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Projections of future rainfall for the upper Ping River Basin using regression-based downscaling

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Abstract

The objective of this study was to use regression modelling, a form of statistical downscaling technique, to predict the daily rainfall occurrence and rainfall amounts for a small river basin, the upper Ping River Basin (UPRB) in northern Thailand. Daily historic (1960−2005) rainfall and a number of daily reanalysis variables (NCEP/NCAR) were used to create regression models that estimate the probabilities of rainfall occurrence (wet days) and amounts (rainfall depth) at each of 29 rain gauge stations located in and around the UPRB. The regression models were calibrated using historic (1960−1989) data and validated using historic (1990−2005) data. Regression models were later applied to historic (1960−2005) GCM outputs (MPI-ESM-LR model) which were adjusted to correspond to the selected reanalysis variables using the Nested Bias Correction (NBC) technique. Rainfall occurrence and amounts were predicted for the periods 2006−2050 and 2051−2100 for RCP2.6, RCP4.5, RCP8.5 scenarios. Results show that the effects of climate change vary considerably across the catchment, with significantly declines in both the number of wet days and rainfall depth in the wet- and especially the dry-season in the middle of the catchment but obviously increase slightly towards the northern part of the catchment. Since the stepwise regression was used to select the atmospheric variables to form the regression models for simulating rainfall occurrence and amount, different stations have their own predictors and can influence future rainfall to vary significantly between 29 rain gauge stations. If the top three predictors were selected to form the regression models for simulating rainfall occurrence and amount for all stations, the future rainfall characteristics possibly change and can be used to compare with those of presented in this study. It will show either atmospheric predictors or climate change scenarios would have more effect on future rainfall characteristics.

Keywords: Statistical downscaling; Nested bias correction; MPI-ESM-LR model; Representation concentration pathways (RCPs); Ping River Basin

1. Introduction

An assessment of climate change impacts on hydrological studies requires outputs of experiments from General Circulation Models (GCMs). However, the GCMs are constrained by their coarse spatial resolution to be used for resolving local scale hydrological processes (Wilby and Wigley, 1997; Wilby et al., 1999; Timbal et al., 2009). Downscaling techniques have therefore emerged to relate the regional scale atmospheric variables to the local scale surface variables. Downscaling approaches can be separated into two categories; dynamical and statistical techniques. Strengths and weaknesses of these two downscaling categories are clearly presented by Wilby et al. (2002). In dynamic downscaling referred to as the Regional Climate Models (RCMs), the time-varying atmospheric conditions supplied by GCMs are used to drive a regional, numerical model in higher spatial resolution (tens of kilometres) to simulate local conditions in greater details. On the other hand, a statistical downscaling establishes a statistical relationship from observations between large scale variables and a single local variable and then subsequently

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applies the developed relationship on the scenario GCM outputs to obtain a range of local variables. Statistical downscaling can be distinguished into three approaches: weather classification schemes, stochastic weather generators, and regression models (Wilby et al., 2004). Regression models have been used by several scientists to simulate future rainfall projections using either linear or nonlinear relationship between local scale surface variables and atmospheric variables (Wilby and Wigley, 1997; Wilby et al., 1999; Dettinger et al., 2004; Feng et al., 2014). Regression-based approach was also successfully applied for simulating daily rainfall occurrence and amount in the Yangtze River Basin (Guo et al., 2012), Godavari River basin in India (Das and Umamahesh, 2016) and 60 stations in South Korean (Min et al., 2011). Yhang et al. (2017) compared the performances of different downscaling methods, focusing on East Asian summer monsoon. The dynamical downscaling was conducted by the Regional Model Program (RMP) of the Global/Regional Integrated Model system (GRIMs), while the statistical downscaling was performed through coupled pattern-based simple linear regression. A combination of dynamical and statistical downscaling has shown to produce the best results of simulating the precipitation in both time and space.

Statistical characteristics of the reanalysis data and the GCM outputs at the corresponding location and period used for generating the regression relationships are normally different. Bias correction technique is therefore usually applied for adjusting these differences. The simplest bias correction method focuses on the monthly mean difference between these two data types (Graham et al., 2007). Haerter et al. (2011) recommended that the differences of the standard deviation (STD) should also be considered together with the mean differences to be able to significantly reduce the statistical differences between the simulated (GCMs) and observed (reanalysis) data. However, Johnson and Sharma (2009) proposed a method called a Nested Bias Correction (NBC) which involved nesting the GCM simulations into monthly and annual time series of observed data, such that monthly and annual means, variances and lag correlations are appropriately simulated. The NBC has proved to provide better performance in terms of prediction error at annual and inter-annual time scales compared to a simple monthly correction method (considering only the differences of means and STD of the two data types). Moss et al. (2010) also suggested that these RCPs scenarios can provide a framework for modeling in the next stages of scenario-based research that will yield valuable insights into the interaction of natural and human-induced climate processes.

Rainfall changes in the upper Ping River Basin (UPRB) would affect runoff flowing into the Bhumibol Dam, the major dam which delivers the water supply for all sectors for the lower Chao Phraya River Basin where Bangkok—the capital city—is located at the downstream of the UPRB. For water resources management of the dam and for finding suitable measures to mitigate water resources problems arising from changes in climate conditions, it is important to estimate future changes in rainfall in UPRB.

According to the flexibility, ease of implementation and low computation requirements of the regression-based approach (Wilby et al., 2004), regression models were used in this study to analyze the future effects of climate change on future rainfall at 29 locations within the UPRB and its surrounding. The NBC and Simple Bias Correction (SBC) were applied to the selected GCM predictors to calculate the bias correction factors to be used for adjusting the scenario GCM outputs. The RCPs scenarios from MPI-ESM-LR model developed under the phase five of the Coupled Model Intercomparison Project (CMIP5) by Max Planck Institute for Meteorology (MPI-M), Germany, were applied to simulate future rainfall occurrence and amounts.

2. Study area and data

2.1. Study area

The UPRB is situated 17°14′30″−19°47′52″N, 98°4′30″−99°22′30″E in Chiangmai and Lamphun province in northern Thailand (Fig. 1) (Mapiam et al., 2014). The UPRB is separated from the lower Ping River Basin (LPRB) by the Bhumibol Reservoir, which has an active storage capacity of 9.7×10^9 m^3. The Ping River, flowing along these two river basins, is one of the main tributaries of Chao Phraya, the largest river basin in Thailand, which drains more than one-third of the country's land area.

2.2. Rainfall data

Daily rainfall occurrence and amounts observed at the 29 stations by the Royal Irrigation Department (Fig. 1) were used to relate to the reanalysis variables to form the regression relationships. The 22 stations with an index starting by 07 and 17 are located in Chiang Mai and Lumphun province, respectively, while the 7 stations with an index starting by 20, 16 and 63 are located in Mae Hong Son, Lampang, and Tak province, respectively. These rainfall stations were selected according to their availability of the data for more than 96% during the study period (1960−2005).

2.3. Reanalysis data

Reanalysis grid point data (2.5° × 2.5°) on a daily basis in 1960−2005 provided by the National Centers for Environmental Prediction/Nation Center for Atmospheric Research (NCEP/NCAR), USA, available at http://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis.html (Kalnay et al., 1996) were utilized for the study.

2.4. General circulation model (GCM) outputs

The GCM outputs (1.875° × 1.875°) on a daily basis simulated using the MPI-ESM-LR model developed under CMIP5 by MPI-M, Germany (available at http://esgf-data.dkrz.de/esgf-web-fe/) were selected for the study. In this study, GCM outputs used are separated into 2 datasets. The

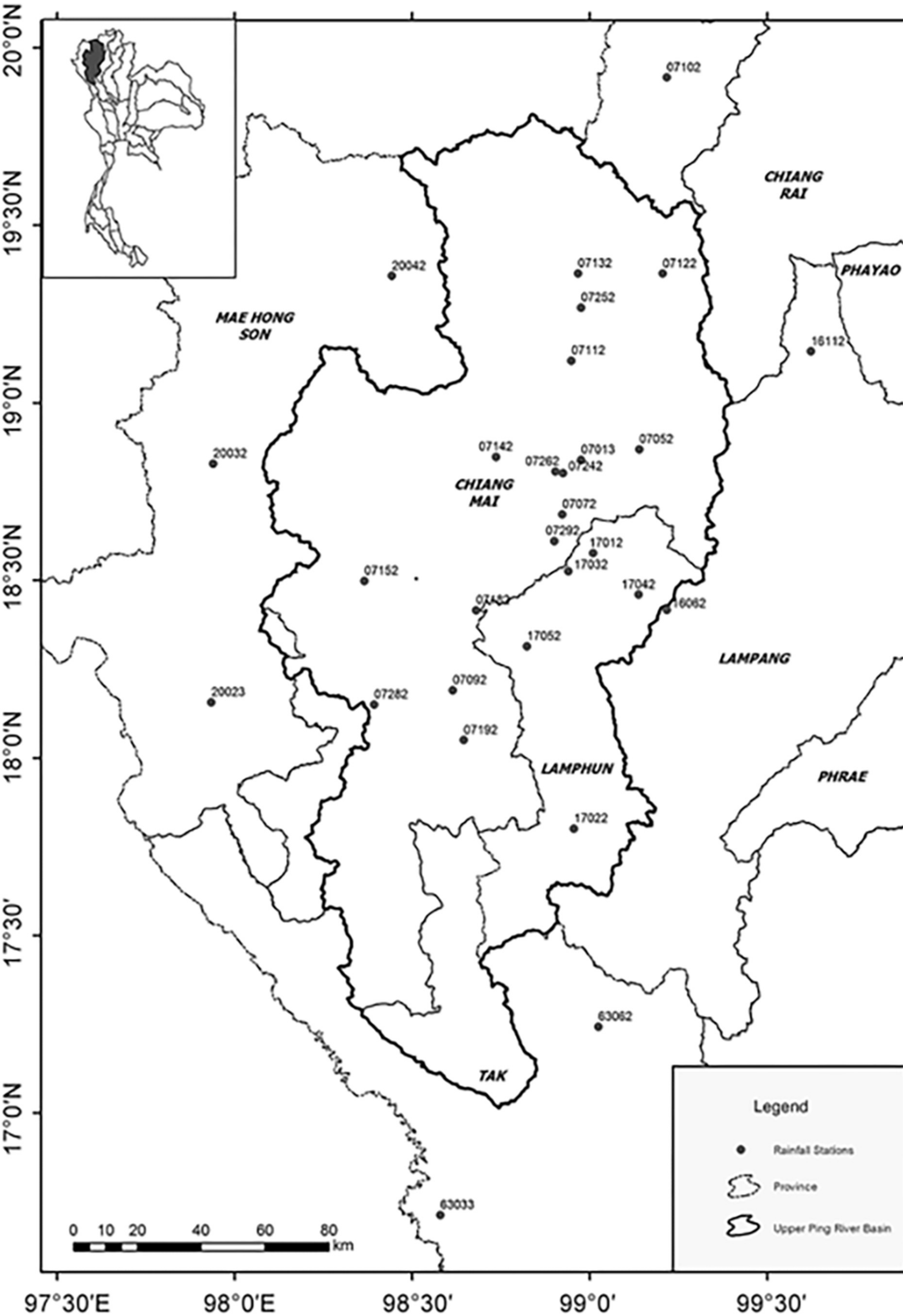

Fig. 1. The 29 rain gauge stations located within the upper Ping River Basin and its surrounding.

first dataset which are the atmospheric variable values from 1960 to 2005 were used as baseline. The second set from 2006 to 2100 simulated under RCP2.6, RCP4.5, and RCP8.5 scenarios were used for future climate simulation.

3. Methodology

3.1. Data selection and preparation

Selected atmospheric variables of the reanalysis data must correspond to the GCM outputs to be suitable for further use. Corresponding 72 atmospheric variables (12 predictors at air pressure varied between 4 and 11 levels) were downloaded from NCEP/NCAR and MPI-ESM_LR model outputs. Before carrying out any analysis on these atmospheric variables available at the 4 and 6 grid points of the reanalysis data and GCM outputs, respectively, these grid point data values were averaged using Inverse Distance Square (IDS) to be the values at the locations of the 29 rain gauge stations for further uses.

3.2. Statistical downscaling for rainfall occurrence and amounts

Regression analysis categorized as a statistical technique was chosen to downscale the large scale atmospheric variable values to be rainfall occurrence and amount at the 29 observed stations. Method used for statistical downscaling are described as in the following sections.

3.2.1. Regression models for estimating historical daily rainfall occurrence and amounts

Rainfall data at 29 observed stations and 4 grid point reanalysis variables covering and surrounding the UPRB were divided into 2 sets to be used for evaluating the historical rainfall occurrence and amounts using the regression models. Data from 1960 to 1989 were used for model calibration to form the regression equations. The acquired equations were later validated for their performance using the data from 1990 to 2005. Only daily rainfall depth above a measurement error of 0.3 mm categorized as a non-zero rainfall or a wet day was used for generating rainfall occurrence and amounts in this study.

(a) Daily rainfall occurrence

Daily probabilities of non-zero rainfall (a wet day) (O_i) comprising the conditional probability of a wet day following a dry day (p_{10}) and the conditional probability of a wet day following a wet day (p_{11}) were calculated at each rain gauge station. A moving window of 31 days length centered on a given day was applied to calculate the daily probability in order to maintain a seasonal transition (Mehrotra and Sharma, 2007; Rajagopalan and Lall, 1999).

Daily probabilities of non-zero rainfall (a wet day) (O_i) for a given day i were correlated to the 72 reanalysis variable values together with the transition probabilities of a wet day (O_{i-1}) for a previous day ($i-1$) to form a regression relationship as suggested by Wilby et al. (1999) for each observed station as shown in Eq. (1). Highly related atmospheric variables ($X_{i_{i=1}}^n$) to the O_i compared to other variables were chosen based on a stepwise multiple linear regression to form the regression relationship. The α_0, α_1, …, α_n parameters corresponding to the selected variables were estimated using linear least square regression.

$$O_i = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \cdots + \alpha_{n-1} X_{n-1} + \alpha_n X_n. \quad (1)$$

Estimated critical probability (O_i) calculated using Eq. (1) for a given station and day was compared to a uniformly distributed random number r ($0 \le r \le 1$). A wet day was returned once $O_i \ge r$.

(b) Daily rainfall amounts

Once a given station and day determined as a wet day, daily rainfall amounts were then calculated using Eq. (2) proposed by Kilsby et al. (1998). This equation is the relationship of atmospheric variables ($X_{i_{i=1}}^n$) highly related to rainfall amounts (R_i in mm) compared to other atmospheric variables.

$$R_i = \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{n-1} X_{n-1} + \beta_n X_n + \varepsilon). \quad (2)$$

The β_0, β_1, …, β_n parameters were estimated using linear least square regression, and ε is the modeling error. The expected rainfall amounts $E(R_i)$ can be estimated using Eq. (3).

$$E(R_i) = \varnothing C_R exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{n-1} X_{n-1} + \beta_n X_n). \quad (3)$$

The C_R value in Eq. (3) is an empirically bias correction ratio to adjust the differences of the downscaled rainfall amounts from the observed values. The random scaling factor $\varnothing$ with a mean of 1 was used to increase the variance of rainfall amounts to better correspond to the observed values (Wilby et al., 1999).

3.2.2. Evaluation of future daily rainfall occurrence and amounts under RCPs scenarios

The acquired regression models used for estimating historical rainfall occurrence and amounts at each of 29 observed stations were later used for evaluating the future rainfall occurrence and amounts at each station under different RCPs scenarios.

Since the statistical characteristics of historical reanalysis daily data differ from the GCM outputs, bias correction for the GCM outputs needs to be carried out to adjust the GCM outputs to correspond to the historical reanalysis data. In this study, a Nested Bias Correction (NBC) proposed by Johnson and Sharma (2009) was selected for bias correction to reduce these differences. To test whether the performance of the NBC is better than a Simple Bias Correction (SBC, a conventional bias correction method), the comparison of their performance was undertaken. A more efficient technique was selected for an adjustment of the GCM outputs. Statistical parameter values were also calculated using a moving window concept with a length of 31 days centered at a given day.

4. Results

4.1. Regression model development

Rainfall occurrence and amounts at 29 observed stations were correlated to 72 reanalysis averaged values at the same locations to form regression models at each rain gauge station.

4.1.1. Regression models for estimating rainfall occurrence

Daily probabilities of a wet previous day (O_{i-1}) were highly correlated to daily probabilities of a wet given day (O_i) at all of 29 rain gauge stations. Therefore, O_{i-1} was selected to form regression models for all stations. However, the 16 from 72 reanalysis predictors were chosen differently between these stations. *Air10*, *omega250*, and *vwnd700* are the top three predictors selected to form the models for generating rainfall occurrence at 28, 23, and 20 rain gauge stations, respectively. Fig. 2 shows that these regression equations can reasonably simulate average wet days on the monthly and annual basis for these 29 stations indicated by the statistical values which are within a reliable range. These regression models are therefore suitable to be confidently applied to predict the daily probabilities of a wet given day at the 29 observed stations to be further used for simulating the rainfall amounts.

4.1.2. Regression models for estimating rainfall amounts

Rainfall amounts of a previous day (R_{i-1}) are correlated to that of a given day only at 18 stations within 29 stations. Their relationships are not that high since rainfall amounts of the consecutive days are not highly related to rainfall amounts of a previous day. It is different from daily probabilities of a wet previous day which were highly correlated to daily probabilities of a wet given day at all study stations as described

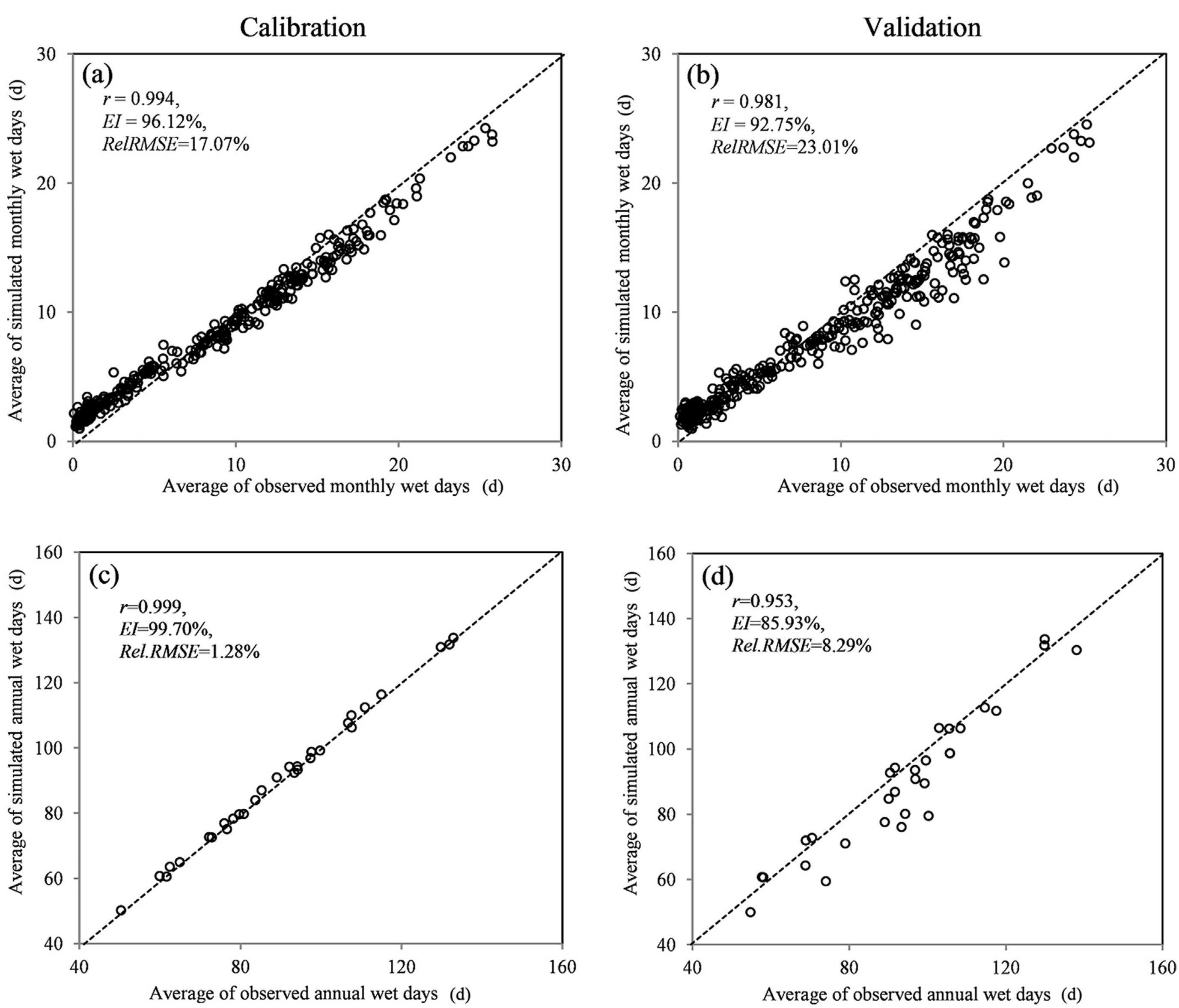

Fig. 2. Scatter plots of the average monthly and annual wet days for 29 rain gauge stations for calibration and validation processes.

earlier. Among 72 predictors, 23 predictors were selected to form the regression models for simulating rainfall amounts for a given day (R_i) at 29 rain gauge stations. *Unwnd850*, *omega700*, and *omega500* are the top three predictors selected to form the models for generating rainfall amounts at 19, 12, and 11 rain gauge stations, respectively. Fig. 3 shows that these regression equations can reasonably simulate rainfall depth on the monthly and annual basis for these 29 stations indicated by the statistical values which are within a reliable range. These regression models are therefore suitable to be confidently applied to predict the rainfall depth at 29 observed stations.

4.2. Performances of NBC and SBC for bias correction

There are 16 and 23 predictors used to form regression models for an estimation of rainfall occurrence and amounts, respectively. However, some predictors were used for both models and then made the overall 29 selected predictors. Bias correction process was applied to these 29 GCM predictors using NBC and SBC. Bias correction factors gained from this process were used to adjust the scenario GCM outputs.

The comparison of the results gained by applying NBC and SBC to the daily GCM predictors is shown in Table 1. It shows that NBC can be used to bias the GCM predictors to be closer to the reanalysis data than those of SBC. It can be seen that the standard deviation and lag 1 autocorrelation of the daily and monthly predictor values provided by NBC are significantly closer to the reanalysis data than those of provided by SBC. However, both methods can be used to bias the average values very well. Three statistical indicators consisting of *r*, *EI*, and *Rel. RMSE* were used to distinguish their performance. Therefore, bias correctors gained from NBC were used to adjust the scenario GCM outputs for predicting the future

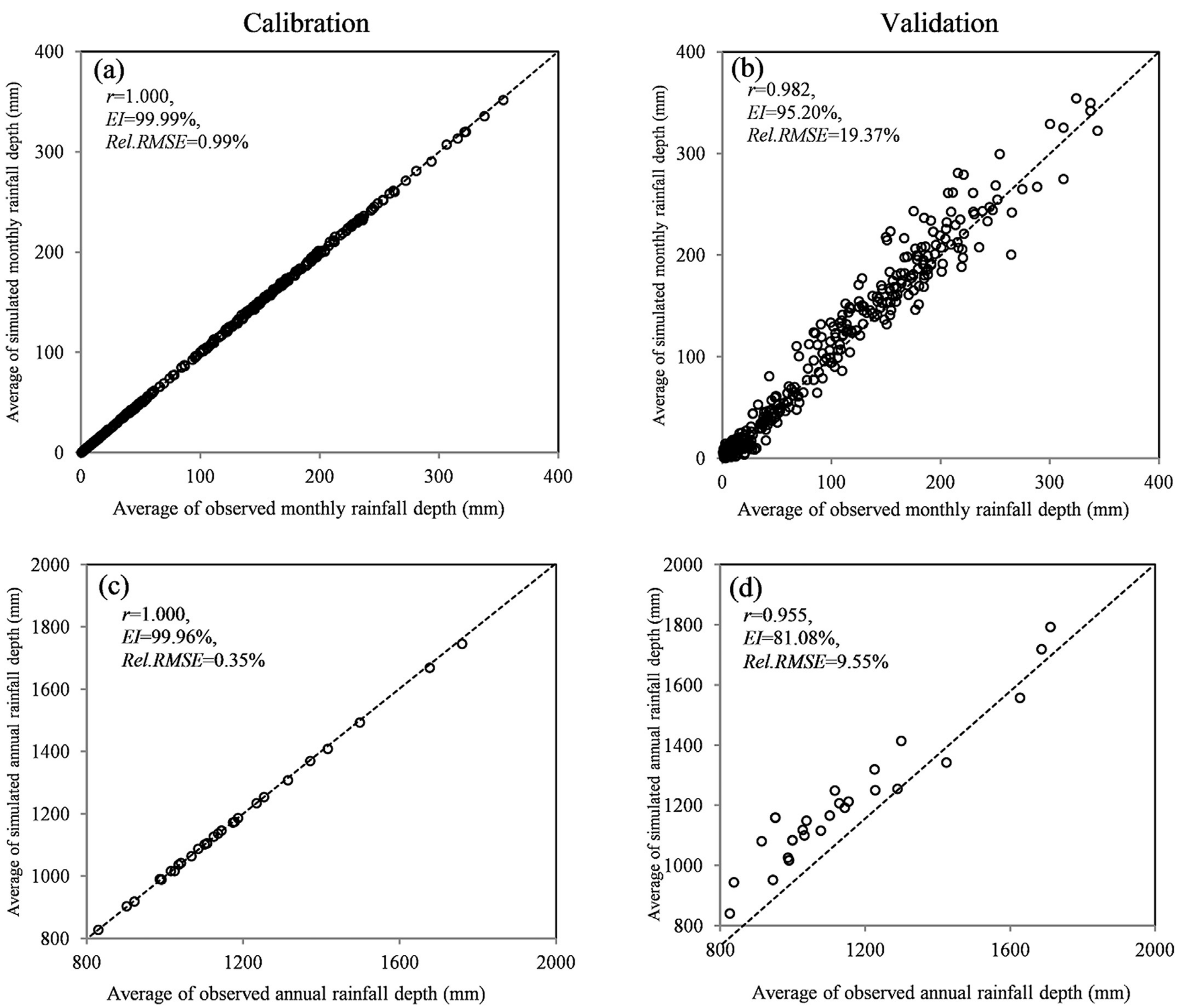

Fig. 3. Scatter plots of the average monthly and annual rainfall amounts for 29 rain gauge stations for calibration and validation processes.

Table 1
Performance comparison between NBC and SBC applied for bias correction of daily and monthly GCM predictors.

Statistical indicators	Predictors		Daily						Monthly					
			r		*EI (%)*		*Rel. RMSE (%)*		*r*		*EI (%)*		*Rel. RMSE (%)*	
			NBC	SBC	NBC	SBC	NBC	SBC	NBC	SBC	NBC	SBC	NBC	SBC
Average	*air150, air50, air30, air10, hgt700, hgt500, omega1000 omega700, omega500, omega250, omega150, omega100, rhum500, uwnd1000, uwnd850, uwnd700, uwnd250, uwnd150, uwnd100, vwnd1000, vwnd850, vwnd700, vwnd500, vwnd250, vwnd100, uwnds, prat, tcdc, ulwrf*	Mean	0.998	0.976	99.49	95.24	11.12	31.63	1.000	0.976	99.99	95.13	0.57	31.38
		Min	0.989	0.610	97.69	23.16	0.00	0.00	1.000	0.608	99.88	22.30	0.00	0.00
		Max	1.000	1.000	99.98	99.94	68.65	322.74	1.000	1.000	100.00	99.98	3.26	327.45
Standard deviation	*air150, air50, air30, air10, hgt700, hgt500, omega1000 omega700, omega500, omega250, omega150, omega100, rhum500, uwnd1000, uwnd850, uwnd700, uwnd250, uwnd150, uwnd100, vwnd1000, vwnd850, vwnd700, vwnd500, vwnd250, vwnd100, uwnds, prat, tcdc, ulwrf*	Mean	0.981	0.960	93.39	96.79	14.40	20.90	0.999	0.630	98.07	85.83	3.64	45.36
		Min	0.939	0.726	57.99	19.74	0.00	0.00	0.990	0.001	84.60	1.87	0.00	0.00
		Max	0.999	0.998	99.76	245.97	76.03	90.70	1.000	0.969	100.00	350.05	19.94	228.27
Lag-1 auto correlation	*air150, air50, air30, air10, hgt700, hgt500, omega1000 omega700, omega500, omega250, omega150, omega100, rhum500, uwnd1000, uwnd850, uwnd700, uwnd250, uwnd150, uwnd100, vwnd1000, vwnd850, vwnd700, vwnd500, vwnd250, vwnd100, uwnds, prat, tcdc, ulwrf*	Mean	0.951	0.505	84.78	385.84	1.74	10.19	0.988	0.288	94.57	348.14	2.84	29.13
		Min	0.770	0.016	9.43	4.51	0.75	1.63	0.932	0.005	75.46	20.03	0.69	15.42
		Max	0.991	0.958	97.94	2641.70	4.66	20.27	0.999	0.835	99.75	1506.48	7.08	49.04

rainfall occurrence and amounts at 29 rain gauge stations in and around the UPRB.

4.3. Future rainfall occurrence and amounts based on RCPs scenarios

4.3.1. Rainfall occurrence

The reduction of the wet days for the scenarios RCP2.6, RCP4.5, and RCP8.5 during the wet season (May to October) are around 4.1%, 4.0% and 4.4%, respectively, and during the dry season (November to April) are around 14.1%, 13.3%, 15.6%, respectively, compared to the historical GCM for 2006–2050. While the reduction of the wet days for these 3 scenarios during the wet season are around 4.3%, 5.1% and 7.8%, respectively, and during the dry season are around 15.0%, 18.5% and 25.8%, respectively, compared to the historical GCM for 2051–2100. The percent reduction for the wet and the dry season for these 3 scenarios are very similar during the period 2006–2050 but the percentage reduction of the wet days for the RCP8.5 are nearly 2 times compared to that of for RCP2.6 during 2051–2100.

To be able to easily distinguish the changes of average wet days among 29 rain gauge stations, the spread of changes of average wet days for each scenario were compared to the wet days obtained from historical GCM and shown as spatial interpolation (carried out using IDS) during the wet- and the dry-season as in Figs. 4 and 5, respectively. Fig. 4 shows that wet days decline less than 10% at 24, 23, and 21 stations for RCP2.6, RCP4.5 and RCP8.5, respectively, during the wet season for 2006–2050. Wet days decline 10%–19% at 4, 4, and 6 stations, respectively, in the middle of the catchment but increase not more than 11% for RCP2.6, for RCP4.5 and RCP8.5 toward northern part of the basin (see the black dots in Fig. 4). Percentage change tends to be more extreme for 2051–2100 when wet days decline less than 10% at 24, 20, and 19 stations, respectively. They decline 10%–40% at 4, 6, and 4 stations, respectively, in the middle of the catchment and decline the most for more than 40% for RCP8.5 in the middle of the catchment (see the biggest grey dots in Fig. 4). They increase no more than 11% for RCP2.6, RCP4.5 and RCP8.5 toward western- and northern-part of the basin (see the black dots in Fig. 4).

Fig. 5 shows that wet days decline less than 19% at 23, 21, and 20 stations for RCP2.6, RCP4.5 and RCP8.5, respectively, during the dry season for 2006–2050. Wet days decline 20%–59% at 6, 6, and 7 stations, respectively, in the middle of the catchment but increase no more than 26% at 2 and 2 stations for RCP4.5 and RCP8.5, respectively, toward northern part of the basin. Percentage change tends to be more extreme for 2051–2100 when wet days decline less than 19% at 22, 19, and 10 stations, respectively. They decline 20%–60% at 6, 8, and 12 stations, respectively, in the middle of the catchment and decline the most for more than 80% in the middle of the catchment (see the biggest grey dots in Fig. 5). They increase not more than 26% for RCP2.6, RCP4.5 and RCP8.5 toward western- and northern-part of the basin (see the black dots in Fig. 5).

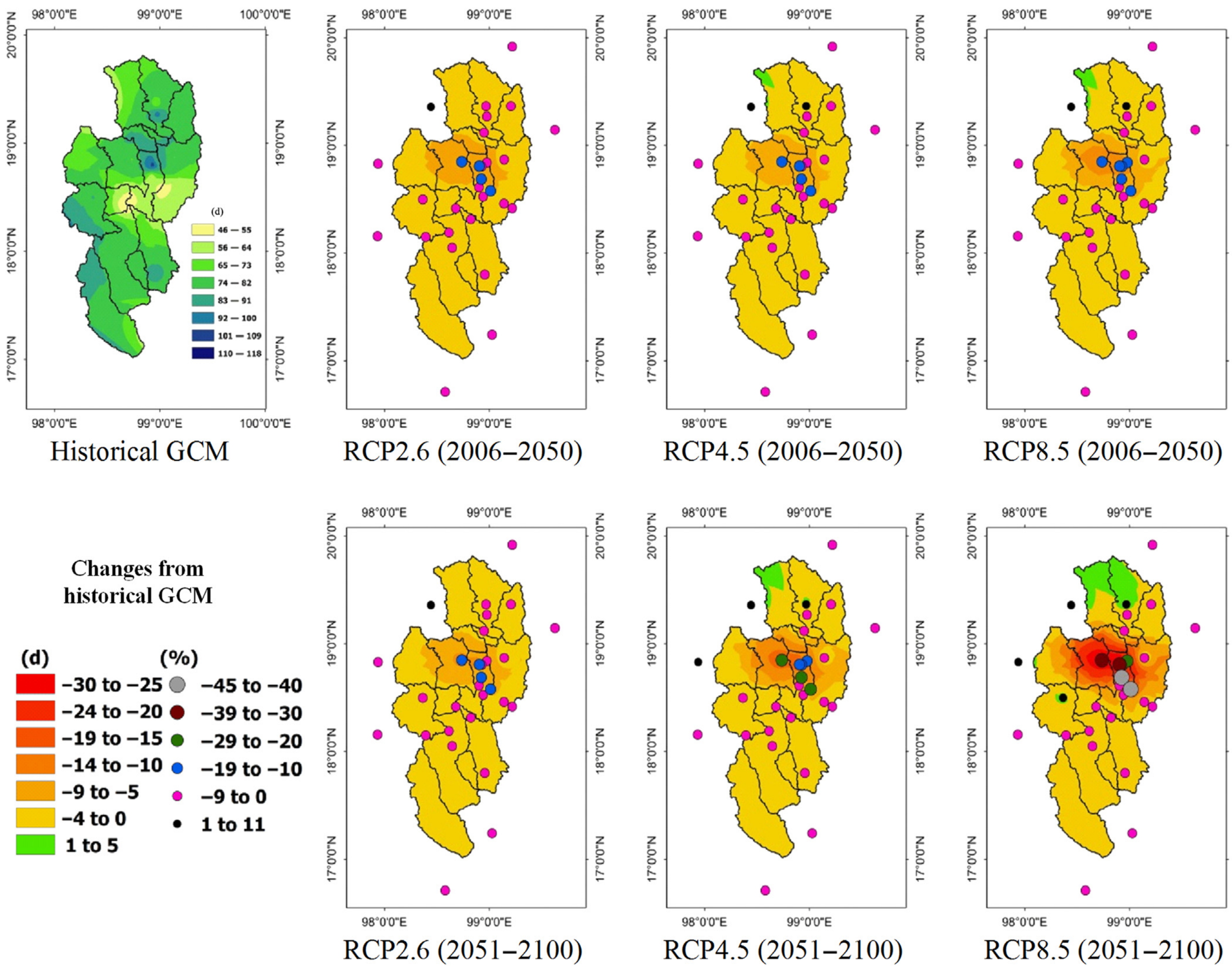

Fig. 4. Changes of average wet days of each scenario compared to historical GCM during the wet season for 2006–2050 and 2051–2100.

4.3.2. Rainfall amounts

The reduction of the rainfall depth for the scenarios RCP2.6, RCP4.5, and RCP8.5 during the wet season are around 5.1%, 3.8% and 4.2%, respectively, and during the dry season are around 11.0%, 10.3%, 11.6%, respectively, for 2006–2050. While the reduction of the rainfall depth for these 3 scenarios during the wet season are around 6.3%, 8.6% and 12.6%, respectively, and during the dry season are around 12.0%, 16.6% and 27.2%, respectively, for 2051–2100. The percent reduction for the wet and dry season for these 3 scenarios are insignificantly different during 2006–2050 but that for the RCP8.5 are around 2 times compared to that of for RCP2.6 during 2051–2100.

To be able to easily distinguish the changes of average rainfall depth of 3 scenarios among 29 rain gauge stations, the spread of changes in average rainfall depth for each scenario were compared to the rainfall depth obtained from historical GCM and shown as spatial interpolation (carried out using IDS) during the wet- and the dry-season as in Figs. 6 and 7, respectively. Fig. 6 shows that rainfall depth declines less than 20% at 22, 20, and 19 stations for RCP2.6, RCP4.5 and RCP8.5, respectively, during the wet season for 2006–2050. The most declines of 20%–39% for RCP4.5 and RCP8.5 located in the middle of the catchment (see the biggest red-brown dots in Fig. 6). It increases not more than 20% at 7, 8, and 8 stations, respectively, towards northern-, southern- and western-part of the basin. Percentage change tends to be more extreme for 2051–2100 when rainfall depth declines less than 20% at 19, 16, and 11 stations, respectively. It declines 20%–39% at 2, 5, and 8 stations, respectively, in the middle of the catchment. The most decline of more than 40% located in the middle and southern part of the catchment for RCP8.5 (see the biggest grey dots in Fig. 6). It increases not more than 20% at 7, 7, and 5 stations, respectively, and increases 21%–70% for RCP2.6, RCP4.5 and RCP8.5 located towards northern- and southern-part of the basin (see the biggest black dot and the big blue dot in Fig. 6).

Fig. 7 shows that rainfall depth declines less than 20% at 16, 16, and 15 stations for RCP2.6, RCP4.5 and RCP8.5, respectively, during the dry season for 2006–2050. It declines

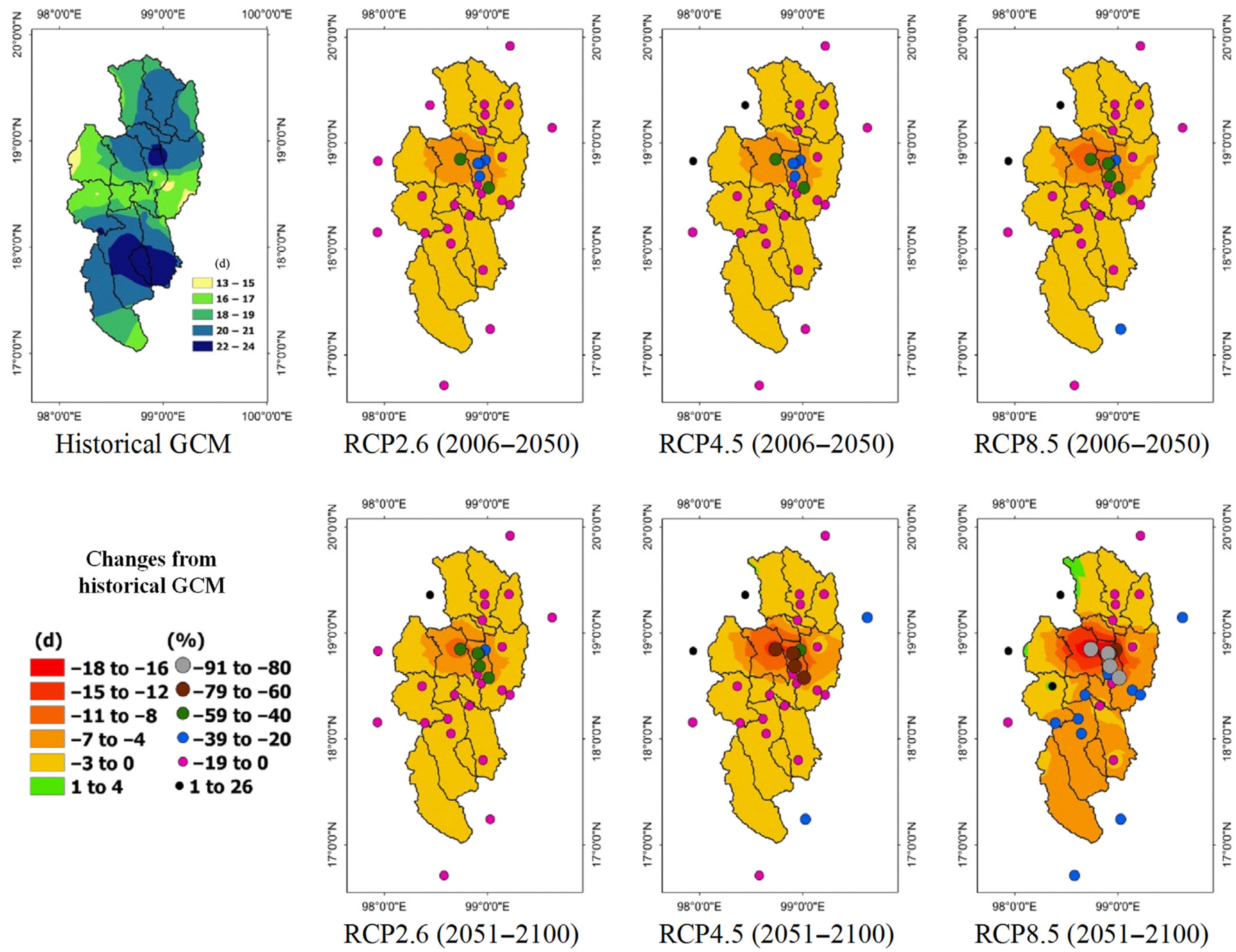

Fig. 5. Changes of average wet days of each scenario compared to historical GCM during the dry season for 2006−2050 and 2051−2100.

20%−40% at 5, 5, and 4 stations, respectively. The most declines of 40%−60% for RCP2.6 and RCP8.5 located in the middle of the catchment (see the biggest green dots in Fig. 7). It increases not more than 20% at 7, 7 and 7 stations for RCP2.6, RCP4.5 and RCP8.5, respectively, towards northern part of the basin. Percentage change tends to be more extreme for 2051−2100 when rainfall depth declines less than 20% at 15, 10, and 6 stations, respectively, and declines 20%−80% at 7, 11, and 12 stations, respectively, in the middle of the catchment. The most declines of 80%−100% for RCP8.5 located in the middle of the catchment (see the biggest grey dots in Fig. 7). It however increases not more than 20% at 7, 8, and 7 stations, respectively, towards northern part of the basin.

5. Conclusions

Future rainfall for the upper Ping River Basin (UPRB) was assessed in this study using regression-based downscaling technique. Stepwise regression was utilized to correlate between daily historic reanalysis variables (NCEP/NCAR) and rainfall occurrence and amounts at 29 rain gauge stations. For rainfall occurrence simulation, daily probabilities of a wet previous day were selected to form the regression models for all stations, while *air10*, *omega250*, and *vwnd250* are among top three predictors selected at around 70% of all stations to form the models. For rainfall amounts simulation, rainfall amounts of a previous day were selected to form the regression models for more than half of all study stations, while *uwnd850*, *omega700*, and *omega500* are the top three predictors selected at around half of all stations to form the models. Statistical indicators consisting of correlation coefficient, efficiency index, and relative root mean square errors are shown to be within acceptable range to define the robustness of the regression models. Nested Bias Correction (NBC) was proved to be a better technique to adjust the historic GCM outputs (MPI-ESM-LR model) to be corresponded to the selected reanalysis variables compared to the Simple Bias Correction (SBC) which is a conventional method normally used.

Based on Stepwise regression models and 3 RCPs climate scenarios, the effects of climate change vary considerably

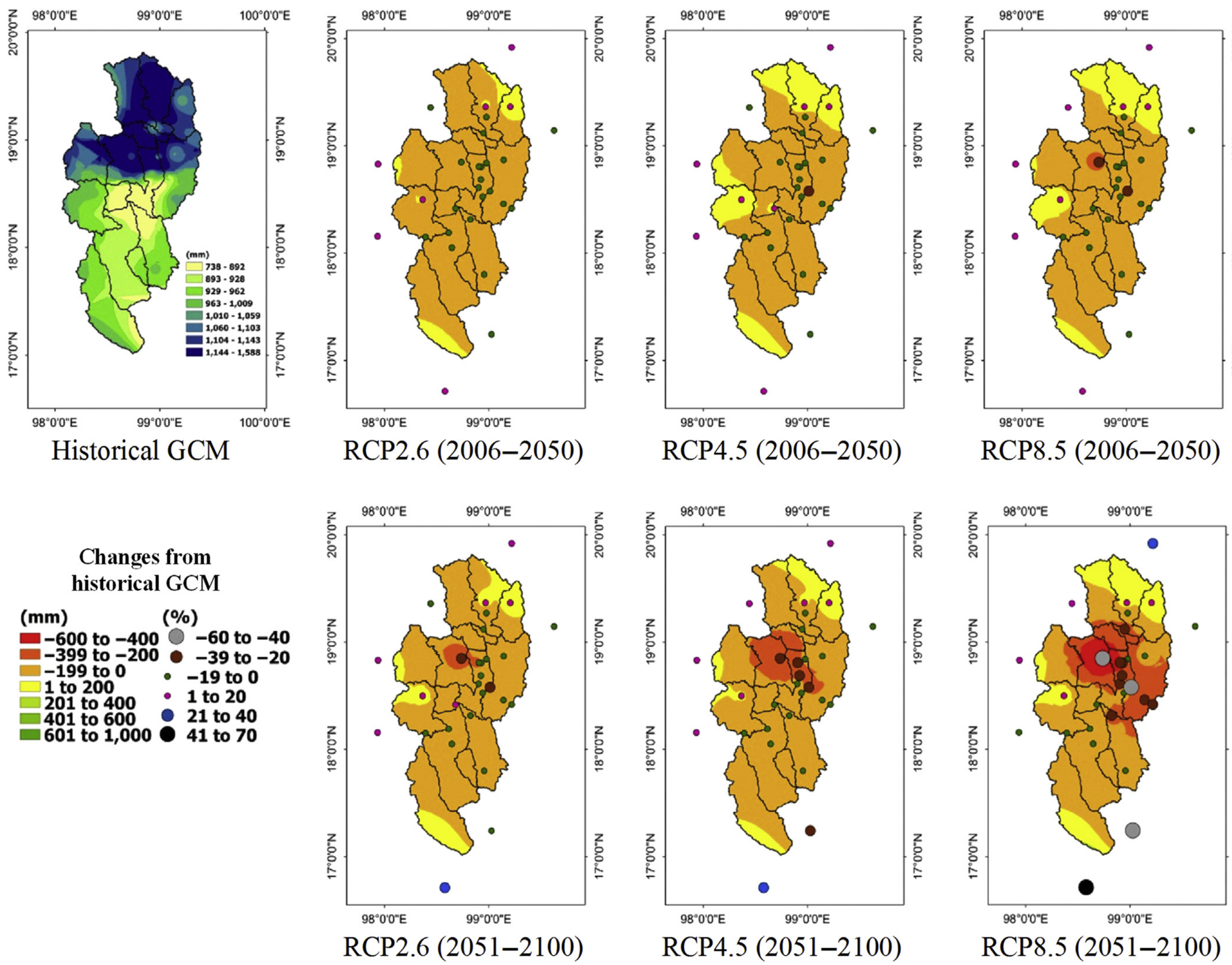

Fig. 6. Changes of average rainfall amounts of each scenario compared to historical GCM during the wet season for 2006–2050 and 2051–2100.

across the UPRB. The number of wet days and rainfall amounts tend to decline for the whole basin, especially in the middle of the catchment but obviously increase slightly towards the northern part of the basin. These changes seem to be more extreme for 2051–2100 than that for 2006–2050 and more severe for the RCP8.5 than RCP4.5 and RCP2.6, respectively. It is interesting for further investigation to see whether climate variables selected for each station would have more or less effect on fluctuation of rainfall occurrence and amounts than the effects caused by applying the models to different scenarios as well as the different GCMs.

6. Discussion

In this study, stepwise regression was used to select the atmospheric variables to form the regression models for simulating rainfall occurrence and amount. Different stations have their own predictors and can influence future rainfall to vary significantly between 29 rain gauge stations. This study corresponds to the study carried out by Pervez and Henebry (2014) who applied SDSM to downscale precipitation for Ganges and Brahmaputra river basins in South Asia. Each of 60 sub-basins had their own predictors however only a few predictors which had high selected frequency were used to form the regression models for simulating rainfall occurrence and amount. Therefore, the results of this study should compare to the results gained by choosing the only top three predictors selected in this study to form the regression models for simulating the rainfall occurrence and amount at all stations. The results would show either atmospheric predictors or climate change scenarios would have more effect on future rainfall characteristics. The dependence between 29 rainfall stations was also not considered in this study. Rainfall occurrence and amount were simulated independently at individual station separately. However, in reality the rainfall at nearby stations can be highly related. Thus, the rainfall generation should be simulated considering spatial correlation while preserving serially independent. These two interesting points should be further investigated to see whether the future rainfall would vary significantly from the results gained in this

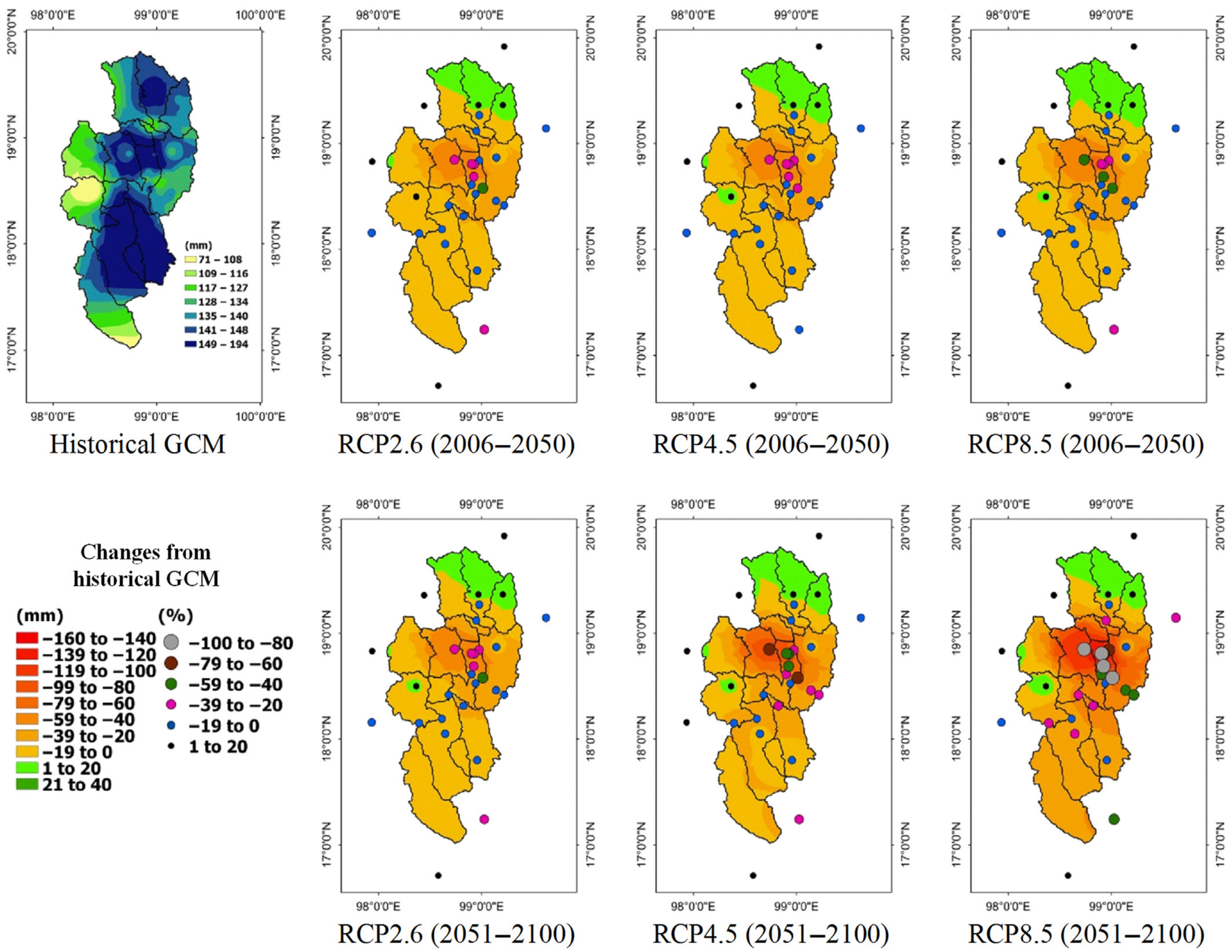

Fig. 7. Changes of average rainfall amounts of each scenario compared to historical GCM during the dry season for 2006–2050 and 2051–2100.

study. Moreover, Gain et al. (2011) and Wilby et al. (1999) emphasis that there is no GCM can thoroughly describe the physical climate system, thus downscaled precipitation gained from any GCM are uncertain. Since only one GCM was used in this study, other GCMs should be utilized for simulating rainfall occurrence and amount for the UPRB to reduce uncertainty of future rainfall characteristics and the results can be more properly used for water management of the basin.

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References

Das, J., Umamahesh, N.V., 2016. Downscaling monsoon rainfall over river Godavari basin under different climate-change scenarios. Water Resour. Manag. 30 (15), 5575–5587.

Dettinger, M.D., Cayan, D.R., Meyer, M.K., et al., 2004. Simulated hydrologic responses to climate variations and change in the Merced, Carson, and American river basins Sierra Nevada, California, 1900-2099. Clim. Change 62, 283–317.

Feng, D.Y., Min, L.Y., Ming, J.J., 2014. Statistical downscaling of FGOALS-s2 projected precipitation in eastern China. Atmos. Ocean. Sci. Lett. 7 (5), 388–394.

Gain, A.K., Immerzeel, W.W., Sperna Weiland, F.C., et al., 2011. Impact of climate change on the stream flow of the lower Brahmaputra: trends in high and low flows based on discharge-weighted ensemble modelling. Hydrology Earth Syst. Sci. 15 (5), 1537–1545.

Graham, L.P., Andre'asson, J., Carlsson, B., 2007. Assessing climate change impacts on hydrology from an ensemble of regional climate models, model scales and linking methods — a case study on the Lule River basin. Clim. Change 81, 293–307.

Guo, J., Chen, H., Xu, C.Y., et al., 2012. Prediction of variability of precipitation in the Yangtze River Basin under the climate change conditions based on automated statistical downscaling. Stoch. Environ. Res. Risk Assess. 26, 157−176. https://doi.org/10.1007/s00477-011-0464-x.

Haerter, J.O., Hagemann, S., Moseley, C., et al., 2011. Climate model bias correction and the role of timescales. Hydrology Earth Syst. Sci. 15, 1065−1079. https://doi.org/10.5194/hess-15-1065-2011.

Johnson, F.M., Sharma, A., 2009. Assessing future droughts in Australia − a nesting model to correct for long-term persistence in general circulation model precipitation simultions. In: Proceeding of 18th World IMACS/MODSIM Congress, Cairns, Australia.

Kalnay, E., Kanamitsu, M., Kistler, R., et al., 1996. The ncep/NCAR 40-year reanalysis project. Bull. Am. Meteorol. Soc. 77, 437−470.

Kilsby, C.G., Cowpertwait, P.S.P., O'Connell, P.E., et al., 1998. Predicting rainfall statistics in England and Wales using atmospheric circulation variables. Int. J. Climatol. 18, 523−539.

Mapiam, P.P., Sharma, A., Sriwongsitanon, N., 2014. Defining the Z~R relationship using gauge rainfall with coarse temporal resolution: implications for flood forecast. J. Hydrologic Eng. 19 (8), 04014003.

Mehrotra, R., Sharma, A., 2007. A semi-parametric model for stochastic generation of multi-site daily rainfall exhibiting low-frequency variability. J. Hydrology 335, 180−193.

Min, Y.M., Kryjov, V.N., Oh, J.H., 2011. Probabilistic interpretation of regression-based downscaled seasonal ensemble predictions with the estimation of uncertainty. J. Geophys. Res. 116 https://doi.org/10.1029/2010JD015284. D08101.

Moss, R.H., Edmond, J.A., Hibbard, K.A., et al., 2010. The next generation of scenarios for climate change research and assessment. Nature 436, 747−756.

Pervez, MdS., Henebry, G.M., 2014. Projections of the Ganges−Brahmaputra precipitation−downscaled from GCM predictors. J. Hydrology 517, 120−134.

Rajagopalan, B., Lall, U., 1999. A *k*-nearest-neighbor simulator for daily precipitation and other weather variables. Water Resour. Res. 35, 3089−3101.

Timbal, B., Fernandez, E., Li, Z., 2009. Generalization of a statistical downscaling model to provide local climate change projections for Australia. Environ. Model. Softw. 24, 341−358.

Wilby, R.L., Wigley, T.M.L., 1997. Downscaling General Circulation Model output: a review of methods and limitations. Prog. Phys. Geogr. 21, 530−548.

Wilby, R.L., Hay, L.E., Leavesley, G.H., 1999. A comparison of downscaled and raw GCM output: implications for climate change scenarios in the San Juan River basin, Colorado. J. Hydrology 225, 67−91.

Wilby, R.L., Dawson, C.W., Barrow, E.M., 2002. SDSM − a decision support tool for the assessment of regional climate change impacts. Environ. Model. Softw. 17, 147−159.

Wilby, R.L., Charles, S.P., Zorita, E., et al., 2004. Guidelines for use of climate scenarios developed from statistical downscaling methods. Supporting Material of the Intergovernmental Panel on Climate Change Which Prepared for Consideration by the IPCC at the Request of its Task Group on Data and Scenario Support for Impacts and Climate Analysis (TGICA).

Yhang, Y.B., Sohn, S.J., Jung, I.W., 2017. Application of dynamical and statistical downscaling to East Asian summer precipitation for finely resolved datasets. Adv. Meteorol. 9. https://doi.org/10.1155/2017/2956373, 2956373.