climates comes from the summer monsoon, similar to South Asia (Kripalani et al. 2007). The monsoons and their variability critically influence people’s livelihoods and socioeconomic status. Recent monsoon floods and droughts in CLMVT have resulted in the loss of lives, property damage, and decreased agricultural productivity. In this study, our focus is on the magnitude of change in precipitation that will affect the whole region. Therefore, we investigated the strength of the monsoon (only in terms of precipitation) by the Southwest and Northeast Monsoon rainfall (SWMR and NEMR).

Figure 10 displays the spatial-averaged mean seasonal monsoon precipitation over CLMVT for the MME model. The 1st, 2nd, 3rd, and 4th columns represent values for the historical, near-future, mid-future, and far-future periods,
respectively. The projection in each column is displayed under both SSP2-4.5 and SSP5-8.5 scenarios. In general, CLMVT is significantly dominated by SWMR, similar to the findings of Chang et al. (2005). There is a robust increase in SWMR along the timeline of the 21st century, with larger increases found under SSP5-8.5 than SSP2-4.5. However,
NEMR does not display significant increases from the historical period. For SSP2-4.5, the SWMR (NEMR) increases by 3.41, 8.44, and 10.89% (−2.58, −0.43, and 2.52%) for the near-, mid-, and far-future, respectively. For SSP5-8.5, the SWMR (NEMR) increases by 3.44, 9.53, and 17.59% (0.78, 2.84, and 5.45%) for the near-, mid-, and far-future, respectively. Both SSP2-4.5 and SSP5-8.5 scenarios display larger increases in the boreal summer. Overall, these results correspond with Wang et al. (2020), who examined 15 CMIP6 models under the SSP2-4.5 scenario and revealed that during the boreal summer (JJAS), the projected monsoon precipitation significantly increases over mainland SEA.

Table 3 displays changes in mean seasonal monsoon precipitation for each country. The SWMR (NEMR) under SSP2-4.5 over Cambodia increases by 2.57, 6.79, and 9.63% (6.36, 5.82, and 8.44%) for the near-, mid-, and far-future, respectively. The SWMR (NEMR) under SSP2-4.5 over Laos increases by 2.42, 9.97, and 11.94% (−1.45, 0.98, and 5.12%) for the near-, mid-, and far-future, respectively. The SWMR (NEMR) for SSP2-4.5 under Myanmar increases by 2.06, 5.47, and 8.45% (2.13, 2.03, and 3.84%) for the near-, mid-, and far-future, respectively. The SWMR (NEMR) under SSP2-4.5 over Vietnam increases by 4.43, 11.75, and 13.48% (1.49, 4.88, and 8.62%) for the near-, mid-, and far-future, respectively. The SWMR (NEMR) under SSP2-4.5 over Thailand increases by 1.15, 4.92, and 7.77% (0.59, 1.20, and 3.22%) for the near-, mid-, and far-future, respectively.

In addition, the SWMR (NEMR) under SSP5-8.5 over Cambodia increases significantly by 2.05, 9.09, and 16.10% (5.61, 12.89, and 14.33%) for the near-, mid-, and far-future, respectively. The SWMR (NEMR) under SSP5-8.5 over Laos increases significantly by 5.47, 10.14, and 18.82% (4.03, 4.85, and 7.06%) for the near-, mid-, and far-future, respectively. The SWMR (NEMR) under SSP5-8.5 over Myanmar increases significantly by 1.71, 6.31, and 15.90% (2.28, 1.97, and 9.46%) for the near-, mid-, and far-future, respectively. The SWMR (NEMR) under SSP5-8.5 over Vietnam increases significantly by 5.02, 12.52, and 20.95% (5.13, 8.33, and 11.58%) for the near-, mid-, and far-future, respectively. The SWMR (NEMR) under SSP5-8.5 over Thailand increases significantly by 1.10, 6.47, and 12.40% (4.24, 5.01, and 4.69%) for the near-, mid-, and far-future, respectively.

Table 3 | Mean seasonal monsoon precipitation over CLMVT

| Country  | Observation | Ref. period | Near-future | Mid-future | Far-future |
|----------|-------------|-------------|-------------|------------|------------|
| Cambodia | 1,847       | 2016        | 1,829       | 1,877      | 1,954      |
| Laos     | 1,566       | 2016        | 1,654       | 1,753      | 1,775      |
| Myanmar  | 1,240       | 2016        | 1,234       | 1,275      | 1,308      |
| Vietnam  | 1,565       | 2016        | 1,626       | 1,708      | 1,845      |
| Thailand | 1,128       | 2016        | 1,154       | 1,171      | 1,243      |

In Table 3, the precipitation values are given in millimeters (mm) for the months May to August (JJAS) for the near-, mid-, and far-future periods.
We examine the future projection of extreme seasonal monsoon precipitation by the Gamma pdf plot in Figure 11. Projection of the NEMR does not fit well the Gamma pdf as compared to the southwest Monsoon rainfall (SWMR). The pdf curve during the wet season becomes flatter, with a peak reduction, increasing spread, and a mean value shift to the right relative to the historical curve. Its median does not show significant changes in magnitude and frequency for the near-future, mid-future, and far-future periods under SSP2-4.5 scenario. On the contrary, projection of the SWMR shows distinct increases (decreases) in magnitude (frequency). Therefore, we expect more (less) extreme rainfall in the wet season (dry season) from the near-future to the far-future periods.

CONCLUSIONS AND DISCUSSION

The present study analyzes the changes in mean temperature and precipitation using the latest Coupled Model Intercomparison Project phase 6 (CMIP6) model simulation over Cambodia, Laos, Myanmar, Vietnam, and Thailand (CLMVT). 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 for emission and land-use scenarios. Here, 18 CMIP6 models were employed to assess future mean climate change for three periods (near-future: 2015–2039, mid-future: 2040–2069, and far-future: 2070–2099) derived from the climate projections under two SSP-RCP scenarios (SSP2-4.5 and SSP5-8.5).

Intercomparison among several observation datasets over southeast Asia (SA-OBS, APHRODITE, CPC-UNI, CRU, GPCP1DD, TRMM, ERA-Interim, JRA55, GPCC, CHIRPS, CMORPH, GsMap, and PERSIANN) reveal that SA-OBS is suitable for use as a reference due to its station-based dataset, which represents the median values (Figure 2). SA-OBS is the currently best available daily gridded observational dataset for Southeast Asia (Else et al. 2017). The model bias correction was employed by using the ‘Variance scaling’ method for the mean temperature and the ‘EQM’ method for the mean precipitation (Section ‘Bias correction method’). The major results can be summarized below.

1. The CMIP6 models in qualitative behavior generally can capture climatological temperature distribution pattern over CLMVT (Figure 3). Most models commonly show cold biases (over Myanmar, Thailand (above lat 13°), and Cambodia) and warm biases (over Laos and Vietnam). Most CMIP6 models display wet biases (along the coastline of Myanmar, Thailand, and southern Vietnam) and dry biases (over northern Laos and northern Vietnam). The wet bias over northern CLMVT and central Vietnam may be linked to the uncertainties from low density of the observed rainfall stations. In general, most regions characterized by high topography give profound differences between the observation and the model. These may be linked to the uncertainties from low density of the observed stations (over northern CLMVT and
central Vietnam) from SA-OBS (Else et al. 2017). The MME show better agreement than any single model.

(2) The models of both temperature and precipitation show consistency monthly variability with the observations. Most models show the highest mean temperature in April or May and display wet (Dry) biases in months JJAS (ONDJ). Most CMIP6 models display the spatial pattern of climatological annual-mean temperature over CMLVT well ($R > 0.9$ and RMSD and SD are significantly decreased). For the annual-mean precipitation, the CMIP6 models display more widespread in RMSD and SD with lower $R$ compared to temperature. Individual CMIP6 model does not show distinct improvement in $R$ but show significant improvements in RMSD and SD. The MME model yields the best results (highest $R$ and lowest RMSD) among individual CMIP6 GCMs (Figure 6).

(3) The projected changes in mean annual temperature over CLMVT countries show a continuous increase with larger magnitudes and trends under SSP5-8.5 rather than SSP2-4.5 scenarios. Overall, the temperature changes do not show any significant differences. However, there are significant precipitation changes with are minimum and maximum over Thailand and Vietnam, respectively (Figure 7). Major differences are apparent between the lowest and the highest values of the individual models due to their projection uncertainties. Uncertainties from inter-model variability and variability among different emission scenarios (Almazroui et al. 2020) are found to increase over time by the inter-modal spreads under both scenarios. The effectiveness of anticipated climate change mitigation and adaptation strategies under the combination of socioeconomic development and radiative forcing projection (SSP2-4.5: peak in 2040 and then decrease in magnitude) results in slowing down the warming trends overall countries after 2050. These findings are generally consistent with Mandapaka & Lo (2018) and Tangang et al. (2020).

(4) CLMVT countries are significantly dominated by the SWMR. There is a robust increase in SWMR along the timeline of the 21st century, with larger increases are found under SSP5-8.5 than SSP2-4.5 (Figure 10). The NEMR displays smaller increases from the historical period compared to SWMR. In general, both SSP2-4.5 and SSP5-8.5 scenarios display larger increases during the boreal summer which generally agree with the work of Wang et al. (2020).

(5) Different projected increase in the seasonal Monsoon rainfall are found over each country in CLMVT (Table 3). Overall, the largest (smallest) increases in SWMR and NEMR are found over Vietnam (Thailand) and Cambodia (Thailand), respectively, for the far-future period under SSP5-8.5 scenario. The projection of the NEMR does not fit well the Gamma pdf as compared to the SWMR (Figure 11). The pdf curve during the southwest Monsoon season becomes flatter, with a peak reduction, increasing spread, and a mean value shift to the right relative to the historical curve. Projection of the SWMR shows distinct increases (decreases) in magnitude (frequency). Therefore, we expect more (less) extreme rainfall in the wet season (dry season) from the near-future to the far-future periods.

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), evaluation of more CMIP6 models still needs to be carried out in the future. However, based on the findings of the 18 CMIP6 models in this paper, significant climate projection in both precipitation and temperature have been improved and are benefitted to CLMVT 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.

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