Projected Changes in the Near-Future Mean Climate and Extreme Climate Events in Northeast Thailand

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Abstract

This study provides an assessment of changes in mean and extreme climate in northeast Thailand, focusing on the near-future period (2021-2050). Spatiotemporal changes in climate extremes and return values are investigated compared to 1981-2010. Climate model-related uncertainties are quantified using 14 models from the Coupled Model Intercomparison Project phase five (CMIP5) and 8 models from phase six (CMIP6). CMIP6 models have a higher sensitivity to external forcings as the CMIP6 ensemble suggests an increase in maximum and minimum temperatures by 1.45°C (0.8-1.9°C) and 1.54°C (1.1-1.9°C) under the high emission scenario, which is greater than by CMIP5 ensemble: 1.10°C (0.5-1.7°C) and 1.13°C (0.7-1.6°C) respectively. No significant changes in annual rainfall are projected, although it will be temporally more uneven with decreases (6-11%) during the pre-rainy season (March-May) and increases (2-8%) during the rainy season (June-October). The bootstrap technique shows the inter-model uncertainties for rainfall projections in CMIP6 have reduced by 40% compared to CMIP5. The annual number of hot days will increase more than twofold and warm nights, more than threefold. Near-future will experience an increase in the rainfall intensity, a decrease in the number of rainy days, and an increase in the 20-year return values of annual maximum 1-day rainfall and consecutive 5-days rainfall (>30%). In addition, the rainy season will be shortened in the future as onset and retreat are delayed, which may have implications in agricultural activities in the basin since cultivation is primarily rainfed. These findings suggest that anthropogenic activities will significantly amplify the climate extremes. The study results will be useful for managing climate-related risks and developing adaptation measures to improve resilience towards potential climate hazards.

Keywords: Climate change, climate extremes, uncertainties, HighResMIP, Thailand

1. Introduction

Anthropogenic activities are major drivers of long-term changes in the earth's climate system. These changes have manifested as rises in global temperature, prolonged heat spells, altered precipitation patterns, increased magnitude and frequency of extreme climatic events, rapid decline of the cryosphere, sea-level rise, etc. (IPCC, 2013). 2015-2019 was the warmest 5-year period in recorded history: it was 1.1 ± 0.1 °C warmer than the per-industrial era (1850-1900) and 0.20 ± 0.08 °C warmer than the 2011-2015 period (WMO, 2019). The estimated rate of temperature increase is currently about 0.2°C (between 0.1°C-0.3°C) per decade due to past and ongoing greenhouse gas emissions (IPCC, 2018). Global warming is expected to further intensify the global water cycle, exacerbate extreme events, and lead to a global redistribution of water resources at multiple temporal and spatial scales (Chen *et al.*, 2017). Warming over the period of several decades has been attributed to changes in large-scale hydrological cycles such as atmospheric water vapor content and changes in rainfall pattern, which ultimately lead to increased flood and drought events (Bates *et al.*, 2008). At the global scale, atmospheric warming and extreme events have been found to have a positive correlation with one another (Alfieri *et al.*, 2017). The impacts of climate change, particularly manifested as increased frequency and severity of extreme hydro-meteorological events, will challenge the reliability of water management systems globally (Quevauviller and Gemmer, 2015).

Extreme climatic events are getting more intense and frequent in recent decades and are likely to worsen under climate change scenarios. Extreme rainfall events are one of the most devastating climate extremes, and they have severe implications for the environment and society (Ohba and Sugimoto, 2019; Kim et al., 2020). With increased temperature, air can hold more moisture and energy, and along with changes in large-scale atmospheric circulation patterns (Schiermeier, 2018), storms are likely to get stronger in the future. Climate change has been reported to contribute to many of the recent extreme events. Burke and Stott (2017) analyzed the data on the East Asian summer monsoon domain from 1960 to 2015 and concluded that anthropogenic climate change has led to a decrease in the summer monsoon rainfall, though most extreme rainfall events are getting more intense and shorter. Sun and Miao (2018) reported that anthropogenic climate change contributed about 35% to extreme precipitation in Yangtze-Huai, China, in June-July 2016. Kew et al. (2019) found the probability of heatwaves in southern Europe, similar to that of 2017 is at least 3.5 times higher now compared to 1950. Funk et al. (2019) found that an increase in sea surface temperatures due to human activities contributed to the East African drought of 2017. In the case of the South Asian summer monsoon, peak seasonal rainfall is found to have decreased over the period of

1951-2011; alongside, there was an increase in the variability of daily-scale rainfall, the frequency of dry spells, and the intensity of wet spells (Singh et al., 2014). In India, the length of dry spells and the total number of dry days have been increasing, along with an increase in short spell heavy rainfall events in recent decades (Mishra and Liu, 2014; Dash and Maity, 2019).

Several recent studies have projected an increase in the frequency and magnitude of extreme rainfall in the future (Hui et al., 2018; Ohba and Sugimoto, 2019; Adeyeri et al., 2019; Di Luca et al., 2020; Kim et al., 2020). A study by Hosseinzadehtalaei et al. (2020) in Europe projected that sub-daily extreme rainfall for 50- and 100-year return periods would be tripled by the end of the 21st century under the high emission scenario. Similarly, Wang et al. (2020) estimated that a rise in global warming by 1.5°C and 2.0°C would increase the 5-day maximum rainfall by 4.0% and 7.6%, and the rainfall in very wet days by 17.4% and 34.4%, respectively. Ali et al. (2019) found that increasing trends in temperature extremes will be higher than the trends of average temperature under all future scenarios in Pakistan. A study conducted by Pendergrass and Knutti (2018) found that almost half of the annual precipitation occurs in the 12 wettest days of the year globally, and this uneven temporal distribution will be amplified in the future.

Thailand is also not immune to extreme climate events as the country frequently experiences floods and droughts. Notably, the recent drought of 2015-17 resulted in an estimated damage of 3.3 billion USD (EM-DAT, 2019) and the catastrophic flooding of 2011/12, prompted by exceptional rainfall events (Limsakul and Singhruck, 2016), caused damages worth approximately 45.7 billion USD (DDPM, 2015). Climate change projection studies in Thailand have shown that temperature will continue to increase in the future; however, projections about rainfall are not unanimous (Babel et al., 2011; Pholkern et al., 2018; Shrestha et al., 2018). Some past studies show that extreme rainfall events in the future are likely to increase (Singhrattna, 2011; Komori et al., 2018; Supari et al., 2020). The assessment of mean climate for the future can provide a broad overview of climate change; however, there are also significant socio-economic impacts on society and the ecosystem due to changes in extreme events, resulting in heatwaves, droughts, storms, and floods (Swain et al., 2020; Tegegne et al., 2020). Thus, it is imperative to assess climate change beyond projected changes in the mean and emphasize changes in extreme events.

Improving projections and understanding future extremes form the basis for formulating policies and addressing climate-related risks. At present, no such detailed assessment of climate extremes is available for northeast Thailand. The present study attempts to fill the knowledge gap by providing a comprehensive assessment of climate projections in terms of changes in mean and extreme events in northeast Thailand. The near-future period (2021-2050) is focused on because of its relevance to adaptation planning and action. Spatiotemporal changes in/of these extreme events are investigated using temperature and rainfall-based indices. In addition, projected shifts in the rainy season in the near-future are also investigated. To reduce uncertainties and provide a robust future projection, a subset of the climate models from the fifth and sixth phases of Coupled Model Intercomparison Project (CMIP), which have proven to be better at simulating the regional climate of the study area, are utilized. The finding of this study will be useful for updating disaster mitigation plans and policies based on projected changes in climate extremes. It will also have relevance in disaster risk reduction and disaster preparedness, infrastructure planning, and developing adaptation measures for the basin to cope with changes in climate extremes in the future.

2. Study Area and Data

2.1. Study area

The Mun River Basin (shown in Fig. 1) is the largest in northeast Thailand and has a catchment area of about 53,800 km^2. It is part of the Korat plateau, where the elevation varies between 64 masl in the central region to 1,351 masl in the surrounding hills in the southwest. The basin comprises four provinces, namely Nakhon Ratchasima, Buriram, Surin, Si Sa Ket, and partially another four (Roi Et, Maha Sarakham, Khon Khen, and Ubon Ratchathani). The Mun River is one of the main tributaries of the Mekong River, which originates in the Khao Yai National Park in the Nakhon Ratchasima province. Located between 14.1 to 16.0°N latitudes and 101.2 to 104.9°E longitudes, the basin experiences a tropical climate with three distinct seasons.

The rainy season typically lasts from June till October, when 80% of the annual rainfall occurs. The southwest monsoonal winds from the Indian Ocean and the Intertropical Convergence Zone (ITCZ) are the main drivers of the rainy season (Singhrattna *et al.*, 2012). However, the rainfall anomaly associated with ITCZ represents only 10% of the total rainfall that typically occurs during the monsoon season (Waliser and Jiang, 2015). Byrne *et al.* (2018) assessed the impacts of climate change on ITCZ characteristics using the CMIP5 models and projects no significant change in its location in the 21st century. However, 22 out of 32 models suggested ITCZ will be narrowed in the future by -0.52%/K, and its strength will reduce by 0.69%/K warming. These findings show that the southwest monsoon will dominate the projected change in the rainfall in the region under climate change with little impact from a changing ITCZ. Similarly, the winter season in the basin occurs due to the northeast monsoons bringing in cool and dry winds from November to February, and the pre-rainy season goes on from March to May. April is the hottest month with an average temperature of about 30.6°C, while December is the coolest month with an average temperature of 20.2°C. Annual average rainfall varies between 900mm in the western parts to 1,600mm in the eastern parts of the basin.

2.2. Data

2.2.1. Observed climatic data

The daily rainfall data collected from 43 stations in the Mun River Basin is interpolated to grids of 0.25 degrees using the inverse distance weighting (IDW) method (as shown in Fig. 1). Similarly, daily maximum temperature (Tmax) and minimum temperature (Tmin) data is acquired from the Climate Prediction Center (CPC) Global Land Surface Air Temperature Analysis (Fan and van den Dool, 2008). In addition to the CPC temperature data, Khadka et al. (unpublished data) compared two other global temperature products - ECMWF Re-Analysis land surface temperature (ERA5 - 0.25° grids) (Hersbach *et al.*, 2020) and The Berkley Earth Surface Temperature land surface air temperature data (BEST – 1.0° grids) (Rohde *et al.*, 2013) - with the observed temperature data available at a few stations within the basin. It was found that the CPC data was closer to the observed data with an average correlation coefficient above 0.95 and a Root Mean Square Error of about 0.8°C. CPC data is available since 1979 at the spatial resolution of 0.5°; this was regridded to 0.25° using bilinear interpolation.

Fig. 2 shows the observed rainfall and temperature in the Mun River Basin for 1981-2010. The annual average rainfall in the basin shows a significant spatial variation with a gradual increment from the west to the east. The Nakhon Ratchasima province in the west receives the least rainfall, while the Si Sa Ket province in the east receives the most rainfall in the basin. The average maximum and minimum temperatures in the basin vary between 32.3°C to 33.3°C and 21.9°C to 23.0°C, respectively. The highest temperature has been recorded in the central part, while the lowest is in the south-western region of the basin.

2.2.2. Climate model simulations

This study used the multimodel ensemble from CMIP5 and CMIP6 for projecting mean and extreme climate for the near-future period (2021-2050). Khadka *et al.* (2021) ranked 28 climate models from CMIP5 and 32 climate models from CMIP6 for their ability to represent regional climate in southeast Asia, with an emphasis on the simulation of the summer monsoon rainfall using 25 metrics. In the current study, 14 top-ranking models from CMIP5 and 8 models from CMIP6 under the High-Resolution Model Intercomparison Project (HighResMIP), for which data was available at the time of the analysis, have been considered. The details of these climate models used from CMIP5 and CMIP6 are provided in Table 1. For future projections, simulations for an intermediate emission scenario, RCP4.5 (Clarke *et al.*, 2007), and a high emission scenario, RCP8.5 (Rohde *et al.*, 2013), are considered for the CMIP5 models. In CMIP6, new socio-economic development scenarios called Shared Socioeconomic Pathways (SSPs) are used for future projections (O'Neill *et al.*, 2017; Almazroui *et al.*, 2020). The future simulations from the HighResMIP climate models are available for SSP5-8.5. The SSP5-8.5 represents a high emission scenario and is similar to RCP8.5 in a radiative forcing pathway (Kriegler *et al.*, 2017).

Biases in the temperature and rainfall represented by the multimodel ensemble (MME) of CMIP5 and CMIP6 during the 1981-2005 period are presented in Fig. 2. Both CMIP5 and CMIP6 MMEs have spatially consistent negative biases for Tmax and Tmin. It can be seen from the subplots 2d, e, g, and h that the biases for Tmax have reduced in the CMIP6 MME (average of -1.4°C) compared to the CMIP5 MME (average of -2.0°C). However, no improvements can be seen for the Tmin, and the biases are slightly higher in CMIP6 MME (average of -1.5°C) than CMIP5 MME (average of -1.1°C). The biases in the MME rainfall for both CMIPs are less consistent within the basin (Fig. 2f and i). The CMIP5 MME has an average wet bias of 149mm/year, while the CMIP6 MME has a dry bias of -81mm/year. Moreover, CMIP5 MME shows higher (wet) rainfall biases in the western part of the basin while less (or dry) biases in the eastern part, while CMIP6 MME show less (or dry) biases in the western part and higher (dry) biases in the eastern part of the basin. The results show some improvements in simulating the observed climate (rainfall and temperature) by CMIP6 MME. Higher spatial resolutions in the CMIP6 model could be one of the reasons for the improvement. However, the results may have also been affected by the different number of models considered from CMIP5 and CMIP6.

3. Methodology

3.1. Bias correction using quantile mapping for future projections

Since all climate models inherit systemic biases, it is imperative to remove such biases before these models are applied in climate change studies. Bias correction techniques vary in method and purpose: simple linear scaling (Lenderink *et al.*, 2007) corrects the monthly mean; power transformation (Leander and Buishand, 2007) and variance scaling (Chen *et al.*, 2011) correct the mean and the variance; quantile mapping (Ines and Hansen, 2006) corrects the higher-order moments of the distribution. Comparative analyses of various bias correction methods have found that quantile mapping is superior for temperature and rainfall other methods (Teutschbein and Seibert, 2012; Teng et al., 2015; Smitha et al., 2018); hence, we adopted this method in the study. The basic concept of quantile mapping is to compare the cumulative distribution function (CDF) of the climate model with that of observed data for the reference period and generate the correction function, which is then applied for a future time series. It can be expressed as

$$Var_{(cor),i} = F_{obs}{}^{-1}\left(F_{GCM}(Var_{(raw),i})\right) \ldots 1$$

Where Var refers to any climatic variables such as temperature or rainfall from a climate model for any day *i*; F_{obs}^{-1} and F_{GCM} are the inverse CDF of the observed climatic variables and the CDF of the corresponding output from the climate model during the reference period.

Bias correction of rainfall data is carried out using empirical distribution, which avoids assumptions about distribution fitting and corrects rainfall intensity and frequency (Boé et al., 2007; Themeßl et al., 2011). This method is more effective in reducing biases than using theoretical distribution (Gudmundsson *et al.*, 2012). For future rainfall values larger than those during the reference period, a correction factor for the highest quantile is used (Boé et al., 2007; Themeßl et al., 2012). Bias correction of temperature (both maximum and minimum) is carried out using a normal distribution (Teutschbein and Seibert, 2012). Theoretical distribution is a better choice when frequent extrapolation, as in future temperature, is required. Observed data from 1979-2005 for CMIP5 and 1979-2014 for CMIP6 are used for bias correction in the current study.

Daily maximum temperature (Tmax), minimum temperature (Tmin), and rainfall are projected for the near-future period of 2021-2050, and the relative changes are assessed with respect to the reference period of 1981-2010. Considering the climate models and the emission scenarios, future projections in the study consist of three cases:

(i) **Case A**: CMIP5 multi-model ensemble under RCP4.5 scenario
(ii) **Case B**: CMIP5 multi-model ensemble under RCP8.5 scenario
(iii) **Case C**: CMIP6 multi-model ensemble under SSP5-8.5 scenario

Case B and Case C allowed for comparison between CMIP5 and CMIP6 models under high emission scenarios. Inter-model uncertainty (IMU) is estimated as the standard deviation (SD) of the projected changes from the climate model ensemble (Hawkins and Sutton, 2012; Gu et al., 2019) given by

$$IMU = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(M_i - \bar{M})^2} \qquad \ldots 2$$

where '$\bar{M}$' is the ensemble mean projected change, and *n* is the number of climate models. *IMU* is expressed as a deviation from the ensemble average (in *°C* for temperature and *mm* for rainfall).

3.2. Climate extreme analysis using ETCCDI

The Expert Team on Climate Change Detection and Indices (ETCCDI), a collaboration between the World Meteorological Organization (WMO), Commission of Climatology (CCI), and the Climate Variability and Predictability project (CLIVAR), has identified 27 indices for climate extremes (Peterson, 2005; Zhang et al., 2011). These temperature and rainfall-based indices are often used in climate change impact studies and to detect changes in climate extremes (Adeyeri et al., 2019; Chen et al., 2020; Kim et al., 2020). In this study, 14 extreme indices (5 for temperature and 9 for rainfall) are used to assess projected changes in climate extremes for the near-future period. The details of these indices are presented in Table 2.

The indices are computed on an annual basis for reference and future periods. The Mann-Kendall (M-K) trend test (Mann, 1945; Kendall, 1975) is applied to assess the trends in climate indices. It is a rank-based test that employs Kendall Tau to measure the monotonic relationship between the variables and is not sensitive to whether the trend is linear or non-linear (Hisdal *et al.*, 2001). The test is nonparametric and independent of the distribution of the data. Trends are tested at a 95% significance level ($p<0.05$). The magnitude of the trends is quantified using Sen's slope estimator, a nonparametric procedure (Sen, 1968). The method computes the linear trend of the time series as a median value of slopes between all data pairs.

3.3. Onset and retreat of the rainy season

The onset and retreat dates of the rainy season are estimated using the cumulative daily anomaly of average rainfall in the basin, following Noska and Misra (2016) and Misra et al.

(2018). The onset date of the rainy season for a given year is defined as the day after the cumulative anomaly reaches the absolute minimum, and the retreat date is defined as the day on which the cumulative anomaly reaches the absolute maximum. The cumulative anomaly for the day *i* of the year *m* is computed as

$$C'_m(i) = \sum_{n=1}^{i}\left[R_m(n) - \bar{\bar{C}}\right] \; ... \; 3$$

where $\bar{\bar{C}} = {}^{1}/_{MN} \sum_{m=1}^{M} \sum_{n=1}^{N} R_m(n)$... 4

$R_m(n)$ is the daily average rainfall for the day *i* of year m in the basin and $\bar{\bar{C}}$ is the climatology of annual average rainfall over *N* days in *M* years.

The onset and retreat dates are computed for each year during the reference and the future periods using observed and climate model simulated rainfall data.

3.4. Probability distribution

To analyze more extreme climate statistics, the annual time series of TXx, TNx, RX1day, and RX5day are fitted into the Generalized Extreme Value (GEV) distribution, and the magnitudes of 20-year return period events during the reference and the near-future periods are estimated. GEV distribution has been extensively applied for climate extremes (Kharin et al., 2013; Kim et al., 2020). The CDF of GEV distribution is given by:

$$F(x|\mu,\sigma,k) = \begin{cases} exp\left[-exp\left(-{}^{x-\mu}/_{\sigma}\right)\right], k = 0 \\ exp\left[-\left\{1 + k\left({}^{x-\mu}/_{\sigma}\right)\right\}^{-1/k}\right], k \neq 0 \end{cases} \; ... \; 5$$

Where μ, σ, and k are the location, scale, and shape parameters, respectively. The parameters are estimated using probability-weighted moments (Greenwood et al., 1979; Hosking et al., 1985).

4. Results and Discussion

4.1. Projected change in mean climate

Fig. 3 and Table 3 present the projections of monthly and annual spatially-averaged Tmax, Tmin, and rainfall for the near-future period using the multimodel ensembles from CMIP5 and CMIP6. In the three cases (CMIP5 under RCP4.5, CMIP5 under RCP8.5, and CMIP6 under SSP5-8.5), the temperature is projected to rise in all the months in the near-future period, and the projected increase in Tmin is higher than Tmax. A higher rise in temperatures will be observed from March to May, while the least increase will occur from September to January, as suggested by CMIP5. However, CMIP6 models show the highest Tmin increment during November and December. The average increases in Tmax and Tmin suggested by CMIP5 multi-models are, respectively, 0.95°C and 0.97°C under the intermediate emission scenario and 1.10°C and 1.13°C under the high emission scenario. Similarly, the CMIP6 multimodel average indicates an increase of 1.29°C and 1.37°C in Tmax and Tmin relative to the reference period. As is evident, CMIP6's estimates are higher than CMIP5's projections. These results are similar to the findings by Almazroui et al. (2020) for South Asia, where temperature projections by CMIP6 models are 1-3°C higher than those by CMIP5 models for the 21st century. Zelinka et al. (2020) found that the increased sensitivity of CMIP6 models to external forcings is mainly due to stronger positive cloud feedback from decreasing low cloud coverages and albedo. The increased feedbacks are more prominent in the extratropics.

Unlike the temperature projections, monthly rainfall projection bands do not show any definite direction of future changes (Fig. 3g, h, and i), indicating high variability among the models' projections. However, using the multimodel average, we can estimate that monthly rainfall will decrease during the pre-rainy season (March to May) and increase during the rainy season (June to October) and the cool season (November to February). The pattern is consistent for CMIP5 and CMIP6 as well as for different cases. Overall, annual rainfall is projected to increase by 3% (37mm) for Case A, 4% (48mm) for Case B, and 0.5% (6mm) for Case C in the near-future.

Annual anomaly time-series of Tmax, Tmin, and rainfall for the reference and the near-future periods are shown in Fig. 4. During the reference period, trends of 0.018°C/year, 0.023°C/year, and 4.37mm/year are observed for Tmax, Tmin, and rainfall, respectively. However, only the temperature trends are significant at a 95% confidence level (CL). In the near-future, temperature shows strong increasing trends, significant at 95% CL. The CMIP6 multimodel average shows the highest trends for temperatures (about 0.05°C/year), while the trends are the lowest for the CMIP5 multimodel average under RCP4.5 (Case A). For rainfall, though all cases show increasing trends, they are significant only for Case B (4.91mm/year).

Spatial patterns for projected changes are presented in Fig. 5. Tmax does not show considerable spatial variation in any cases, though the highest temperature rise can be seen in the western part (the Nakhon Ratchasima province) and the south-eastern part (the Si Sa Ket province). For Tmin, the highest increase is in the eastern part (Surin, Roi Et, and Si Sa Ket provinces). The increase is close to 2°C (for Case C), compared to the reference period. The spatial pattern for projected change in rainfall shows variations in the basin within the range of -3% to +9%. Case A projects a decrease in rainfall for some locations in the western parts of the basin (Fig. 5g), while the highest projected increase is in the central part. A similar spatial pattern can also be seen for Case B, although with a higher percentage change. Mixed patterns are observed for Case C, with a projected decrease in rainfall (up to 3%) in the northwest and southeast of the basin. In all the cases, the highest increase is expected in the central part of the basin, while the western part (Nakhon Ratchasima) will observe the least change(increase or decrease) in annual rainfall.

The spatial pattern of Inter-model uncertainty (IMU), expressed as one standard deviation (SD) from the multimodel average, is presented in Fig. 6. Variations in IMU for temperature projections by the CMIP5 models lie between 0.20°C to 0.36°C and are found to be higher for Tmax. Since IMU for both Tmax and Tmin is less than the projected change for the near-future period, we can conclude that there is good agreement among the models and higher confidence in the projections. Interestingly, temperature projections using CMIP6 models show larger IMU (up to 0.6°C as shown in Fig. 6c and f) than CMIP5 models, despite having fewer ensemble members. It indicates high variation in temperature projections among the ensemble members in CMIP6.

In contrast, IMU for rainfall is larger in the CMIP5 ensembles than in the CMIP6 ensembles (Fig. 6g, h, and i). IMU for CMIP5 under RCP8.5 (Case B) ranges from 69mm to 158mm in the basin, while for CMIP6 (Case C), it varies between 42mm and 97mm. One argument could be that the reduced IMU in CMIP6 is because of fewer models considered (8 in CMIP6 compared to 14 in CMIP5). To address this issue, we applied the bootstrap technique for CMIP5 models in which 8 models are sampled from a pool of 14 models without replacement, and the corresponding IMU is calculated. The procedure is repeated 1,000 times to generate 1,000 realizations for statistics. From these 1,000 sets, it is found that the minimum IMU in the basin has an average value of 62mm (with SD of 10mm) and an average maximum value of 156mm (with SD of 19mm). These values of IMU are not very different from those calculated using the 14 models and are still higher than the IMU for the CMIP6 multimodel ensemble. Thus, analysis shows that the models' uncertainties for rainfall projection in CMIP6 have reduced compared to CMIP5. Nevertheless, the IMU for rainfall in all cases is significantly higher than the projected changes in the near-future period, which implies that rainfall simulations by these climate models do not have the same level of confidence as for temperature.

4.2. Projected changes in climate extremes

Fig. 7 presents the projected changes in the climate extremes using ETCCDI indices compared to the baseline period using model ensemble. There is an explicit agreement among the cases that temperature extremes will increase in the near-future and will be more than in the mean temperature (Fig. 7a and b). A 20-year return value of Tmax and Tmin are projected to increase on average by 2.3, 2.4, and 3.3°C and 1.7, 2.0, and 1.8°C for Case A, Case B, and Case C, respectively. In all cases, the increase in TN90p is higher than TX90p, which means a higher frequency of warm nights. It is similar to the findings of Ali et al. (2019). Model ensembles for Case A, Case B, and Case C show that TX90p will increase by 29, 33, and 38 days; TN90p will increase by 78, 90, and 110 days; and WSDI will increase by 26, 29, and 32 days in the near-future. The spread among the model projections is higher for Case C.

Projections for the changes in the rainfall extremes are presented in Fig. 7c and d. SDII in the near-future will increase 5-10%. While few GCMs project decrease in the R95p and R99p, the ensemble average suggests an average increase of 4-6% and 8-11%. The 20-year RVs of 1-day and 5-day maximum rainfall are expected to increase by 30-35% and 30-50%, respectively. Similarly, R20 and R40 are also projected to slightly increase (1-5 days) in the future. Interestingly, the annual number of rainy days is projected to decrease by 7, 8, and 6 days for Case A, Case B, and Case C, respectively. Model ensembles suggest there will be no change in CDD, although the projected range by individual models varies between -13 to +23 days. Annual CWD is projected to increase marginally (1-3 days).

The spatial patterns of the projected changes in the climate extremes based on the ensemble average are presented in Fig. 8, Fig. 9, and Fig. 10. TX90p is projected to increase between 25-33, 29-37, 34-44 days, and TN90p is projected to increase between 69-88, 80-100, and 90-135 days for Case A, Case B, and Case C, respectively. The central part of the basin will observe a higher increase in TX90p, while the southern part will observe a higher increase in TN90p. In addition, WSDI will increase by 21-33 days for Case A, 23-37 days for Case B, and 26-40 days for Case C in the basin. These results are suggestive of increased hot days frequency in the near-future.

All cases suggest increment in the future SDII, particularly in the northern and western parts of the basin (up to 16, 18, and 11% for Case A, Case B, and Case C, respectively). The number of rainy days will also decrease (Fig. 9n, o, and p), which is more prominent in the western part. CMIP5 models show that a higher increase in R95p and R99p will occur in the western parts (Nakhon Ratchasima and Buriram provinces) under both scenarios. In contrast, the CMIP6 model ensemble shows the highest increases in the southern part of Nakhon Ratchasima and Si Sa Ket provinces. CMIP5 models show that an increase in CDD will occur over a larger area and to greater magnitudes than CMIP6 models, although both sets of models agree that the decrease will be more in the western part of the basin. In some areas in the Nakhon Ratchasima province, the projected increase in CDD is up to 13 days. These are the exact locations where extreme rainfall is also projected to increase in the future. It implies that future rainfall will be temporally more uneven, resulting in increased severity for both extremities (wet and dry).

4.3. Analysis of climate trends for the reference and the near-future periods

Trends for Tmax, Tmin, and rainfall during the reference and the near-future periods are shown in Fig. S1 (Supplementary Material). For the reference period, spatially, the trends for Tmax and Tmin vary between 0.01 – 0.04°C/year and 0.01 – 0.03°C/year, respectively. Trends are more robust in the northeast and southwest for Tmax, while they are stronger in the western part of the basin for Tmin. The spatial variation of these trends appears to reduce in future projections. The near-future trends for Tmax and Tmin are projected to be between 0.014-0.020°C/year and 0.021-0.030°C/year for Case A and between 0.021-0.027°C/year and 0.029-0.039°C/year for Case B, respectively. Compared to CMIP5, CMIP6 models project significantly higher trends (0.042-0.057°C/year for Tmax and 0.048-0.064°C/year for Tmin). The annual average rainfall during the reference period also shows slightly increasing trends in most of the grids (Fig. S1i), and the results from the CMIP5 multimodel ensemble indicate that the increasing trend will prevail in the near-future period as well (trends under RCP8.5 are higher and up to 10 mm/year in the east). No significant trend is observed for most of the grid points using the CMIP6 multimodel ensemble.

Temperature extremes also show robust increasing trends (presented in Fig. S2 - Supplementary Material), particularly for TN90p. The spatial patterns of rainfall extremes trends are not as consistent or prominent as the temperature, although the variabilities will reduce in the near-future (Fig. S3 – Supplementary Material). The significance of the trend analysis for the climate indices is checked at 95% CL for each grid point. Fig. 11 is a boxplot providing information on the number of grids for which the trends are significant in the climate model ensemble during the reference and the near-future periods. The number of grids with trends significant at 95% CL is higher for temperature indices than the rainfall indices. During the reference period, the trends significant at 95% CL for annual Tmin are observed in 91 grids (entire basin) while they are significant in 75 grids for annual Tmax and 29 grids for annual rainfall. The number of grid points with trends significant at 95% CL for annual rainfall will be less in the future compared to the reference period For temperature indices, number of grids with significant trends will increase for all cases while for rainfall indices, only a few grids (below 20) have significant trends. Further details on the trend analyses can be referred in the Appendix S1 (Supplementary Material). Overall analyses suggest more confidence in the increase in temperature extremes than in rainfall extremes. It is also evident that temperature extremes will be felt across a larger spatial extent.

4.4. Projected changes in the onset and retreat of the rainy season

The simulations of the onset and retreat dates of the rainy season vary significantly among the climate models during the reference period. While the median onset date for the observation is 27 April, most climate models (10 out of 14 CMIP5 and 4 out of 8 CMIP6 GCMs) show the late onset of the rainy season (Fig. 12). Similarly, the median retreat dates are early for 12 out of 14 CMIP5 and all 8 CMIP6 climate models compared to the observed date (16 October) for the reference period. In general, climate models appear to simulate a shorter rainy season than the observed data suggests. The variability of the onset date, measured by inter-quartile range (IQR), for most climate models is also higher than the observed data. However, the variability is comparable for the retreat dates.

In the near-future period, projections using climate models show a general trend of delay in the onset of the rainy season. The projected changes in the median value of the onset, retreat, and length of the rainy season are presented in Fig. S4 (Supplementary Material). For Case A, 9 out of 14, for Case B, 11 out of 14, and for Case C, 6 out of 8 models show a delay in the onset dates compared to the respective median dates during the reference period. Similarly, median values also show that for Case A, 10 out of 14, for Case B, 9 out of 14, and for Case C, 4 out of 8 models predict a late retreat of the rainy season in the near-future period. However, results from most of the models show a reduction in the length of the rainy season. For Case A, 9 models show a decrease in the rainy season length on average by 9 days; Case B, 6 models show an average decrease of 5 days, while 8 models show an average increase of 5 days; Case C, 5 models show an average decrease of 13 days. Among CMIP5 models, FGOALS-s2 and MIROC5 show the most changes in the onset and retreat dates, while similar changes are exhibited by CNRM-CM6-1, EC-Earth3P-HR, and HadGem3-GC31-MM in CMIP6.

Fig. 12 also suggests that variability (especially for the onset date) in the near-future period will be significantly more than during the reference period. With the reduced length of the rainy season and increased variabilities in the onset and retreat dates, future rainfall is likely to have more extremes (as previously suggested by the extreme indices). The projected changes in the onset date of the rainy season will not only have implications for climate extremes and severely affects agricultural activities in the basin since cultivation here is primarily rainfed.

4.5. Return periods of annual maxima of temperature and rainfall

Spatial patterns of 20-year return period values (RVs) for TXx, TNx, RX1day, and RX5day during the reference and the near-future periods (using the multimodel average) are presented in Fig. 13. 20-year RVs of TXx and TNx are expected to increase by 2.30 and 1.72 for Case A, by 2.38 and 2.05 for Case B, and 3.18 and 1.87 °C for Case C. Higher increment in the RV of TXx is projected for the northwestern part (in the Nakhon Ratchasima province) while for TNx, the RV is projected for the northeastern part of the basin (in Roi Et and Si Sa Ket provinces). The results show that projected changes in RVs are greater than the average temperature changes. Similarly, RVs of RX1day and RX5day are also expected to increase in the future. The CMIP5 multimodel ensemble suggests that projected increases in RX5day will be higher than in RX1day, while the CMIP6 model ensemble shows a similar percentage increase in both extremes. RX1day and RX5day are projected to increase by 31 and 48% for Case A, 32 and 49% for Case B, and 31 and 26% for Case C in the near-future period. The RVs for rainfall are higher in the eastern part of the basin compared to the western part.

The projected changes in the future rainfall can be either attributed to changes in the dynamic component (pertinent to changes in the large-scale convergence) or the thermodynamic component (pertinent to changes in the atmospheric moisture content). The Asian monsoon systems are primarily caused by shifts in atmospheric circulation (Oh *et al.*, 2018), driven by the thermal contrast between the Euroasian landmass and the surrounding oceans (Wang *et al.*, 2014). For the South Asian Summer monsoon (covering the study area), (Walker *et al.*, 2015) estimate that the dynamic component accounts for 92% of the annual rainfall variability while the thermodynamic component accounts for only 8%. This implies that changes in the dynamic components under climate change are the main driver of future rainfall changes. In addition, Sørland and Sorteberg (2015) and Sudharsan *et al.* (2020) reported that changes in dynamics also dominate changes in the extreme rainfall event over the South Asian Monsoon domain. Under the climate change scenario, Dairaku and Emori (2006) also found that extreme rainfall over the South Asian landmass will be enhanced due to changes in the dynamics. In the case of the study area, although the annual rainfall is not projected to change significantly in the future, extreme rainfall events (as indicated by SDII, R95p, R99p, RX1day, and RX5day) will increase and are likely to be contributed by changes in the atmospheric circulation governing the summer monsoonal rainfall. Verification of contributions of dynamics and thermodynamics changes in the extreme climate in the basin is beyond the scope of the present study and will be undertaken in future work.

4.6. Inter- and Intra- CMIP comparison of near-future projections for the high emission scenario

The projected mean and the extreme climate by the individual models from CMIP5 and CMIP6 under the high emission scenario (RCP8.5 for CMIP5 and SSP5-8.5 for CMIP6 models) are compared. Although the numbers of models considered in CMIP5 and CMIP6 are different, the results can still show the climatic response of the models under the high emission external forcings scenario. Table 4 presents the basin's average projected changes in mean and the extreme climate indices by each model considered in the study. The 14-member CMIP5 ensemble shows that the highest increase in average temperature is projected by HadGEM2-AO, FGOALS-s2, GFDL-CM3, and IPSL-CM5A-MR, while CNRM-CM5, BNU-ESM, and NorESM1-M project the lowest increases. It is also found that changes in mean temperature have strong positive correlations with changes in temperature extremes (correlation of 0.90 with TX90p, 0.93 with TN90p, and 0.81 with WSDI). HadGEM2-AO projected the highest increases in temperature extremes (64, 123, and 63 days annually for TX90p, TN90p, and WSDI respectively) while CNRM-CM5 projected the lowest increases (13, 53, and 8 days annually for TX90p, TN90p, and WSDI, respectively). Similarly, like temperature indices, projected changes in average rainfall also appear to have a strong correlation with the projected changes in rainfall extremes. For instance, rainfall has a positive correlation with SDII (0.65), R20 (0.91), R40 (0.84), and wet days count (0.72), and a negative correlation with R95p (-0.51) and R99p (-0.41). No significant correlation is found with CDD and CWD. Can-ESM2, IPSL-CM5A-MR, MPI-ESM-MR, and NorESM1-M show the biggest changes in rainfall extremes in the near-future period.

For the 8-member CMIP6 ensemble, all the models from MOHC have projected higher increases in temperature indices, while models from CNRM have projected the least increase (same as in the CMIP5 ensemble). The correlations between average temperature changes with changes in temperature extremes are above 0.9 for CMIP5 models. Similarly, the correlations between average rainfall changes with rainfall extremes are also more in CMIP6 (0.86 for SDII, 0.98 for R20, 0.81 for R40, 0.83 for wet days count, -0.54 for R95p, and -0.60 for R99p). It shows that an increase in average rainfall in the future will most likely be reflected as an increase in extreme rainfall. Overall, the assessment of the climate in CMIP6 shows higher temperature extremes than by CMIP5 models. However, the multimodel ensemble of CMIP6 is primarily influenced by climate models from MOHC (4 out of 8), which have projected the highest increases. For extreme rainfall indices, the CMIP6 ensemble results are less severe than the results of the CMIP5 ensemble. It is also worth noting that models which project higher severities in temperature indices show moderate severities in rainfall indices and vice-versa.

5. Conclusions

There is consensus among the scientific community that climate change has been contributing to many recent extreme events, and such events are likely to increase in severity and frequency in the future. Assessments of how the extremes will change under climate change scenarios can provide vital information for managing climate-related risks and developing climate change adaptation measures, ultimately helping to improve human resilience towards these potential hazards. This study provides a comprehensive assessment of the changes in mean and extreme climate conditions in northeast Thailand for the near-future period (2021-2050).

Climate simulations from 14 CMIP5 and 8 CMIP6 models are bias-corrected using the quantile mapping method, and the projected changes are assessed using 14 ETCCDI and 20-year return values. We found that the rate of temperature increase in the near-future will be higher than the rate observed in the recent decades, and the project changes in extremes will exceed the mean changes. Notably, the latest climate models from CMIP6 show that temperature might increase by up to 0.5°C per decade. The maximum increase in average temperature will be during the pre-rainy season months (March to May). The projected changes in annual rainfall are not as unanimous among the climate models as for temperature. Only about half of the climate models from both phases suggest an increase in annual rainfall. Though no significant change in annual average rainfall is projected, monthly climatology shows that rainfall will decrease during the pre-rainy season (March to May) and increase during the rainy season (June to October). For temperature, model-related uncertainties (assessed using IMU) are higher in CMIP6 than CMIP5, although the projected temperature changes in both CMIP phases are much more significant than the uncertainties. For rainfall, model-related uncertainties are reduced in CMIP6 (by 40%); however, they are still larger than the projected changes. As rainfall involves complicated physical processes, feedback, and interactions among various climate system components, it may not be fully represented by current climate models. Moreover, rainfall often occurs at a spatial extent smaller than a climate model's resolutions. So, rainfall projections are associated with larger uncertainties than temperature. In CMIP6, an improved resolution of the models could be a reason for reduced IMU for rainfall than in CMIP5 models. The reduced length of the rainy season, along with the increased variability in the onset and retreat dates, will certainly have implications for future extremes and agricultural activities in the basin.

Significant increases in TX90p, TN90p, and WSDI are projected for the near-future period, especially under high emission scenario and by CMIP6 climate models. Increases in Tmin indices are higher than those for Tmax, suggesting that warmer nights in the future will heavily contribute to the rise in temperature. The results also suggest that hot spells will be more frequent and more prolonged in the near-future period. The magnitude of extreme rainfall is also expected to increase, although the projected increase by CMIP6 models is smaller than by CMIP5 models. All the CMIP6 models (except HadGem3-GC31-HM) project that average rainfall intensity will increase in the future, and most of the models (10 out of 14 CMIP5 and 7 out of 8 CMIP6) indicate a decrease in the annual number of rainy days, by as much as 15 days. Along with these, the projected increase in R20, R40, R95p, and R99p points towards the temporal redistribution of rainfall, which will result in increased severity of both rainfall extremities (wet and dry). The multimodel ensembles used here also suggest that the 20-year RV of RX1day and RX5day will increase by more than 30%. It will have severe implications for the design of infrastructure since the current design criteria may prove inadequate.

This study has provided an assessment of climate extremes based on multimodel ensembles from CMIP5 and CMIP6. The present work can be taken further to assess impacts on the basin's hydrology and for developing appropriate water resources management strategies.

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Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Table 1: *Details of climate models selected from CMIP5 and CMIP6.*

S.N.	Model Designation	Modeling Group	Atmospheric resolution (lat × lon)	Number of vertical levels	Ensemble member
	CMIP5				
1.	ACCESS1-0	Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM), Australia	1.25° × 1.875°	38	r1i1p1
2.	BNU-ESM	Beijing Normal University	2.8° × 2.8°	26	r1i1p1
3.	CanESM2	Canadian Centre for Climate Modelling and Analysis	2.8° × 2.8°	35	r1i1p1
4.	CCSM4	US National Center for Atmospheric Research	0.9° × 1.25°	27	r1i1p1
5.	CMCC-CM	Centro Euro-Mediterraneo per I Cambiamenti Climatici	0.75° × 0.75°	31	r1i1p1
6.	CNRM-CM5	Centre National de Recherches Meteorologiques / Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique	1.4° × 1.4°	31	r1i1p1
7.	FGOALS-s2	The State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics, The Institute of Atmospheric Physics	1.7° x 2.8°	26	r1i1p1
8.	GFDL-CM3	NOAA Geophysical Fluid Dynamics Laboratory	2° × 2.5°	24	r1i1p1
9.	HadGEM2-AO	National Institute of Meteorological Research/ Korea Meteorological Administration	1.25° x 1.875°	60	r1i1p1
10.	HadGEM2-ES	UK Met Office Hadley Centre	1.25° × 1.875°	38	r1i1p1
11.	IPSLCM5A-MR	Institut Pierre-Simon Laplace, France	1.25° × 2.5°	39	r1i1p1
12.	MIROC5	University of Tokyo, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	1.4° x 1.4°	40	r1i1p1
13.	MPI-ESM-MR	Max Planck Institute for Meteorology (MPI-M)	1.875° × 1.875°	95	r1i1p1
14.	Nor-ESM1-M	Norwegian Climate Centre	1.9° × 2.5°	26	r1i1p1
	CMIP6				
1.	CNRM-CM6-1	Centre National de Recherches Meteorologiques (CNRM)/ Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique	1.4° x 1.4°	91	r1i1p1f2
2.	CNRM-CM6-1-HR	Centre National de Recherches Meteorologiques (CNRM) / Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique	0.5° x 0.5°	91	r1i1p1f2
3.	EC-Earth3P	EC-EARTH consortium	0.7° x 0.7°	91	r1i1p2f1
4.	EC-Earth3P-HR	EC-EARTH consortium	0.35° x 0.35°	91	r1i1p2f1
5.	HadGEM3-GC31-HH	UK Met Office Hadley Centre	0.23° x 0.35°	85	r1i1p1f1
6.	HadGEM3-GC31-HM	UK Met Office Hadley Centre	0.23° x 0.35°	85	r1i1p1f1
7.	HadGEM3-GC31-MM	UK Met Office Hadley Centre	0.55° x 0.83°	85	r1i1p1f1
8.	HadGEM3-GC31-LL	UK Met Office Hadley Centre	1.25° x 1.875°	85	r1i1p1f1

Table 2: *Details of ETCCDI used in the study.*

S.N.	Index	Description	unit
1.	TX90p	Time when daily maximum temperature > 90th percentile	day
2.	TN90p	Time when daily minimum temperature > 90th percentile	day
3.	TXx	1-day maximum of daily maximum temperature	°C
4.	TNx	1-day maximum of daily minimum temperature	°C
5.	WSDI	Annual count when at least six consecutive days of maximum temperature > 90th percentile	day
6.	RX1day	Annual maximum 1 day precipitation	mm
7.	RX5day	Annual maximum consecutive 5 days precipitation	mm
8.	SDII	The ratio of annual total precipitation to the number of wet days (≥ 1 mm)	mm/day
9.	R20	Annual count when precipitation ≥ 20 mm	day
10.	R40	Annual count when precipitation ≥ 40 mm	day
11.	CDD	Maximum number of consecutive days when precipitation < 1 mm	day
12.	CWD	Maximum number of consecutive days when precipitation ≥ 1 mm	day
13.	R95p	Annual total precipitation from days > 95th percentile	mm
14.	R99p	Annual total precipitation from days > 99th percentile	mm

Table 3: *Monthly and annual projected changes in Tmax, Tmin, and rainfall in the near-future period using the multimodel average of CMIP5 and CMIP6.*

Climatic variables	Period	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Tmax (°C)	**1981-2010**	31.23	33.67	35.56	36.3	34.66	33.64	32.99	32.41	31.9	31.27	30.74	29.97	32.86
	2021-2050						Projected change in °C							
	CMIP5 - RCP4.5	0.85	0.76	1.27	1.42	1.20	0.83	1.18	1.00	0.81	0.75	0.67	0.69	0.95
	CMIP5 - RCP8.5	1.12	0.93	1.41	1.50	1.37	1.00	1.24	1.10	0.97	0.84	0.86	0.80	1.10
	CMIP6 – SSP5-8.5	1.10	1.23	1.45	1.52	1.44	1.07	1.20	1.27	1.12	1.22	1.45	1.42	1.29
Tmin (°C)	**1981-2010**	18.17	20.67	23.06	24.80	24.91	24.87	24.52	24.34	24.02	23.13	20.74	18.07	22.61
	2021-2050						Projected change in °C							
	CMIP5 - RCP4.5	1.03	0.94	1.09	1.16	1.06	0.91	1.18	1.07	0.73	0.82	0.92	0.90	0.98
	CMIP5 - RCP8.5	1.34	1.15	1.25	1.27	1.20	1.07	1.29	1.25	0.88	0.93	1.06	0.92	1.13
	CMIP6 – SSP5-8.5	1.45	1.43	1.29	1.26	1.40	1.28	1.50	1.41	0.96	1.11	1.65	1.77	1.37
Rainfall (mm)	**1981-2010**	5.0	15.1	40.9	83.1	163.1	154.5	164.6	203.4	244.5	137.3	28.8	2.8	1,243
	2021-2050						Projected change in mm							
	CMIP5 - RCP4.5	1.2	2.5	-2.5	-10.5	-9.9	2.1	0.6	11.2	27.6	9.3	4.2	1.6	37
	CMIP5 - RCP8.5	2.5	2.0	-6.2	-11.1	-13.3	4.5	9.0	16.4	24.9	15.2	3.6	1.2	49
	CMIP6 – SSP5-8.5	1.3	-0.5	-3.0	-8.9	-4.1	16.8	0.6	-4.4	6.2	0.8	0.1	1.4	6

Table 4: *Comparison of projections by climate models from CMIP5 and CMIP6 for the high emission scenario.*

ID	Climate models	Projected changes in														Projected changes in 20-year return period			
		Tmax	**Tmin**	**Rainfall**	**TX90p**	**TN90p**	**WSDI**	**SDII**	**R20**	**R40**	**wet days**	**R95p**	**R99p**	**CDD**	**CWD**	**TXx**	**TNx**	**RX1day**	**RX5day**
	(units)	(°C)	**(°C)**	**(%)**	**(days)**	**(days)**	**(days)**	**(%)**	**(days)**	**(days)**	**(days)**	**(%)**	**(%)**	**(days)**	**(days)**	**(°C)**	**(°C)**	**(%)**	**(%)**
	CMIP5																		
1.	ACCESS1-0	1.22	1.17	-6.7%	51	106	51	10%	-0.2	0.5	-17.9	5.0%	2.5%	-4	4	1.18	1.81	10%	30%
2.	BNU-ESM	0.75	0.92	12.1%	21	95	15	11%	2.7	1.8	0.8	1.4%	0.8%	16	7	1.79	1.55	18%	56%
3.	Can-ESM2	1.20	1.16	14.3%	37	98	26	20%	4.1	1.9	-5.4	3.1%	2.3%	-11	1	2.51	2.10	44%	53%
4.	CCSM4	1.04	0.75	-1.0%	17	68	16	4%	0.1	0.0	-6.5	1.5%	0.9%	4	1	2.82	1.41	21%	33%
5.	CMCC-CM	1.01	1.24	1.9%	29	82	27	15%	2.1	1.4	-14.0	4.2%	1.7%	23	1	1.86	2.36	22%	13%
6.	CNRM-CM5	0.47	0.81	10.5%	13	54	8	8%	1.4	0.8	2.1	0.5%	1.7%	-13	0	1.38	1.72	85%	63%
7.	FGOALS-s2	0.91	1.44	-3.8%	31	119	23	7%	-0.5	0.9	-11.9	5.6%	3.7%	-1	0	2.69	3.14	28%	44%
8.	GFDL-CM3	1.56	1.46	-0.8%	46	116	40	10%	1.1	0.5	-12.6	3.3%	1.5%	6	7	2.91	2.32	19%	69%
9.	HadGEM2-ES	0.87	0.90	-10.1%	30	70	35	3%	-1.6	-0.3	-16.1	4.6%	2.6%	1	1	0.34	0.63	19%	29%
10.	HadGEM2-AO	1.71	1.59	-2.9%	65	124	63	3%	-1.7	0.1	-7.7	2.4%	2.6%	-5	2	2.17	2.11	26%	35%
11.	IPSL-CM5A-MR	1.50	1.15	12.0%	45	110	38	21%	3.3	1.8	-9.7	3.0%	2.2%	2	7	5.10	2.93	82%	129%
12.	MIROC5	0.95	1.23	6.7%	26	79	19	4%	1.4	0.5	2.5	-1.3%	-0.6%	0	6	2.45	2.49	11%	24%
13.	MPI-ESM-MR	1.18	1.29	10.6%	33	78	29	20%	3.6	2.1	-8.7	3.4%	1.9%	13	1	2.63	2.53	24%	33%
14.	NorESM1-M	0.97	0.77	12.9%	20	63	22	12%	3.2	2.0	1.0	2.2%	1.2%	-13	2	3.52	1.58	36%	72%
	CMIP6																		
1.	CNRM-CM6-1-HR	0.99	1.12	9.9%	32	81	20	8%	3.0	0.9	1.0	-0.9%	-0.5%	-11	4	2.49	1.05	5%	6%
2.	CNRM-CM6-1	1.14	1.18	-1.5%	30	70	21	2%	-0.5	0.2	-5.0	2.0%	1.7%	-7	3	2.32	1.48	21%	33%
3.	EC-Earth3P-HR	1.18	1.42	2.1%	26	99	30	7%	1.3	0.7	-5.8	2.0%	1.2%	5	4	2.23	2.25	16%	21%
4.	EC-Earth3P	0.80	1.07	2.6%	17	67	20	7%	0.8	1.0	-4.5	2.6%	1.6%	-1	2	1.86	1.65	16%	16%
5.	HadGem3-GC31-HH	1.82	1.89	-0.1%	49	141	43	5%	0.0	0.1	-6.2	2.2%	2.2%	1	-2	4.10	2.21	70%	42%
6.	HadGem3-GC31-HM	1.97	1.97	-5.2%	53	144	36	-1%	-1.1	-0.4	-6.1	1.4%	1.0%	-6	-2	4.17	1.80	32%	13%
7.	HadGem3-GC31-LL	1.80	1.93	2.3%	49	144	49	8%	1.2	1.0	-6.9	3.7%	2.3%	-6	0	4.15	1.99	44%	46%
8.	HadGem3-GC31-MM	1.90	1.80	-5.2%	54	139	42	1%	-1.2	0.1	-8.4	3.0%	2.1%	-5	-2	5.18	1.94	44%	28%