



# Projection of future precipitation extremes across the Bangkok Metropolitan Region

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## ABSTRACT

There is a pressing need to develop local-scale climate projection profiles for supporting climate impact assessments. This study contributes plausible future precipitation scenarios for the Bangkok Metropolitan Region (BMR), which builds on the existing evidence base that projects increasing future precipitation. Meteorological data sets from 16 stations located within the BMR and nearby provinces were used for bias correcting five regional climate model scenarios, and future extreme indices were graphed and spatially interpolated to interpret how precipitation extremes may develop to the end of the 21st century. Results indicate that over the coming century, total annual rainfall will increase, with the volume and number of days with heavy/very heavy rainfall also increasing. Total monthly and monthly heavy/very heavy rainfall are projected to increase in the late monsoon, and monthly five-day cumulative and one-day maxima project higher amounts of late monsoonal rains. Spatial interpolation of selected indices indicate substantial projected increases in extreme rainfall across the BMR, with its northern part receiving the heaviest amounts of precipitation. In comparison to the past period (1980–2009), over the long-term (2070–2098) the total monthly heavy/very heavy precipitation during October is projected to increase by 100–120% over Pathum Thani province and 80–100% over the remainder of the BMR. Together with the study's associated R and Python scripts, this study aims to provide an open and reproducible approach to deriving plausible future projections of climate variables at the city scale.

## 1. Introduction

The world is rapidly urbanising, with 68% of the global population projected to be living in urban areas by 2050 (UN, 2018). Against this background of ongoing urban expansion is the growing threat of climate change. Much of this urban growth is seen in Asia, with its low-lying coastal cities at particular risk to the impacts of climate change (ADB, 2015; Fuchs et al., 2011; OECD, 2014). This study focuses on the Bangkok Metropolitan Region (BMR), and its impetus came from the author's participation in international climate change adaptation research projects and the need to better understand possible future climate changes and associated impacts in coastal cities of Southeast Asia. One particular study was the five-year International Development Research Center (IDRC) of Canada's *Coastal Cities at Risk (CCaR): Building Adaptive Capacity for Managing Climate Change in Coastal Megacities* project,<sup>1</sup> which had the aim to advance knowledge and build capacity on climate change adaptation and disaster risk reduction in coastal

megacities of Southeast Asia (Bangkok and Manila), West Africa (Lagos) and North America (Vancouver) (McBean, 2014). A second project—*Climate Change Risk Assessment and Adaptation for Loss and Damage of Urban Transportation Infrastructure (UTI) in Southeast Asia*<sup>2</sup>—funded through the Asia Pacific Network (APN) for Global Change Research, was a three-country initiative that focused on coastal cities in Thailand, Cambodia and Vietnam.

The Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) provides an overall picture of potential future climate changes and impacts at the regional level. Although variable across the Southeast Asia region, it has been observed that yearly rainfall extremes have risen per decade by 10 mm, with the frequency of extremes rising in northern areas but falling in Myanmar (Hijioka et al., 2014). Projections for the region suggest the increased likelihood of extreme rainfall associated with tropical cyclones at landfall, including in the Gulf of Thailand, and “very likely” increased monsoonal-related rainfall extremes (Hijioka et al., 2014; Stocker et al., 2013). In terms of

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<sup>1</sup> IDRC of Canada project: <http://hdl.handle.net/10625/56615>.

<sup>2</sup> APN project: <http://www.apn-gcr.org/resources/items/show/1951>.

tropical cyclone frequency and intensity, regional projections were described as being of “low confidence” (Hijioka et al., 2014). With regard to data gaps across Asia, AR5 describes the urgent need for better precipitation projections, and highlights considerable knowledge gaps in observed and projected impacts in Southeast Asia (Hijioka et al., 2014).

Given its populated coastal areas and the importance of agriculture to the economy, the Southeast Asia region is considered to be especially susceptible to the effects of climate change, including from flooding, tropical cyclones, heat waves and sea level rise (ADB, 2009). The IPCC’s AR5 report highlights potential impacts to health, biodiversity, food security, and aggravation of existing social, economic and political tensions (Hijioka et al., 2014). Recurrent major flooding of Bangkok has occurred over the last century, with flooding typically reaching its peak towards the end of the southwest monsoon: either one or more causes, including runoff from the upper Chao Phraya River basin, rainfall from tropical storms passing over the BMR region and environs, and high tides are typically the cause of major flooding episodes in the BMR (Cooper, 2014). The southwest monsoon or rainy season over much of Thailand, including Bangkok, extends from mid-May to mid-October (Thai Meteorological Department, 2015).

Regional climate model (RCM) data is especially valuable to planners who require information at regional and local levels (Foley, 2010). However, end users need to be aware of the hierarchy of uncertainties in RCM data, including those that are inherent in the source global climate models (GCMs) which relate to potential emissions scenarios and natural forcings, the robustness of modelling processes, and variability of internal climate processes (Collins et al., 2013; Foley, 2010). Spatial downscaling of climate data may be achieved through two approaches – dynamical using a regional climate model (RCM) and statistical – and both of these assume that weather phenomena existing at a broader scale are representative at the downscaled local level (Maraun et al., 2010). Statistical downscaling is more commonly used given its relatively minor computational requirements, but it does not integrate the climate-related physical processes of dynamical approaches (Tryhorn and DeGaetano, 2011). While regional climate models better capture daily and extreme precipitation events compared to GCMs (Maraun et al., 2010 and included references), the presence of bias in RCM simulations is widely recognised and has been attributed to a number of issues including GCM boundary conditions, model formulation, and parameterisations (Ehret et al., 2012; PaiMazumder and Done, 2015; Rojas et al., 2011; Sippel et al., 2016; Teutschbein and Seibert, 2012). Chen et al. (2013) concluded that “RCM-simulated daily precipitation is usually biased, sometimes severely”, and Gudmundsson et al. (2012) similarly stated that “it is well established that precipitation simulations from regional climate models (RCMs) are biased” and of the need for bias correction prior to conducting impact studies.

Climate change impact studies, such as those applied to hydrology, agriculture, and ecosystems, need fine-scale and unbiased data (Bennett et al., 2014; Glotter et al., 2014; Teutschbein and Seibert, 2013). A post-processing step called *bias correction* is often used to adjust climate model outputs against observational records (Ehret et al., 2012; Maraun, 2012; Sippel et al., 2016), and though given acknowledged limitations, offers an important approach for adjusting climate model data to improve its usability in climate impact studies (Chen et al., 2013; PaiMazumder and Done, 2015; Sippel et al., 2016). Sippel et al. (2016) describes bias correction as being “crucial in order to produce credible climate model simulations”; Chen et al. (2013) describes it as typically a “prerequisite step” in climate change impact studies; and PaiMazumder and Done (2015) states that “some form of post-processing bias correction of RCM output data is a necessary step for most climate change impact studies”. It is however important to note, as mentioned by Maraun (2016), that the success of any bias correction will depend on plausible climate model input.

Bias correction is an active area of research (Halmstad et al., 2013; Teng et al., 2015). A variety of bias correction techniques have been examined, including relatively simple scaling to more complex distri-

bution mapping methods (Chen et al., 2013; Teutschbein and Seibert, 2012; Teutschbein and Seibert, 2013). Techniques range from adding or multiplying a factor to model data, to using parametric and non-parametric approaches to address data variability (Hempel et al., 2013). As yet, no single best practise approach has been advocated (Gudmundsson et al., 2012), but a number of comprehensive reviews have recently been published that highlight positive and negative aspects of bias correction methods (Chen et al., 2013; Ehret et al., 2012; Gudmundsson et al., 2012; Lafon et al., 2013; Teng et al., 2015; Teutschbein and Seibert, 2013). In the review by Teng et al. (2015), it was reported that based on selected recent studies, overall distribution-based techniques provided better results compared to techniques such as linear scaling, and Chen et al. (2013) reported that the performance of bias correction was dependent on the area studied. While at the same time recognising the current limitations of models and the need for climate change impact studies in the near-term, Ehret et al. (2012) recommended that bias correction methods be fully documented and results from corrected and raw model data presented. Concurring with the latter authors, Argüeso et al. (2013) reiterate that until improvements are made to climate models, the application of bias correction is considered a necessity.

In addition to the abovementioned uncertainties there are other issues that users of RCM-based information products should be aware. With regard to RCM model data, the process of gridding may cause an increased frequency of days with light precipitation and smaller extremes (Seneviratne et al., 2012). RCMs may also underestimate precipitation extremes due to the spatial resolution limits of models in simulating convective rainfall processes (Maraun et al., 2010). Other potential errors may arise from the observational data sets used for bias correcting model data. In this study, meteorological in situ records were used for bias corrections after being quality assessed for inhomogeneities and outliers (see Materials and methods).

Outputs from this study will contribute to the evidence base of future climate projections for the BMR and provide a basis for understanding potential future impacts. This paper is targeted at researchers and sustainable development practitioners with an interest in applying RCM data for developing future projections of extreme precipitation at the city/local scale. In summary, the research aims to: (i) generate plausible future extreme precipitation projections of the Bangkok Metropolitan Region; and (ii) present a practicable and reproducible methodology for generating climate extremes information at city/local scale. The following paper is divided into three main sections: Materials and methods; Results and discussion; and Conclusions. A Supplementary contents section contains all other outputs not included in the main paper, including figures, tables, and copies of drafted R and Python scripts.

## 2. Materials and methods

This section addresses the following topics: a description of data sources used; data preprocessing methods applied; bias corrections of RCM raw data and assessment of bias correction performance; calculation of extreme climate indices and their visualisation and interpretation; and spatial interpolation of selected extreme indices. The overall methodology is illustrated in Fig. 1.

### 2.1. Data sources

In situ precipitation data supplied by the Thai Meteorological Department (TMD) were used for bias correcting RCM data from the Southeast Asia Climate Analyses and Modeling (SEACAM) Framework project (SEACAM, 2014). Precipitation data from TMD comprised 16 recording stations, including four stations within the city of Bangkok and six within the BMR (Fig. 2). A station-based approach to analysis was adopted, with extreme precipitation projections presented for each of the 16 stations and then maps of selected indices generated by interpolating station values across the BMR and surrounding provinces.

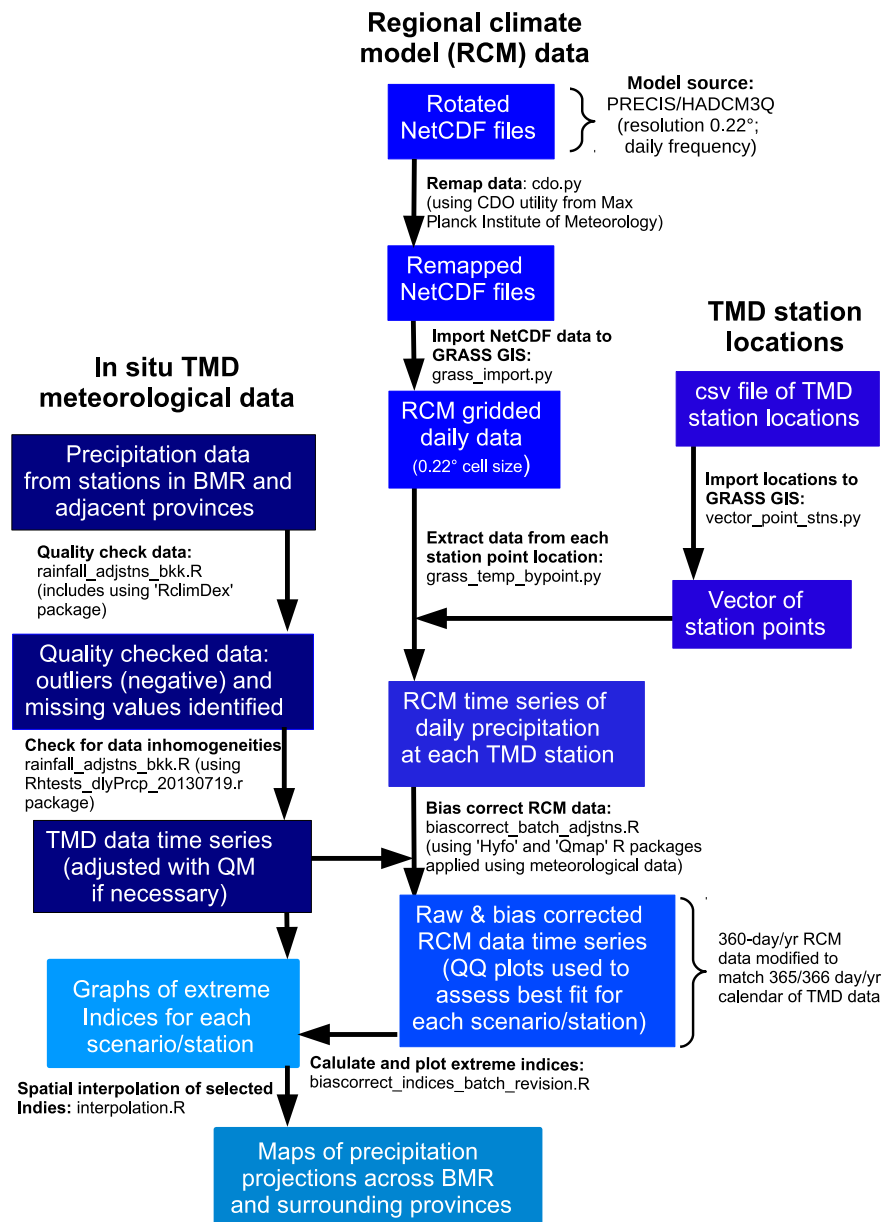


Fig. 1. Methodological framework.

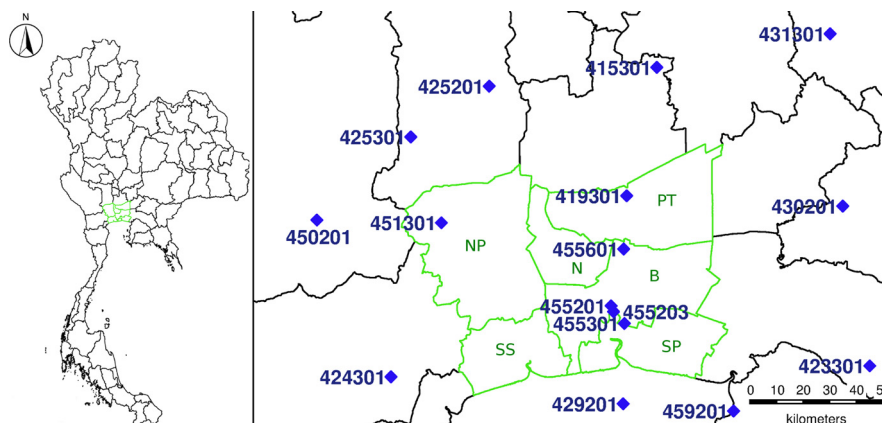


Fig. 2. Thailand Meteorological Department station locations in BMR (Nakhon Pathom (NP), Nonthaburi (N), Pathum Thani (PT), Bangkok city (B), Samut Prakan (SP), Samut Sakhon (SS)) and nearby provinces.

**Table 1**

QUMP ensemble members used in this study (see McSweeney and Jones, 2010; McSweeney et al., 2012; SEACAM, 2014).

| HadCM3Q ensemble member | Filename ID (derived from NetCDF source) | Description of future climate projections |
|-------------------------|------------------------------------------|-------------------------------------------|
| HadCM3Q0                | CAHPA                                    | standard (unperturbed) model              |
| HadCM3Q3                | CAHPC                                    | lower sensitivity model                   |
| HadCM3Q10               | CAHPD                                    | driest projection                         |
| HadCM3Q11               | CAHPE                                    | wettest projection                        |
| HadCM3Q13               | CAHPF                                    | higher sensitivity model                  |

There is limited regional climate model data coverage of Southeast Asia. Existing datasets include those created and distributed by the Southeast Asia START Regional Center (Chinvanno, 2009; SEA START RC, 2018) and more recently by the SEACAM Framework project (SEACAM, 2014). Many studies in Thailand (Baimoung et al., 2014; Chinvanno, 2009; Lacombe et al., 2012; Plangoen et al., 2013) have used downscaled RCM data derived from PRECIS (*Providing Regional Climates for Impacts Studies*), a regional climate model developed by the UK Met Office (Jones et al., 2004). Recent work by the Southeast Asia team of the Coordinated Regional Climate Downscaling Experiment (CORDEX) have applied *Regional Climate Model version 4* (Ngo-Duc et al., 2016; SEACLID, 2018; Tangang et al., 2018). Other RCM data sets relevant to the region include those from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP).<sup>3</sup> In the current study data comes from the SEACAM project, which were derived from downscaling five HadCM3Q GCM ensemble members using PRECIS (SEACAM, 2014).

Outputs from the SEACAM (2014) project, comprising dynamically downscaled data ( $0.22^\circ \times 0.22^\circ$  spatial resolution) from five members of the 17-member *Quantifying Uncertainties in Model Predictions* (QUMP) *Perturbed Physics Ensemble* (PPE), were analysed in this study (Table 1). These PPE members were selected as they were considered representative of the Southeast Asia climate (McSweeney and Jones, 2010; McSweeney et al., 2012; SEACAM, 2014). Each PPE member simulates climate under the IPCC Special Report on Emissions Scenarios (SRES) A1B emission scenario (see Nakićenović et al., 2000) but with different parameterisations, with the aim being to develop a fuller picture of how varying parameterisations influence climate simulations (McSweeney and Jones, 2010). Each QUMP member used here is referred to by its filename ID (derived from its source NetCDF file as detailed in Table 1).

## 2.2. Data preprocessing

The following sections describe the methods applied for preprocessing of in situ historical data and the steps used for extracting daily values of RCM model time series data.

### 2.2.1. In situ meteorological data inhomogeneities

Preprocessing of in situ meteorological data required compiling and formatting of TMD data (data were supplied manually as a series of html and xls files), and detection of missing data and inhomogeneities. Details of these steps are incorporated in an R script (*rainfall\_adjstns\_bkk.R*) included in the Supplementary contents section. The latter script addresses data quality issues including removal of negative values, identification of missing values, and detection and correction of inhomogeneities. Missing values by station are detailed by month and year in the Supplementary section. Note that the long sequences of missing data in late 2011/early 2012 in the Bangkok/Chao Phraya River basin area corresponds to the time of the most recent flood disaster in Thailand.

Homogeneous long-term data sets are critical for accurate analysis of climate variables, and any data inhomogeneities need to be identified and addressed prior to conducting climate analyses (Wang et al., 2007; Wang et al., 2010). Such data inhomogeneities refer to abrupt shifts or change points in climate variable records, which are changes not related

to climate (Wang et al., 2007; Wang, 2008; Wang et al., 2010). In the case of data used in this study, given that no metadata records were previously maintained, it was important that potential inhomogeneities were investigated.

Evidence of data inhomogeneities in the daily precipitation data acquired from TMD were evaluated using *Rhtests\_dlyPrp.R* software as developed by Wang and Feng (2013).<sup>4</sup> This software provides a convenient graphical user interface within the statistical and data visualisation R software, together with comprehensive guidelines for its use (Wang and Feng, 2013). A time series of data can be considered homogeneous if no significant change points are found, and the software outputs quantile-matched (QM)-adjusted data if change points are revealed (Wang and Feng, 2013).

Evidence of inhomogeneities were discovered in six of the 16 stations analysed. Of these six stations, a single change point was detected in five and two change points in one station (station 423301), though statistical differences between the original station data and QM-adjusted data sets were relatively minor (Supplementary content). The QM-adjusted data were used for subsequent analyses.

### 2.2.2. Regional climate model data

The two main steps for preprocessing SEACAM RCM data included rotating the original model data, and then importing into GRASS GIS<sup>5</sup> to extract precipitation data for each TMD station location and for each of the five climate scenarios (Fig. 1). A series of Python scripts were written for this process which are included in the Supplementary contents section.

**CDO remapping of rotated grid.** The PRECIS climate model data were supplied with a rotated grid where the x and y coordinates of the North Pole were shifted. Remapping of the rotated grid data to normal (non-rotated) latitude–longitude coordinates was achieved using the *Climate Data Operators* (CDO version 1.6.7) software from the Max Planck Institute for Meteorology<sup>6</sup>; files were remapped using bilinear interpolation.<sup>7</sup>

**Time series data extraction.** For each TMD station, precipitation values were extracted from daily increments of each model scenario. This processing was done within GRASS GIS, making use of its temporal framework functionality,<sup>8</sup> including the *t.rast.what* module that samples daily precipitation values for each station (point) location. Time series data, output for each station and scenario, were then further analysed within R software, where they were bias corrected, extreme value indices calculated and graphed, and maps projecting selected extreme indices created by interpolating results across the BMR and surrounding provinces.

## 2.3. Bias correction

Bias correction involves calibrating climate model time series data against a historical reference series, in this case in situ daily precipitation data, and then adjusting the entire modelled time series (Table 2).

<sup>4</sup> <http://etccdi.pacificclimate.org/software.shtml>.

<sup>5</sup> <https://grass.osgeo.org>.

<sup>6</sup> <https://code.zmaw.de/projects/cdo>.

<sup>7</sup> <https://code.zmaw.de/boards/2/topics/3197>.

<sup>8</sup> <https://grass.osgeo.org/documentation/general-overview>.

<sup>3</sup> <https://cds.nccs.nasa.gov/nex-gddp/>.

**Table 2**  
Hindcast data periods by station and applied bias correction techniques.

| Station ID            | Hindcast start date | Hindcast end date | Bias correction methods                                                                                                                                 |
|-----------------------|---------------------|-------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------|
| 415301                | 1 Jan 1993          | 31 Dec 2004       | <i>hyfo</i> : scaling <sup>a</sup> , EQM <sup>b</sup> , GQM <sup>c</sup> ; <i>qmap</i> : QUANT <sup>d</sup> , RQUANT <sup>e</sup> , SSPLIN <sup>f</sup> |
| 419301                | 1 Jan 1999          | 31 Dec 2004       |                                                                                                                                                         |
| 423301QM <sup>g</sup> | 1 Jan 1989          | 31 Dec 2004       |                                                                                                                                                         |
| 424301                | 1 Jan 1992          | 31 Dec 2004       |                                                                                                                                                         |
| 425201                | 1 Jan 1960          | 31 Dec 2012       |                                                                                                                                                         |
| 425301QM              | 1 Jan 1969          | 31 Dec 2004       |                                                                                                                                                         |
| 429201QM              | 1 Jan 1986          | 31 Dec 2012       |                                                                                                                                                         |
| 430201                | 1 Jan 1960          | 31 Dec 2012       |                                                                                                                                                         |
| 431301QM              | 1 Jan 1971          | 31 Dec 2004       |                                                                                                                                                         |
| 450201                | 1 Jan 1960          | 31 Dec 2012       |                                                                                                                                                         |
| 451301                | 1 Jan 1986          | 31 Dec 2004       |                                                                                                                                                         |
| 455201                | 1 Jan 1960          | 31 Dec 2012       |                                                                                                                                                         |
| 455203                | 1 Jan 1994          | 31 Dec 2012       |                                                                                                                                                         |
| 455301                | 1 Jan 1967          | 31 Dec 2013       |                                                                                                                                                         |
| 455601QM              | 1 Jan 1960          | 31 Dec 2010       |                                                                                                                                                         |
| 459201                | 1 Jan 1960          | 31 Dec 2012       |                                                                                                                                                         |

<sup>a</sup> scaling: multiplicative scaling (Xu, 2015; SantanderMetGroup 2016).

<sup>b</sup> EQM: empirical quantile mapping (Xu, 2015; SantanderMetGroup 2016).

<sup>c</sup> GQM: gamma quantile mapping (Xu, 2015; SantanderMetGroup 2016).

<sup>d</sup> QUANT: “estimates values of the empirical cumulative distribution function of observed and modelled time series for regularly spaced quantiles” (Gudmundsson 2014).

<sup>e</sup> RQUANT: “estimates the values of the quantile-quantile relation of observed and modelled time series for regularly spaced quantiles using local linear least square regression” (Gudmundsson 2014).

<sup>f</sup> SSPLIN: “fits a smoothing spline to the quantile-quantile plot of observed and modelled time series” (Gudmundsson 2014).

<sup>g</sup> QM indicates QM-adjusted data set.

For each TMD station location, bias correction was conducted using annual daily precipitation data over the hindcast (calibration) period. A range of bias correction techniques have been applied and published in the scientific literature, and the techniques selected here represent some of more established methods and those readily accessible and reproducible.

Bias correction techniques applied to RCM data in this study included parametric and non-parametric quantile mapping, and a scaling technique. Bias correction of RCM data was conducted using two R software packages: *hyfo* (Xu, 2017) and *qmap* (Gudmundsson et al., 2012; Gudmundsson, 2016). Bias correction methods used in *hyfo* are derived from the *downscaleR* package (SantanderMetGroup, 2018; Xu, 2017), and three of these techniques were applied here: multiplicative scaling, empirical quantile mapping (EQM) and gamma quantile mapping (GQM). Multiplicative scaling refers to calculating the quotient of the means from the observed and model data over the hindcast period and multiplying projected model data values (Wetterhall et al., 2012; Xu, 2017). Empirical quantile mapping is a technique where modelled data are adjusted by consideration of differences between given quantiles of observed and modelled data, with GQM assuming a gamma distribution for observed and modelled data (Piani et al., 2010; Xu, 2017). Techniques applied from *qmap* included non-parametric empirical quantile mapping (QUANT, SSPLIN), which are methods described as giving the best results for extreme percentiles (Gudmundsson et al., 2012), and RQUANT (see Table 2). The *qmap* quantile mapping techniques differ slightly by way of deriving the mapped (corrected) values: QUANT generates empirical cumulative distribution functions of modelled and observed data from tables of empirical percentiles and these are used to determine corrected values; RQUANT uses local linear least square regression in quantile-quantile plots to estimate corrected values of given percentiles; and SSPLIN uses a smoothing spline to fit the quantile-quantile plot (Boé et al., 2007; Gudmundsson et al., 2012; Gudmundsson, 2016). The applied techniques involved bias correcting as well as spatial downscaling of RCM data from a spatial resolution of 0.22° to station (point) scale.

### 2.3.1. Assessment of bias correction performance

A variety of approaches have been used to assess the performance of bias correction, including the use of cross-validation and calculation of various statistical metrics. Lafon et al. (2013) noted that while comparing raw, corrected and observed data sets is adequate for providing an

overall evaluation of bias correction, a stronger assessment was articulated through applying cross-validation to assess performance on test data not included in the training sample. Cross-validation techniques have in some recent studies been used for evaluating bias correction performance, for instance, K-fold cross-validation was conducted by Grillakis et al. (2017) and Gudmundsson et al. (2012), and other variations of the technique have been applied elsewhere (e.g., Bennett et al., 2014; Teng et al., 2015). The value of cross-validation, as noted by Bennett et al. (2014), is that it tests the predictive ability of the bias correction technique on future model data, although this may only be indicative as future climate model bias may not remain unchanged and the success of the cross-validation is constrained by the bias captured during the period of historical data availability. Recent studies by Maraun et al. (2017) and Maraun and Widmann (2018) have argued against conducting cross-validation for evaluating bias corrections, with the latter authors noting that differences between model data and observations may result from internal climate variability and not model error in free-running models where internal climate variability is unsynchronised between model and observational data.

In light of the above findings, and the current absence of a recognised approach for evaluation of bias correction outputs (see Maraun and Widmann, 2018), this study evaluated bias correction through comparison of observed, raw and corrected model data through graphical visualisation of extreme climate indices and determination of their associated statistical metrics (i.e., mean, median, standard deviation and 90th percentile) over the hindcast (calibration) period (1980–2009). Similar practise has been adopted elsewhere. In a study of climate change impacts on hydrological extremes in the Yangtze River basin, Gu et al. (2015) evaluated bias correction of regional climate model RegCM4.0 data through a comparison of time series and spatial plots. The impact of climate change on precipitation over Mumbai by Rana et al. (2014) evaluated bias correction of multiple CMIP5 GCM data through comparison of various statistical measures (mean, standard deviation, total rainfall over various periods and coefficient of variation) and plots of extreme statistics. Dosio and Paruolo (2011) evaluated bias correction of regional climate model data from the European Union 6th Framework Programme project ENSEMBLES by comparing spatial plots and graphs of observational, raw and bias corrected data, and calculation of Kolmogorov-Smirnov two sample statistics. Maraun et al. (2017) highlighted the need to develop standardised methods for assessing the application of bias correction, recommending that a sample of selected

bias corrected data be compared to observations to ensure that the bias correction is physically plausible.

A potential limitation in the current study for conducting bias correction may relate to some stations having relatively short periods of observational data available (Table 2), which could mean that not all internal climate variability is captured (see Dosio and Paruolo, 2011). Monsoonal precipitation in Southeast Asia likely exhibits multi-decadal variability influenced by multiple climate phenomena including the El Niño/Southern Oscillation (ENSO) and Pacific Decadal Oscillation (PDO) (Hernaman et al., 2017; Limsakul and Singhruck, 2016; Ratna et al., 2017), and Siberian High, Western Pacific Subtropical High, and Arctic Oscillation (Loo et al., 2015). In Thailand, Loo et al. (2015) reported that monsoon rain variability may be captured over a period of at least three decades (i.e., in relation to total annual monsoon precipitation), though this may be an underestimation as it may be contingent on the variable studied which could be higher for extremes (Maraun and Widmann, 2018). However, in a study of total precipitation, discharge and runoff across 10 drainage basins worldwide, Chen et al. (2011) found that uncertainties associated with applying different decadal periods for bias correction were relatively minor compared to those related to the choice of GCM or emissions scenario. Furthermore, as indicated by Chen et al. (2011), the choice of bias correction technique may also introduce additional uncertainty; e.g., over fitting of data may be experienced with non-parametric approaches (Gudmundsson et al., 2012). Based on the bias correction performances achieved in this research, it was decided to retain all stations for final spatial interpolation of extreme indices across the study area.

In this study, bias correction performance was assessed through plotting of quantile-quantile (QQ) plots of annual daily precipitation over the hindcast (calibration) period, and subsequent visualisation and interpretation of extreme indices through presentation of line plots, box-and-whisker plots, and consideration of associated medians, means, standard deviations, and 90th percentiles of selected indices. Quantile-quantile plots involved the plotting of quantiles of daily observation data against bias corrected (and raw/uncorrected data) over equivalent time periods (i.e., over the observational data time series at each station) (Table 2). Optimal simulations in QQ plots would be demonstrated with data points closely aligning along the 45° diagonal line extending from zero (see Results and Discussion). Given that extreme precipitation values were especially of interest, a good fit would be demonstrated where the upper end of the model distribution more closely aligned to the continuous diagonal line drawn in each plot. A plot was considered optimal where the distribution above the 90th percentile (of wet days with  $\geq 1$  mm precipitation) best aligned with the diagonal line; the 90th percentile was selected as events at or above this value have been defined as extreme weather (e.g., IPCC, 2014; WMO, 2018). Details of the coding used for QQ plotting can be found in `biascorrect_batch_adjstns.R` script (copied in Supplementary contents).

In addition to visual assessment of line and box-and-whisker plots, selection of an optimal scenario for spatial interpolation also considered calculation of statistical metrics: including the number of stations by scenario where bias correction improved correspondence (i.e., closeness) of statistical measures between model and observation data; and the combined mean and 90th percentile values by scenario for all 16 TMD stations to provide an overall indication of how bias correction influences these statistical measures across the whole study area. Calculated means, medians, standard deviations and 90th percentiles are given in Tables 5 and 6 in the Results and discussion and other tables are included in the Supplementary section.

#### 2.4. Extreme climate indices

Future projections of extreme precipitation in this study are based on the CCI/CLIVAR/JCOMM Expert Team on Climate Change Detec-

tion and Indices (Alexander et al., 2006; Klein Tank et al., 2009).<sup>9</sup> The ETCCDI indices have been applied in various studies worldwide and regionally to project future climate extremes and to study historical trends in climate (e.g. Klein Tank et al., 2006; Sillmann et al., 2013). Recent studies in the Asia-Pacific region include those by Wu and Huang (2016) who used the RegCM4.0 regional climate model to project ETCCDI extreme indices for the Zhujiang River basin in southern China; Xu et al. (2018) projected ETCCDI of temperature extremes across major river basins in China using 27 Coupled Model Intercomparison Project Phase 5 (CMIP5) GCMs and two representative concentration pathways (RCP 4.5 and 8.5); and Zhou et al. (2014) studied projections of temperature and precipitation extremes over China using the CMIP5 model ensemble. In the Feilaixia drainage basin in southern China, Wu et al. (2014) generated temperature and precipitation extremes from observed meteorological data to examine historical changes. In Thailand, ETCCDI indices have been applied to meteorological observations from 1955 to 2014 (Limsakul and Singhruck, 2016), with findings indicating that Bangkok now experiences more frequent and heavier rainfall events.

In the present study, a selection of ETCCDI indices were used to project future precipitation extremes, and these were further complemented by including modified indices based on the standard rainfall intensity categories adopted by the Thai Meteorological Department (NSO, 2014; RID, 2014; TMD, 2018); the annual and monthly indices applied are presented in Table 3 and Table 4. Bias corrected RCM data sets showing the best correspondence with in situ data (see Results and discussion) were used for analysing extreme indices over four periods: past (1980–2009); present/near-term future (2010–2039), mid-term future (2040–69); and long-term future (2070–2098). Indices were computed and plotted using the code included in the `biascorrect_indices_batch_revision.R` script (Supplementary contents).

#### 2.5. Spatial interpolation

Five selected extreme indices were spatially interpolated across the BMR and nearby provinces (refer to Results and discussion). Mean values of bias corrected scenario data from the past (1980–2009) and future periods were spatially interpolated using inverse distance weighting (IDW). This method is one of various interpolation techniques that has been widely applied to precipitation data (e.g., Keblouti et al., 2012; Ly et al., 2013; Yang et al., 2015). Inverse distance weighted interpolation estimates unknown precipitation values by calculation of weightings in relation to distance from observed values, and incorporates a power function selected by the user prior to calculation (Chen and Liu, 2012; Keblouti et al., 2012; Ly et al., 2013). A weighting factor of 2 was used in this study given its adoption elsewhere (e.g., Ozelkan et al., 2015) and also after inspection of plots of RMSE against weighting factor. All plots of RMSE against weighting factor showed a steep decline in RMSE between 1 and 2 weight factors and sometimes gave the lowest RMSE values at higher weight factors, but the latter tended to give outputs that were more jagged and irregular in shape than lower weightings. Spatial interpolation was conducted across a raster of 100 m resolution, which is the approximate resolution that matches the internationally recognised positioning accuracy of meteorological observing stations at a resolution of 1 to 1000 in degrees of latitude and longitude (WMO, 2008). The differences between past and future selected extreme indices were plotted to show projected percentage changes.

### 3. Results and discussion

The Results and discussion is divided into six main sections. The first section on bias correction identifies the optimal approaches for bias correcting RCM data. The second section addresses each climate index through plotting of line and box-and-whisker plots and calculation

<sup>9</sup> <http://etccdi.pacificclimate.org/software.shtml>.

**Table 3**  
Annual extreme indices and outputs.

| Type of analysis [ETCCDI index in square brackets] <sup>a</sup>                                        | Period of analysis and outputs                                                           |
|--------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------|
| (i) Annual total precipitation on wet days <sup>b</sup> [PRCPTOT]                                      | (a) Line charts of decadal maxima from 1960s to 2090s.                                   |
| (ii) Longest annual run of consecutive wet days [CWD]                                                  | (b) Box plots comparing four periods:<br>1980–2009, 2010–2039, 2040–2069, and 2070–2098. |
| (iii) Longest annual run of consecutive dry days [CDD]                                                 |                                                                                          |
| (iv) Annual precipitation (mm) by daily intensity (light, moderate, and heavy/very heavy) <sup>c</sup> |                                                                                          |
| (v) Annual number of rainy days by daily intensity (light, moderate, heavy/very heavy)                 |                                                                                          |
| (vi) Annual maximum 5-day cumulative precipitation                                                     | Box plots comparing four periods:<br>1980–2009, 2010–2039, 2040–2069, and 2070–2098.     |
| (vii) Annual maximum 1-day precipitation                                                               |                                                                                          |

<sup>a</sup> ETCCDI indices: see [http://etccdi.pacificclimate.org/list\\_27\\_indices.shtml](http://etccdi.pacificclimate.org/list_27_indices.shtml)

<sup>b</sup> wet day:  $\geq 1.0$  mm day<sup>-1</sup> precipitation

<sup>c</sup> TMD standard categories of daily rainfall intensity (TMD 2016; NSO, 2014; RID, 2014): light ( $\geq 0.1$  and  $\leq 10.0$  mm); moderate ( $\geq 10.1$  and  $\leq 35.0$  mm); heavy ( $\geq 35.1$  mm and  $\leq 90.0$  mm); very heavy ( $\geq 90.1$  mm)

**Table 4**  
Monthly extreme indices and outputs.

| Type of analysis [ETCCDI index in square brackets]                 | Period of analysis and outputs                                                           |
|--------------------------------------------------------------------|------------------------------------------------------------------------------------------|
| (i) Monthly sum of daily rainfall (mm)                             | (a) Box plots over single 30-year period:<br>1980–2009.                                  |
| (a) Monthly sum of rainfall on <b>wet days</b>                     |                                                                                          |
| (b) Monthly sum of <b>heavy/very heavy</b> rainfall                | (b) Box plots comparing four periods:<br>1980–2009, 2010–2039, 2040–2069, and 2070–2098. |
| (ii) Monthly sum of rainy days                                     |                                                                                          |
| (a) Monthly number of <b>wet days</b>                              |                                                                                          |
| (b) Monthly number of days with <b>heavy/very heavy</b> rain       |                                                                                          |
| (iii) Monthly maximum 5-day cumulative precipitation (mm) [Rx5day] |                                                                                          |
| (iv) Monthly maximum 1-day precipitation (mm) [Rx1day]             |                                                                                          |

of statistical metrics for selected indices, and then the selected climate indices are spatially interpolated across the BMR and surrounding provinces. Subsequent sections present a future extreme precipitation profile of BMR based on the above findings; an overview of the existing evidence base of projected future precipitation change to which the findings of this study now complement; potential influences of urbanisation; and future research opportunities. Note, that as a large number of plots were necessarily output for each of the TMD stations, plots from station 455201, which is located within the capital city of Bangkok, are presented in the Results and discussion section, whereas others are included in the Supplementary contents for reference.

### 3.1. Bias corrections

Quantile-quantile plots for station 455201 are shown in Fig. 3, with other station QQ plots presented in the Supplementary contents. Each QQ plot displays all five scenarios at each TMD station. Percentiles of wet day ( $\geq 1.0$  mm) distributions are shown above the x-axis to aid interpretation. The best performance of each bias correction technique for each scenario at each station was determined by considering the best fit above the 90th percentile.

Both QUANT and EQM techniques gave reliable performances in the bias corrections. For the most part across the whole precipitation distribution range, raw RCM data from all five climate scenarios underestimate precipitation values of observational data at all 16 TMD stations. Outputs from QUANT were selected for deriving all of the proposed annual and monthly extreme metrics (as listed in Table 3 and Table 4), and outputs from the EQM method were subsequently applied to calculating and interpreting selected extreme indices for comparison.

### 3.2. Extreme climate indices

Each of the annual and monthly extreme indices were visualised and interpreted in terms of past (1980–2009), present/near-term future (2010–2039), mid-term future (2040–2069) and long-term future (2070–2098) periods. Two types of plots were interpreted: line graphs of decadal maxima that aim to reveal long-term trends in maxima over the entire study period (for annual metrics only); and box plots comparing metrics over the four periods to uncover any future trends that may be reflected in their median values and data distributions (annual

and monthly metrics). In the former, bias corrected data, as line plots, are superimposed on raw model scenario data which are represented as shaded bands derived from minimum and maximum values, and in situ TMD data are plotted as dashed lines. With regard to box plots, the interquartile range (IQR) (between the 25th percentile or lower quartile and 75th percentile or upper quartile) is represented by the box height; the enclosed horizontal line is the median; the whiskers are up to 1.5 times as long as the IQR; and the asterisk points represent outliers beyond the latter (Krzywinski and Altman, 2014; Wickham, 2018).

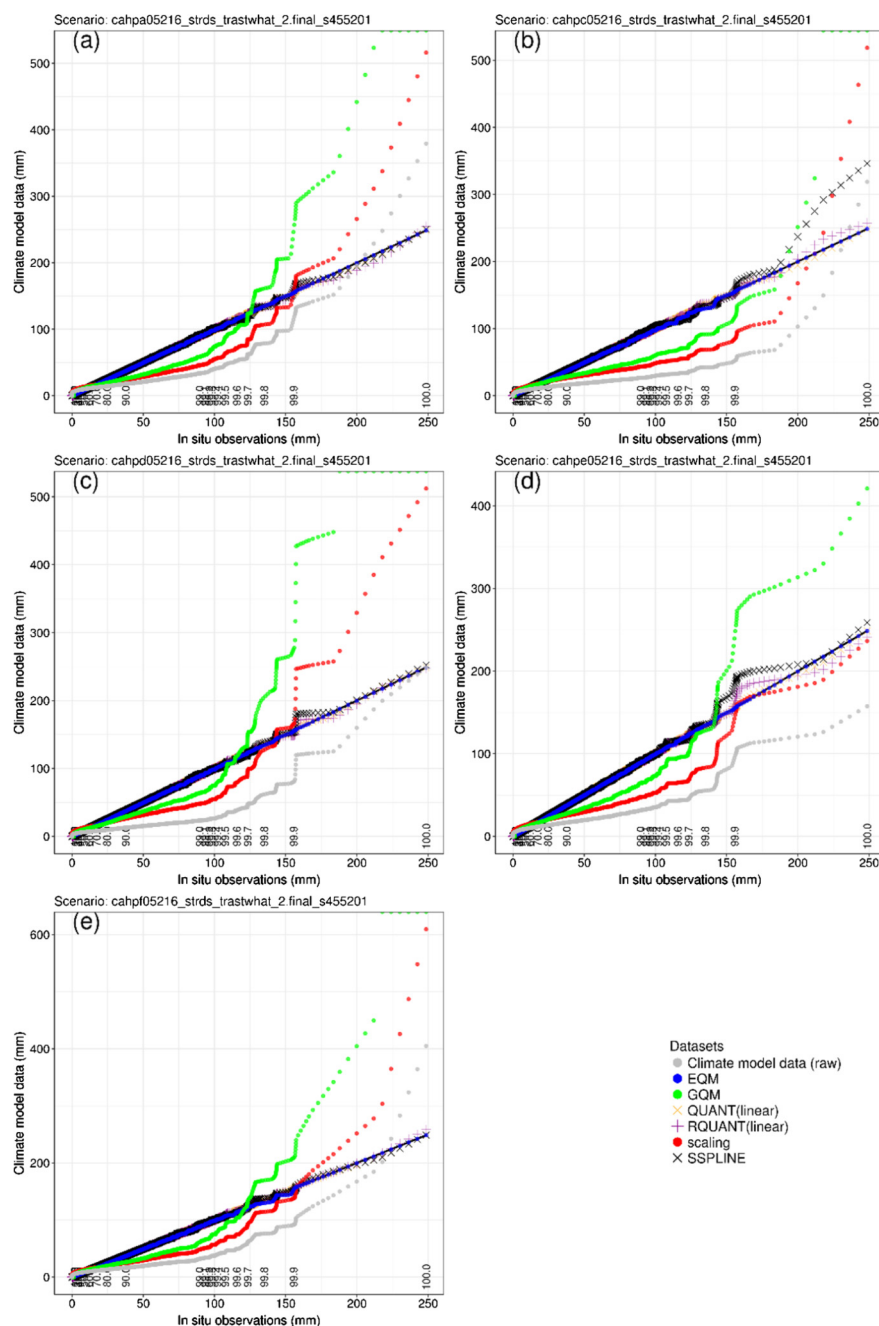
The approach taken to determine the potential reliability of future precipitation projections for each extreme index was to first compare the scenario and in situ metrics of the past, that is to compare data sets over the 30-year period from 1980 to 2009, and then to examine how each metric was projected into the future for those scenarios that best correspond to in situ data over the past period. It should be noted that box plots used for comparing TMD and model data over the 1980–2009 period may not contain a full 30-years of data (i.e., model data was selected to match the continuous period where TMD data was available). With regard to the long-term period (2070–2098), the year 2099 was omitted given incomplete data for that year. Similarly for line plots of decadal metrics, a full decade of data may not be available for all TMD stations.

#### 3.2.1. Annual metrics

(i) **Total annual precipitation on wet days (PRCPTOT).** The PRCPTOT metric was visualised as decadal maxima of total annual precipitation of TMD in situ data and all model scenarios data from the 1960s to 2090s (Fig. 4a and Supplementary content). Generally, there is reasonable correspondence between raw model and in situ data at all stations in the earlier decades of the observational data sets, except for 455203 and 430201 where raw data more notably underestimate observational values. Future projections of this metric for all scenarios, although variable from decade to decade, tend to show a slight increasing trend in decadal maxima.

Comparison of box plots of raw, corrected and observational data sets over the past period (1980–2009) demonstrate the value of bias correction in improving correspondence of median values between model and observed data sets at a number of stations (Fig. 5).

Calculation of medians, means, standard deviations and 90th percentiles of this metric supplemented interpretation of the box-and-



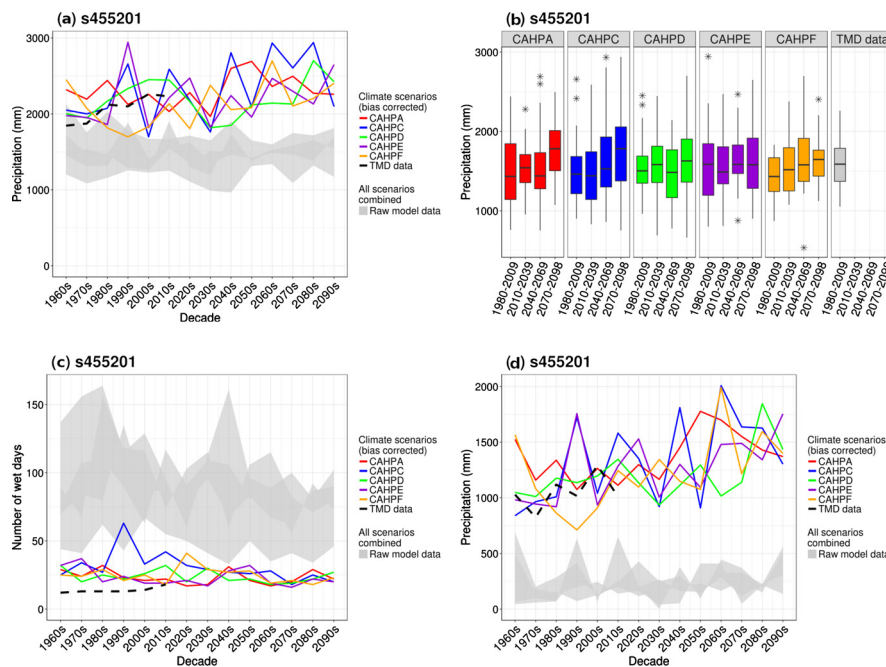
**Fig. 3.** QQ plots of bias corrections for TMD station 455201 (0.1 and 10% divisions shown above and below the 90th percentile respectively). Panels (by scenario): (a) CAHPA, (b) CAHPC, (c) CAHPD, (d) CAHPE, (e) CAHPF. Other stations are presented in Supplementary content.

whisker plots (Table 5). Analysis of median differences indicates that for most scenario data sets (74 of 80), bias correction shifted median values of raw RCM data closer to those of observed data sets for this annual metric. With regard to mean differences, 72 (out of 80) data sets show closer correspondence of mean values to those of observation data. The combined mean across all stations by scenario indicates that the smallest mean difference between observed and bias corrected data is shown by the CAHPD scenario (3.6 mm difference) and CAHPE (−5.3 mm difference). Overall, bias correction shifted the 90th percentiles closer to those of observed data (in 62 of 80 data sets), though it was less successful in improving correspondence of standard deviations (33 out of 80 data sets).

Examination of median values over past and future periods in all scenarios generally indicate increasing trends, being more consistent in CAHPA, CAHPC and CAHPF (Fig. 4b and Supplementary contents).

**(ii) Longest run of consecutive wet days (CWD).** Decadal maxima of the maximum number of consecutive wet days per year of TMD in situ data and all model scenarios data from the 1960s to 2090s are visualised in Fig. 4c and Supplementary content. Raw model data values of all scenarios and stations are substantially greater compared to in situ data over the past, and bias corrections reduced model data values for the most part. Box plots of maximum annual consecutive wet days over the single period of 1980–2009 indicate little overlap between IQRs of observational data with bias corrected data, thus making this metric unreliable for future projections (Supplementary section).

**(iii) Longest run of consecutive dry days (CDD).** Decadal maxima of the maximum number of consecutive dry days (i.e.,  $<1.0 \text{ mm day}^{-1}$  precipitation) per year for in situ and scenarios data from the 1960s to 2090s were examined (Supplementary content). Though variable, raw scenarios data for the most part have slightly higher values compared



**Fig. 4.** Station 455201: (a) Decadal maxima of total annual rainfall (on wet days) of raw, corrected and TMD in situ data. (b) Boxplots of total annual rainfall (on wet days) over four periods of corrected and TMD in situ data. (c) Decadal maxima of annual longest number of consecutive wet days of raw, corrected and TMD in situ data. (d) Decadal maxima of total annual heavy/very heavy rainfall of raw, corrected and TMD in situ data. Other stations are presented in Supplementary content.

**Table 5**

Statistical analysis of total annual rainfall (on wet days) of hindcast years occurring in the period from 1980 to 2009. The upper table indicates the number of stations by scenario (out of a total of 16 stations) where bias correction improved correspondence with observation data set statistics (SD is standard deviation). Lower table shows combined mean (of all stations by scenario) and associated mean differences between observed (obs) and raw and corrected (cor) data, and mean shift in mm. A positive mean shift indicates movement (in mm) towards the observation data mean after bias correction. Maximum 90th percentiles by scenario across all stations are also indicated.

| Statistic                       | CAHPA | CAHPC | CAHPD | CAHPE | CAHPF | Total |
|---------------------------------|-------|-------|-------|-------|-------|-------|
| Station count (90th percentile) | 11    | 13    | 14    | 11    | 13    | 62    |
| Station count (mean)            | 15    | 13    | 16    | 15    | 13    | 72    |
| Station count (median)          | 15    | 13    | 16    | 14    | 16    | 74    |
| Station count (SD)              | 2     | 8     | 8     | 5     | 10    | 33    |

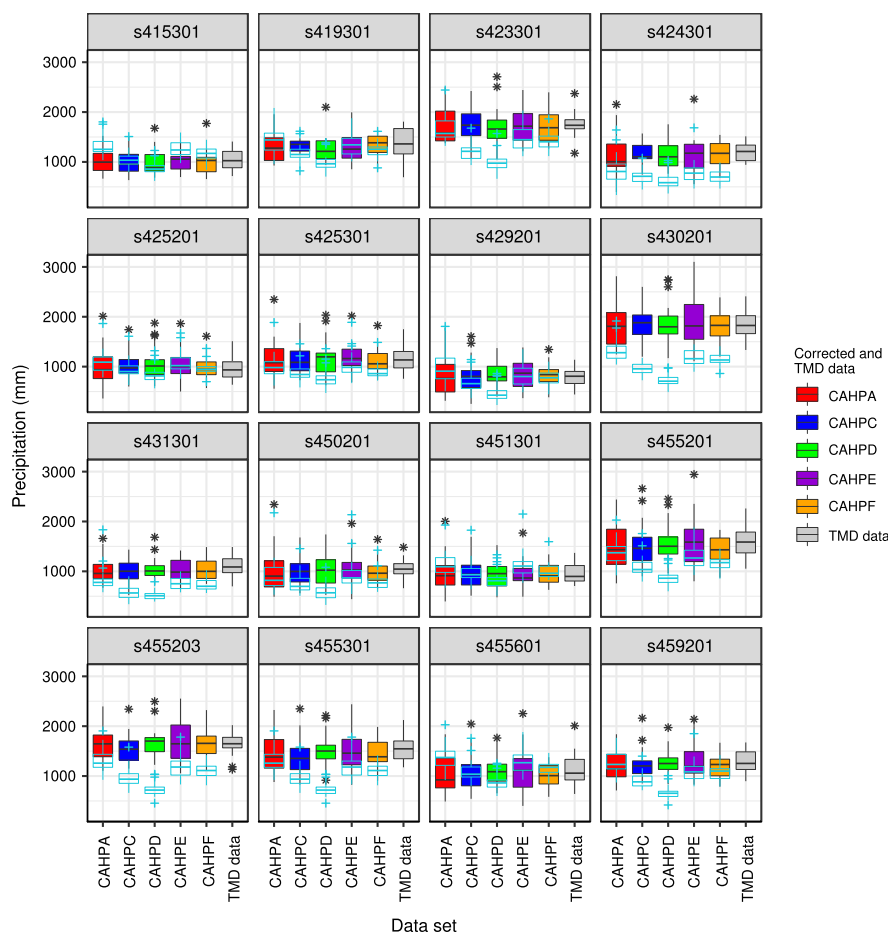
  

| Statistic                     | CAHPA | CAHPC | CAHPD | CAHPE | CAHPF |
|-------------------------------|-------|-------|-------|-------|-------|
| Mean (obs)                    | 1275  | 1275  | 1275  | 1275  | 1275  |
| Mean (raw)                    | 1176  | 922.1 | 745.4 | 1116  | 1004  |
| Mean (cor)                    | 1226  | 1228  | 1272  | 1280  | 1220  |
| Mean difference (obs – raw)   | 98.9  | 353   | 529.6 | 158.6 | 271.3 |
| Mean difference (obs – cor)   | 49.6  | 46.6  | 3.6   | –5.3  | 55.5  |
| Mean shift                    | 49.4  | 306.4 | 526.1 | 163.9 | 215.9 |
| Maximum 90th percentile (obs) | 2131  | 2131  | 2131  | 2131  | 2131  |
| Maximum 90th percentile (raw) | 1945  | 1502  | 1244  | 1779  | 1615  |
| Maximum 90th percentile (cor) | 2595  | 2177  | 2282  | 2418  | 2276  |

to in situ data over the past, and bias corrections did not improve correspondence with raw model data. Overall, box plots showed that IQRs of in situ data for the 1980–2009 period have poor correspondence with bias corrected data across all stations and scenarios (Supplementary content), and thus future projections were considered unreliable for this metric.

**(iv) Total annual precipitation (mm) by daily intensity (light, moderate, heavy/very heavy).** This metric is based on the standard categories of daily rainfall intensity used by the Thai Meteorological Department (see footnote in Table 3). Similar ETCCDI metrics would be R95pTOT and R99pTOT that define the total annual precipitation above the 95th and 99th percentiles respectively; the latter are not presented, but were substituted in this study by analysing total heavy/very heavy rainfall. Findings for light and moderate rainfall are included in the Supplementary content.

**Heavy/very heavy rainfall.** Raw model data from all scenarios and stations substantially underestimate in situ data (except station 429201), as shown in the line plots of decadal maxima of total annual heavy/very heavy rainfall (Fig. 4d and Supplementary content) and box plots (Fig. 6). Bias corrections however, markedly adjusted model data to more closely correspond to values of in situ observations (except more notably for decadal maxima of station 429201 where corrected data overestimated in situ data), and future projections generally showed a gradual, albeit variable, upward trend of decadal maxima values. Box plots of total annual heavy/very heavy rainfall show that IQRs of in situ data correspond well with bias corrected data in the 1980–2009 period of all scenarios and stations (Fig. 6). Analysis of median differences (Supplementary content tables) indicated that for most scenario data sets (74 of 80), bias correction adjusted median values of raw RCM data closer to those of observed data sets for this annual metric. With regard to mean differences, 68 (of 80) data sets showed closer



**Fig. 5.** Boxplots of total annual rainfall (on wet days) over the single period of 1980 to 2009 (panels by TMD station number). Raw model data box plots in light blue outline.

correspondence of mean values to those of observation data, and the 90th percentiles were adjusted closer to those of observational data in most data sets (in 58 out of 80 data sets).

Median values generally show noticeably increasing trends over future periods in all scenarios, though less so with CAHPD (driest scenario) (Fig. 7a and Supplementary section). Scenario CAHPA was spatially interpolated across the BMR and surrounding provinces (see section on spatial interpolation of selected extreme indices); Scenario CAHPA was chosen as it more frequently gave the highest median values during the 2070–2098 period (at 6 stations), while CAHPC had five of the highest median values during this period.

**(v) Annual number of rainy days by daily intensity (Rnnmm).** This metric is based on the ETCCDI index which is the annual sum of days with precipitation above a defined value (Rnnmm). The values here are taken from the rainfall intensity categories used by the Thai Meteorological Department. The metric is presented as line graphs of decadal maxima of heavy/very heavy rainfall and box plots of heavy/very heavy rainfall over four periods; findings for light and moderate rainfall are also included in the Supplementary content for completeness.

Raw model data substantially underestimate decadal maxima of heavy/very heavy rainfall, with bias corrections improving correspondence at all stations for all scenarios; bias corrected data generally show a slight upward drift in decadal maxima over future decades (Fig. 7b and Supplementary figures).

Box plots of total annual number of days with heavy/very heavy rainfall show that IQRs of in situ data and bias corrected data for all scenarios and stations during the 1980–2009 period overlap to some extent (Supplementary figures), with median values of scenarios gener-

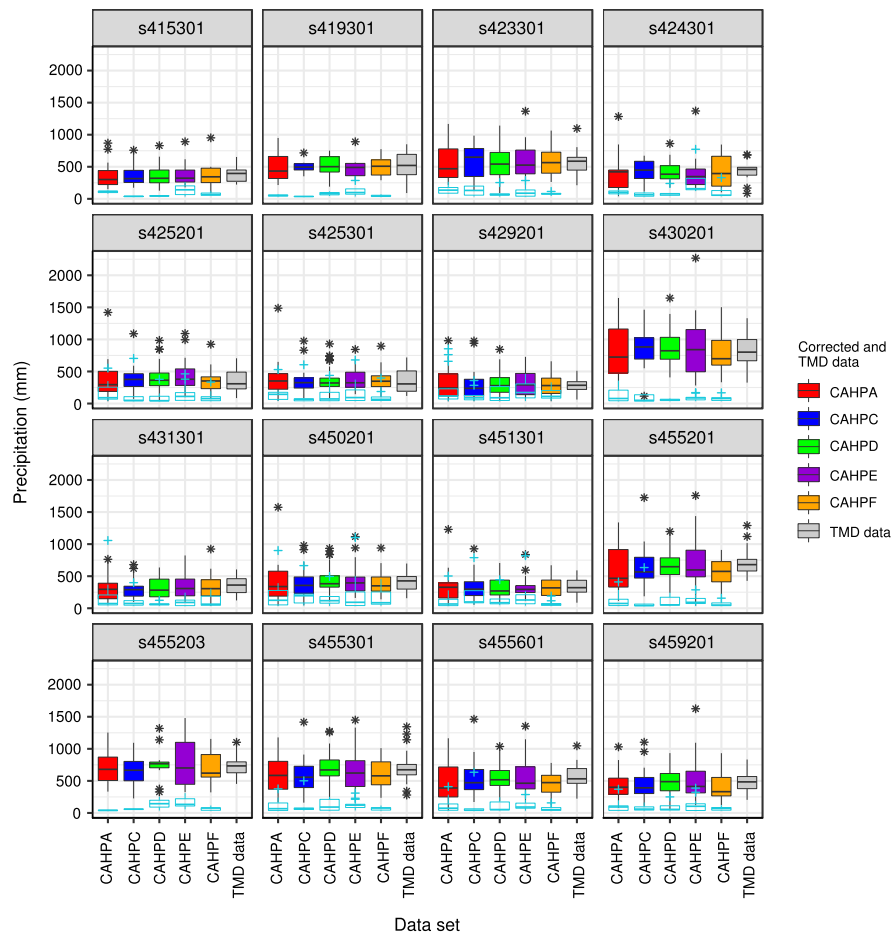
ally trending upwards over the long-term (Fig. 7c and Supplementary figures). This metric projects future periods with increasing numbers of days experiencing heavy/very heavy rainfall, which also corresponds to findings of the previous metric of future projected increases of total annual heavy/very heavy rainfall.

**(vi) Annual maximum 5-day cumulative precipitation.** This metric is based on ETCCDI's monthly metric (Rx5day), but with the period of analysis extended to a year; the monthly index is also presented below. Box plot IQRs of in situ data overlap with those of corrected data from most scenarios and stations in the earliest period (Supplementary figures), and generally scenario medians increase in value over future periods, though more consistently for scenarios CAHPA and CAHPC (Fig. 7d and Supplementary figures).

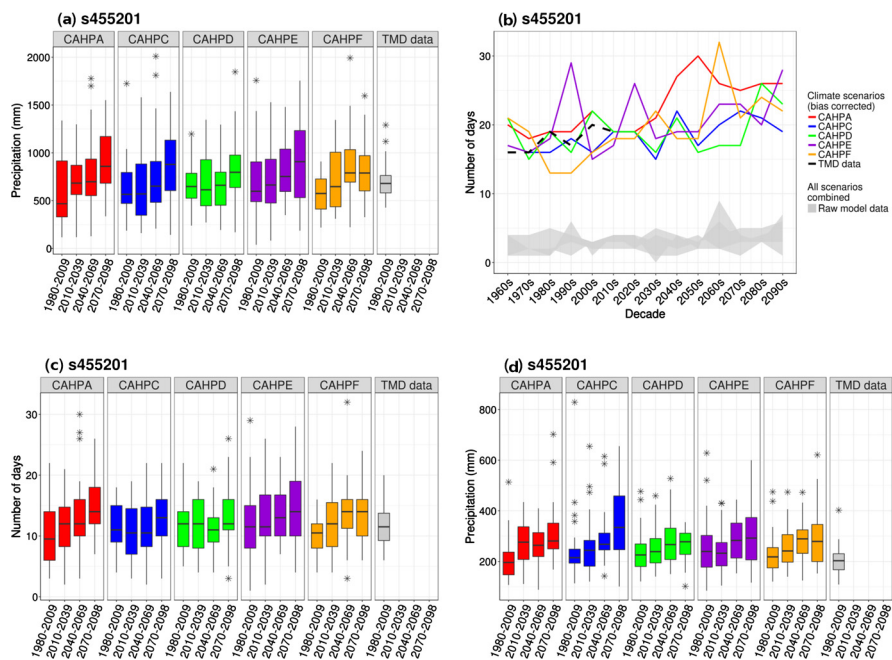
**(vii) Annual maximum 1-day precipitation.** This annual metric is based on ETCCDI's monthly metric (Rx1day), which is also examined below. Box plots indicate that in situ data IQRs of the earliest period overlap considerably with those of bias corrected data for most scenarios and stations (Supplementary figures). An increase in median values of this metric is indicated over future periods, which is more evident in scenarios CAHPA and CAHPC (Supplementary figures).

### 3.2.2. Monthly metrics

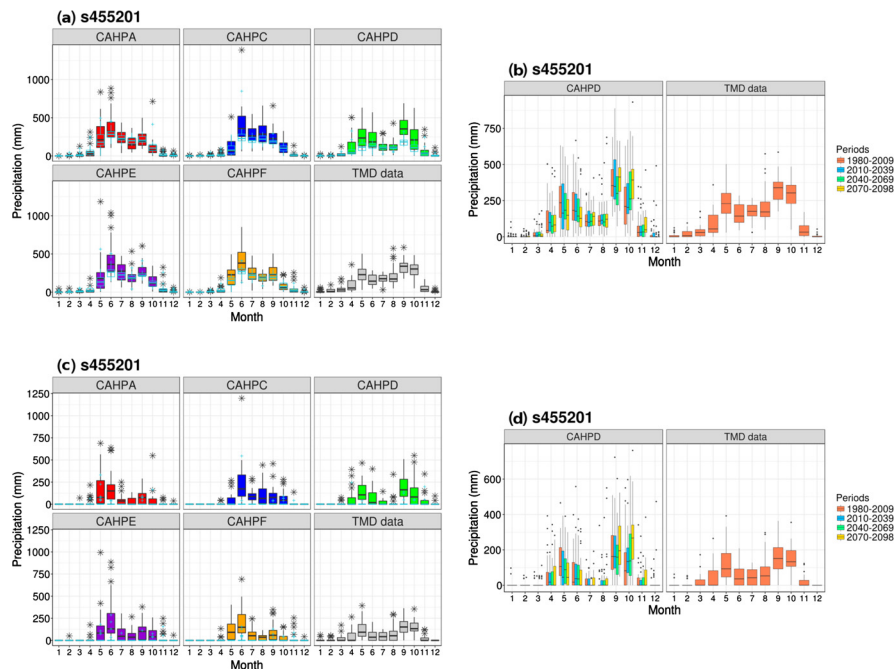
As with the annual metrics, the approach taken to assess plausible future precipitation projections involved a two step process: (i) to first compare extreme indices of in situ and scenarios' data over the past (i.e., over the 1980 to 2009 period), and (ii) to visually examine how each metric is projected into the future for those scenarios that best correspond with measured observations over the past period.



**Fig. 6.** Box plots of total annual heavy/very heavy rainfall over the single period of 1980 to 2009 (panels by TMD station number). Raw model data box plots in light blue outline.



**Fig. 7.** Annual metrics of station 455201: (a) Box plots of total annual heavy/very heavy rainfall over four periods of corrected and TMD in situ data. (b) Decadal maxima of annual number of days with heavy/very heavy rainfall of raw, corrected and TMD in situ data. (c) Box plots showing total annual number of days with heavy/very heavy rainfall intensity over four periods of corrected and TMD in situ data. (d) Box plots of annual maximum 5-day cumulative rainfall over four periods of corrected and TMD in situ data.



**Fig. 8.** Monthly metrics of station 455201: (a) Box plots of total monthly rainfall (on wet days) over single period of 1980–2009 of corrected and TMD in situ data (raw model data box plots in light blue outline). (b) Box plots of total monthly rainfall (on wet days) over four periods of corrected (CAHPD) and TMD in situ data. (c) Box plots of total monthly heavy/very heavy rainfall over single period of 1980–2009 of corrected and TMD in situ data (raw model data box plots in light blue outline). (d) Box plots of total monthly heavy/very heavy rainfall over four periods of corrected (CAHPD) and TMD in situ data.

**(i) Total monthly sum and heavy/very heavy rainfall.** Total monthly rainfall on wet days and heavy/very heavy rainfall (according to the TMD precipitation category) were examined. Each metric is presented as a series of box plots.

*Total monthly sum of rainfall on wet days.* All corrected scenarios capture the general southwest monsoon pattern of heavier rains between May and October (Fig. 8a and Supplementary figures). In terms of monthly median values and IQRs, all corrected scenarios are reasonably comparable to in situ data with the peak late monsoon rains of September/October, but are more consistently captured by scenario CAHPD. The onset of the heaviest monsoon rains in May is delayed to June in most scenarios, but captured better in CAHPD.

Analysis of median differences for May to October (Supplementary section) generally show a mixed performance of bias correction in shifting median values of raw data closer to those of observed data sets for this monthly metric. Of the 80 data sets examined, bias correction was found to improve (figures in brackets) median correspondence in May (46), June (17), September (56), and October (43). With regard to assessment of mean values of the metric, of the 80 data sets examined, bias correction was found to improve correspondence with observed mean values (figures in brackets) in May (51), June (19), September (58), and October (61). Bias correction proved particularly effective in improving median and mean values for CAHPD scenarios at all stations in October. Bias correction notably improved correspondence of 90th percentiles in September and October by 71 and 67 data sets respectively. Regarding combined means across all stations, scenario CAHPD gave the smallest differences between observation and bias corrected data for June, September and October.

Examination of the trends of CAHPD over future periods (Fig. 8b and Supplementary figures) show that in the early monsoon (May/June) the median values tend to shift downwards over time, and in the late monsoon (September/October) the medians trend upwards. Overall, simulations indicate decreasing total monthly rainfall over the early monsoon and increasing rainfall over the late monsoon (especially in October).

*Total monthly sum of heavy/very heavy rainfall.* Raw RCM data considerably underestimate observed monthly heavy/very heavy rainfall

(Fig. 8c and Supplementary figures). However, bias corrected data present a picture similar to the total monthly rainfall as discussed previously. The patterns of monsoon rain peaking in May/June and September/October are reasonably captured at all stations and scenarios after bias correction, though CAHPD tends to better capture the heaviest early monsoon rains in May/June.

Analysis of median and mean differences indicate that bias correction shifted median and mean values of raw data closer to those of observed data sets for this monthly metric, especially for the months of September and October (Table 6 and Supplementary tables). Of the 80 data sets examined, bias correction was found to improve (figures in brackets) median correspondence with observation data sets in May (48), June (6), September (78), and October (45); and improve mean correspondence in May (61), June (17), September (80), and October (80). It is interesting to note that while bias correction generally showed poor performance for the month of June, it did improve correspondence of scenario CAHPD mean values at 14 out of the 16 TMD stations. Regarding combined means across all stations, scenario CAHPD gave the smallest differences between observation and bias corrected data for June, September and October, and bias correction of CAHPD generally was more consistent in improving standard deviations across all months (May, June, September and October) compared to other scenarios.

Examining future trends of the CAHPD scenario (Fig. 8d and Supplementary section), the medians of the early monsoon rains tend to remain static or decrease into the future, and in the late monsoon (September/October) over future periods the median values tend to increase (noticeably in October). This metric suggests static or decreasing heavy/very heavy monthly rainfall over the early monsoon, though increasing in the late monsoon in October. This metric (scenario CAHPD) was spatially interpolated across the BMR (see section on spatial interpolation).

**(ii) Total monthly number of wet and heavy/very heavy rainfall days.** Two metrics were visualised, including the total monthly number of wet days and the total monthly number of days with heavy/very heavy rainfall.

*Total monthly number of wet days.* The overall pattern of increasing numbers of southwest monsoonal wet days is captured in all stations

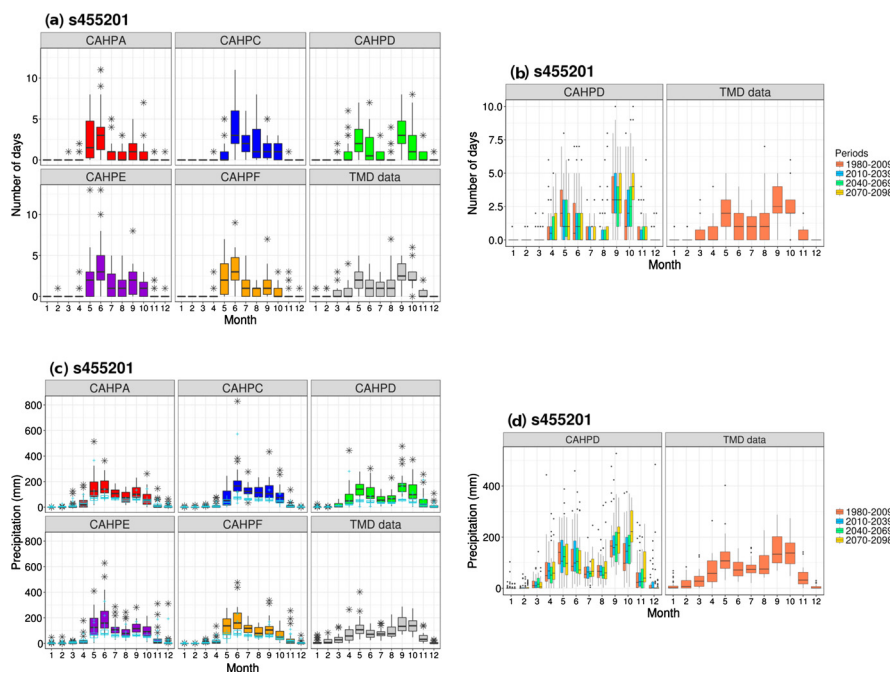
**Table 6**

Statistical analysis of total monthly sum of heavy/very heavy rainfall for the month of October of hindcast years occurring in the period from 1980 to 2009. Other details as per Table 5.

| Statistic                       | CAHPA | CAHPC | CAHPD | CAHPE | CAHPF | Total |
|---------------------------------|-------|-------|-------|-------|-------|-------|
| Station count (90th percentile) | 16    | 15    | 15    | 16    | 15    | 77    |
| Station count (mean)            | 16    | 16    | 16    | 16    | 16    | 80    |
| Station count (median)          | 8     | 10    | 14    | 10    | 3     | 45    |
| Station count (SD)              | 14    | 14    | 12    | 14    | 14    | 68    |

| Statistic                     | CAHPA | CAHPC | CAHPD | CAHPE | CAHPF |  |
|-------------------------------|-------|-------|-------|-------|-------|--|
| Mean (obs)                    | 92.7  | 92.7  | 92.7  | 92.7  | 92.7  |  |
| Mean (raw)                    | 7     | 8.8   | 5.9   | 8.8   | 6.8   |  |
| Mean (cor)                    | 49.1  | 60.1  | 95.9  | 59.4  | 45    |  |
| Mean difference (obs – raw)   | 85.8  | 84    | 86.9  | 83.9  | 85.9  |  |
| Mean difference (obs – cor)   | 43.6  | 32.6  | –3.2  | 33.3  | 47.7  |  |
| Mean shift                    | 42.2  | 51.4  | 90    | 50.6  | 38.2  |  |
| Maximum 90th percentile (obs) | 265.9 | 265.9 | 265.9 | 265.9 | 265.9 |  |
| Maximum 90th percentile (raw) | 59.9  | 112   | 87.2  | 88.3  | 114.1 |  |
| Maximum 90th percentile (cor) | 411.8 | 243.2 | 399.2 | 248.7 | 191.3 |  |



**Fig. 9.** Monthly metrics of station 455201: (a) Box plots of total monthly number of days with heavy/very heavy rain over single period of 1980–2009 of corrected and TMD in situ data. (b) Box plots of total monthly number of days with heavy/very heavy rain over four periods of corrected (CAHPD) and TMD in situ data. (c) Box plots of monthly maximum 5-day cumulative rainfall over single period of 1980–2009 of corrected and TMD in situ data (raw model data box plots in light blue outline). (d) Box plots of monthly maximum 5-day cumulative rainfall over four periods of corrected (CAHPD) and TMD in situ data.

and scenarios, with CAHPD simulating the early and late monsoon better than other scenarios (Supplementary figures). Scenario CAHPD better captures the peak in median values of wet days in May/June compared to other scenarios where typically substantial differences between May and June were evident. The annual peak in September was also better reproduced in CAHPD compared to other scenarios. Over future periods, median values tend to be static or decreasing in May/June and increasing in October in CAHPD simulations (Supplementary content).

**Total monthly number of days with heavy/very heavy rainfall.** All scenarios generally show a pattern of an increasing number of days of heavy/very heavy rainfall during the southwest monsoon period (Fig. 9a and Supplementary content). Overall, scenario CAHPD better simulates September as the month with most days of heavy/very heavy rainfall. Over future periods, the median values in CAHPD appear static in May/June, but increases are seen at all stations in October (Fig. 9b and Supplementary content).

**(iii) Monthly maximum 5-day cumulative precipitation [Rx5day].** The monthly maximum 5-day cumulative precipitation is based on the ETCCDI metric and presented here as box plots over past and future periods. At all stations, all scenarios reproduce the general increase in precipitation seen over the southwest monsoon period, however scenario CAHPD better captures the May peak in the early onset of the monsoon and September/October annual peak when compared with observed measurements (Fig. 9c and Supplementary figures).

For the months of September and October, analysis of median and mean differences indicate that bias correction delivered mixed performance in shifting median and mean values of raw data closer to those of observed data sets for this monthly metric (Supplementary section). Of the 80 data sets examined, bias correction was found to improve (figures in brackets) median correspondence in May (43), June (14), September (78), and October (72); and improve correspondence of means in May (43), June (15), September (78), and October (78). Whereas bias correction generally showed poor performance for the month of June, it did improve correspondence of scenario CAHPD me-

dian values at 10 stations and of mean values at 13 stations (out of the total 16 TMD stations); at most only 1 station for other scenarios showed any improvement following bias correction of means or medians.

Over future periods median values of the CAHPD scenario appear static in the early monsoon, with increasing precipitation evident in September and more noticeably October (Fig. 9d and Supplementary figures). Monthly (October) maximum 5-day cumulative precipitation was spatially interpreted across the study area (see section on spatial interpolation).

**(iv) Monthly maximum 1-day precipitation [Rx1day].** The monthly maximum 1-day precipitation is based on the ETCCDI metric and presented here as box plots over past and future periods. All scenarios at all stations reproduce the increase in rains of similar magnitude to in situ data over the southwest monsoonal period (Supplementary figures). However, the peak median values in the early monsoon (month of May) were more consistently reproduced in scenario CAHPD.

Analysis of median and mean differences indicate that bias correction shifted median and mean values of raw data closer to those of observed data sets for this monthly metric, especially for the months of May, September, and October (Supplementary section). Of the 80 data sets examined, bias correction was found to improve (figures in brackets) median correspondence in May (79), June (49), September (80), and October (79); and improve correspondence of means in May (72), June (41), September (80), and October (80). Whereas bias correction generally showed poorer performance for the month of June, it did improve the correspondence of scenario CAHPD mean values at all 16 TMD stations. With regard to combined means across all stations, scenario CAHPD gave the smallest differences between observation and bias corrected data for June, September and October; and bias correction of CAHPD generally improved correspondence of standard deviation values across all four months of May, June, September and October. Overall bias correction adjusted the 90th percentiles closer to those of observed data in all months, but was more successful in September and October (in 79 and 77 data sets respectively).

Over future periods, scenario CAHPD shows that rainfall remains static or decreases in amount in the early monsoon, but increases in October (Supplementary figures). This metric was spatially interpolated across the BMR (see section on spatial interpolation).

### 3.2.3. Comparison of QUANT and EQM methods

In addition to the analyses conducted with outputs from using the QUANT bias correction technique, box plots of five selected extreme indices (i.e., the metrics that were spatially interpolated across the BMR as indicated in the next section) and associated statistical analyses were computed for bias corrected data derived from the EQM method (as supplied in the *hyfo* R package). Plots and statistical analyses reveal minimal differences between outputs of the two software techniques (Supplementary section), with differences likely attributable to how each method addresses extrapolation of model values. While both QUANT and EQM employ empirical quantile mapping techniques, one notable difference concerns how extrapolation constrains corrected values: in EQM the corrected values do not exceed the observed range used in hindcasting, whereas in QUANT if a model value exceeds the hindcast range, then a constant correction equivalent to that used for the highest quantile is applied (Boé et al., 2007; Gudmundsson et al., 2012; Xu, 2017). The consequence of this can be seen by comparing the maximum 90th percentile values by scenario (from all 16 stations) of QUANT and EQM outputs, where EQM outputs did not exceed any of the corrected values from the QUANT method (tables in Supplementary section).

### 3.2.4. Spatial interpolation of selected extreme indices

Five different extreme indices were spatially interpolated across the BMR and nearby provinces: (i) total annual heavy/very heavy precipitation (CAHPA); (ii) total monthly (October) precipitation (CAHPD);

(iii) total monthly (September and October) heavy/very heavy precipitation (CAHPD); (iv) monthly (October) maximum 5-day cumulative precipitation (CAHPD); and (v) monthly (October) maximum 1-day precipitation (CAHPD). The selection of CAHPA and CAHPD scenarios for interpolation are discussed above. Eight interpolated maps were generated to show the percentage differences in precipitation between the past (1980–2009) and present/future periods for the five different extreme indices (Fig. 10).

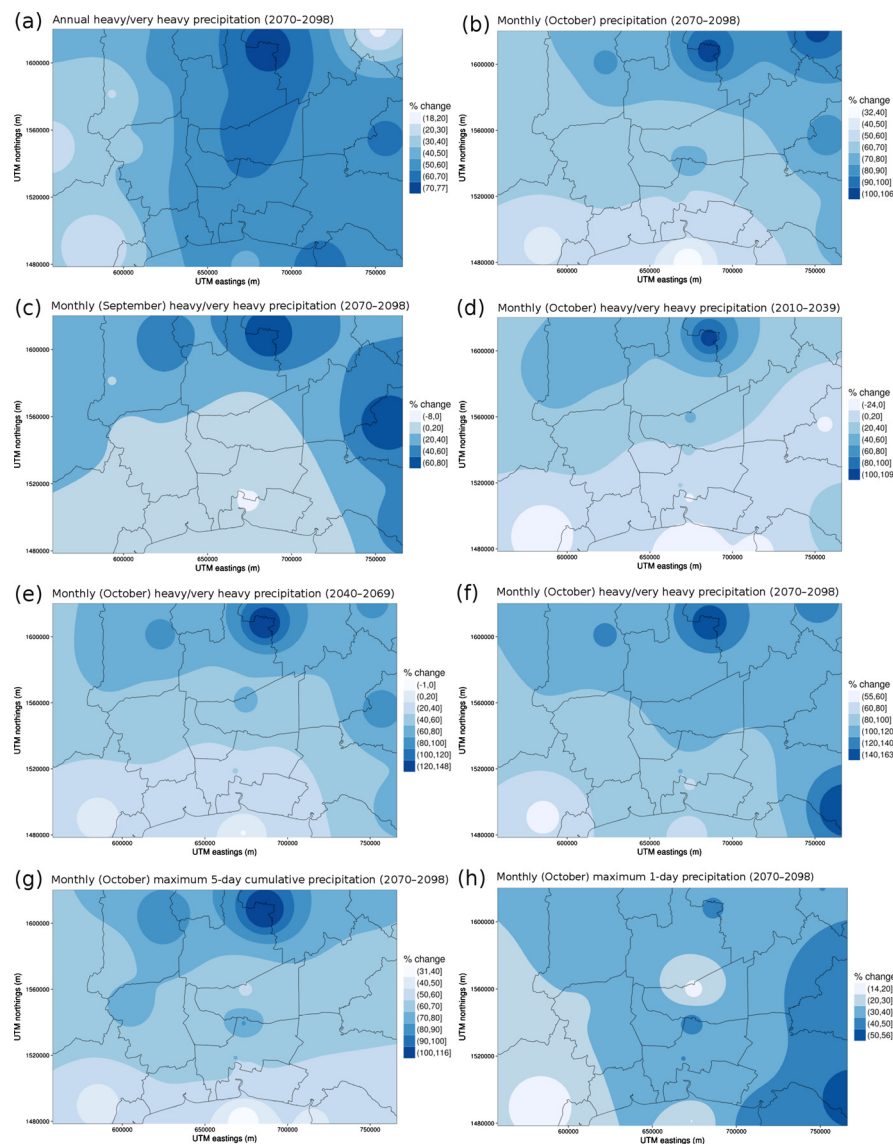
Across the BMR, total annual heavy/very heavy precipitation is projected to increase between 30–70% in the long-term (Fig. 10a). Over the long-term, the total monthly (October) precipitation is projected to increase by 50–80% across the BMR with the northern half of the region receiving the heaviest rains (Fig. 10b). Regarding the total monthly heavy/very heavy precipitation over the long-term, the heaviest rainfall is indicated in October (Fig. 10f) compared to September (Fig. 10c); during October rainfall is shown to be highest with a 100–120% increase over Pathum Thani province and 80–100% over the remainder of the BMR (Fig. 10f). Increases in October heavy/very heavy precipitation over the near-term (up to 40% over the northern BMR) and mid-term (up to 60% over the northern BMR) are shown in Figs. 10d and 10e respectively. Monthly (October) maximum 5-day cumulative precipitation is shown to increase from 50% to 80% across the BMR in the long-term with the heaviest precipitation in the northern BMR provinces (Fig. 10g). In the long-term, monthly (October) maximum 1-day precipitation is projected to increase by 30–40% over much of the BMR (Fig. 10h).

### 3.3. Future extreme precipitation profile of BMR

The following profile of future extreme precipitation projections for the BMR is based on the above interpretation of extreme indices generated from bias corrected SEACAM model scenarios and selected spatial interpolations.

The annual PRCPTOT metric points to increasing total annual precipitation over the future, as shown by the upward shift in decadal maxima line plots and box plot medians (of CAHPA, CAHPC and CAHPF scenarios). There was generally poor agreement between in situ and corrected data for the CWD metric of the longest run of consecutive wet days per year to make any useful conclusion, and results were also inconclusive with regard to the metric on the length of dry spells (CDD) per year. The analysis of TMD-defined daily rainfall intensities shows that the total annual amount of heavy/very heavy rainfall is projected to increase to the end of the century. The annual number of days with heavy/very heavy precipitation (Rnnmm) is also projected to increase in the future. Future increases in annual maximum 5-day cumulative precipitation are projected, and the annual maximum 1-day metric shows an increase in this metric over future periods.

Monthly extreme indices provide an indication of how well bias corrected RCM data reproduce seasonal southwest monsoonal rains and presents a picture of potential future changes. Examination of scenario CAHPD which best captures total monthly precipitation simulates future increases in this metric over the late monsoon. Again as best reproduced by scenario CAHPD, the total monthly sum of heavy/very heavy rainfall is projected to be static or decreasing over the early monsoon, though increasing in the late monsoon in October. With regard to the total monthly number of wet days, overall the CAHPD scenario better captures the early and late monsoon than other scenarios, and over future periods indicates that the median number of wet days will be static or decreasing in May/June and increasing in October. Plots of the total monthly number of days with heavy/very heavy rainfall display similar findings to the latter metric. The monthly maximum 5-day cumulative precipitation (Rx5day) and monthly 1-day maximum (Rx1day) indices show future projections with rainfall static or decreasing over the early monsoon, but increasing in the late monsoon and most noticeably in October.



**Fig. 10.** Spatial interpolation (across all 16 TMD stations) of selected extreme indices showing percentage change from baseline (1980–2009): (a) total annual heavy/very heavy precipitation (2070–2098); (b) total monthly (October) precipitation (2070–2098); (c) total monthly (September) heavy/very heavy precipitation (2070–2098); (d) total monthly (October) heavy/very heavy precipitation (2010–2039); (e) total monthly (October) heavy/very heavy precipitation (2040–2069); (f) total monthly (October) heavy/very heavy precipitation (2070–2098); (g) monthly (October) maximum 5-day cumulative precipitation (2070–2098); (h) monthly (October) maximum 1-day precipitation (2070–2098).

Spatial interpolation of the five selected extreme indices are especially informative for the BMR given its susceptibility to flooding during the late southwest monsoon. Overall, spatial interpolation of these indices presents a picture of substantial increases in extreme rainfall projected across the BMR, with the northern part of the BMR receiving the heaviest amounts of precipitation. The higher projections of heavy/very heavy precipitation in the northern part of the BMR should be of particular concern as this area has historically been more frequently flooded (Cooper, 2014).

### 3.4. Existing evidence of future precipitation increases

The above profile builds on the relatively limited research on using RCM data to generate future climate projections over Bangkok and its surroundings. Most studies, as far as this author is aware, have focused on using RCM data at the national or regional level. Studies across Thailand have projected future variable increases in precipitation. Chinvarno (2009) projected increases in rainfall towards the end of the 21st century across Thailand by downscaling the ECHAM4 GCM

A2 scenario using the PRECIS regional climate model developed by the UK Hadley Centre; in the BMR region a 15–50% increase is predicted in the 2090s (Figure 9 in Chinvarno, 2009). Across the central region of Thailand/Chao Phraya River basin an increase of approximately 10% (median value of 8 GCMs) in annual average precipitation was projected for the 2045–2065 period (SEA START RC, 2010). Using models from IPCC's Fourth Assessment Report, a 2 to 3% increase in rainfall (mean of June–August) was projected across Bangkok by 2050 under the B1 and A1FI IPCC scenarios (World Bank, 2009). Lacombe et al. (2012), using the PRECIS regional climate model and ECHAM4 GCM with respect to A2 and B2 scenarios, reported annual increases of precipitation over the Gulf of Thailand and most notably in the wet season to the middle of the 21st century. Compared to the period from 1981 to 2000, Sillmann et al. (2013) found that total annual wet-day rainfall (ETCCDI PRCPTOT index) will increase over Southeast Asia towards the close of the 21st century based on projections from CMIP3 and CMIP5 GCMs.

### 3.5. Incorporating potential influences of urbanisation

In this study, all meteorological station data, whether their location is urban or non-urban, have been included in the generation of precipitation projections, as inclusion of data from bias corrected urban-located stations may prove beneficial as a means of incorporating any urban influence into future RCM data projections. Hatchett et al. (2016) advocated such an approach with regard to the urban heat island (UHI) effect where bias correction of climate model data would reduce the cold bias in modelled data. Nevertheless, as indicated by Hatchett et al. (2016), the correction could be only be considered a minimal correction assuming stationarity of the urban heat island effect over the historical bias correction period, as for instance, future land use changes may additionally affect future climate. According to the latter authors, 'by including even a stationary UHI effect compared to neglecting this effect shows promise for improving urban climate projections of regionally downscaled GCM output'.

Past research elsewhere appears inconclusive as to whether urbanisation influences precipitation. Recent research by Shastri et al. (2015) indicates that precipitation extremes have increased due to urbanisation in the city of Mumbai, and Kishtawal et al. (2010) reported that urban areas experienced more heavy rainfall events than rural areas during the Indian summer monsoon. In the Pearl River Delta (PRD) of China, which has grown to become the most extensive urban area globally, Zhang et al. (2019) found that urbanisation increased the number of summer extreme rainfall events through an analysis using the Weather Research and Forecasting (WRF) model. Also based on outputs from WRF modelling, Wang et al. (2013) similarly reported an increase in the frequency of days with heavy rainfall associated with urbanisation of the PRD. However, in contrast, Mishra et al. (2015) observed that there was no statistically significant difference in extreme precipitation between urban and non-urban locations based on a global analysis over a 40-year (1973–2012) period. An analysis of 25 years of meteorological data indicated that summer rainfall had decreased in the northeastern part of Beijing, China, and is correlated to urbanisation of the area (Zhang et al., 2009).

As a preliminary exploration of such urbanisation bias, the above spatial interpolations were repeated for all stations minus four stations located in the extensive urbanised areas of Bangkok (455201, 455203, 455301, 455601) and Chonburi (459201). Findings indicate that exclusion of the five urban TMD stations does not substantially alter the patterns of projected rainfall of any of the presented interpolated indices across the BMR compared to those with all 16 TMD stations, except more noticeably the 1-day maximum metric which projects more extensive heavier rain (30–40% increase) when all urban stations are included (Fig. 10h) compared to a 20–30% increase when urban stations were excluded (Supplementary figure).

### 3.6. Future research

This study provides further evidence of future projected increases in extreme precipitation across the BMR and the potential of increased flood risk. To strengthen findings it is recommended that future work focus on applying other regional climate model data, including existing downscaled CMIP5 data sets from the NASA Earth Exchange Global Daily Downscaled Projections. Selection of optimal CMIP5 models for the Southeast Asia region can be informed by McSweeney et al. (2015) and Hernaman et al. (2017). Additionally, future research could examine outputs from the Southeast Asia CORDEX initiative (as mentioned above). Hernaman et al. (2017) advocate selecting a subset of models for climate impact studies and adopting an adaptive management approach to using available evidence for informing practice. From an engineering perspective, the temporal resolution of meteorological data used in the current study are inadequate for guiding design of water infrastructure, but this could otherwise be supported if sub-daily frequency data are available for generating Intensity–Duration–Frequency

(IDF) curves: such an approach was presented by Shrestha et al. (2017) who analysed data from a single urban meteorological station in Bangkok and nine GCMs which predicted future increased precipitation intensities.

## 4. Conclusions

This study generates plausible future precipitation scenarios for the Bangkok Metropolitan Region and builds on the existing evidence base that projects increasing future precipitation over the BMR. Annual extreme indices project increasing total annual precipitation, with an increasing volume and number of days experiencing heavy/very heavy rainfall. Monthly extreme metrics project future increases in total monthly precipitation over the late southwest monsoon and also of heavy/very heavy intensity. Five-day cumulative and one-day maxima are also projected to increase in the late monsoon. These projected increases occur during a critical time of the year in Bangkok, when heavy rains, river run-off and high-tide coincide, and indicates greater potential risk for future flooding. Spatial interpolations of selected extreme indices show that the northern region of the BMR is projected to receive higher amounts of precipitation in the future. In particular, over the long-term, heavy/very heavy rainfall during October is projected to increase by 100–120% over Pathum Thani Province and 80–100% over the remainder of the BMR. While this study provides a plausible descriptive narrative of future extreme precipitation projections, it could be further expanded to other climate variables and strengthened by evaluating other sources of regional climate model data.

The methodology applied offers an open and practicable approach to deriving future projections of extreme climate variables at city-scale. Within the context of rapidly developing fields of regional climate modelling and climate impact assessment, this research has attempted to knit together contemporary approaches to bias correction and visualisation of extreme indices to present a credible profile of future precipitation extremes that can be applied at city-scale. Bias correction techniques, as developed in previous published research, and extreme indices based on the work of ETCCDI, were used to build a picture of how precipitation patterns could develop to the end of the 21st century in the Bangkok Metropolitan Region. The bias correction plots, graphs of extreme indices, and maps of selected spatially interpolation indices should provide valuable information to urban planners and other practitioners interested in addressing future city resilience.

This study demonstrates the value of bias correction as a practicable approach to enabling the application of regional climate model data to local-scale impact studies. Presented QQ plots indicate substantial bias in the SEACAM RCM data, and bias correction offers an important technique, if not ideal, for adjusting RCM data for projecting plausible future climate variables. The QQ plots enable optimal 'scenario-bias correction technique' pairs to be identified, and plots of extreme indices enable further selection of the scenario(s) that best reproduce past observations and thereby provide greater confidence in determining possible future precipitation projections.

## Declarations

### Author contribution statement

Richard T. Cooper: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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## Competing interest statement

The authors declare no conflict of interest.

## Additional information

Please refer to the separate PDF file – MMC 2 – for details on scripts generated during the research.

Data is accessible by contacting SEACAM project partners and the Thai Meteorological Department. SEACAM regional climate model data was supplied thanks to Mr. Suppakorn Chinvanho from SEA START RC (<http://start.or.th>). The Thai Meteorological Department, Bangkok (<http://tmd.go.th/>) supplied in situ precipitation data.

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## References

- ADB, 2009. The Economics of Climate Change in Southeast Asia: A Regional Review. Asian Development Bank. <http://www.adb.org/publications/economics-climate-change-southeast-asia-regional-review>.
- ADB, 2015. Asia's Booming Cities Most At Risk from Climate Change. Asian Development Bank. <https://www.adb.org/news/features/asias-booming-cities-most-risk-climate-change>.
- Alexander, L.V., Zhang, X., Peterson, T.C., Caesar, J., Gleason, B., Klein Tank, A.M.G., Haylock, M., et al., 2006. Global observed changes in daily climate extremes of temperature and precipitation. *J. Geophys. Res.* 111 (D5), D05109.
- Argüeso, D., Evans, J.P., Fita, L., 2013. Precipitation bias correction of very high resolution regional climate models. *Hydrol. Earth Syst. Sci.* 17 (11), 4379–4388.
- Baimoung, Somchai, Oki, Taikan, Archevarahuprok, Boonlert, Yuttaphan, Aphantree, Pangpoom, Manoon, 2014. Bias correction techniques for meteorological data of A2 scenario climate model output in Chao Phraya River Basin of Thailand. *Hydrol. Res. Lett.* 8 (1), 71–76.
- Bennett, James C., Grose, Michael R., Corney, Stuart P., White, Christopher J., Holz, Gregory K., Katzfey, Jack J., Post, David A., Bindoff, Nathaniel L., 2014. Performance of an empirical bias-correction of a high-resolution climate dataset. *Int. J. Climatol.* 34 (7), 2189–2204.
- Boé, J., Terray, L., Habets, F., Martin, E., 2007. Statistical and dynamical downscaling of the Seine basin climate for hydro-meteorological studies. *Int. J. Climatol.* 27 (12), 1643–1655.
- Chen, Cui, Haerter, Jan O., Hagemann, Stefan, Piani, Claudio, 2011. On the contribution of statistical bias correction to the uncertainty in the projected hydrological cycle. *Geophys. Res. Lett.* 38 (20).
- Chen, Feng-Wen, Liu, Chen-Wu, 2012. Estimation of the spatial rainfall distribution using Inverse Distance Weighting (IDW) in the middle of Taiwan. *Paddy Water Environ.* 10.
- Chen, Jie, Brissette, François P., Chaumont, Diane, Braun, Marco, 2013. Finding appropriate bias correction methods in downscaling precipitation for hydrologic impact studies over North America. *Water Resour. Res.* 49 (7), 4187–4205.
- Chinvanho, Suppakorn, 2009. Future climate projection for Thailand and surrounding countries: climate change scenario of 21st century. In: The First China-Thailand Joint Seminar on Climate Change. 23–24 March, 2009, Bangkok, Thailand. 1–7 pp. [http://startcc.iwlearn.org/doc/Doc\\_eng\\_12.pdf](http://startcc.iwlearn.org/doc/Doc_eng_12.pdf).
- Collins, M., Knutti, R., Arblaster, J., Dufresne, J.-L., Fichet, T., Friedlingstein, P., Gao, X., et al., 2013. Long-term climate change: projections, commitments and irreversibility. In: Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M. (Eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- Cooper, Richard T., 2014. Open data flood mapping of Chao Phraya River Basin and Bangkok Metropolitan region. *Br. J. Environ. Clim. Change* 4 (2), 186–216.
- Dosio, A., Paruolo, P., 2011. Bias correction of the ENSEMBLES high-resolution climate change projections for use by impact models: evaluation on the present climate. *J. Geophys. Res.* 116, D16106.
- Ehret, U., Zehe, E., Wulfmeyer, V., Warrach-Sagi, K., Liebert, J., 2012. HESS opinions 'Should we apply bias correction to global and regional climate model data?'. *Hydrol. Earth Syst. Sci.* 16 (9), 3391–3404.
- Foley, A.M., 2010. Uncertainty in regional climate modelling: a review. *Prog. Phys. Geogr.* 34 (5), 647–670.
- Fuchs, Roland, Conran, Mary, Louis, Elizabeth, 2011. Climate change and Asia's coastal urban cities: can they meet the challenge? *Environ. Urban. Asia* 2 (1), 13–28.
- Glott, Michael, Elliott, Joshua, McInerney, David, Best, Neil, Foster, Ian, Moyer, Elisabeth J., 2014. Evaluating the utility of dynamical downscaling in agricultural impacts projections. *Proc. Natl. Acad. Sci.* 111 (24), 8776–8781.
- Grillakis, Manolis G., Koutroulis, Aristeidis G., Daliakopoulos, Ioannis N., Tsanis, Ioannis K., 2017. A method to preserve trends in quantile mapping bias correction of climate modeled temperature. *Earth Syst. Dyn.* 8 (3), 889–900.
- Gu, Huanghe, Yu, Zhongbo, Wang, Guiling, Wang, Jigan, Ju, Qin, Yang, Chuanguo, Fan, Chuanhao, 2015. Impact of climate change on hydrological extremes in the Yangtze River Basin, China. *Stoch. Environ. Res. Risk Assess.* 29 (3), 693–707.
- Gudmundsson, L., Bremnes, J.B., Haugen, J.E., Engen-Skaugen, T., 2012. Technical note: downscaling RCM precipitation to the station scale using statistical transformations – a comparison of methods. *Hydrol. Earth Syst. Sci.* 16 (9), 3383–3390.
- Gudmundsson, Lukas, 2016. Package 'Qmap': statistical transformations for post-processing climate model output. The comprehensive R archive network. <https://cran.r-project.org/web/packages/qmap/qmap.pdf>.
- Halmstad, Andrew, Reza Najafi, Mohammad, Moradkhani, Hamid, 2013. Analysis of precipitation extremes with the assessment of regional climate models over the Willamette River Basin, USA. *Hydrol. Process.* 27 (18), 2579–2590.
- Hatchett, Benjamin J., Koračin, Darko, Mejía, John F., Boyle, Douglas P., 2016. Assimilating urban heat island effects into climate projections. *J. Arid Environ.* 128, 59–64.
- Hempel, S., Frieler, K., Warszawski, L., Schewe, J., Piontek, F., 2013. A trend-preserving bias correction – the ISI-MIP approach. *Earth Syst. Dyn.* 4 (2), 219–236.
- Hernaman, V., Grose, M., Clarke, J.M., 2017. Evaluating the Performance of the Latest Climate Models over Southeast Asia. A report for the Asian Development Bank, Australia: CSIRO.
- Hijioka, Y., Lin, E., Pereira, J.J., Corlett, R.T., Cui, X., Insarov, G.E., Lasco, R.D., Lindgren, E., Surjan, A., 2014. Asia. In: Barros, V.R., Field, C.B., Dokken, D.J., Mastrandrea, M.D., Mach, K.J., Bilir, T.E., Chatterjee, M., et al. (Eds.), *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1327–1370. [http://www.ipcc.ch/pdf/assessment-report/ar5/wg2/WGIIAR5-Chap24\\_FINAL.pdf](http://www.ipcc.ch/pdf/assessment-report/ar5/wg2/WGIIAR5-Chap24_FINAL.pdf).
- IPCC, 2014. In: Pachauri, R.K., Meyer, L.A. (Eds.), *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team]*. IPCC, Geneva, Switzerland. <http://www.ipcc.ch/report/ar5/syr/>.
- Jones, R.G., Noguera, M., Hassall, D.C., Hudson, D., Wilson, S.S., Jenkins, G.J., Mitchell, J.F.B., 2004. Generating High Resolution Climate Change Scenarios Using PRECIS. Met Office Hadley Centre, Exeter, UK. [http://www.metoffice.gov.uk/media/pdf/6/5/PRECIS\\_Handbook.pdf](http://www.metoffice.gov.uk/media/pdf/6/5/PRECIS_Handbook.pdf).
- Keblouti, Mehdi, Ouerdachi, Lahbassi, Boutaghane, Hamouda, 2012. Spatial interpolation of annual precipitation in Annaba-Algeria - comparison and evaluation of methods. *Energy Proc.* 18, 468–475. *Terragreen 2012: Clean Energy Solutions for Sustainable Environment (Cesse)*.
- Kishtawal, C.M., Niyogi, Dev, Tewari, Mukul, Pielke, Roger A., Shepherd, J. Marshall, 2010. Urbanization signature in the observed heavy rainfall climatology over India. *Int. J. Climatol.* 30 (13), 1908–1916.
- Klein Tank, A.M.G., Peterson, T.C., Quadri, D.A., Dorji, S., Zou, X., Tang, H., Santhosh, K., et al., 2006. Changes in daily temperature and precipitation extremes in Central and South Asia. *J. Geophys. Res.* 111 (D16), D16105.
- Klein Tank, A.M.G., Zwiers, F.W., Zhang, Xuebin, 2009. Guidelines on analysis of extremes in a changing climate in support of informed decisions for adaptation. In: *Climate Data and Monitoring WCDMP-No. 72*. [http://www.wmo.int/pages/prog/wcp/wcdmp/CA\\_3.php](http://www.wmo.int/pages/prog/wcp/wcdmp/CA_3.php).
- Krzywinski, Martin, Altman, Naomi, 2014. Points of significance: visualizing samples with box plots. *Nat. Methods* 11 (2), 119–120.
- Lacombe, Guillaume, Thai Hoanh, Chu, Smakhtin, Vladimir, 2012. Multi-year variability or unidirectional trends? Mapping long-term precipitation and temperature changes in continental Southeast Asia using PRECIS regional climate model. *Clim. Change* 113 (2), 285–299.
- Lafon, Thomas, Dadson, Simon, Buys, Gwen, Prudhomme, Christel, 2013. Bias correction of daily precipitation simulated by a regional climate model: a comparison of methods. *Int. J. Climatol.* 33 (6), 1367–1381.
- Limsakul, Atsamon, Singhruck, Patama, 2016. Long-term trends and variability of total and extreme precipitation in Thailand. *Atmos. Res.* 169, 301–317.
- Loo, Yen Yi, Billa, Lawal, Singh, Ajit, 2015. Effect of climate change on seasonal monsoon in Asia and its impact on the variability of Monsoon rainfall in Southeast Asia. *Geosci. Front.* 6 (6), 817–823. Special issue: Geoinformation techniques in natural hazard modeling.
- Ly, Sarann, Charles, Catherine, Degré, Aurore, 2013. Different methods for spatial interpolation of rainfall data for operational hydrology and hydrological modeling at watershed scale: a review. *Biotechnol. Agron. Soc. Environ.* 17 (2), 392–406. <https://popups.uliege.be/443/1780-4507/index.php?id=10003>.
- Maraun, D., 2012. Nonstationarities of regional climate model biases in European seasonal mean temperature and precipitation sums. *Geophys. Res. Lett.* 39 (6), L06706.

- Maraun, D., Wetterhall, F., Ireson, A.M., Chandler, R.E., Kendon, E.J., Widmann, M., Brien, S., et al., 2010. Precipitation downscaling under climate change: recent developments to bridge the gap between dynamical models and the end user. *Rev. Geophys.* 48 (3), RG3003.
- Maraun, Douglas, 2016. Bias correcting climate change simulations - a critical review. *Curr. Clim. Change Rep.* 2 (4), 211–220.
- Maraun, Douglas, Widmann, Martin, 2018. Cross-validation of bias-corrected climate simulations is misleading. *Hydrol. Earth Syst. Sci.* 22 (9), 4867–4873.
- Maraun, Douglas, Shepherd, Theodore G., Widmann, Martin, Zappa, Giuseppe, Walton, Daniel, Gutiérrez, José M., Hagemann, Stefan, et al., 2017. Towards process-informed bias correction of climate change simulations. *Nat. Clim. Change* 7 (11), 764–773.
- McBean, Gordon, 2014. Building resilience. *International Innovation*. <http://www.internationalinnovation.com/building-resilience/>.
- McSweeney, C.F., Jones, R.G., Lee, R.W., Rowell, D.P., 2015. Selecting CMIP5 GCMs for downscaling over multiple regions. *Clim. Dyn.* 44 (11–12), 3237–3260.
- McSweeney, Carol F., Jones, Richard G., Ben Booth, B.B., 2012. Selecting ensemble members to provide regional climate change information. *J. Climate* 25 (20), 7100–7121.
- McSweeney, Carol, Jones, Richard, 2010. Selecting Members of the ‘QUMP’ Perturbed-Physics Ensemble for Use with PRECIS. Met Office Hadley Centre, UK. <http://www.metoffice.gov.uk/media/pdf/e/3/SelectingGCMsToDownscale.pdf>.
- Mishra, Vimal, Ganguly, Auroop R., Nijssen, Bart, Lettenmaier, Dennis P., 2015. Changes in observed climate extremes in global urban areas. *Environ. Res. Lett.* 10 (2), 024005.
- Nakićenović, N., Alcamo, J., Davis, G., de Vries, B., Fenhann, J., Gaffin, S., Gregory, K., et al., 2000. IPCC Special Report on Emissions Scenarios (SRES). Cambridge University Press, UK. <http://www.ipcc.ch/ipccreports/sres/emission/index.php?idp=0>.
- Ngo-Duc, Thanh, Tangang, Fredolin T., Santisiromboon, Jerasorn, Cruz, Faye, Trinh-Tuan, Long, Nguyen-Xuan, Thanh, Phan-Van, Tan, et al., 2016. Performance evaluation of RegCM4 in simulating extreme rainfall and temperature indices over the CORDEX-Southeast Asia region. *Int. J. Climatol.* 37 (3), 1131–1664.
- NSO, 2014. Meteorology statistics, Chapter 23. In: Statistical Yearbook Thailand 2014. National Statistical Office of Thailand, Ministry of Information and Communication Technology. [http://web.nso.go.th/en/pub/e\\_book/esyb57/#1/z](http://web.nso.go.th/en/pub/e_book/esyb57/#1/z).
- OECD, 2014. Cities and Climate Change, Policy Perspectives, National Governments Enabling Local Action. Organisation for Economic Cooperation and Development. <https://www.oecd.org/env/cc/Cities-and-climate-change-2014-Policy-Perspectives-Final-web.pdf>.
- Ozelkan, Emre, Bagis, Serdar, Ozelkan, Ertugun Cem, Ustundag, Burak Berk, Yucel, Meric, Ormeci, Cankut, 2015. Spatial interpolation of climatic variables using land surface temperature and modified inverse distance weighting. *Int. J. Remote Sens.* 36 (4), 1000–1025.
- PaiMazumder, Debasish, Done, James M., 2015. The roles of bias-correction and resolution in regional climate simulations of summer extremes. *Clim. Dyn.* 45 (5–6), 1565–1581.
- Piani, C., Haerter, J.O., Coppola, E., 2010. Statistical bias correction for daily precipitation in regional climate models over Europe. *Theor. Appl. Climatol.* 99 (1–2), 187–192.
- Plangoen, Pheerawat, Singh Babel, Mukand, Clemente, Roberto S., Shrestha, Sangam, Kumar Tripathi, Nitin, 2013. Simulating the impact of future land use and climate change on soil erosion and deposition in the Mae Nam Nan sub-catchment, Thailand. *Sustainability* 5 (8), 3244–3274.
- Rana, Arun, Foster, Kean, Bosshard, Thomas, Olsson, Jonas, Bengtsson, Lars, 2014. Impact of climate change on rainfall over Mumbai using distribution-based scaling of global climate model projections. *J. Hydrol. Reg. Stud.* 1, 107–128.
- Ratna, Satyaban B., Ratnam, J.V., Behera, S.K., Tangang, Fredolin T., Yamagata, T., 2017. Validation of the WRF regional climate model over the subregions of Southeast Asia: climatology and interannual variability. *Clim. Res.* 71 (3), 263–280.
- RID, 2014. Daily report on water situation in rainy season 2014. Water watch and monitoring system for Warning Center, Royal Irrigation Department, Thailand. <http://www.rid.go.th/eng/water/13june2014.pdf>.
- Rojas, R., Feyen, L., Dosio, A., Bavera, D., 2011. Improving pan-European hydrological simulation of extreme events through statistical bias correction of RCM-driven climate simulations. *Hydrol. Earth Syst. Sci.* 15 (8), 2599–2620.
- SantanderMetGroup, 2018. DownscaleR: an R package for bias correction and statistical downscaling. <https://github.com/SantanderMetGroup/downscaleR/wiki>.
- SEA START RC, 2010. Preparation of Climate Change Scenarios for Climate Change Impact Assessment in Thailand. Southeast Asia START Regional Center. [http://startcc.iwlearn.org/doc/Doc\\_eng\\_15.pdf](http://startcc.iwlearn.org/doc/Doc_eng_15.pdf).
- SEA START RC, 2018. Data Distribution System. Southeast Asia START Regional Center. <http://ccs.gms-eoc.org/climatechange/datadistribution/index.html>.
- SEACAM, 2014. A regional climate modelling experiment for Southeast Asia: using PRECIS regional climate model and selected CMIP3 global climate models. Southeast Asia Climate Analyses and Modeling Framework. <http://ccrs.weather.gov.sg/wp-content/uploads/2015/03/Regional-Climate-Modelling-Experiment-for-Southeast-Asia.pdf>.
- SEACLID, 2018. Southeast Asia Regional Climate Downscaling Project (SEACLID). <http://www.apn-gcr.org/resources/items/show/1886>.
- Seneviratne, S.I., Nicholls, N., Easterling, D., Goodess, C.M., Kanae, S., Kossin, J., Luo, Y., et al., 2012. Changes in climate extremes and their impacts on the natural physical environment. In: Field, C.B., Barros, V., Stocker, T.F., Qin, D., Dokken, D.J., Ebi, K.L., Mastrandrea, M.D., et al. (Eds.), *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC)*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 109–230.
- Shastri, Hiteshri, Paul, Supantha, Ghosh, Subimal, Karmakar, Subhankar, 2015. Impacts of urbanization on Indian summer monsoon rainfall extremes. *J. Geophys. Res., Atmos.* 120 (2), 2014JD022061.
- Shrestha, Ashish, Babel, Mukand, Weesakul, Sutat, Vojinovic, Zoran, 2017. Developing Intensity–Duration–Frequency (IDF) curves under climate change uncertainty: the case of Bangkok, Thailand. *Water* 9 (2), 145.
- Sillmann, J., Kharin, V.V., Zwiers, F.W., Zhang, X., Bronaugh, D., 2013. Climate extremes indices in the CMIP5 multimodel ensemble: Part 2. Future climate projections. *J. Geophys. Res., Atmos.* 118 (6), 2473–2493.
- Sippel, S., Otto, F.E.L., Forkel, M., Allen, M.R., Guillod, B.P., Heimann, M., Reichstein, M., Seneviratne, S.I., Thonicke, K., Mahecha, M.D., 2016. A novel bias correction methodology for climate impact simulations. *Earth Syst. Dyn.* 7 (1), 71–88.
- Stocker, T.F., Qin, D., Plattner, G.-K., Alexander, L.V., Allen, S.K., Bindoff, N.L., Bréon, F.-M., et al., 2013. Technical summary. In: Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M. (Eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 33–115. [www.climatechange2013.org](http://www.climatechange2013.org).
- Tangang, Fredolin, Supari, Supari, Xiang Chung, Jing, Cruz, Faye, Salimun, Ester, Tieh Ngai, Sheau, Juneng, Liew, et al., 2018. Future changes in annual precipitation extremes over Southeast Asia under global warming of 2°C. *APN Sci. Bull.* 8.
- Teng, J., Potter, N.J., Chiew, F.H.S., Zhang, L., Wang, B., Vaze, J., Evans, J.P., 2015. How does bias correction of regional climate model precipitation affect modelled runoff? *Hydrol. Earth Syst. Sci.* 19 (2), 711–728.
- Teutschbein, C., Seibert, J., 2013. Is bias correction of Regional Climate Model (RCM) simulations possible for non-stationary conditions? *Hydrol. Earth Syst. Sci.* 17 (12), 5061–5077.
- Teutschbein, Claudia, Seibert, Jan, 2012. Bias correction of regional climate model simulations for hydrological climate-change impact studies: review and evaluation of different methods. *J. Hydrol.* 456–457 (August), 12–29. <https://doi.org/10.1016/j.jhydrol.2012.05.052>.
- Thai Meteorological Department, 2015. The Climate of Thailand. Thai Meteorological Department [https://www.tmd.go.th/en/archive/thailand\\_climate.pdf](https://www.tmd.go.th/en/archive/thailand_climate.pdf).
- TMD, 2018. Daily rainfall. Weather monitoring and prediction system (in Thai). <http://www.metalarm.tmd.go.th/dailyrainfall>.
- Tryhorn, Lee, DeGaetano, Art, 2011. A comparison of techniques for downscaling extreme precipitation over the Northeastern United States. *Int. J. Climatol.* 31 (13), 1975–1989.
- UN, 2018. World urbanization prospects: the 2018 revision. <https://population.un.org/wup/Publications/Files/WUP2018-KeyFacts.pdf>.
- Wang, Xiaolan L., 2008. Penalized maximal F test for detecting undocumented mean shift without trend change. *J. Atmos. Ocean. Technol.* 25 (3), 368–384.
- Wang, Xiaolan L., Feng, Yang, 2013. RHtests\_dlyPrp UserManual. Climate Research Division, Atmospheric Science and Technology Directorate, Science and Technology Branch, Environment Canada, Toronto, Ontario, Canada. <http://etccdi.pacificclimate.org/software.shtml>.
- Wang, Xiaolan L., Chen, Hanfeng, Wu, Yuehua, Feng, Yang, Pu, Qiang, 2010. New techniques for the detection and adjustment of shifts in daily precipitation data series. *J. Appl. Meteorol. Climatol.* 49 (12), 2416–2436.
- Wang, Xiaolan L., Wen, Qiuzi H., Wu, Yuehua, 2007. Penalized maximal T test for detecting undocumented mean change in climate data series. *J. Appl. Meteorol. Climatol.* 46 (6), 916–931.
- Wang, Xuemei, Liao, Jingbiao, Zhang, Jian, Shen, Chong, Chen, Weihua, Xia, Beicheng, Wang, Tijian, 2013. A numeric study of regional climate change induced by urban expansion in the Pearl River Delta, China. *J. Appl. Meteorol. Climatol.* 53 (2), 346–362.
- Wetterhall, F., Pappenberger, F., He, Y., Freer, J., Cloke, H.L., 2012. Conditioning model output statistics of regional climate model precipitation on circulation patterns. *Non-linear Process. Geophys.* 19 (6), 623–633.
- Wickham, Hadley, 2018. Package ‘ggplot2’: create elegant data visualisations using the grammar of graphics. The Comprehensive R Archive Network <https://cran.r-project.org/web/packages/ggplot2/ggplot2.pdf>.
- WMO, 2008. Guide to Meteorological Instruments and Methods of Observation, WMO-No. 8. World Meteorological Organization. <https://www.weather.gov/media/epz/mesonet/CWOP-WMO8.pdf>.
- WMO, 2018. Guidelines on the Definition and Monitoring of Extreme Weather and Climate Events. Final Draft Produced by the WMO Commission for Climatology Task Team on the Definition of Extreme Weather and Climate Events. World Meteorological Organization. [http://www.wmo.int/pages/prog/wcp/ccl/documents/GUIDELINESONTHEDEFINITIONANDMONITORINGOFEXTREMEWEATHERANDCLIMATEEVENTS\\_09032018.pdf](http://www.wmo.int/pages/prog/wcp/ccl/documents/GUIDELINESONTHEDEFINITIONANDMONITORINGOFEXTREMEWEATHERANDCLIMATEEVENTS_09032018.pdf).
- World Bank, 2009. Climate Change Impact and Adaptation Study for Bangkok Metropolitan Region: Final Report. 50898. The World Bank. <https://openknowledge.worldbank.org/handle/10986/3113>.
- Wu, Chuanhao, Huang, Guoru, 2016. Projection of climate extremes in the Zhujiang River Basin using a regional climate model. *Int. J. Climatol.* 36 (3), 1184–1196.
- Wu, Chuanhao, Huang, Guoru, Yu, Haijun, Chen, Zhiqing, Ma, Jingguang, 2014. Spatial and temporal distributions of trends in climate extremes of the Feilaixia Catchment

- in the upstream area of the Beijiing River Basin, South China. *Int. J. Climatol.* 34 (11), 3161–3178.
- Xu, Kai, Wu, Chuanhao, Hu, Bill X., 2018. Projected changes of temperature extremes over nine major basins in China based on the CMIP5 multimodel ensembles. *Stoch. Environ. Res. Risk Assess.*
- Xu, Yuanchao, 2015. Hyfo: hydrology and climate forecasting R package for data analysis and visualization. <http://yuanchao-xu.github.io/hyfo/>.
- Xu, Yuanchao, 2017. Package ‘Hyfo’: hydrology and climate forecasting. The Comprehensive R Archive Network. <https://cran.r-project.org/web/packages/hyfo/hyfo.pdf>.
- Yang, Xihua, Xie, Xiaojin, Liu, De Li, Ji, Fei, Wang, Lin, 2015. Spatial interpolation of daily rainfall data for local climate impact assessment over Greater Sydney Region. *Advances in Meteorology* 2015, 563629.
- Zhang, Chao Lin, Chen, Fei, Guang Miao, Shi, Li Chun, Qing, Ao Xia, Xiang, Yi Xuan, Chun, 2009. Impacts of urban expansion and future green planting on summer precipitation in the Beijing Metropolitan Area. *J. Geophys. Res.* 114 (D2), D02116.
- Zhang, Han, Wu, Chuanhao, Chen, Wenjie, Huang, Guoru, 2019. Effect of urban expansion on summer rainfall in the Pearl River Delta, South China. *J. Hydrol.* 568, 747–757.
- Zhou, Botao, Han Wen, Qiuzi, Xu, Ying, Song, Lianchun, Zhang, Xuebin, 2014. Projected changes in temperature and precipitation extremes in China by the CMIP5 multimodel ensembles. *J. Climate* 27 (17), 6591–6611.