

A High-Resolution Future Climate Dataset for Vietnam based on Coupled Model Intercomparison Project Phase 5 (CMIP5) products

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Abstract

This study generates a projected daily temperature and precipitation dataset over Vietnam at the high resolution of 0.1° . The Bias Correction and Spatial Disaggregation (BCSD) method is applied to the outputs of 31 global climate models (GCMs) of the Coupled Model Intercomparison Project Phase 5 (CMIP5) to create a new dataset, called CMIP5-VN. Observed gridded temperature and precipitation data during the period 1980–2005 are used to correct the biases in the CMIP5 GCMs and to construct a statistical transfer function to be applied for the future period 2006–2100. The changes in the future CMIP5 projections are disaggregated to the target resolution of 0.1° and then scaled with the observed daily values to match the downscaled monthly products. Results show that the CMIP5-VN could well illustrate the changes in future temperature and precipitation while still preserving the seasonal patterns of local climatology. Warming over the entire Vietnam is projected to continue to the end of the 21st century under all four representative concentration pathways (RCP) scenarios RCP2.6, RCP4.5, RCP6.0, and RCP8.5. Average temperature over Vietnam is projected to increase by $1.3 \pm 0.52^\circ\text{C}$ under RCP2.6 and by $3.85 \pm 0.85^\circ\text{C}$ under RCP8.5 between 2080–2099 and 1986–2005. The future increase is more intense in the northern regions than in the southern regions and higher in summer than in winter. Precipitation is projected to increase by $1.16 \pm 7.1\%$ under RCP2.6 and by $4.41 \pm 9.2\%$ under RCP8.5. In Central Vietnam, there is a consistent rainfall increase in the

future rainy season.

Keywords

CMIP5, BCSD, Bias correction, Spatial disaggregation, Climate downscaling, Vietnam

Introduction

The Earth is getting warmer. The Sixth Assessment Report (AR6) of the Intergovernmental Panel on Climate Change (IPCC) indicates that the global average surface temperature during 2010–2019 has increased by $\sim 1.09^{\circ}\text{C}$ compared to 1850–1900 (Arias et al. 2021). The warming is projected to be virtually certain in the future at global and regional scales (Arias et al. 2021). To assess the impacts of global warming on human and natural systems and to prepare for climate change adaptation and mitigation measures, future climate information at different spatial scales, including local and regional ones, is useful (Milly et al. 2008; Giorgi and Bi 2009).

The Coupled Model Intercomparison Project (CMIP) is an international experimental protocol coordinated by the World Climate Research Programme (WCRP) for producing and studying the outputs of global climate models (GCMs). Providing the scientific ground for the IPCC Fifth Assessment Report (AR5) (IPCC 2013), the CMIP Phase 5 (CMIP5) provides simulations from state-of-the-art GCMs that reflect a joint effort involving many climate research organizations worldwide (Taylor et al. 2012). In the CMIP5 project, a number of climate models

run one historical simulation and four Representative Concentration Pathway (RCP) future scenarios. The RCP scenarios are developed based on the future estimated radiative forcing, covering a period up to the year 2100 or later (van Vuuren et al. 2011). The four RCPs consist of RCP2.6 (a scenario characterized by a low radiative forcing level), RCP4.5 and RCP6.0 (medium stabilization scenarios), and RCP8.5 (a high radiative forcing scenario), representing different pathways upon the projected impacts of land use and emission of greenhouse gases. Accordingly, RCP2.6 expresses a low greenhouse gas concentration scenario in the future with radiative forcing estimated at 2.6 W/m^2 by 2100, and so forth with the other RCPs (Moss et al. 2010).

Though CMIP5 outputs can generally reproduce the major climate indicators at global scales, it is still challenging to directly use them to produce relevant climate information at local to regional scales due to their coarse spatial resolution (typically coarser than 100 km) (Taylor et al. 2012; Eyring et al. 2016). This raises concerns about adequately using such products as the driving force in other comprehensive environment-socio-economic assessment models to obtain reliable results to support researchers and policymakers in regional planning. As a consequence, downscaling methods, which transfer GCMs' data from a coarse grid resolution into a much higher spatial resolution, should be applied for limited-area domains.

There are two popular approaches to perform the downscaling: dynamical and statistical. For

dynamical downscaling, higher-spatial resolution models, which are often known as regional climate models (RCMs), are used. The large-scale lateral boundary conditions taken from GCMs are nested into RCMs. Although dynamical downscaling has the advantage of well representing the local scale feedback and dynamical processes (Seaby et al. 2013; Tangang et al. 2020), it is an extremely computationally demanding method; thus, its application for downscaling multiple GCMs and scenarios is limited. For statistical downscaling, it is conducted based on empirical, spatial, and temporal relationships between large-scale and local-scale climate variables (e.g. Murphy 1999; Wilby et al. 2004; Fowler, Blenkinsop, and Tebaldi 2007). These relationships are assumed to be unchanged with time; thus, they can be used to project future conditions. The primary advantage of statistical downscaling is that it is computationally inexpensive and much faster than dynamical downscaling so that it can be easily applied to generate high-resolution simulations with multiple GCMs. Additionally, statistical downscaling can provide climate information at any specific resolution, so its results can be directly used in climate change impact assessments.

Previous studies showed the skillful performance of different statistical methods that could be comparable to dynamical downscaling (e.g. Salathé 2003; Widmann et al. 2003; Maurer and Hidalgo 2008). Among those methods, the bias correction and spatial disaggregation (BCSD) approach is considered reliable and effective for downscaling temperature and precipitation

data (Wood et al. 2004). The BCSD has been extensively adopted in various climate impact studies in many parts of the world (e.g. Rasmussen et al. 2016; Eum et al. 2017; Xu and Wang 2019; Zhang et al. 2019).

Located in the tropical region in Southeast Asia, with a long coastline of about 3260 km and an estimated total area of 329,560 km², Vietnam has been known as one of the countries heavily affected by climate change (MONRE 2009). This situation urged the government to establish reliable climate change information for short-term and long-term action plans to cope with climate change. As a result, Vietnam sea level rise and climate change (SLRCC) scenarios were released in 2009 and 2012 (MONRE 2009; MONRE 2012) and followed up with the latest version in 2016 (MONRE 2016). Outputs of 16 dynamical downscaling experiments based on five different RCMs and ten driving GCMs for two RCP scenarios, 4.5 and 8.5, were analyzed in the latest SLRCC. It should be noted that the accuracy of an RCM simulation depends on the quality of its driving GCM (van Oldenborgh et al. 2009; Déqué et al. 2012; Diaconescu and Laprise 2013; Tang et al. 2017; Tamara et al. 2019), thus using several GCMs for limited downscaling cases may result in inconsistent future projections. Under the framework of the Coordinated Regional Climate Downscaling Experiment – Southeast Asia (CORDEX–SEA), different dynamical downscaling simulations using seven different RCMs were conducted (Trinh-Tuan et al. 2019; Tangang et al. 2020; Nguyen-Thuy et al. 2021), providing additional

projected climate information for Vietnam. However, the number of driving GCMs (11) and scenarios (2) used in CORDEX-SEA is still limited, leading to the possibility that future projection might fall outside what has been accounted for in the selected GCMs. Therefore, our present study is a primary attempt to develop a new comprehensive and high-resolution dataset over Vietnam from a large number of CMIP5 GCMs. The new data, hereafter called CMIP5-VN, consisting of daily mean, maximum, and minimum temperature, and precipitation, are created using the BCSD downscaling method based on a total of 31 CMIP5 GCMs and four RCPs. The new CMIP5-VN dataset is expected to supplement the existing climate change data in Vietnam that were previously obtained by the dynamical downscaling method.

Methods

Study domain

Characterized by the diverse topography and specific location in the eastern part of the Indochina Peninsula, the climatic conditions in Vietnam vary significantly among regions. Based on radiation, temperature, and rainfall criteria, Vietnam's climate has been divided into seven regions, including 1) the Northwest (denoted as R1), 2) the Northeast (denoted as R2), 3) the Red River Delta (denoted as R3), 4) the North Central (denoted as R4), 5) the South Central (denoted as R5), 6) the Central Highland (denoted as R6), and 7) the South region (denoted as R7) (Nguyen and Nguyen 2004; Phan et al. 2009) (Fig. 1).

Daily observation data

Daily temperature and rainfall data respectively at 147 and 481 stations from 1980–2005 are acquired from the Vietnam Meteorological and Hydrological Administration (VMHA) (Fig. 1). Then, the observed station data are interpolated to a $0.1^\circ \times 0.1^\circ$ gridded dataset (hereinafter called OBS) by using the Sphere map interpolation technique (Willmott et al. 1985) for rainfall and the Kriging interpolation technique (Switzer 2014) for temperature variables, including near-surface daily average (T2m), daily maximum (Tmax) and minimum (Tmin) temperatures. Nguyen-Xuan et al. (2016) showed that the Spheremap interpolation technique has advantages in creating a gridded rainfall dataset over Vietnam in comparison with several other interpolation methods such as Cressman (Cressman 1959), Inverse Distance Weighted (Shepard 1968), or Kriging (Switzer 2014). Besides, the Kriging technique is an effective interpolation method for continuous spatial variables such as temperature (Sluiter 2009; Wu and Li 2013). The newly-created gridded OBS dataset is used in this study to bias-correct GCM data and to estimate future climate patterns in Vietnam.

Model data

Daily rainfall (R) and temperatures (T2m, Tmax, Tmin) from 31 CMIP5 GCMs (Table 1) are obtained via the Earth System Grid Federation portal (ESGF, <https://esgf-node.llnl.gov/projects/cmip5/>). The present-day simulations for the period 1980–2005 are used

as the basis to construct statistical relationships between the high-resolution OBS dataset and the coarse resolution GCMs. Those relationships are further used to statistically downscale the projected GCM variables for the period 2006–2100 under the RCPs 2.6, 4.5, 6.0, and 8.5.

The BCSD approach

The bias-correction and spatial disaggregation (BCSD) technique, initially developed by Wood et al. (2002, 2004), has been widely used to generate precipitation and temperature data at high resolution while effectively reducing climatological biases in GCMs. Herein, we apply the BCSD method to create a fine-scale daily climate dataset over Vietnam from the CMIP5 GCM outputs.

The different steps of the BCSD method are shown in Fig. 2. The BCSD downscaling process can be divided into two major stages, namely bias correction and spatial disaggregation. In the first stage, a quantile mapping (QM) approach is applied to bias-correct the raw GCM outputs. More precisely, a transfer function that maps the distribution of simulations onto observations (Gudmundsson et al. 2012) is created. The cumulative distribution functions (CDFs) for both observations and historical GCM simulations are separately constructed for each climate variable (P, Tmax, Tmin, T2m) for each of the 12 months (January – December) within each grid cell. Then, the biases in the GCM monthly outputs, re-gridded to the same intermediate resolution of $1^\circ \times 1^\circ$, are corrected by mapping the quantiles at the same probability between

the GCM simulated data and the OBS dataset. The primary objective of the QM is to find the BC climate fields with the assumption:

$$X_{BC} = F_o^{-1}(F_{GCM}(X_{GCM})) \quad (1)$$

where X_{BC} and X_{GCM} respectively denote the BC and original GCM data during a specific reference period. $F_{GCM}()$ and $F_o^{-1}()$ are the CDFs of the GCM simulated data and the inverse CDF of the observed data, respectively. For temperature, the BC is first applied on the detrended data, then the trend at each grid point is added back afterward to preserve the climatic trends in the original GCM (Wood et al. 2004; Maurer 2007; Sobie et al. 2012). Then, the climatological mean bias adjustment between the GCM and the OBS temperature at each grid point is subsequently applied, producing the final BC temperature data.

In the second stage, the spatial disaggregation (SD) is adopted to spatially translate the BC GCM data from the intermediate resolution of $1^\circ \times 1^\circ$ to the targeted high-resolution of $0.1^\circ \times 0.1^\circ$, by implementing the following steps: (1) the additive and multiplicative change-factors at the intermediate resolution between the BC data and observations for the reference period are estimated for temperature and precipitation, respectively, then spatially downscaled to the targeted high-resolution using a bilinear interpolation (BIP); (2) the high-resolution change-factors are added (for Tmax, Tmin, and T2m) or multiplied (for R) to the high-resolution observation climatology to construct the high-resolution downscaled BC monthly

climatological fields; (3) finally, the BC GCM daily values of a future month are obtained by randomly taking the same month of the observations in the reference period and additively (for temperature) and multiplicatively (for precipitation) adjusting its daily values to reproduce the monthly BC data. This step is called “temporal disaggregation”. For precipitation downscaling, temporal disaggregation requires an assessment of the scaling factor and the number of wet days to avoid unrealistic precipitation values. For example, if the number of wet days in the selected month is less than three and its scaling factor is greater than three, another year with more wet days in that month will be selected.

In this study, the implementation of the BCSD approach contains two main phases as follows:

- Phase 1 — Testing: the climatological fields of the period 1980–1995 from the OBS and GCM are used to develop the statistical relationship between the simulations and observations. Then, the BCSD is applied to the independent period 1996–2005, and the results (hereafter called BCSD-CMIP5) are compared with OBS to examine the performance of the BCSD in reproducing past climate conditions.
- Phase 2 — Future downscaling: To maximize the construction period of the BCSD approach (Reiter et al. 2016; Trinh-Tuan et al. 2019), the total 26 years period from 1980 to 2005 is used to bias correct the GCM projections and to guide spatial disaggregation

for the future period 2006–2100. The BCSD is applied to all GCM models and RCP scenarios listed in Table 1 to generate the targeted CMIP5-VN dataset.

The performance of the BCSD downscaled data for the CMIP5 GCMs, i.e. the BCSD-CMIP5, in representing the observed temporal and spatial distributions is assessed in Section 3.1. In Section 3.1, we also compare the performance of the BCSD with the traditional and effortless BIP data (hereafter called BIP-CMIP5) using the added value (AV) metric (Di Luca et al, 2013) as follows:

$$AV = (X_{\text{BIP-CMIP5}} - X_{\text{OBS}})^2 - (X_{\text{BCSD-CMIP5}} - X_{\text{OBS}})^2 \quad (2)$$

where the subscripts OBS, BIP-CMIP5, and BCSD-CMIP5 denote the values given by these different datasets, respectively. Accordingly, the higher the AV value is, the better the BCSD compares to the BIP.

Results and Discussion

Performance of the BCSD-CMIP5

We first evaluate the spatial distribution of annual temperature obtained from the ensemble mean of 31 BCSD downscaled CMIP5 models (hereafter called BCSD-ENS) over the independent period 1996–2005 (Fig. 3a,b). There is a very good agreement between the simulated temperature patterns and observed data. The model ensemble can sensibly resolve the subtle and smooth temperature transition between regions, with a relatively higher

temperature in Southern Vietnam and lower temperature in mountainous areas in the North and Central Highlands. The biases, i.e. BCSD-ENS minus OBS, indicated in Fig. 3(c-i) (Fig. 3(h-l)) are relatively small, ranging only between -0.36°C and 0.56°C (between -0.34°C and 0.35°C) throughout the year for the independent (training) period. The average annual bias over Vietnam is 0.05°C for the training period, slightly less than the value of 0.07°C for the independent period. Moreover, the bias patterns seem to appear throughout the regions randomly. Seasonal temperature biases are generally larger than the annual average bias (Fig 3(c-l)). For each season, the temperature bias range is higher in the northern regions (-0.36°C to $+0.56^{\circ}\text{C}$) than in the southern regions (-0.2°C to $+0.3^{\circ}\text{C}$), suggesting that the QM accuracy might be sensitive to the magnitude of annual and seasonal ranges of temperature. It is worth noting that over the regions with large BCSD-ENS biases, the BC-GCMs generally show a strong agreement in their bias tendency, i.e. at least $\frac{2}{3}$ of the model members having the same bias sign with the BCSD-ENS. The BCSD-ENS biases in maximum and minimum daily temperature (Supplement Fig. A1, A2) are relatively higher than those in average daily temperature for both annual and seasonal averages. For those two variables, the difference between cold and warm bias patterns becomes more intense. Previous studies suggested that the poor performance of GCMs in addressing extreme climate events (Rana et al. 2014; Tran Anh and Taniguchi 2018; Panjwani et al. 2020)

could potentially exacerbate the bias.

The BCSD outputs for precipitation also show a good agreement with OBS, partly illustrated by the average bias of 4.99% for the independent period (Fig. 4(a-c)). Locations of the rainfall centers in Vietnam (e.g. in the North, Central, and South of Central Highlands) are well represented by the BCSD-ENS (Fig. 4(a-b)). Although the bias patterns are distributed differently between seasons and regions, the BCSD-ENS in the independent period tends to underestimate precipitation by up to -36% in the South Central, Central Highlands, and South regions and overestimate precipitation by up to 28% in the North, particularly in September-October-November (SON) (Fig 4(d-g)). For the training period 1986–1995, the BCSD-ENS results (Fig 4(i-l)), with an annual average bias of 2.8%, are better than those for the independent period, which is reasonable. Winter season rainfall exhibits the largest bias range among all seasons in the BCSD results for both dependent (-19.28%–27.95%) and independent (-35.89%–34.24%) datasets. However, it is worth mentioning that relatively small absolute biases may appear as significant percentage biases in regions and seasons with dry (i.e. little rainfall) conditions, e.g. in December-January-February (DJF). Since precipitation usually has more considerable spatial and temporal variability than temperature, the bias ranges of BC precipitation (in percentage) are much larger than that of temperature.

The ability of the BCSD-ENS in reproducing the seasonal cycle is illustrated in Fig. 5, where

temporal correlations between the BC outputs and OBS for the independent period are displayed. The average correlation values are very high, i.e. 0.998 and 0.97 for temperature and precipitation, respectively, indicating a good agreement between the BCSD-ENS and OBS (Fig. 5(a,c)). Although the simple BIP downscaled CMIP5 GCMs ensemble (BIP-ENS) also shows good seasonal cycles compared to OBS, with average correlations of 0.97 and 0.88 for temperature and precipitation, respectively (Fig 5 c, d), the BCSD-ENS exhibits noticeably better results in all regions.

The reproducibility of the BCSD outputs for the seasonal cycles of temperature and precipitation are further investigated in Fig. 6 by comparing the BCSD-ENS, the BIP-ENS, 31 individual CMIP5 models downscaled by both methods, and OBS for all seven climatic sub-regions. Significant agreements in seasonal temperature variation between the BCSD outputs and OBS are clearly illustrated with low root mean square (RMSE) values, ranging from 0.26°C in the South region to 0.45°C in the Northwest. While it is difficult to distinguish the seasonal cycles of the BCSD-ENS from OBS, the differences between the BIP-ENS and OBS are clear.

The BIP-ENS product generally underestimates autumn-winter rainfall from the Northwest to North Central and consistently overestimates rainfall in the remaining months and regions.

Since the variations among the BIP members are much larger than among the BCSD members, the RMSEs of the BIP-ENS results, ranging from 0.62°C in the South to 1.47°C in Central

Highlands, are much larger than those of the BCSD-ENS.

Fig. 7 shows the good performance of the BCSD downscaled results in reproducing the observed seasonal precipitation cycles. The BCSD outputs can well capture the phase and amplitude of the seasonal cycles over all the climatic sub-regions, including R4 (North Central) and R5 (South Central), where the rainy season comes late in the last months of the year. Both BCSD and BIP downscaling results exhibit higher dispersions in months with higher precipitation amounts. The average RMSEs are relatively small for the BCSD-ENS, ranging from 0.5 mm/day in R1 (Northeast) and R3 (North Delta) to 1.35 mm/day in R5. In all regions, the BCSD RMSEs are significantly lower than BIP (1.0–4.55 mm/day). The added values of the BCSD downscaling over the simple BIP method are presented by the AV values (Equation 1) shown in Fig. 8 and Fig. 9 for temperature and precipitation, respectively.

The positive AV grids dominate most of the Vietnam territory in all BCSD models' outputs for temperature downscaling, from 94.8% in CSIRO-Mk3-6-0 to 99.3% in NorESM1-M. The BCSD-ENS has 97.3% of grid points with positive AVs. The negative AV range in the models (-1–0) is much narrower than the positive range (0–70), suggesting only minor differences between the BCSD and BIP in the locations where the BIP is better than the BCSD.

Over Vietnam, the percentage of positive AV regions for precipitation downscaling in all BCSD-CMIP5 outputs vary from 88.7% in MIROC5 to 97.2% in CMCC-CM (Fig. 9). Notably,

the BCSD-ENS has 99.9% of grid points with positive AVs. Similar to temperature, the negative AVs vary within the narrow range of (-1–0), highlighting minor differences between the BCSD and BIP in those areas.

In summary, this subsection has demonstrated the overwhelming performance of the BCSD downscaling method for temperature and precipitation over Vietnam, even when examining for the independent period 1996–2005. For each CMIP5 GCM and the ensemble mean, the BCSD outperforms the simple BIP method over almost all territories of Vietnam.

Future projections

Future global (obtained from the CMIP5 GCMs) and Vietnam (obtained from the CMIP5-VN) warming levels over the 21st century compared to the baseline period 1986–2005 are displayed in Fig. 10. While the average warming trends in Vietnam are slightly smaller, the warming variability in Vietnam is larger than the global average for all RCPs at the end of the century. The average temperature in Vietnam increases by $1.3 \pm 0.52^\circ\text{C}$ under RCP2.6 and by $3.85 \pm 0.85^\circ\text{C}$ under RCP8.5. The model variability for each RCP is generally larger in Vietnam than that of the global scale except for the RCP6.0 scenario, which has a limited number of models. It is worth mentioning that our results for Vietnam are aligned with the latest IPCC sixth assessment report, which concluded with high confidence that future warming in Southeast Asia (including Vietnam) will be slightly less than the global average (Gutiérrez et

al. 2021).

The progress of global warming in the seven climatic sub-regions of Vietnam at the end of the 21st century is illustrated in Fig. 11, where the BCSD-ENS temperature seasonal cycles of the future 2080–2099 and baseline 1986–2005 periods are compared. Results indicate that regional mean temperatures, which vary between regions, are projected to increase by 1.10°C–1.37°C under RCP2.6 and by 3.11°C–3.70°C under RCP8.5. The warming in the northern regions (R1–R4) is more intense than in the south (R5–R7), by 0.10°C and 0.31°C warmer on average under RCP2.6 and RCP8.5, respectively. In the northern regions, projected temperature increases are about 0.44°C–0.76°C higher in summer than in winter for all RCPs. Our findings here correlate fairly well with MONRE (2016)’s results, which were based on a limited number of dynamical downscaling experiments and projected more severe warming conditions in the northern regions than in the southern regions of Vietnam.

Projection of CMIP5-VN precipitation change in Vietnam related to the 1986–2005 period is illustrated in Fig. 12. Contrary to the clear increasing temperature trends across all models, the trends of precipitation contain more uncertainties (Fig. 12a). The average precipitation in the far future 2080–2099 is projected to generally increase by $1.16 \pm 7.1\%$ under RCP2.6 and by $4.41 \pm 9.2\%$ under RCP8.5. The uncertainties increase with time and are highest under the high greenhouse gas concentration scenario RCP8.5. Over entire Vietnam, the BCSD-ENS shows a

slight increasing precipitation trend, except for some small areas in the North and South (Central Vietnam) under RCP2.6 (RCP6.0) (Fig. 12(b–e)). There is a more robust agreement of the CMIP5-VN products on the increasing precipitation trend in Central Vietnam (including R4 and the northern parts of R5 and R6) under RCP4.5 and RCP8.5 than in the remaining regions and scenarios.

The slight changes in the projected mean precipitation at the end of the 21st century are also demonstrated by the slight increases in the average seasonal precipitation over the seven climatic sub-regions (Fig. 13). The average changes of the BCSD-ENS vary from 0.31%–3.54% under RCP2.6 and from 2.10%–9.50% under RCP8.5. In the dry months, only a small increase or decrease in future rainfall can cause a large percentage change. For example, the BDS-ENS rainfall is projected to increase by 35% in February under RCP6.0 and to decrease by -25% in March under RCP8.5 in the South region (R7); however, the average monthly rainfall values of R7 in these months are less than 0.5 mm/day, which are very small. There is a tendency of rainfall reduction in the dry months, particularly during March–April–May, suggesting that dry conditions are exacerbated in the future, especially under RCP8.5. On the other hand, more rainfall is projected from June to the end of the year in most climatic sub-regions under all RCPs. In particular, rainfall is projected to increase under RCP4.5 and RCP8.5 by more than 10% in North Central (R4), and by 5–20% in South Central (R5) from September to November,

which are the months with the highest rainfall of the year, suggesting more extreme rainfall events in the future in these regions.

Conclusions

In this study, the high-resolution (10km) daily temperature (including near-surface daily average, daily maximum, and minimum temperatures) and precipitation dataset for Vietnam, called CMIP5-VN, has been successfully developed by applying the BCSD method for 31 CMIP5 GCMs for the baseline period 1980–2005 and the future period 2006–2100 under four greenhouse gas concentration scenarios RCP2.6, 4.5, 6.0 and 8.5.

The 1980–2005 observed daily precipitation and temperature data were used to bias-correct the CMIP5 GCMs and guide spatial disaggregation for future projections. The validation of the BCSD method was conducted based on a 16-years (1980–1995) training dataset and a 10-years (1996–2005) independent testing dataset. Afterward, the whole 26-years historical records were used to build the CMIP5-VN. The results showed that the BCSD products in the independent period could reproduce the observed spatial patterns over Vietnam with the average annual biases of 0.07°C for temperature and 4.99% for precipitation. There are very high temporal correlations between the BCSD-ENS and OBS, with the nationwide average values of 0.998 and 0.97 for temperature and precipitation, respectively. Moreover, for each CMIP5 GCM and the ensemble mean, the BCSD method overwhelmingly outperforms the simple BIP method in

reproducing the observed climate characteristics over almost all territories of Vietnam.

The newly-built CMIP5-VN dataset shows that temperature is projected to increase in all climatic sub-regions, by $1.3 \pm 0.52^\circ\text{C}$ under RCP2.6 and by $3.85 \pm 0.85^\circ\text{C}$ under RCP8.5 at the end of the 21st century compared to the baseline period 1986–2005. The warming is more intense in the northern regions (R1–R4) than in the southern regions (R5–R7) and is higher in summer than in winter for all RCPs. Meanwhile, the average precipitation over Vietnam is projected to slightly increase by $1.16 \pm 7.1\%$ under RCP2.6 and by $4.41 \pm 9.2\%$ under RCP8.5. Central Vietnam has a rather robust increase in the rainy months under RCP4.5 and RCP8.5, with over $\frac{2}{3}$ of the models having the same increasing sign.

With the CMIP5-VN dataset, future scenarios for Vietnam are not only limited to RCP4.5 and RCP8.5 (see previous studies, e.g. MONRE 2016; Trinh-Tuan et al. 2019; Nguyen-Thuy et al. 2021) but also available for RCP2.6 and RCP6.0, which were previously little mentioned in Vietnam. The daily CMIP5-VN dataset, which is about 1.08 Terabytes in size, can be downloaded free of charge at the following address: <http://remosat.usth.edu.vn/Download/CMIP5-VN/>. The CMIP5-VN is recommended for studies on climate change assessment and climate change impacts in Vietnam.

Authors' contributions

QTA, TND, EE discussed and conceptualized the research. QTA carried out the downscaling experiments and performed the analysis. LTT processed and prepared the observation data. QTA and TND drafted the manuscript. All authors discussed the results and commented on the manuscript.

Funding

This work is funded by the Agence Française de Développement GEMMES Vietnam project; the Vietnam National Foundation for Science and Technology Development (NAFOSTED).

Conflict of Interest

The authors declare that they have no competing interest.

Data availability statement

The newly created daily CMIP5-VN dataset can be downloaded free of charge at the following address: <http://remosat.usth.edu.vn/Download/CMIP5-VN/>

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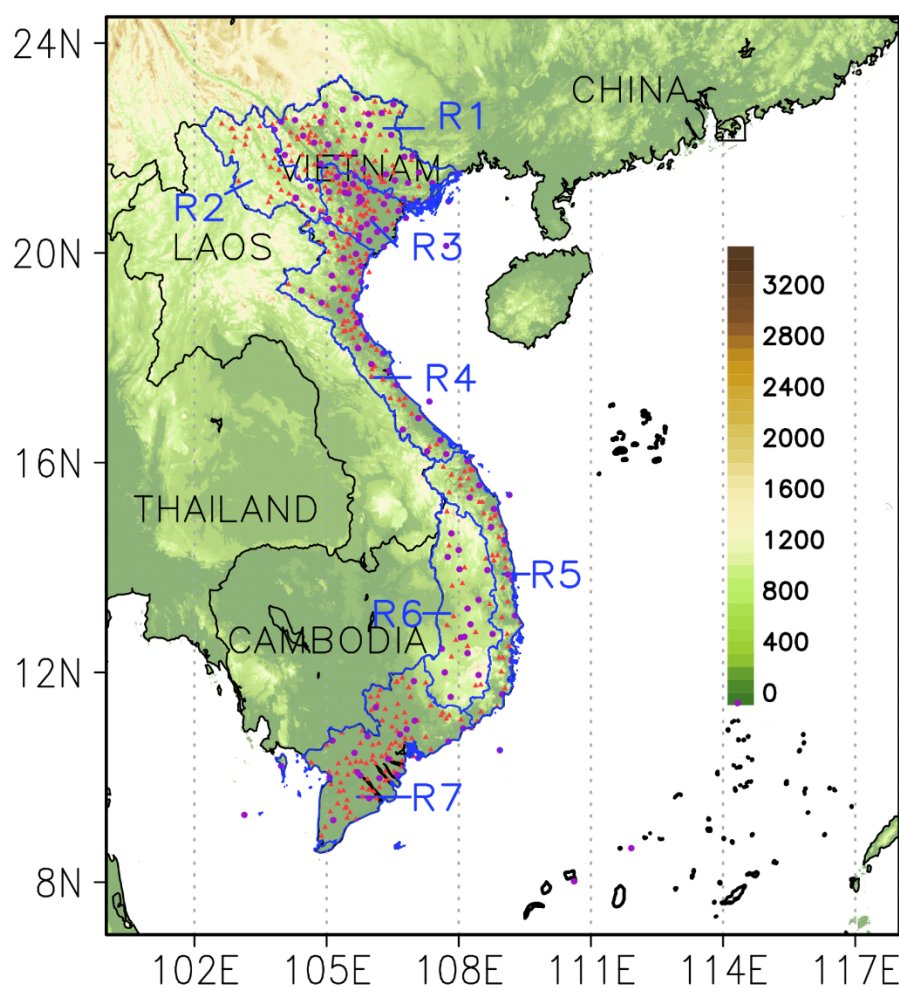
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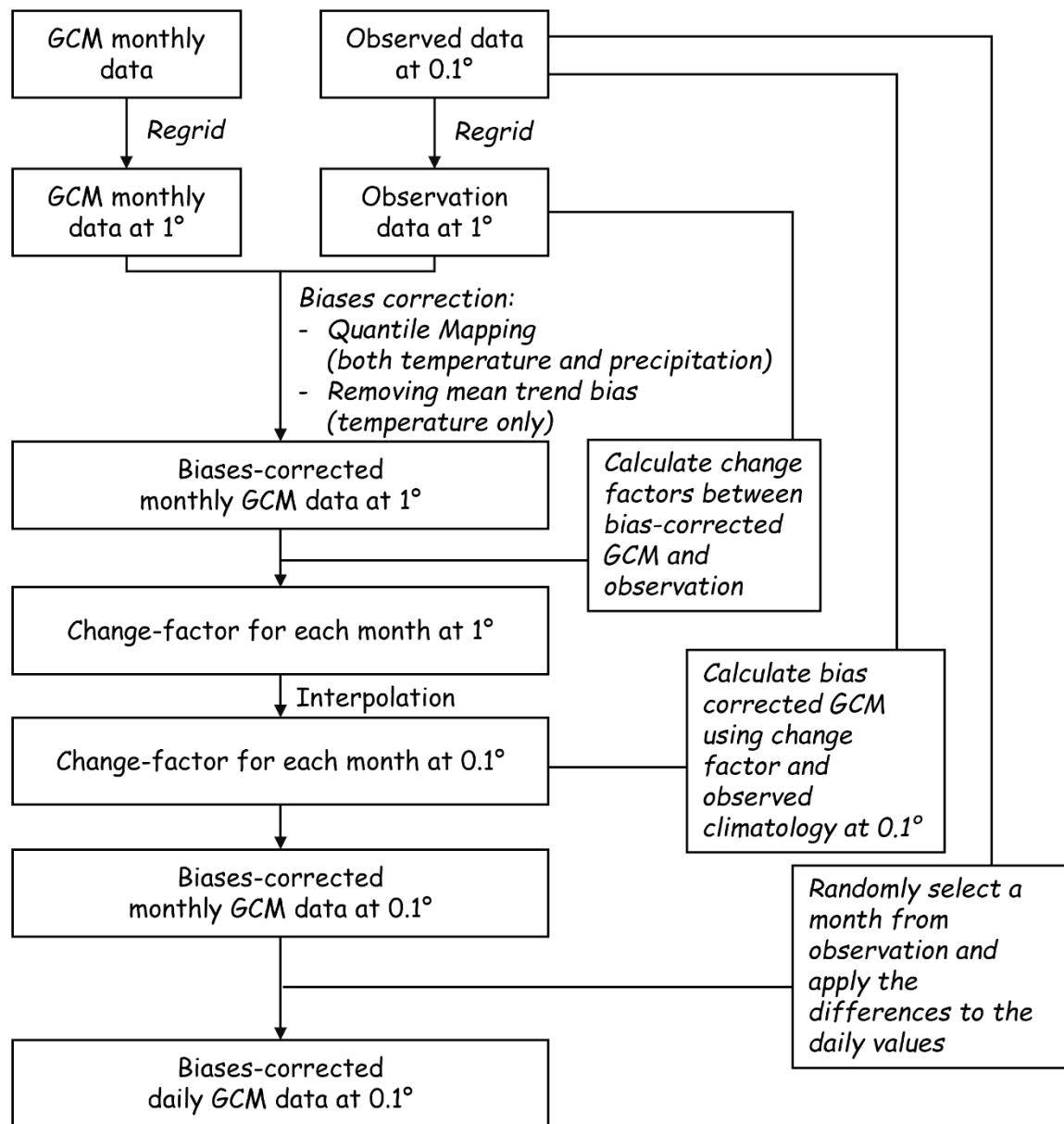
556 235 (2020).

557

558 **Figure legends**

559
560 Figure 1. The seven climatic sub-regions of Vietnam. Purple and red circles show the locations
561 of 157 temperature- and 481 rainfall-stations of which data are used in this study,
562 respectively. Topography over Vietnam (shaded, in m) is obtained from the
563 Hydrological data and maps based on Shuttle Elevation Derivatives at multiple Scales

564 (HydroSHEDS) (Lehner 2013).



565
566 Figure 2. The schema of the BCSD algorithm applied in this study.

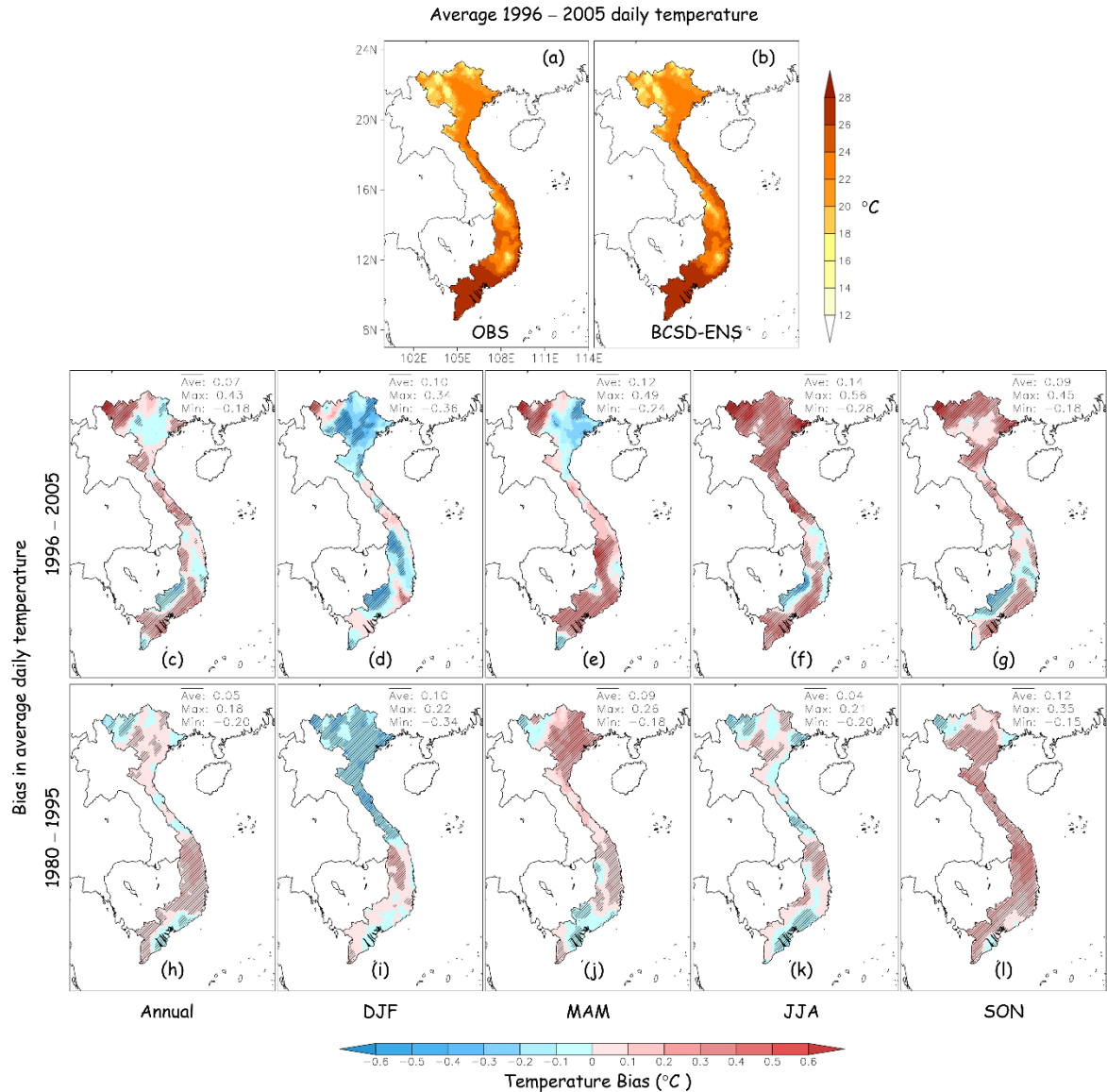
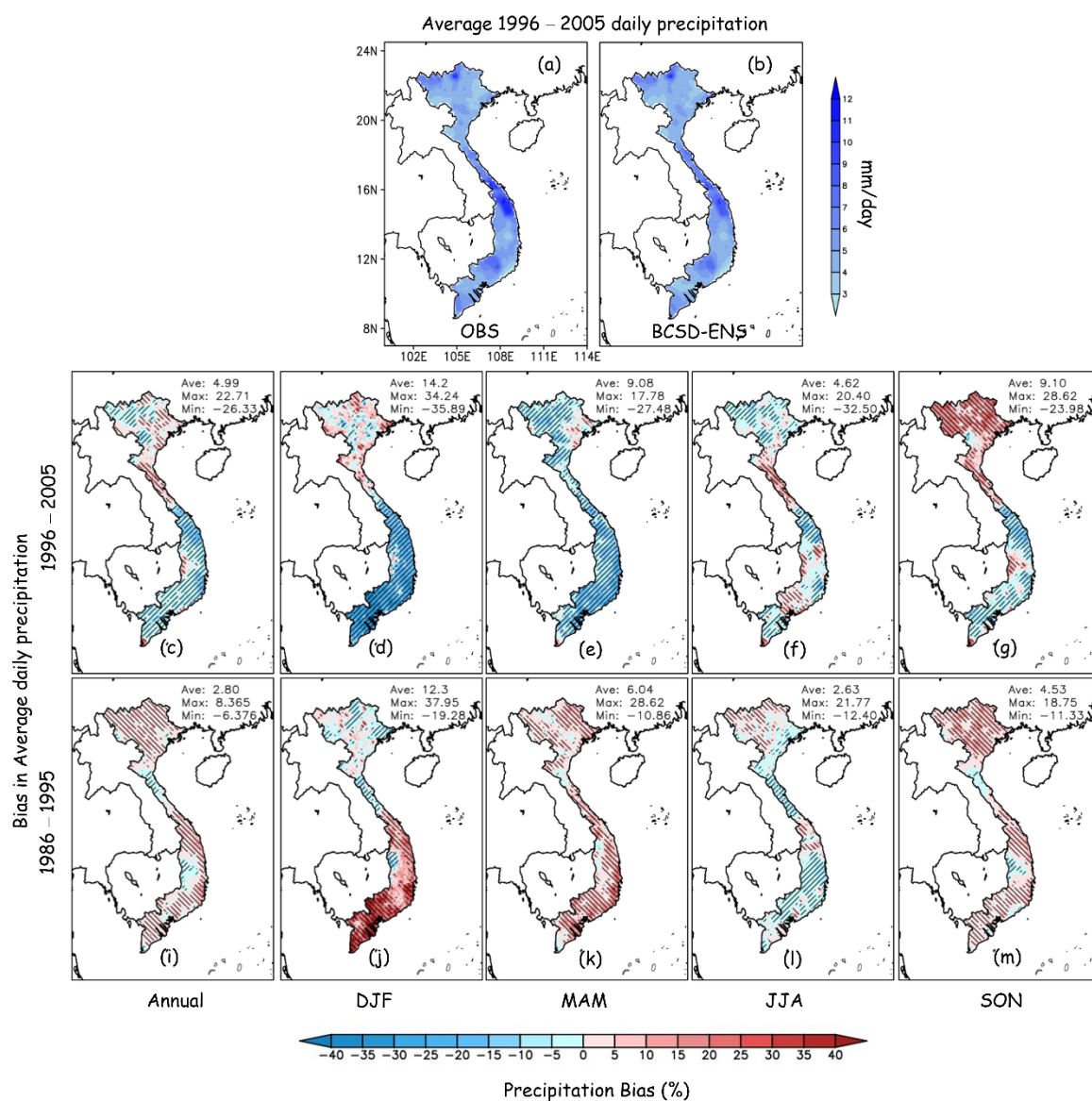


Figure 3. Spatial distribution of annual average temperature in Vietnam by OBS and BCSD-ENS. (a, b) indicate the average 1996–2005 temperature by OBS and BCSD-ENS; (c–g) and (h–i) indicate the biases of BSCD-ENS compared to OBS for the independent period 1996–2005 and the training period 1980–1995, respectively. The hatching lines show the regions where over $\frac{2}{3}$ of CMIP5 models have the same bias sign with BCSD-ENS.



574

575 Figure 4. Same as Figure 3 but for precipitation.

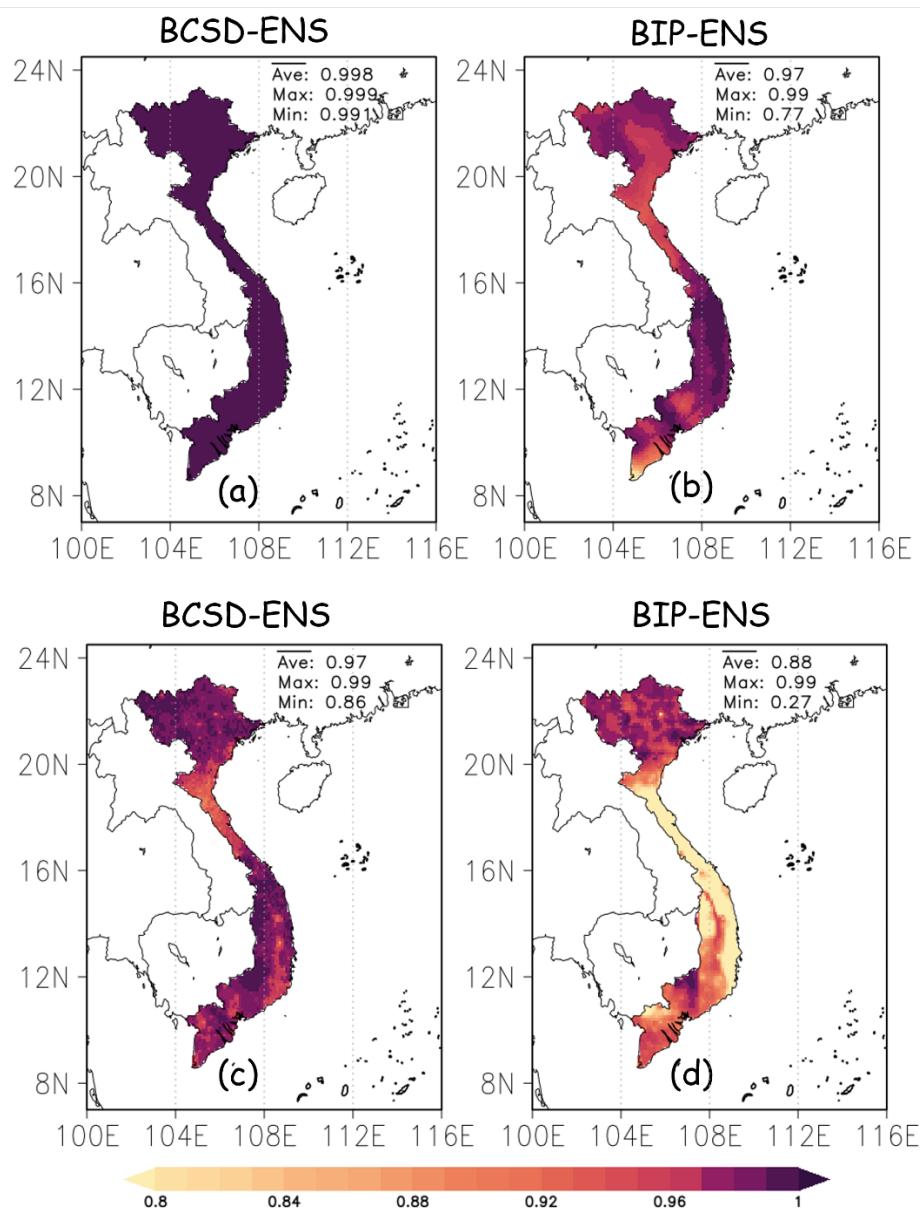


Figure 5. Temporal correlations of the 1996–2005 seasonal cycle between the BCSD-ENS (left) and BIP-ENS (right) with OBS for (a, b) temperature and (c, d) precipitation.

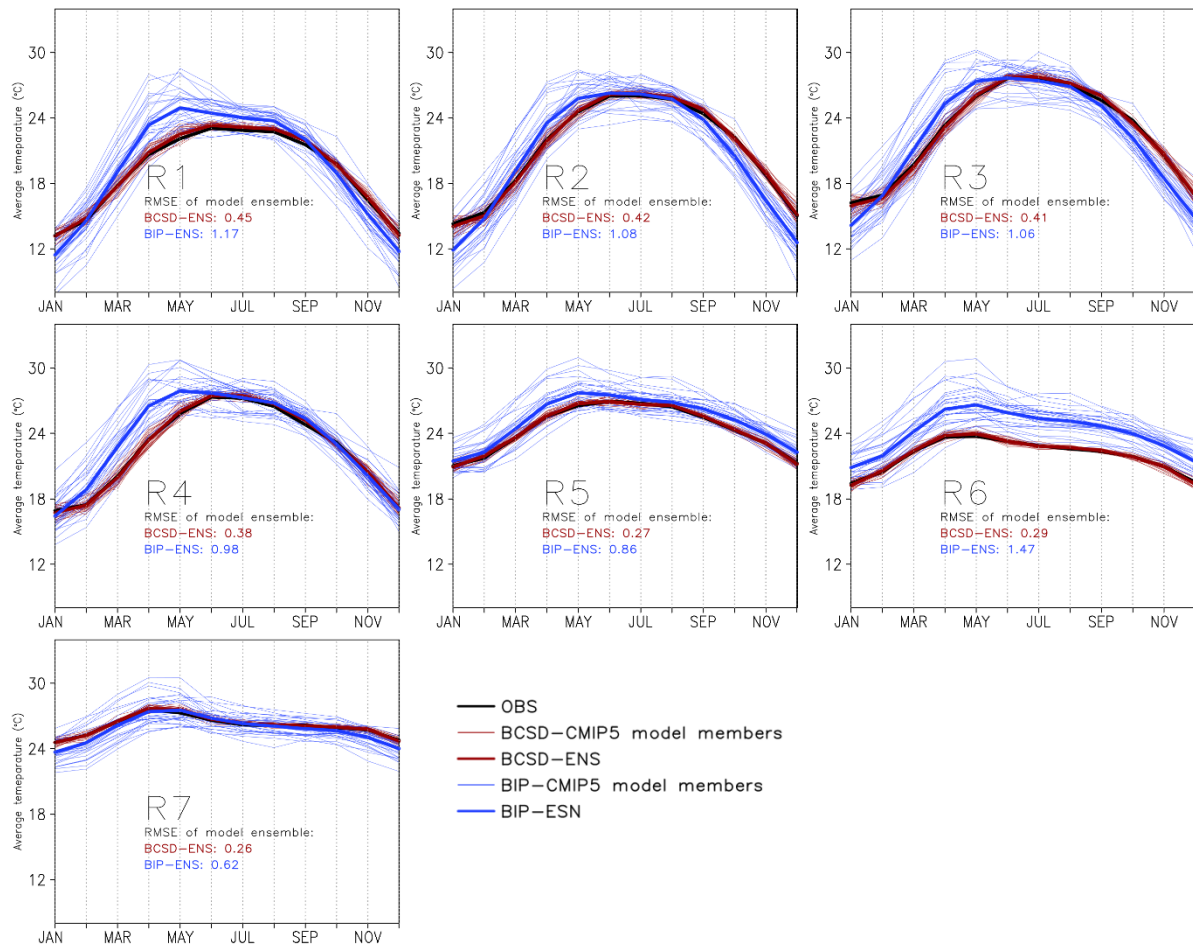
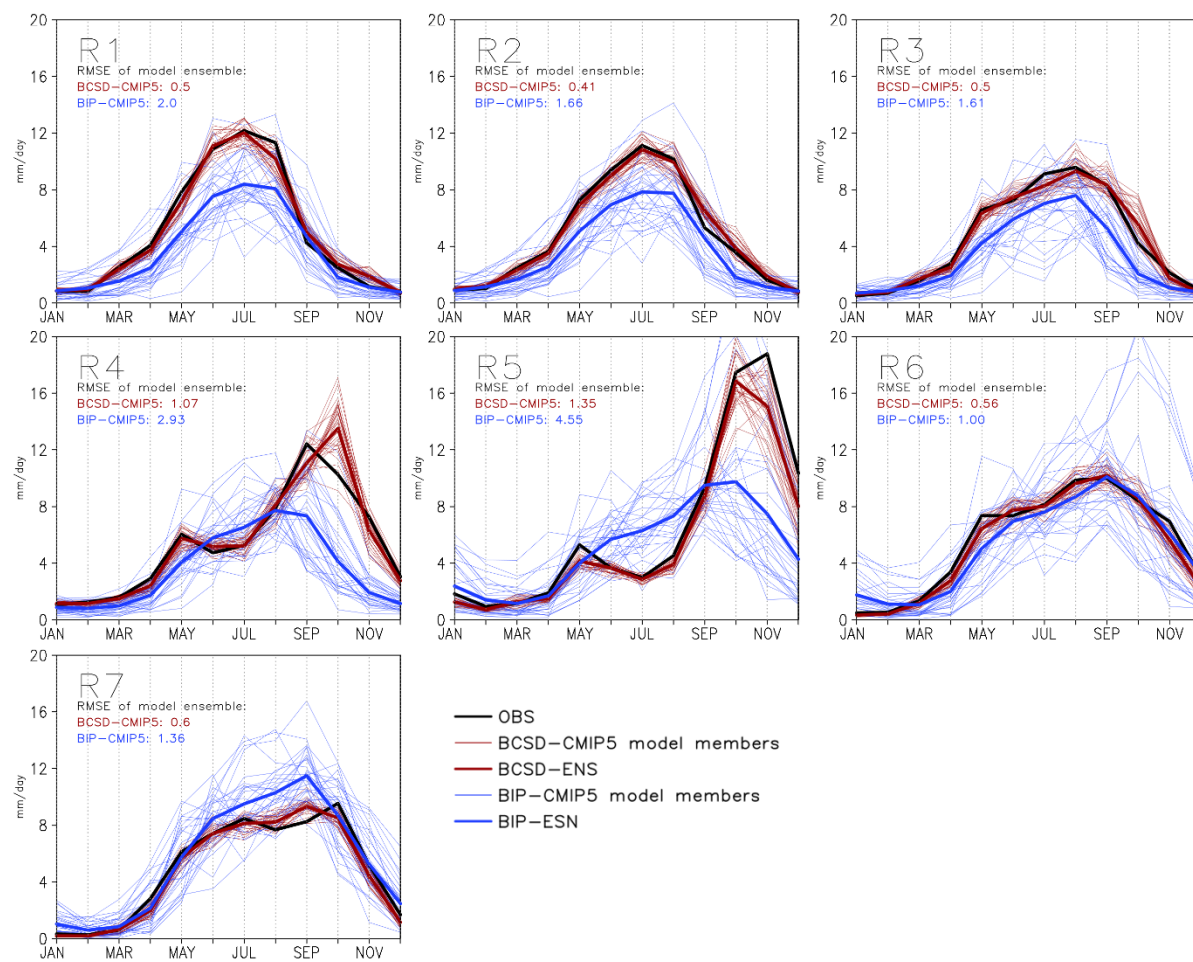


Figure 6. Comparison of seasonal temperature cycles by OBS, BCSD, and BIP for the seven climatic sub-regions for the period 1996–2005. The seasonal cycle is shown for OBS (black), for 31 downscaled individual CMIP5 model members by BCSD (dim red) and BIP (dim blue), and two models ensemble mean, the BCSD-ENS (dark red) and the BIP-ENS (dark blue). Mean square errors (MSE) of the BCSD-ESN and BIP-ENS are also indicated.



586

587 Figure 7. Same with Figure 6 but for precipitation.

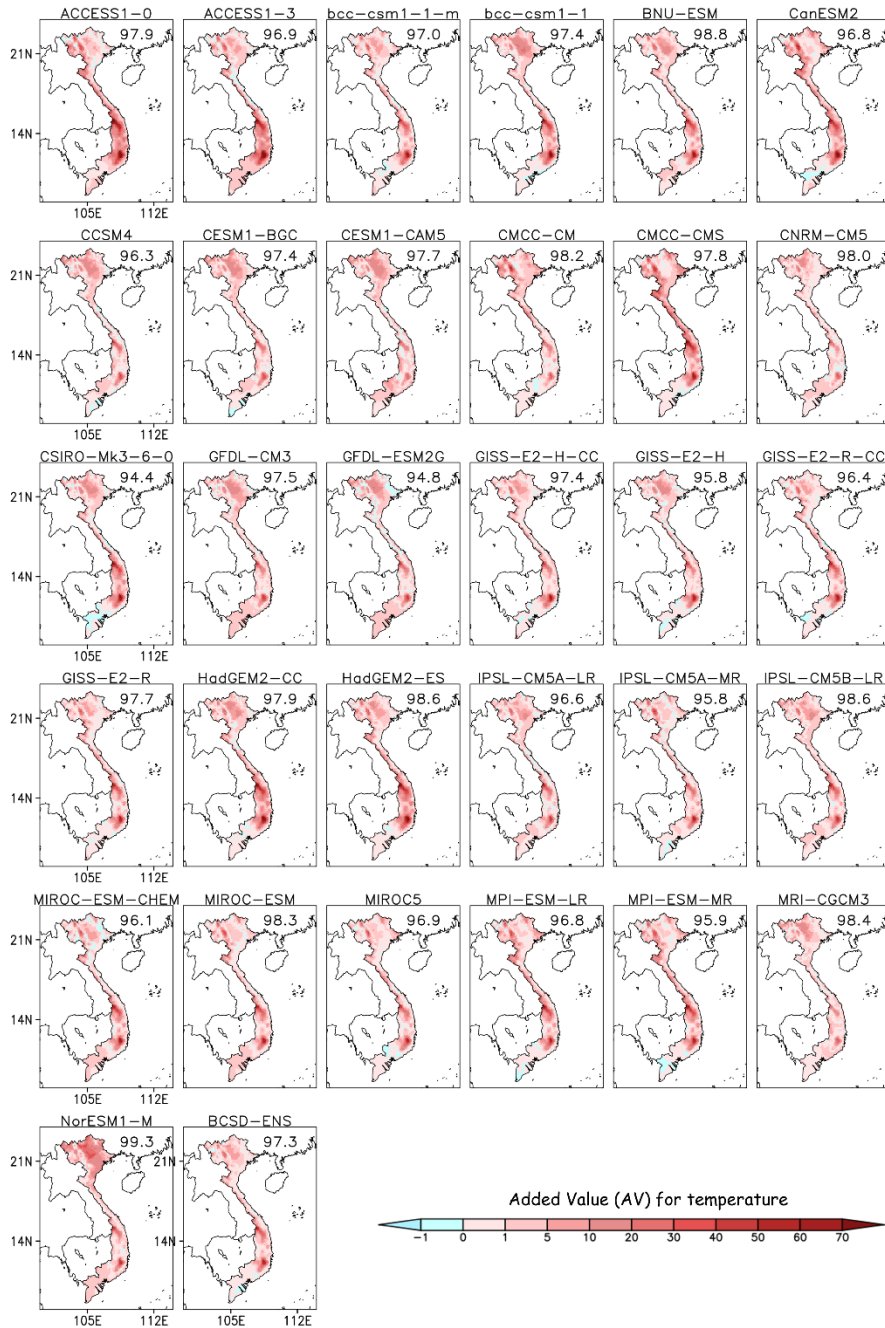
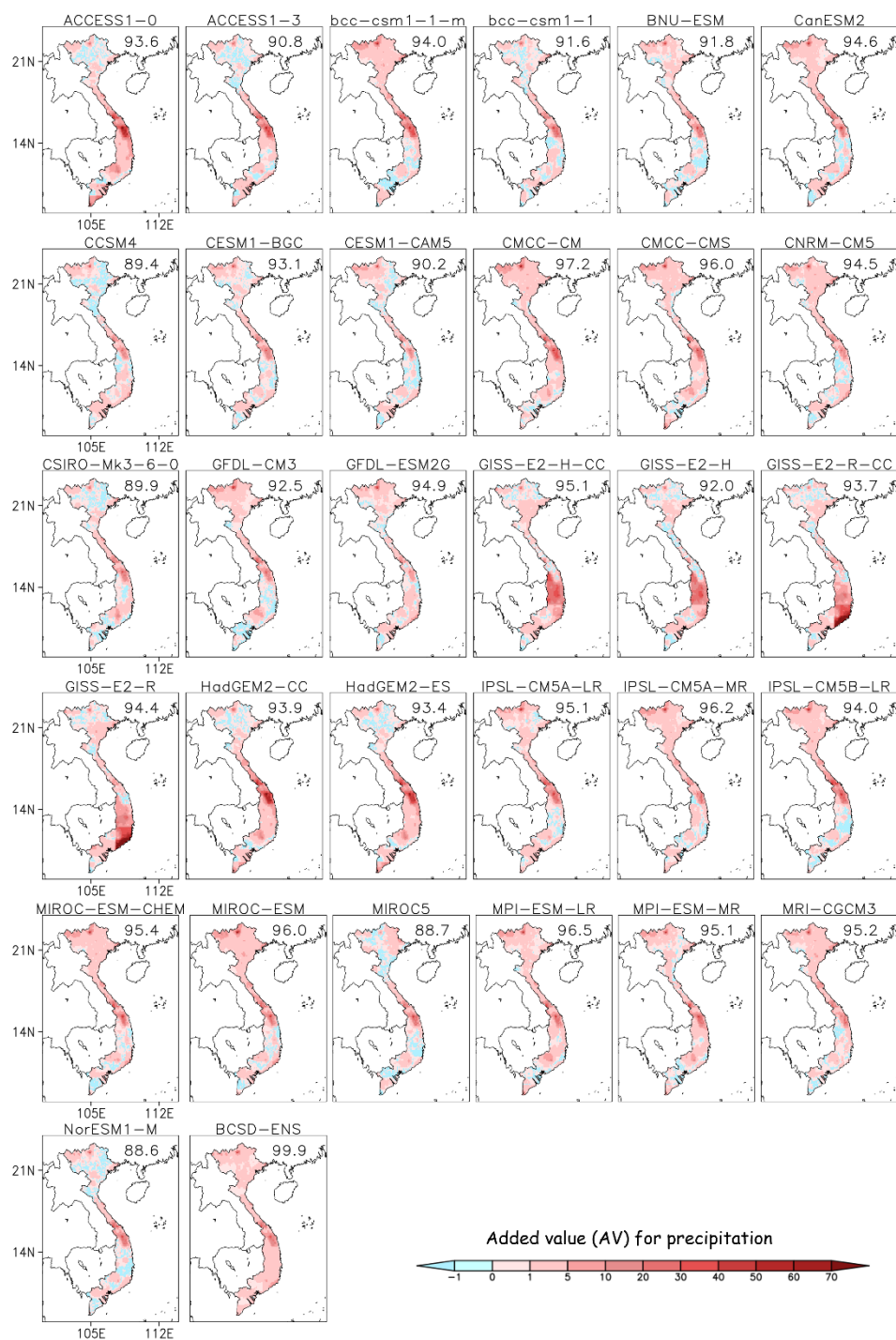


Figure 8. AVs of individual BCSD-CMIP5 and BCSD-ENS for temperature over the BIP-CMIP5 for the 1996–2005 period. The darker saturation of warm/cold color denotes the more skillful/unskillful of the BCSD. The number in the top right corner indicates the percentage of the grids having positive AV values.



593

594 Figure 9. Same as Figure 8 but for precipitation.

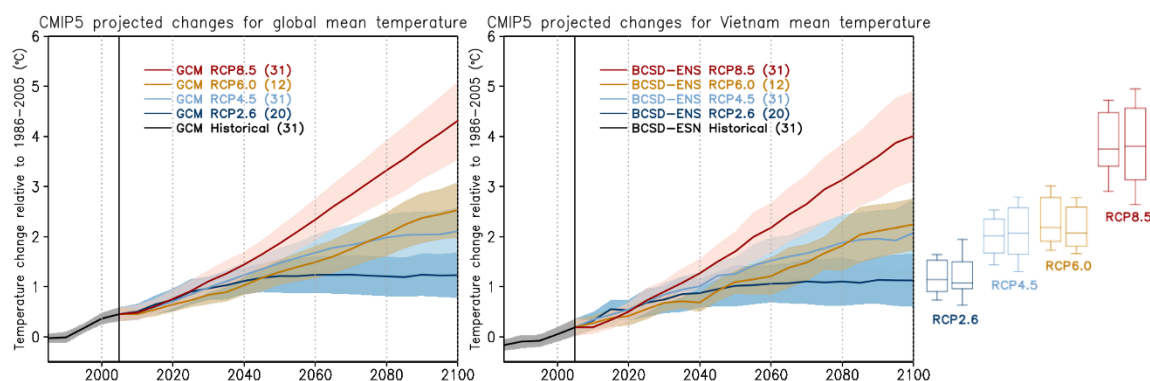


Figure 10. Projected temperature changes relative to the baseline period 1986–2005 based on the CMIP5 GCMs and BCSD-CMIP5 data for global average (left) and Vietnam (right), respectively. 5-year moving averages are applied. Colored lines show the ensemble means of the models and colored shaded areas present the uncertainty ranges (± 1 standard deviation) for each RCP. The number of models used for each RCP is shown in brackets. Box plots on the right display the occurrence statistics (quartile, median, 10th, and 90th percentile) for warming levels on the global scale (left boxes) and in Vietnam (right boxes) at the end of the 21st century 2080–2099.

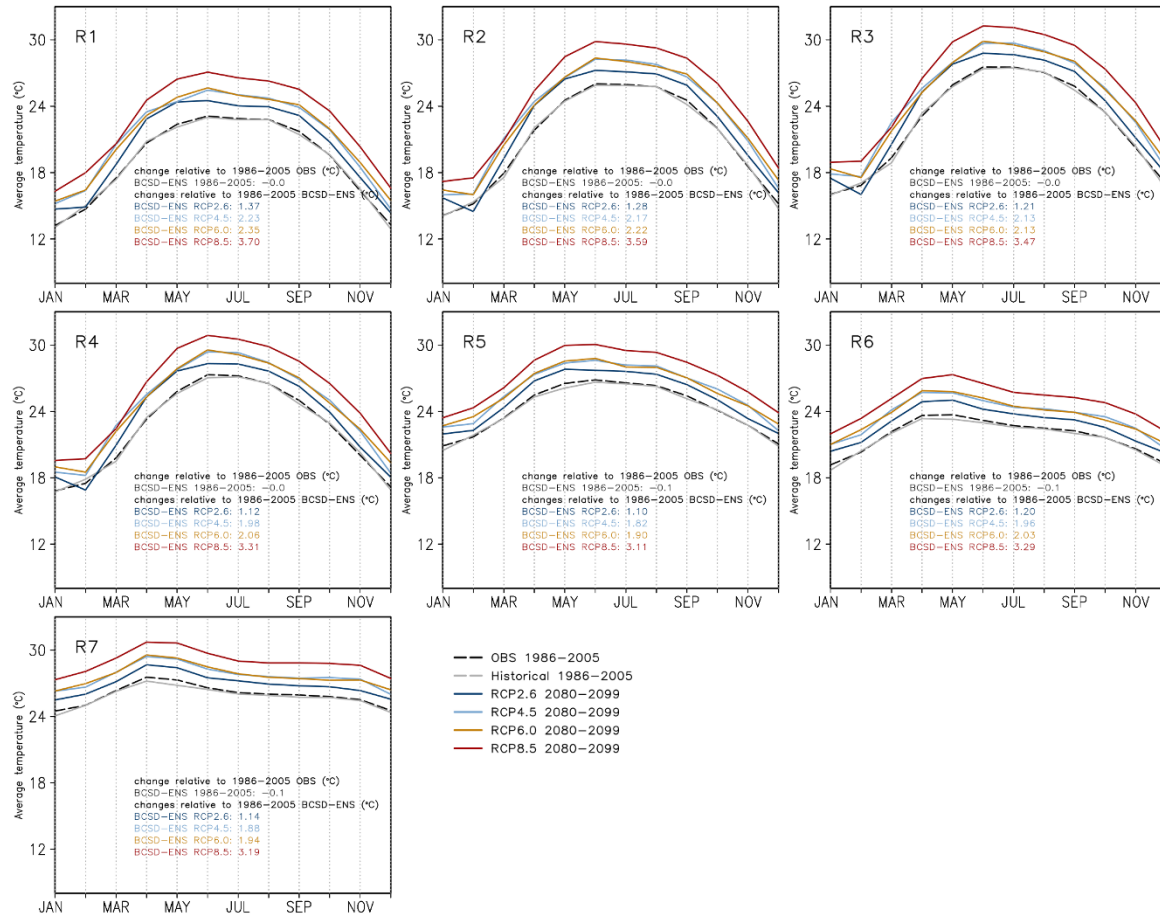


Figure 11. Comparison between the seasonal temperature cycles of the BCSD-ENS and OBS over the seven climatic sub-regions of Vietnam. Black and grey dashed lines respectively represent the OBS and BCSD-ENS cycles for 1986–2005, while color lines represent the future 2080–2099 seasonal cycles for each RCP. Average changes between the future 2080–2099 BCSD-ENS and the 1986–2005 OBS with the historical 1986–2005 BCSD-ENS are also displayed.

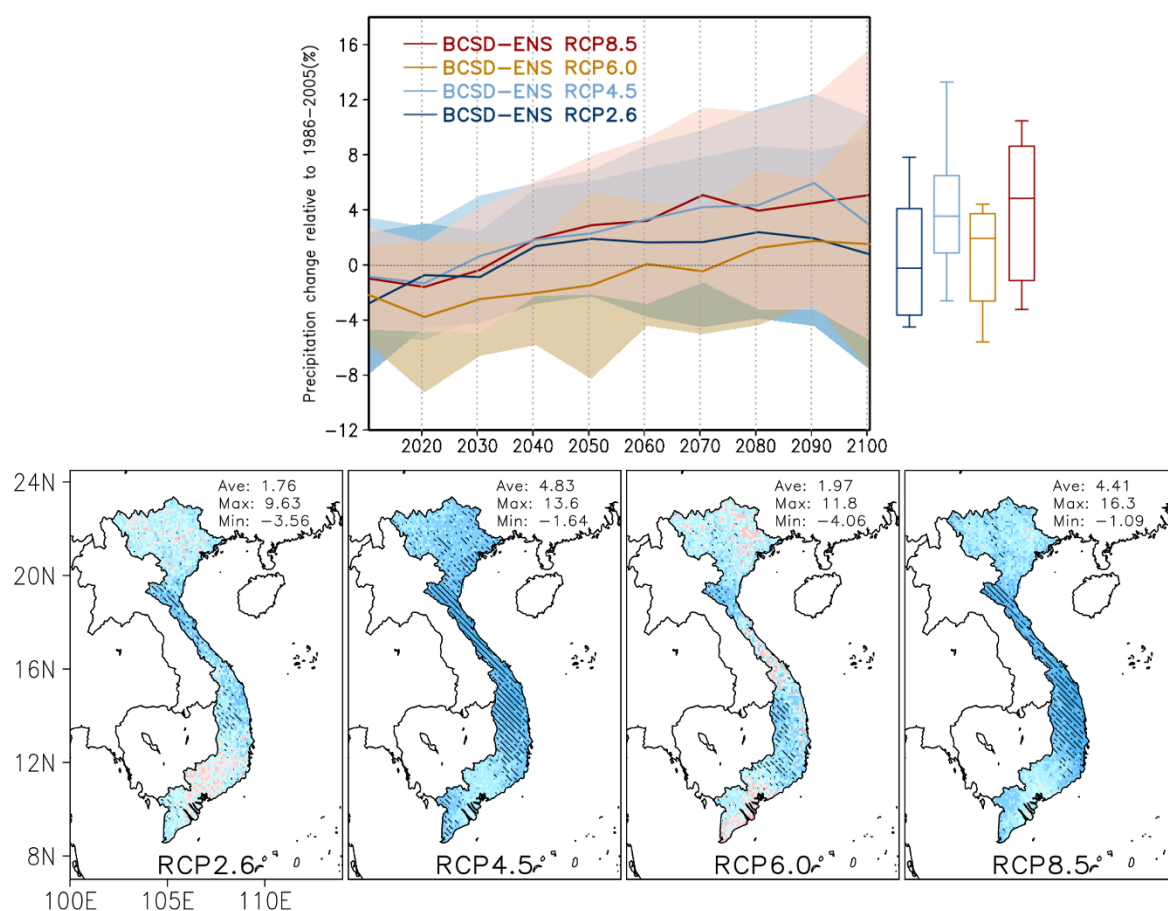


Figure 12. Projected precipitation changes in Vietnam under different RCPs. (a) Colored lines present the 10-year moving average of the BCSD-ENS and colored shaded areas show the uncertainty ranges (± 1 standard deviation). Box plots on the right display the occurrence statistics (quartile, median, 10th, and 90th percentile) for precipitation changes at the end of the 21st century 2080–2099. (b, c, d, e) Distribution of change patterns between the 2080–2099 and 1986-2005 periods derived by the BCSD-ENS. The hatching lines show the regions where over $\frac{2}{3}$ of BCSD CMIP5 models have the same bias sign as the BCSD-ENS.

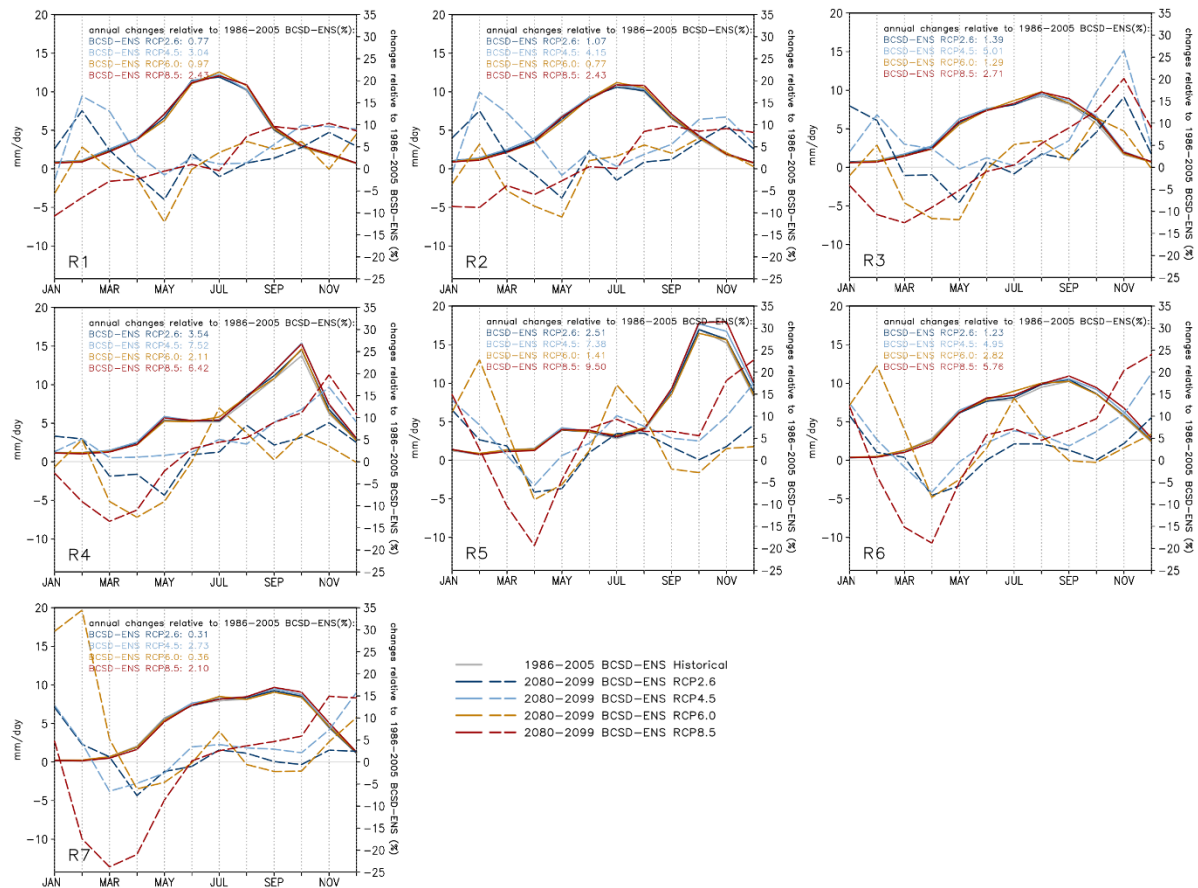


Figure 13. Precipitation seasonal cycles (left axis, solid lines) under different RCPs and their percentage changes (right axis, dash lines) relative to the 1986–2005 BCSD-ENS over the seven climatic sub-regions of Vietnam. Average changes (%) of the BCSD-ENS between the future 2080–2099 and the baseline 1986–2005 period are also displayed.

629 Table 1. List of 31 CMIP5 GCMs, their resolutions, and RCP availability that are used in this
630 study.

N o.	Climate Modeling Group	CMIP5 Model ID	Grid Resolution (degree)		Availability (* means Yes)			
			Lon.	Lat.	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
1	Commonwealth Scientific and Industrial Research Organization and Bureau of Meteorology, Australia	ACCESS1-0	1.25	1.875		*		*
2		ACCESS1-3	1.25	1.875		*		*
3	Beijing Climate Center, China Meteorological Administration	BCC-CSM1-1	2.791	2.813	*	*	*	*
4		BCC-CSM1-1-M	2.791	2.813	*	*		*
5	College of Global Change and Earth System Science, Beijing Normal University	BNU-ESM	2.791	2.813	*	*		*
6	Canadian Centre for Climate Modelling and Analysis	CanESM2	2.791	2.813	*	*		*
7	National Center for Atmospheric Research	CCSM4	0.942	1.25		*	*	*
8	Community Earth System Model Contributors	CESM1-BGC	0.942	1.25		*		*
9		CESM1-CAM5	0.942	1.25	*	*	*	*
10	Centro Euro-Mediterraneo per I Cambiamenti Climatici	CMCC-CM	0.748	0.75		*		*
11	Centre National de Recherches Météorologiques/ Centre Européen de Recherche et	CNRM-CM5	1.401	1.406	*	*		*

	Formation Avancée en Calcul Scientifique							
12	Commonwealth Scientific and Industrial Research Organization, Queensland Climate Change Centre of Excellence	CSIRO-Mk3-6-0	1.865	1.875	*	*	*	*
13	NOAA Geophysical Fluid Dynamics Laboratory	GFDL-CM3	2	2.5	*	*		*
14		GFDL-ESM2G	2.023	2	*	*	*	*
15	NASA Goddard Institute for Space Studies	GISS-E2-H	2	2.5	*	*	*	*
16		GISS-E2-H-CC	2	2.5		*		*
17		GISS-E2-R	2	2.5	*	*	*	*
18		GISS-E2-R-CC	2	2.5		*		*
19	Met Office Hadley Centre	HadGEM2-CC	1.25	1.875		*		*
20	(additional HadGEM2 ES realizations contributed by Instituto Nacional de Pesquisas Espaciais)	HadGEM2-ES	1.25	1.875	*	*		*
21	Institut Pierre-Simon Laplace	IPSL-CM5A-LR	1.897	3.75	*	*		*
22		IPSL-CM5A-MR	1.268	2.5	*	*	*	*
23		IPSL-CM5B-LR	1.895	3.75		*		*
24	Japan Agency for Marine-Earth Science and Technology,	MIROC-ESM	2.791	2.813	*	*	*	*
25	Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	MIROC-ESM-CHEM	2.791	2.813		*	*	*
26	Atmosphere and Ocean Research Institute (The University of	MIROC5	1.401	1.406	*	*	*	*

	Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology							
27	Max-Planck-Institut für	MPI-ESM-LR	1.865	1.875	*	*		*
28	Meteorologie (Max Planck Institute for Meteorology)	MPI-ESM-MR	1.865	1.875	*	*		*
29	Meteorological Research Institute	MRI-CGCM3	1.121	1.125	*	*		*
30	Norwegian Climate Centre	NorESM1-M	1.895	2.5	*	*	*	*
31		NorESM1-ME	1.895	2.5		*		*
	Total number of available models for each RCP				20	31	12	31

631

632 [Supplemental Figures]

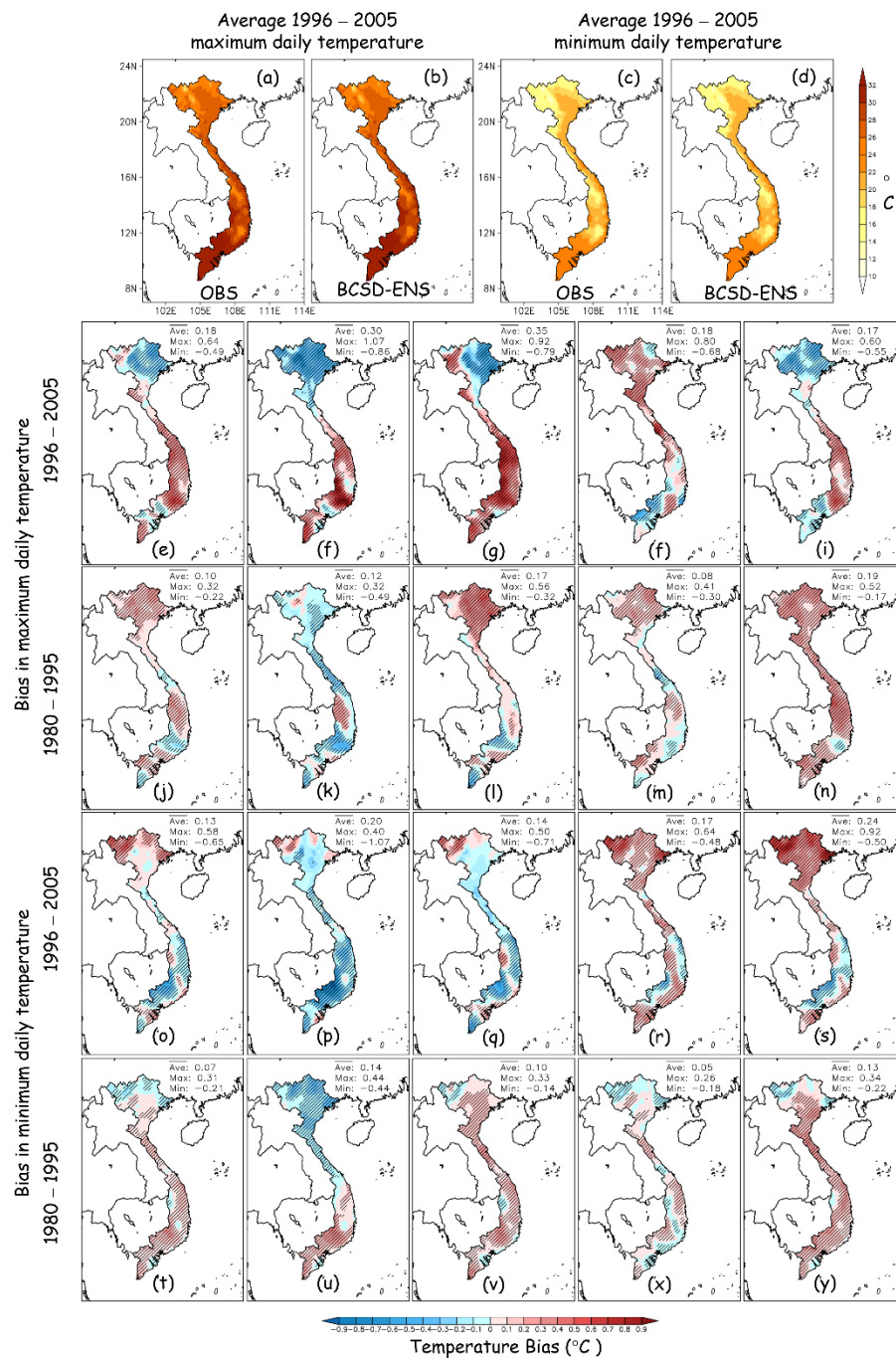


Figure A1. Spatial distribution of annual average maximum and minimum temperature in Vietnam by OBS and BCSD-ENS. (a, b) and (c, d) indicate the average 1996–2005 maximum and minimum temperature by OBS and BCSD-ENS, respectively. The biases

of BSCD-ENS compared to OBS for the independent period 1996–2005 and the training period 1980–1995 are displayed in (e-n) for maximum temperature and (o-y) for minimum temperature. The hatching lines show the regions where over $\frac{2}{3}$ of CMIP5 models have the same bias sign with BCSO-ENS.

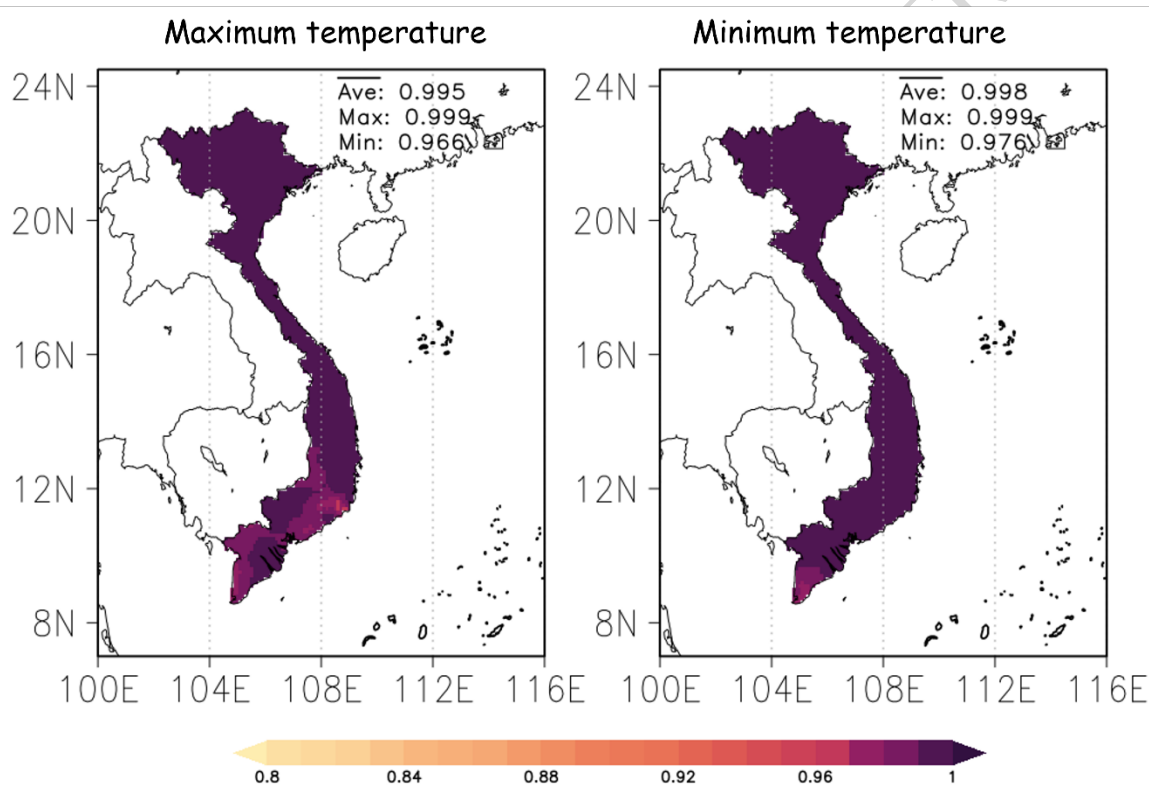


Figure A2. Temporal correlations of the 1996–2005 seasonal cycle between the BCSO-ENS and OBS for (left) maximum temperature and (right) minimum temperature.

Table 1. List of 31 CMIP5 GCMs, their resolutions, and RCP availability that are used in this study.

N o.	Climate Modeling Group	CMIP5 Model ID	Grid Resolution (degree)		Availability (* means Yes)			
			Lon.	Lat.	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
1	Commonwealth Scientific and Industrial Research Organization and Bureau of Meteorology, Australia	ACCESS1-0	1.25	1.875		*		*
2		ACCESS1-3	1.25	1.875		*		*
3	Beijing Climate Center, China Meteorological Administration	BCC-CSM1-1	2.791	2.813	*	*	*	*
4		BCC-CSM1-1-M	2.791	2.813	*	*		*
5	College of Global Change and Earth System Science, Beijing Normal University	BNU-ESM	2.791	2.813	*	*		*
6	Canadian Centre for Climate Modelling and Analysis	CanESM2	2.791	2.813	*	*		*
7	National Center for Atmospheric Research	CCSM4	0.942	1.25		*	*	*
8	Community Earth System Model Contributors	CESM1-BGC	0.942	1.25		*		*
9		CESM1-CAM5	0.942	1.25	*	*	*	*
10	Centro Euro-Mediterraneo per I Cambiamenti Climatici	CMCC-CM	0.748	0.75		*		*
11	Centre National de Recherches Météorologiques/ Centre Européen de Recherche et Formation Avancée en Calcul Scientifique	CNRM-CM5	1.401	1.406	*	*		*
12	Commonwealth Scientific and Industrial Research Organization,	CSIRO-Mk3-6-0	1.865	1.875	*	*	*	*

	Queensland Climate Change Centre of Excellence							
13	NOAA Geophysical Fluid Dynamics Laboratory	GFDL-CM3	2	2.5	*	*		*
14		GFDL-ESM2G	2.023	2	*	*	*	*
15	NASA Goddard Institute for Space Studies	GISS-E2-H	2	2.5	*	*	*	*
16		GISS-E2-H-CC	2	2.5		*		*
17		GISS-E2-R	2	2.5	*	*	*	*
18		GISS-E2-R-CC	2	2.5		*		*
19	Met Office Hadley Centre	HadGEM2-CC	1.25	1.875		*		*
20	(additional HadGEM2 ES realizations contributed by Instituto Nacional de Pesquisas Espaciais)	HadGEM2-ES	1.25	1.875	*	*		*
21	Institut Pierre-Simon Laplace	IPSL-CM5A-LR	1.897	3.75	*	*		*
22		IPSL-CM5A-MR	1.268	2.5	*	*	*	*
23		IPSL-CM5B-LR	1.895	3.75		*		*
24	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	MIROC-ESM	2.791	2.813	*	*	*	*
25		MIROC-ESM-CHEM	2.791	2.813		*	*	*
26	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	MIROC5	1.401	1.406	*	*	*	*
27	Max-Planck-Institut für Meteorologie (Max Planck Institute for Meteorology)	MPI-ESM-LR	1.865	1.875	*	*		*
28		MPI-ESM-MR	1.865	1.875	*	*		*
29	Meteorological Research Institute	MRI-CGCM3	1.121	1.125	*	*		*

30	Norwegian Climate Centre	NorESM1-M	1.895	2.5	*	*	*	*
31		NorESM1-ME	1.895	2.5		*		*
	Total number of available models for each RCP				20	31	12	31

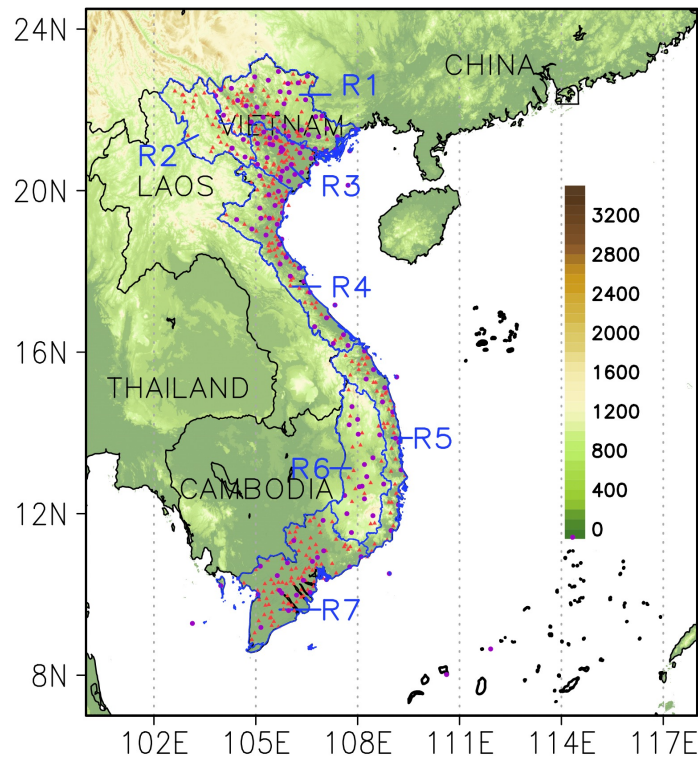


Figure 1. The seven climatic sub-regions of Vietnam. Purple and red circles show the locations of 157 temperature- and 481 rainfall-stations of which data are used in this study, respectively. Topography over Vietnam (shaded, in m) is obtained from the Hydrological data and maps based on Shuttle Elevation Derivatives at multiple Scales (HydroSHEDS) (Lehner 2013).

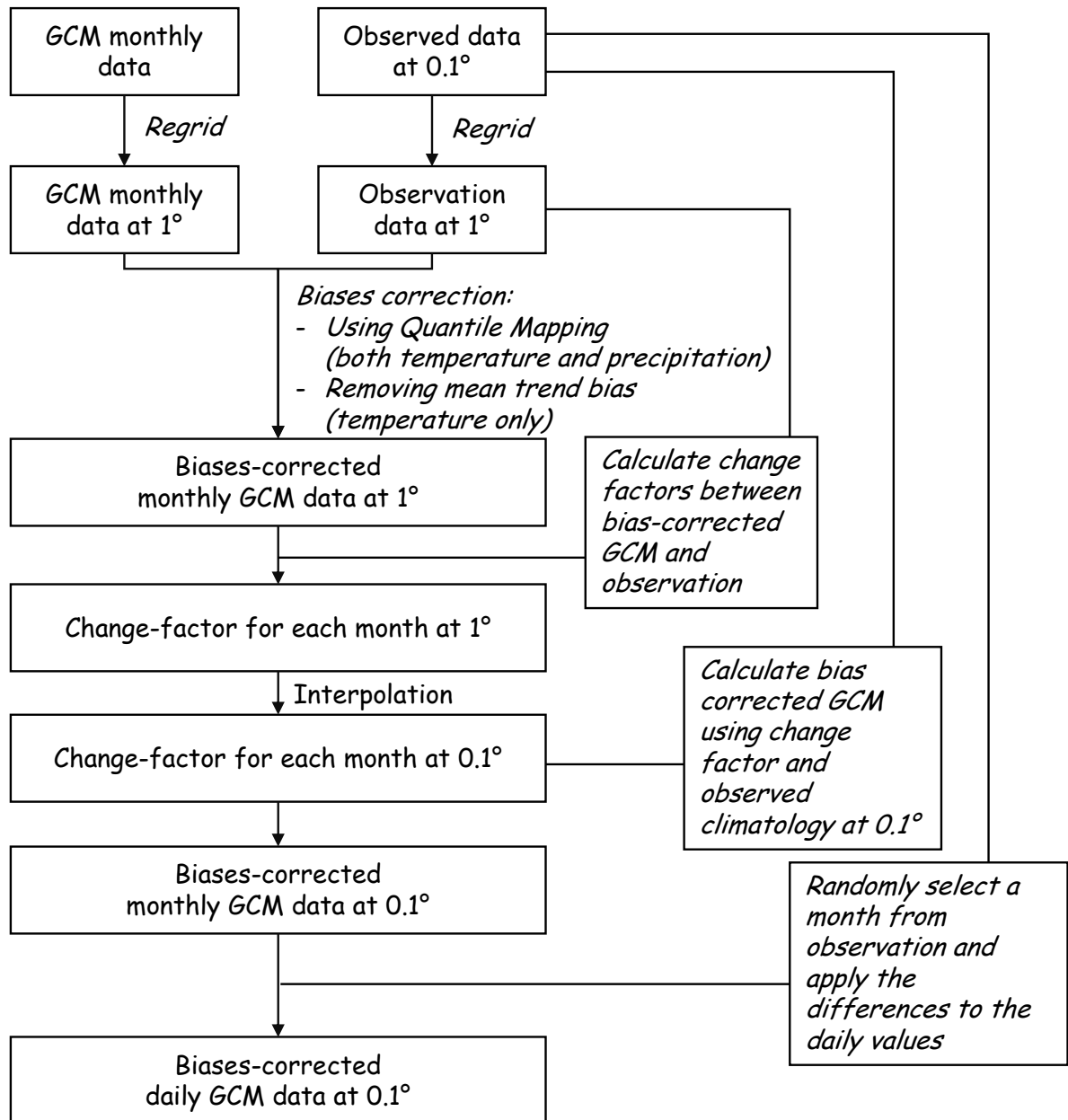


Figure 2. The schema of the BCSD algorithm applied in this study.

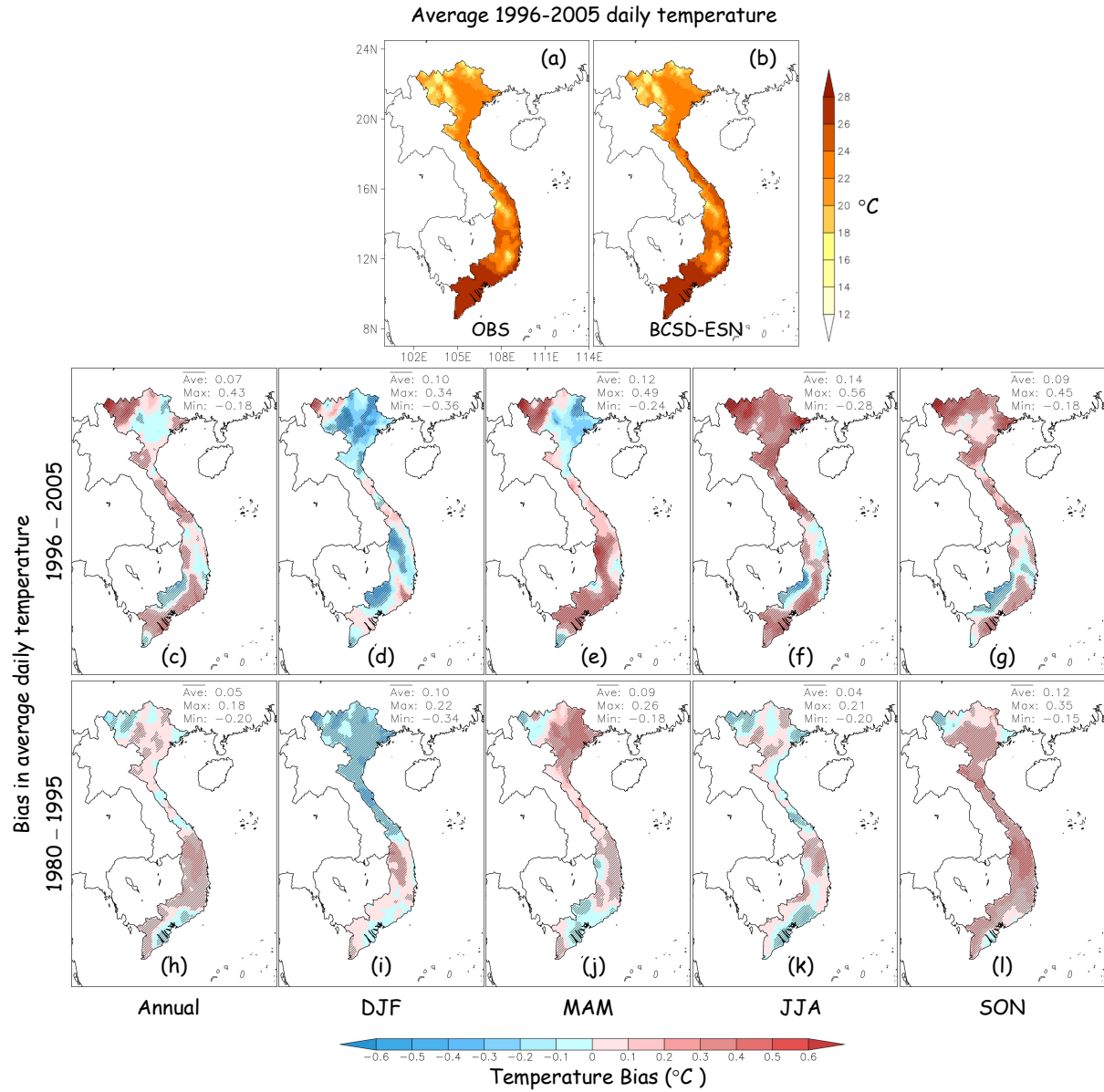


Figure 3. Spatial distribution of annual average temperature in Vietnam by OBS and BCSD-ENS. (a, b) indicate the average 1996–2005 temperature by OBS and BCSD-ENS; (c–g) and (h–l) indicate the biases of BCSD-ENS compared to OBS for the independent period 1996–2005 and the training period 1980–1995, respectively. The hatching lines show the regions where over $\frac{2}{3}$ of CMIP5 models have the same bias sign with BCSD-ENS.

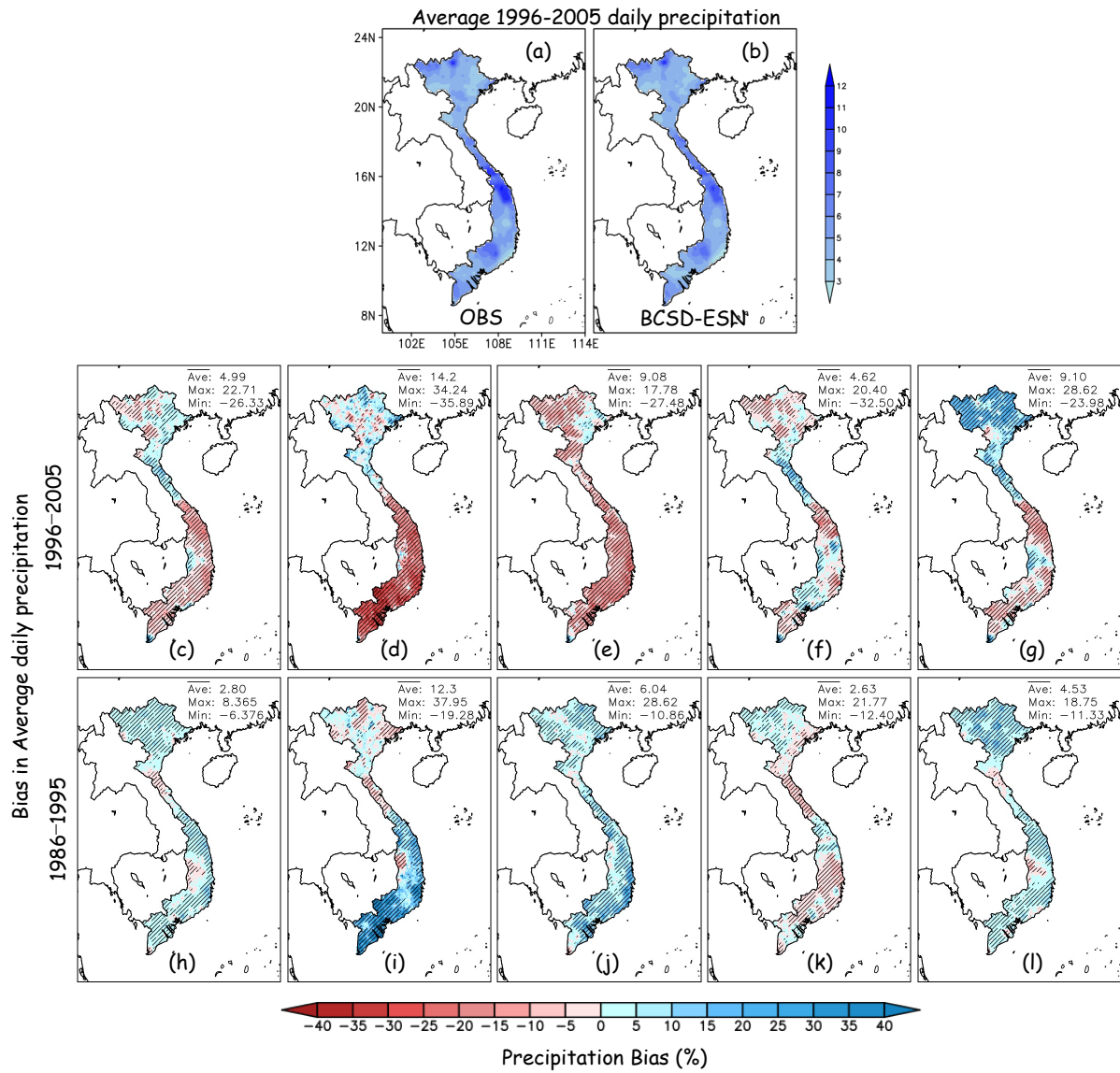


Figure 4. Same as Figure 3 but for precipitation.

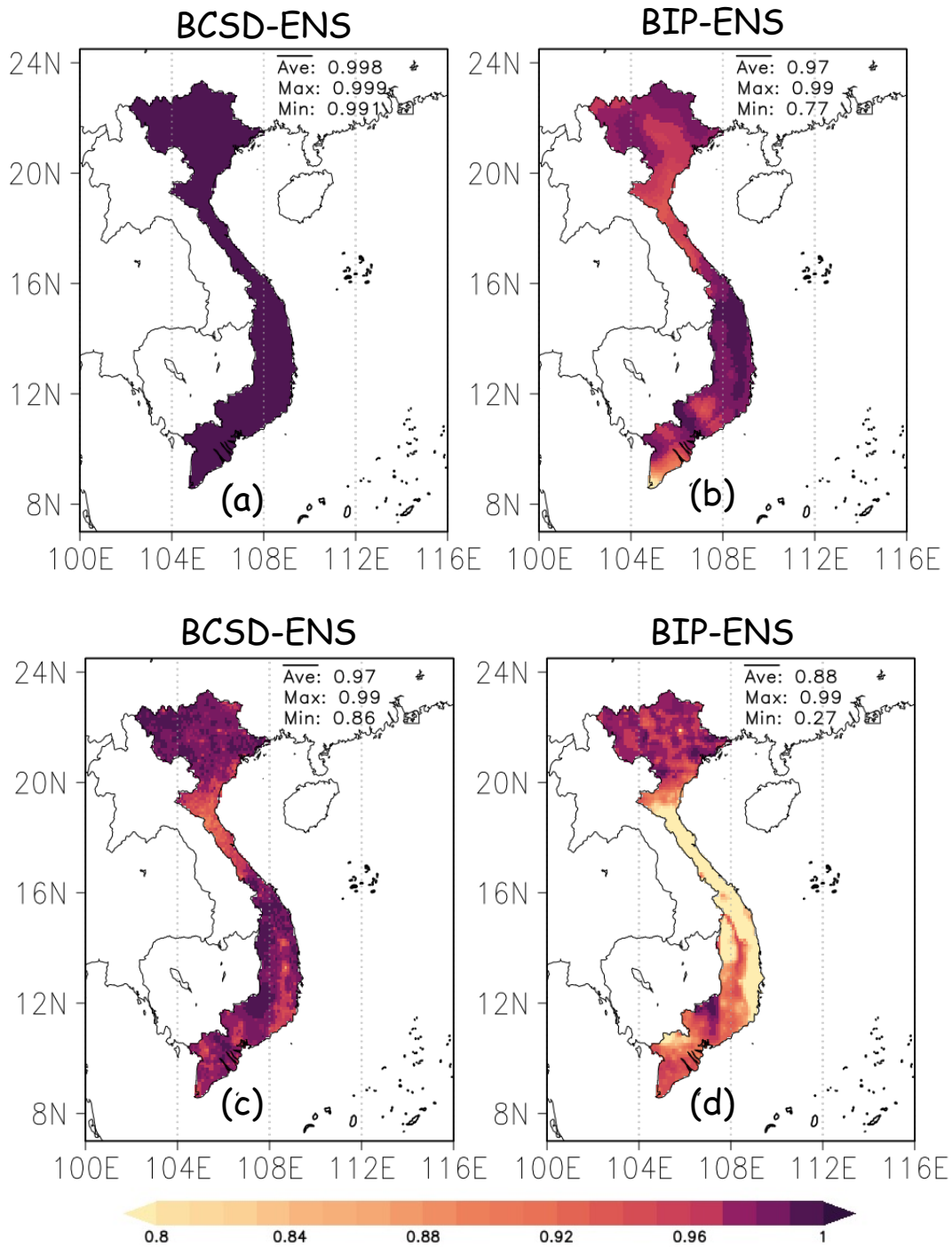


Figure 5. Temporal correlations of the 1996–2005 seasonal cycle between the BCSD-ENS (left) and BIP-ENS (right) with OBS for (a, b) temperature and (c, d) precipitation.

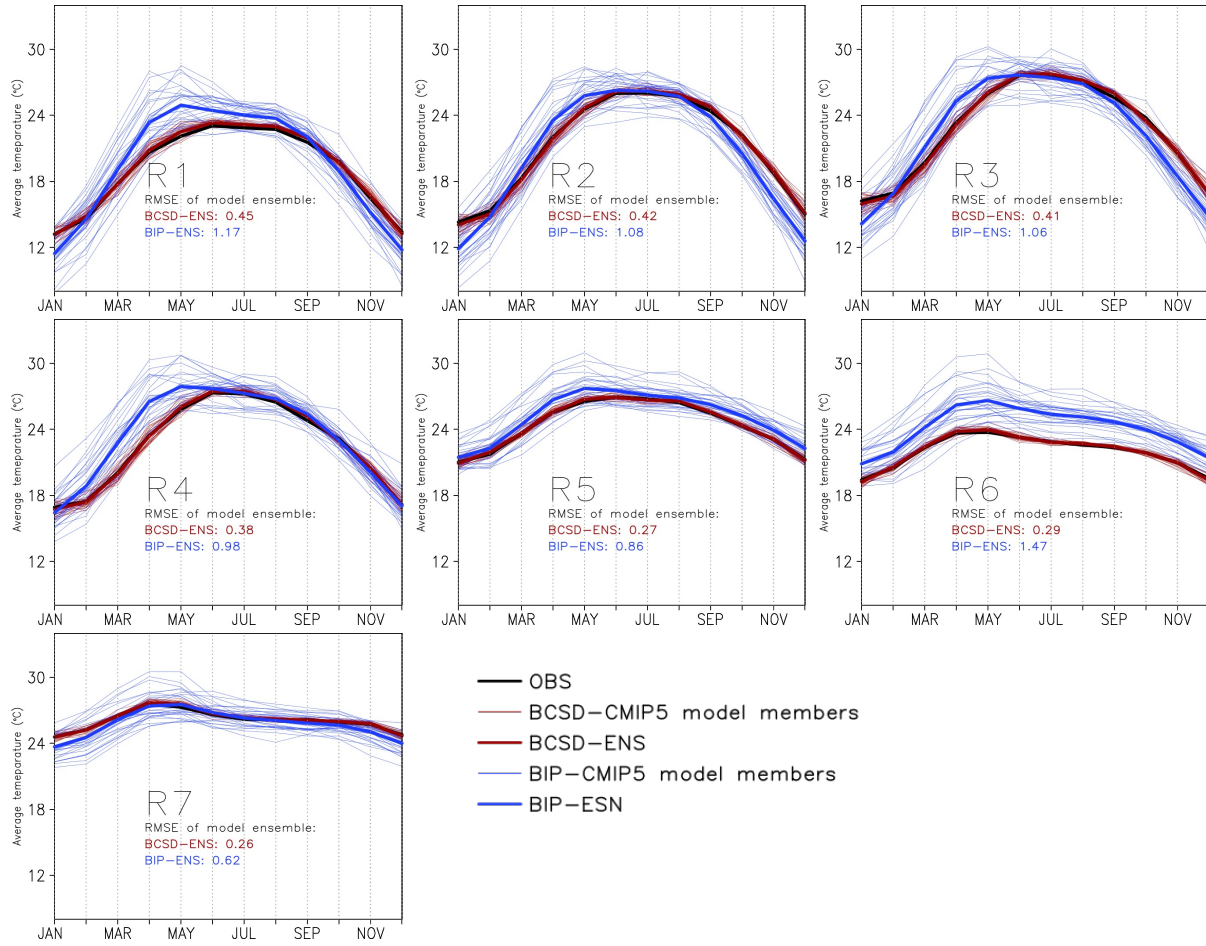


Figure 6. Comparison of seasonal temperature cycles by OBS, BCSD, and BIP for the seven climatic sub-regions for the period 1996–2005. The seasonal cycle is shown for OBS (black), for 31 downscaled individual CMIP5 model members by BCSD (dim red) and BIP (dim blue), and two models ensemble mean, the BCSD-ENS (dark red) and the BIP-ENS (dark blue). Mean square errors (MSE) of the BCSD-ESN and BIP-ENS are also indicated.

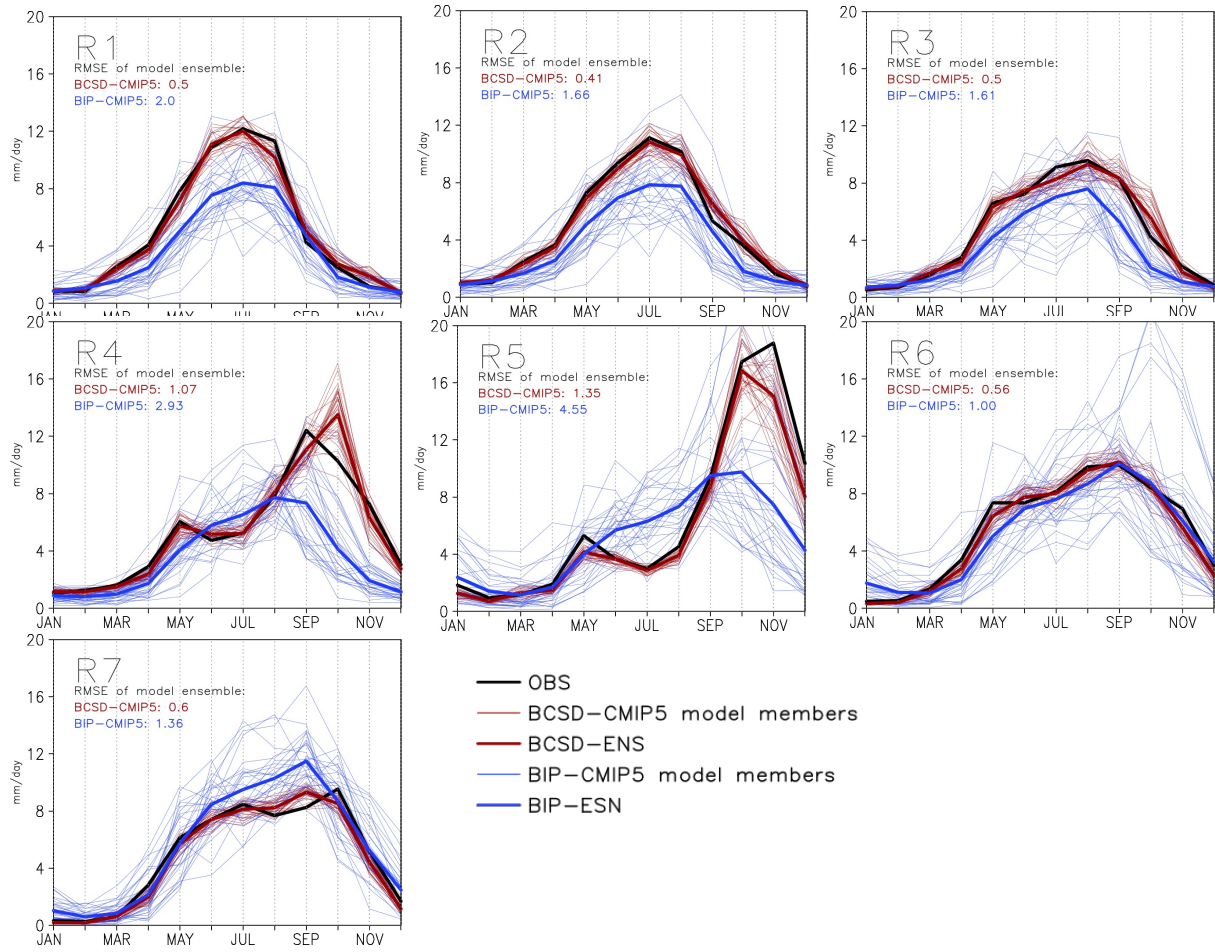


Figure 7. Same with Figure 6 but for precipitation.

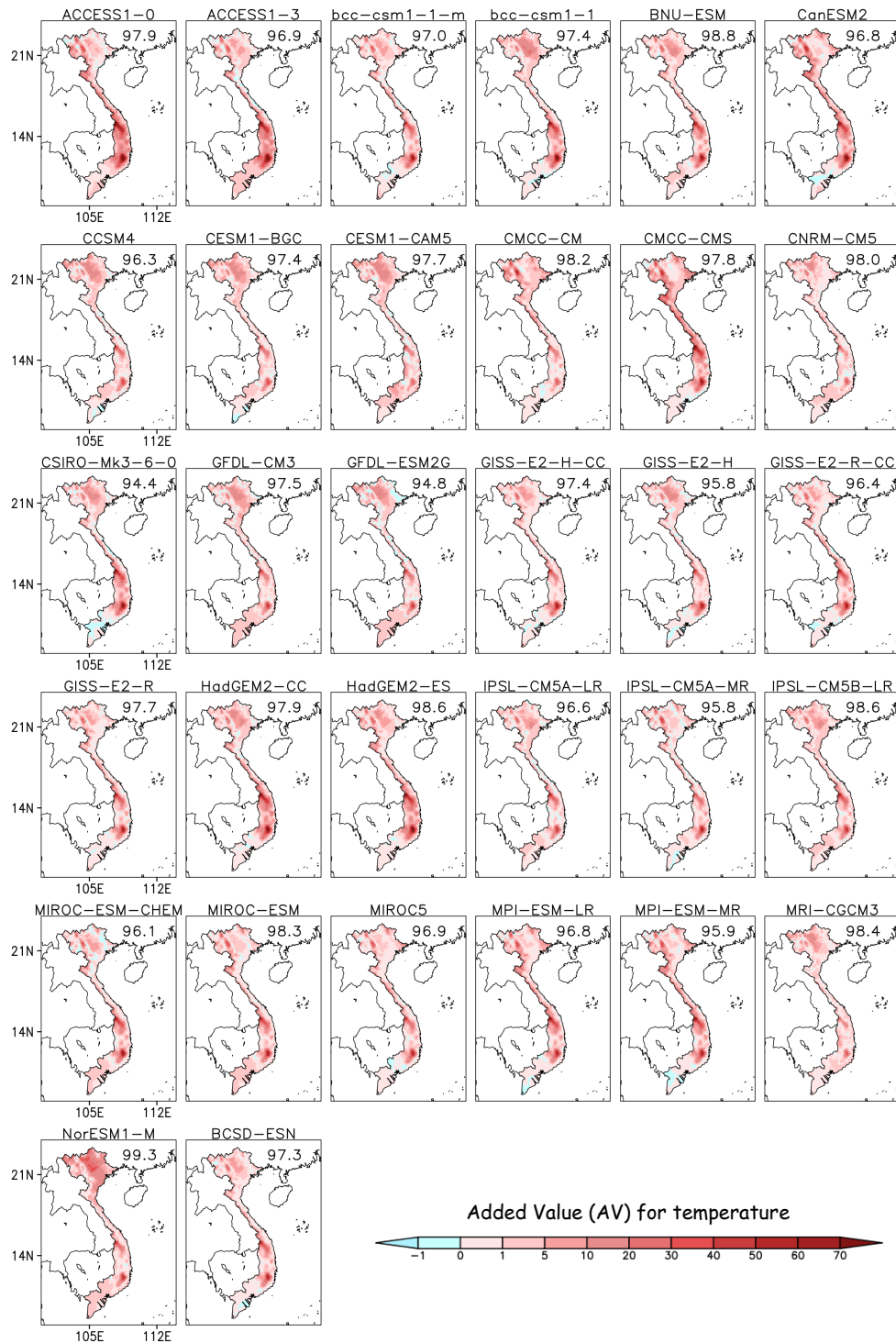


Figure 8. AVs of individual BCSD-CMIP5 and BCSD-ENS for temperature over the BIP-CMIP5 for the 1996–2005 period. The darker saturation of warm/cold color denotes the more

skillful/unskillful of the BCSD. The number in the top right corner indicates the percentage of the grids having positive AV values.

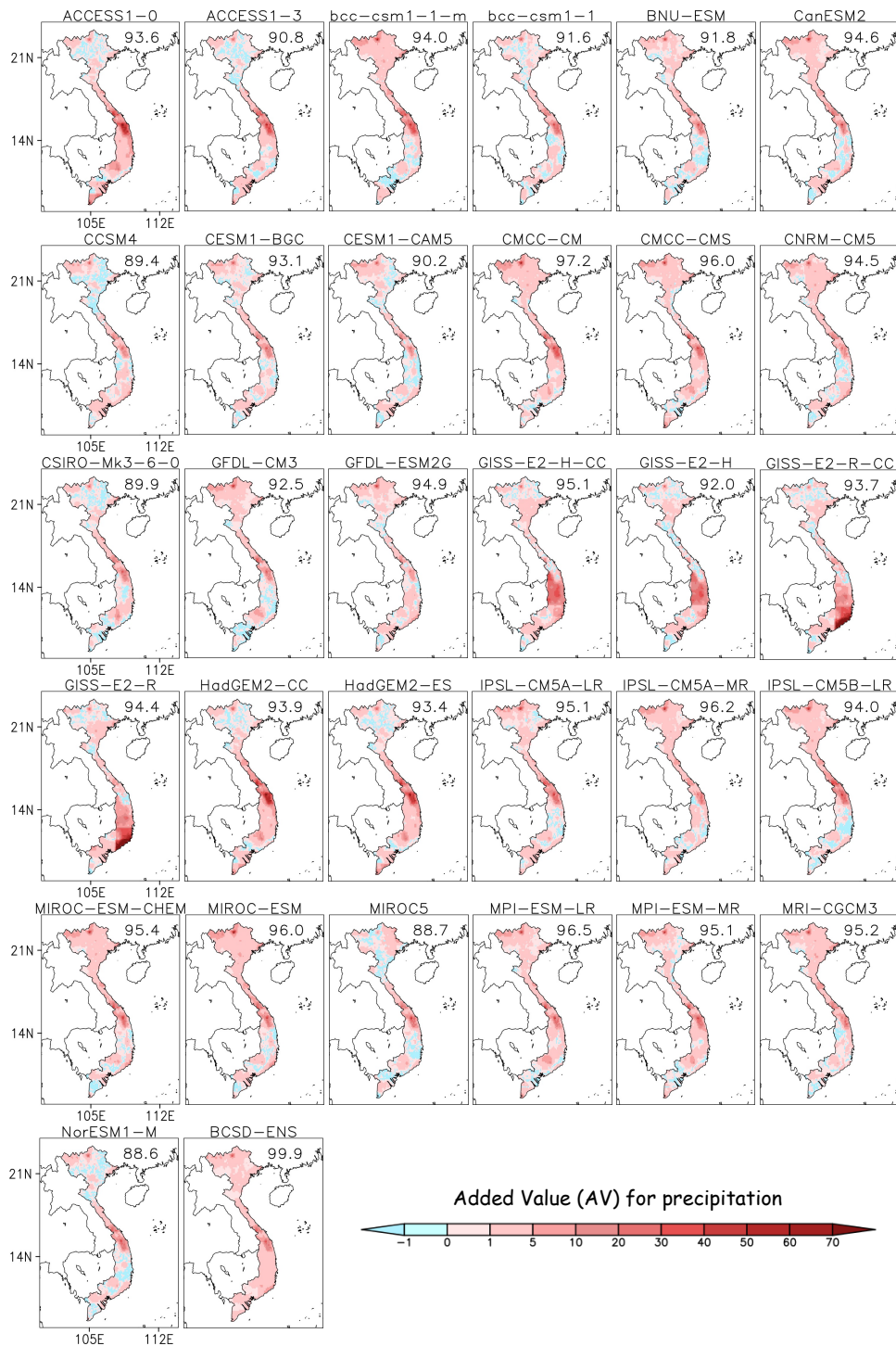


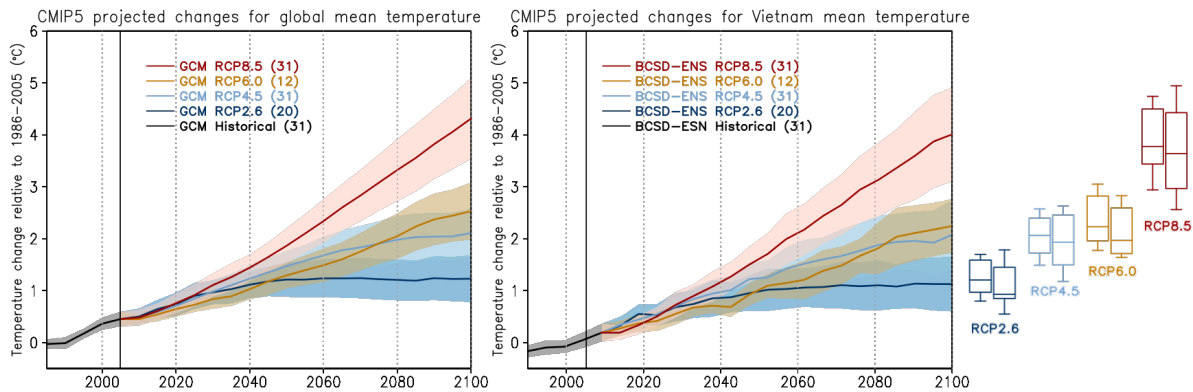
Figure 9. Same as Figure 8 but for precipitation.

Figure 10. Projected temperature changes relative to the baseline period 1986–2005 based on the CMIP5 GCMs and BCSD-CMIP5 data for global average (left) and Vietnam (right), respectively. 5-year moving averages are applied. Colored lines show the ensemble means of the models and colored shaded areas present the uncertainty ranges (± 1 standard deviation) for each RCP. The number of models used for each RCP is shown in brackets. Box plots on the right display the occurrence statistics (quartile, median, 10th, and 90th percentile) for warming levels on the global scale (left boxes) and in Vietnam (right boxes) at the end of the 21st century 2080–2099.

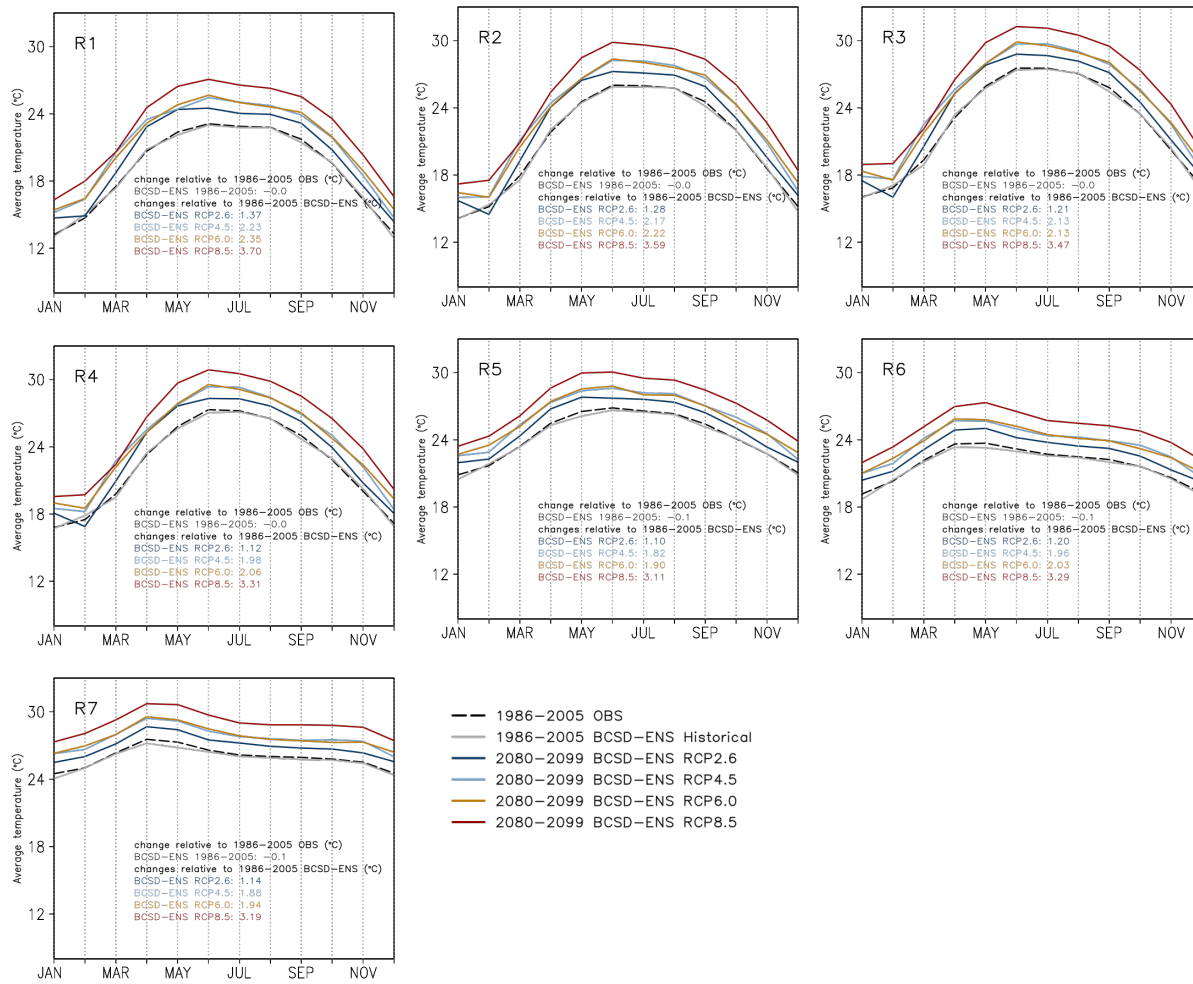


Figure 11. Comparison between the seasonal temperature cycles of the BCSD-ENS and OBS over the seven climatic sub-regions of Vietnam. Black and grey dashed lines respectively represent the OBS and BCSD-ENS cycles for 1986–2005, while color lines represent the future 2080–2099 seasonal cycles for each RCP. Average changes between the future 2080–2099 BCSD-ENS and the 1986–2005 OBS with the historical 1986–2005 BCSD-ENS are also displayed.

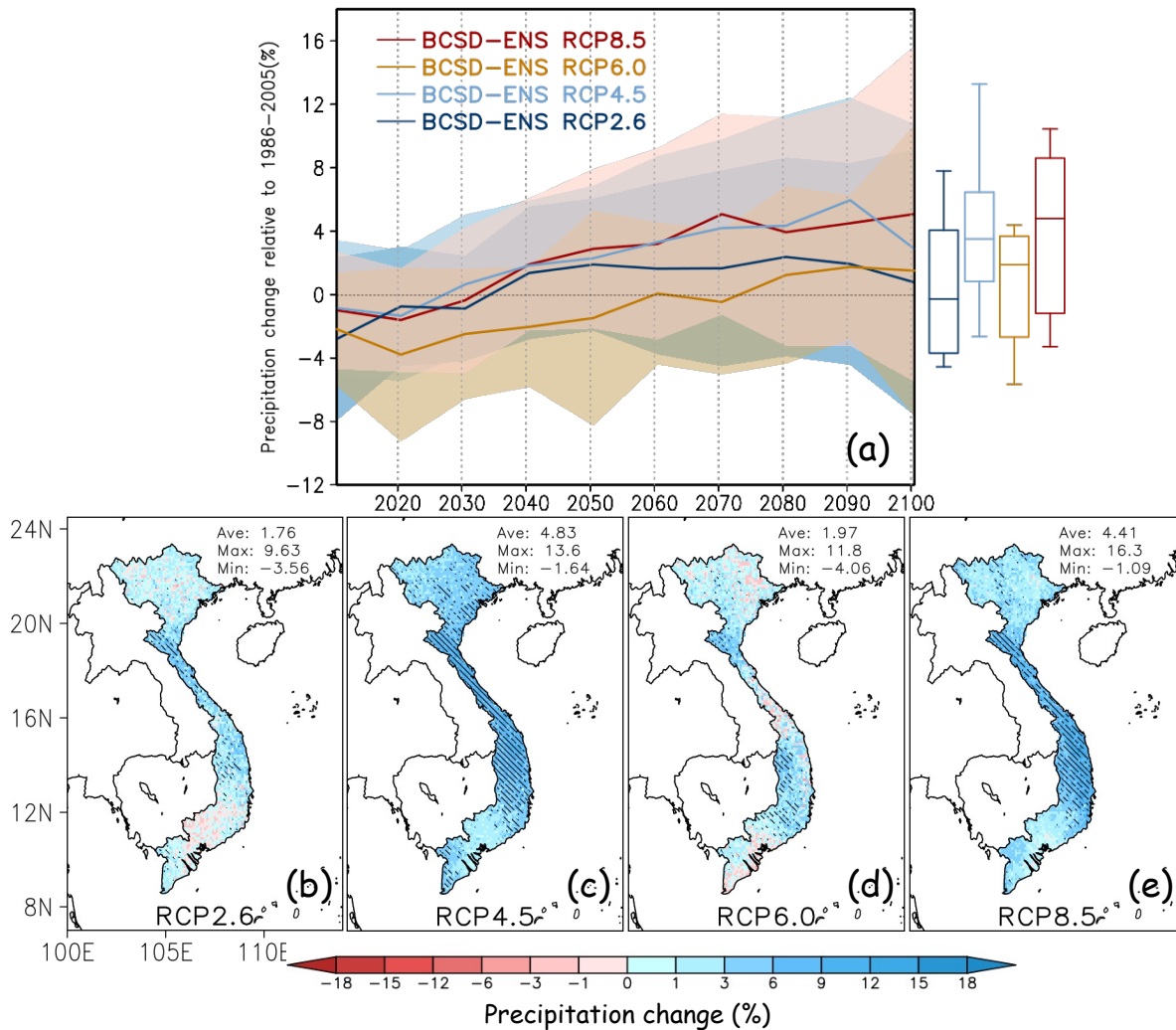


Figure 12. Projected precipitation changes in Vietnam under different RCPs. (a) Colored lines present the 10-year moving average of the BCSD-ENS and colored shaded areas show the uncertainty ranges (± 1 standard deviation). Box plots on the right display the occurrence statistics (quartile, median, 10th, and 90th percentile) for precipitation changes at the end of the 21st century 2080–2099. (b, c, d, e) Distribution of change patterns between the 2080–2099 and 1986–2005 periods derived by the BCSD-ENS. The hatching lines show the regions where over $\frac{2}{3}$ of BCSD CMIP5 models have the same bias sign as the BCSD-ENS.

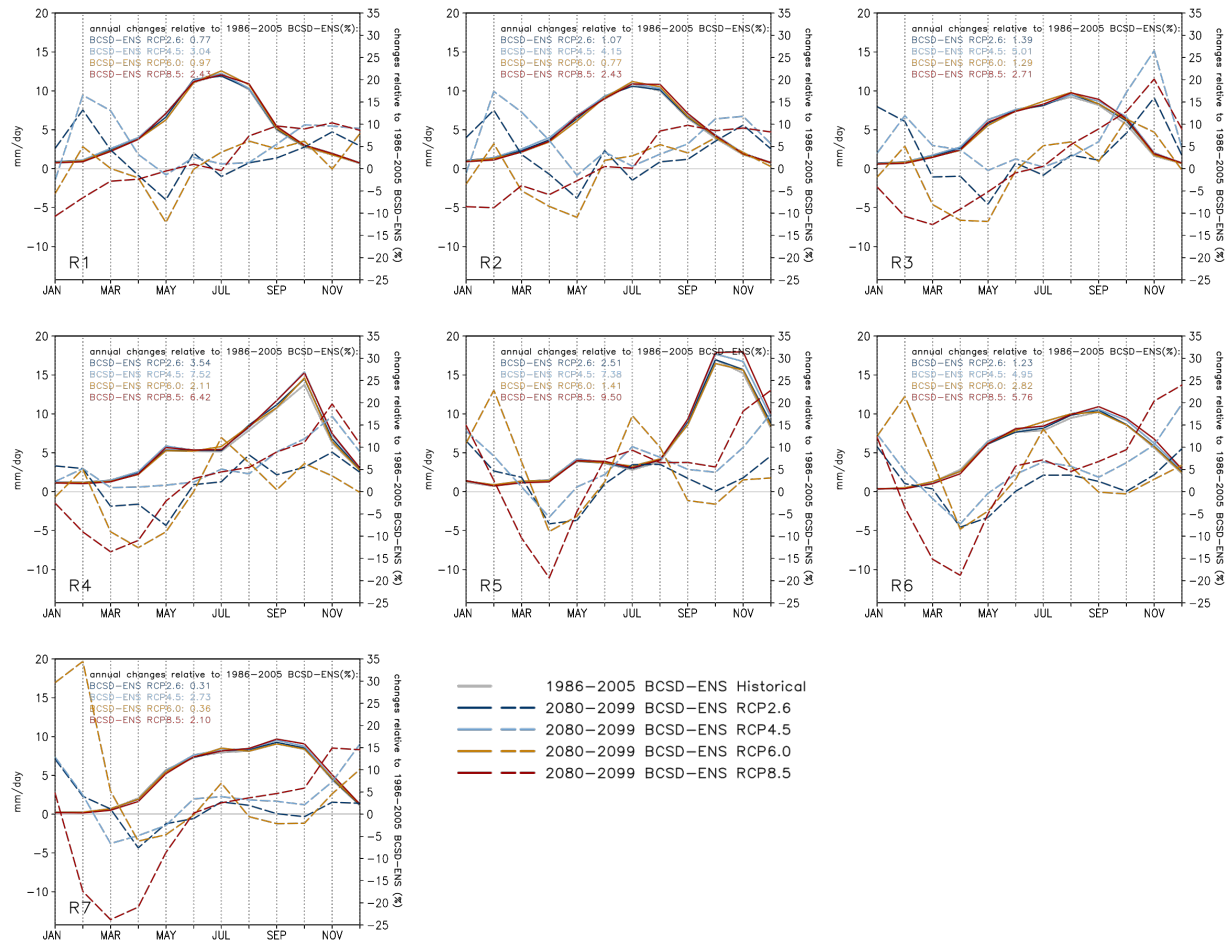


Figure 13. Precipitation seasonal cycles (left axis, solid lines) under different RCPs and their percentage changes (right axis, dash lines) relative to the 1986–2005 BCSD-ENS over the seven climatic sub-regions of Vietnam. Average changes (%) of the BCSD-ENS between the future 2080–2009 and the baseline 1986–2005 period are also displayed.

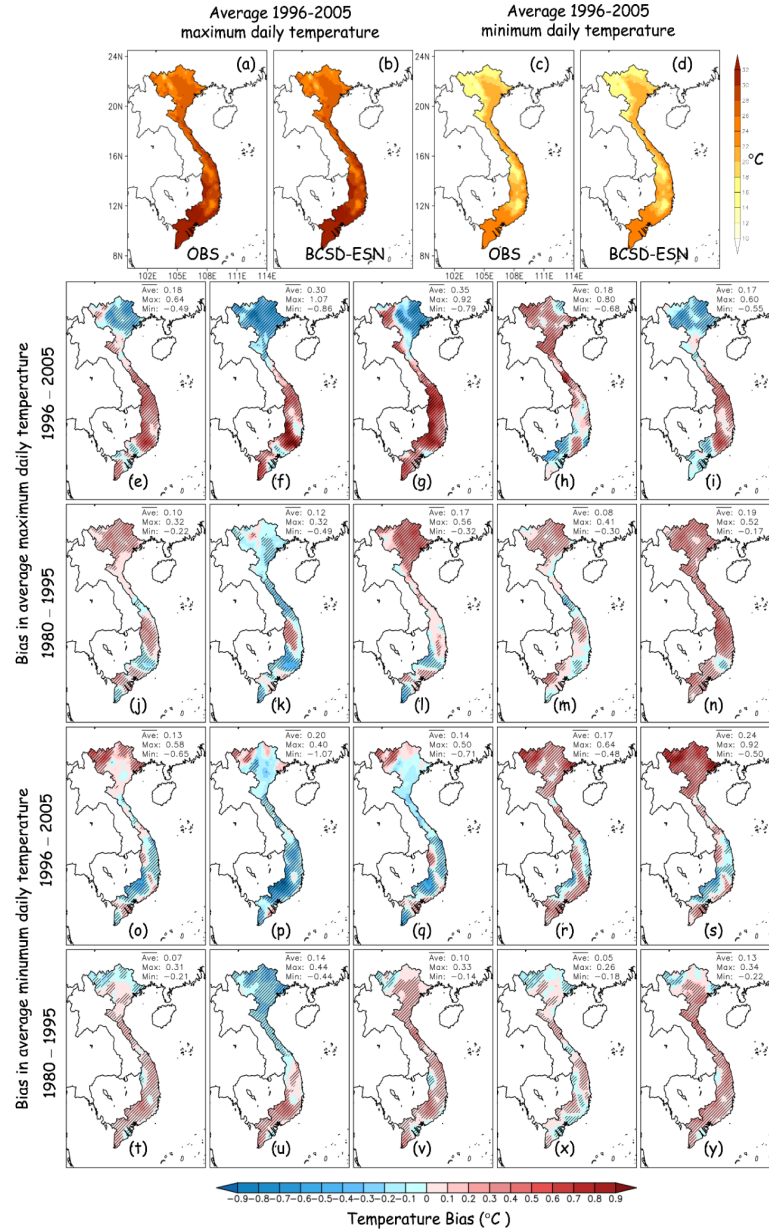
[Supplemental figures]

Figure A1. Spatial distribution of annual average maximum and minimum temperature in Vietnam by OBS and BCSD-ENS. (a, b) and (c, d) indicate the average 1996–2005 maximum and minimum temperature by OBS and BCSD-ENS, respectively. The biases of BCSD-ENS compared to OBS for the independent period 1996–2005 and the training period 1980–1995 are displayed in (e-n) for maximum temperature and (o-y) for minimum temperature. The hatching

lines show the regions where over $\frac{2}{3}$ of CMIP5 models have the same bias sign with BCSD-ENS.

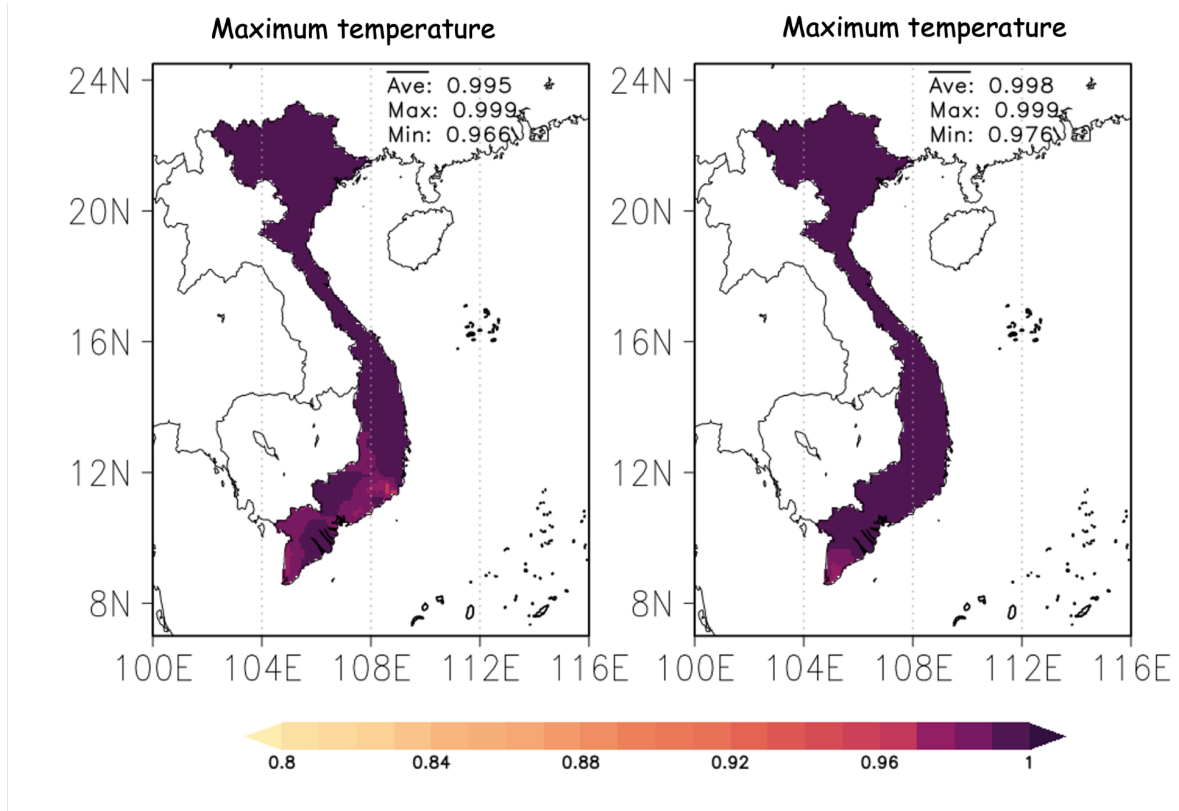


Figure A2. Temporal correlations of the 1996–2005 seasonal cycle between the BCSD-ENS and OBS for (left) maximum temperature and (right) minimum temperature.

APPENDIX

Supplementary Verification for CMIP5-VN

a. Spatial distribution of maximum and minimum temperature

The spatial distribution of annual maximum and minimum temperature obtained from BCSD-ESN over the independent period 1996-2005 are illustrated in Fig A(a-d), where simulated temperature patterns are very identical to the observed data. The simulation biases for the independent (training) period indicated in Fig. A(e-y) are relatively small, ranging between -0.86°C (-0.49°C) and 0.92°C (0.56°C) in average maximum temperature and between -1.07°C (-0.44°C) and 0.92°C (0.44°C) in average minimum temperature. The average annual biases for the training period is noticeably less than those in the independent dataset in both maximum/minimum temperature, e.g. $0.10^{\circ}\text{C}/0.07^{\circ}\text{C}$ compared to $0.18^{\circ}\text{C}/0.13^{\circ}\text{C}$. Since the QM method might be sensitive to the magnitude of annual and seasonal ranges of temperature, it explains the larger biases in maximum temperature in minimum temperature.

In both independent and training periods, seasonal temperature biases are generally larger than the annual average bias (Fig 3(e-y)). There is a strong agreement in the bias tendency among the models at the places with large bias where more than $\frac{2}{3}$ of the model members having the same bias sign with the BCSD-ENS.

Compare to the biases of BCSD-ENS outputs for near surface temperature for the independent period (Fig. 3), those biases for maximum and minimum temperature are slightly higher and the difference between cold and warm bias patterns is more intense.

b. Temporal distribution

The reproducibility of BCSD-ESN for the seasonal cycles of maximum and minimum temperature of the independent period is investigated in Fig. A2, where correlation values between BCSD-ENS and OBS are calculated for each grid cells. The average correlation values are very high, i.e. 0.995 and 0.998 for maximum and minimum temperature, respectively, indicating a very good agreement between the BCSD-ENS and OBS.

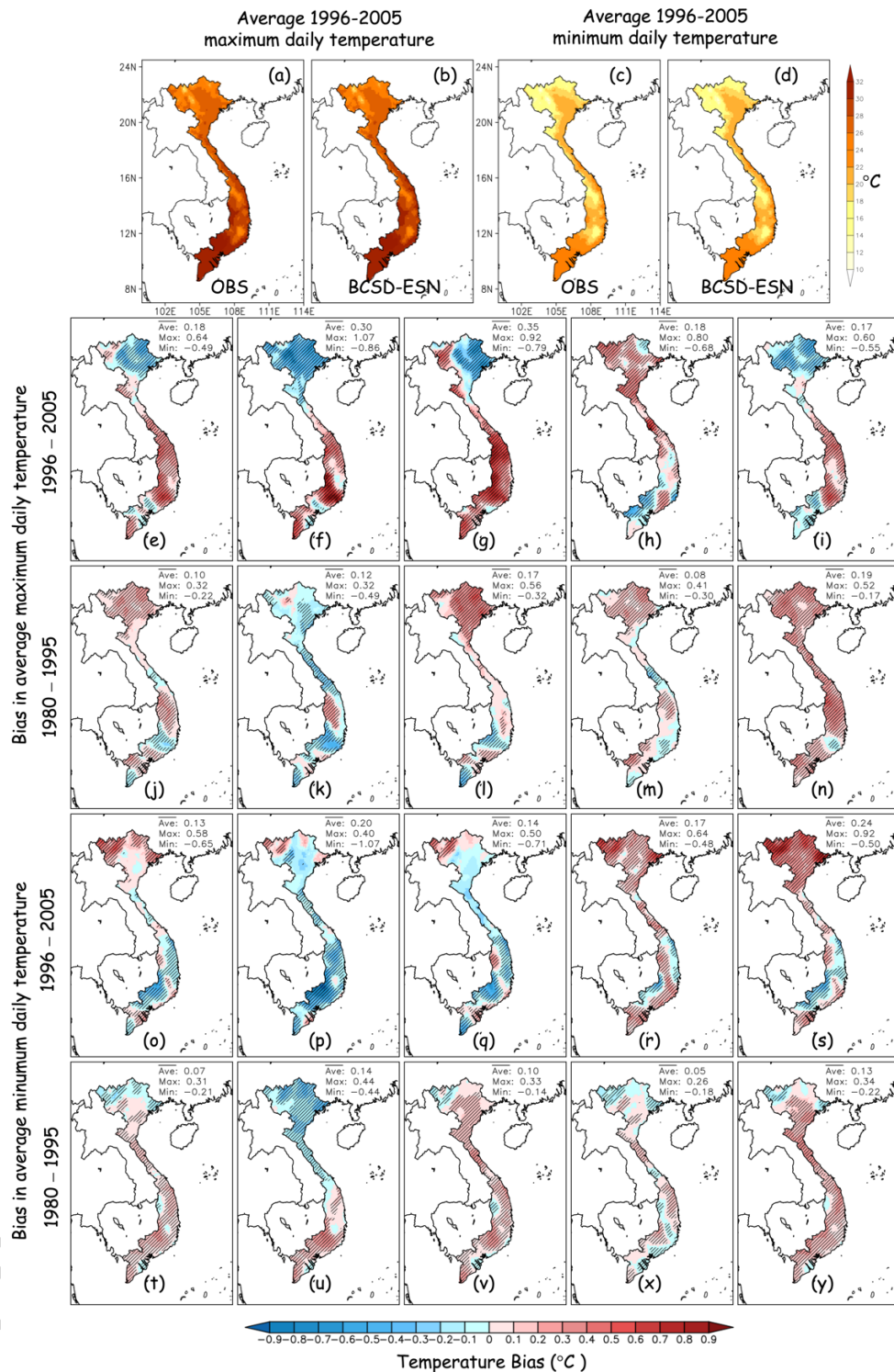


Figure A1. Spatial distribution of annual average maximum and minimum temperature in Vietnam by OBS and BCSD-ENS. (a, b) and (c, d) indicate the average 1996–2005 maximum and minimum temperature by OBS and BCSD-ENS, respectively; The biases of BCSD-ENS compared to OBS for the independent period 1996–2005 and the training period 1980–1995 are displayed in (e–n) for maximum temperature and (o–y) for minimum temperature. The hatching lines show the regions where over $\frac{2}{3}$ of CMIP5 models have the same bias sign with BCSD-ENS.

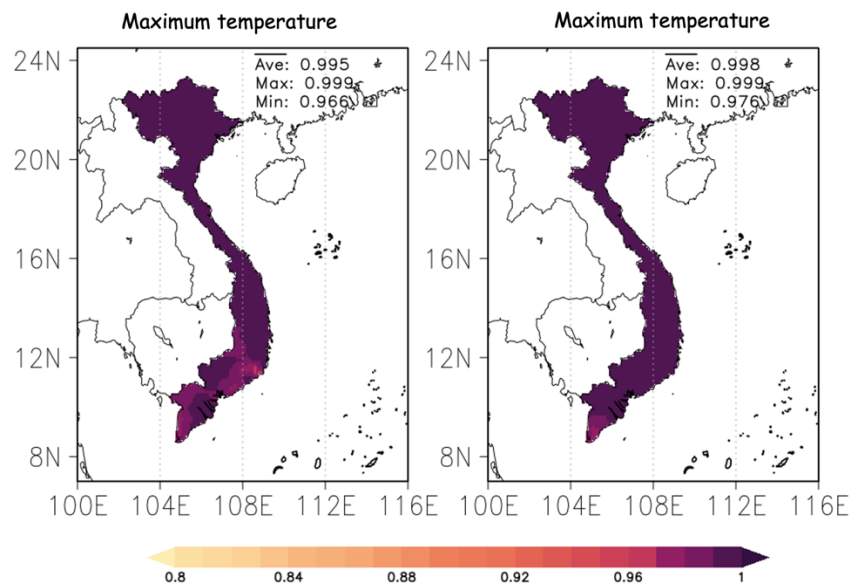


Figure 5. Temporal correlations of the 1996–2005 seasonal cycle between the BCSD-ENS and OBS for (left) maximum temperature and (right) minimum temperature