Assessment of Various Rainfall Bias Correction Techniques in Peninsular Malaysia

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Abstract. Climate impact assessment models can have outputs that are sensitive to biases on the local scale. Hence, bias correction methods are used to amend the distribution of the climate impact assessment model in order to match the local observations. A great deal of errors can be removed from the model after bias correction is applied. This study focuses on identifying the best bias correction method after applying it on the observed rainfall data over Peninsular Malaysia. The bias correction methods used in this study includes the quantile mapping method, the delta method and the quantile delta mapping method. The rainfall data of 15 rainfall stations were obtained from the Malaysian Meteorological Department, whereas the General Circulation Model data used follows the CNRM-CM5 model. The quantile mapping method is well-known for seasonal forecasting which has grown extensively due to its broad use in correcting climatological biases in studies projecting future climate change. The delta method uses observations as a basis and is a stable and robust method that produces future time series with dynamics similar to current conditions, but it does not take into account the potential future changes in climate dynamics. The quantile delta mapping method is a break from other typical quantile mapping methods whereby it is not constrained by stationary assumptions. The results show that the quantile mapping method is the best bias correction method among the three methods used in this study.

Keywords: Bias Correction · Quantile Mapping · Delta Method · Quantile Delta Mapping · General Circulation Model

1 Introduction

Global climate modelling (GCM) has had immense improvements in recent years, with having a higher spatial resolution and hence increasing the GCM's accuracy. In spite of that, there is still a lot of room for improvement when it comes to the procedure itself that illustrates the rainfall formation. Simulated rainfall outputs from GCM can evince large systematic biases relative to observational datasets [1, 2]. As GCM rainfall series are used as inputs to process models [3, 4] and gridded statistical downscaling models

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[5–7], various algorithms have been developed and further studied in order to correct and further minimize these biases.

Systematic biases in climate model outputs can arise from different factors [8]. For example, Eden [9] classify errors in GCM rainfall fields as being due to 1) unrealistic large-scale variability 2) unpredictable internal variability that differs from observations 3) errors in convective parameterizations and unresolved sub grid-scale orography.

While not without controversy [10, 11], bias correction is a common component of climate change impacts studies [8]. The underlying idea is the identification of possible biases between observed and GCM-simulated variables, which form the basis for correcting both current and future GCM simulations [12]. Corrections can be made to the modelled mean, variance, and also higher moments of a distribution, with many methods now applying bias corrections to all quantiles [13]. One of the most popular bias correction methods used is the quantile mapping (QM) method which have been reviewed in the context of hydrological impacts studies and have been found to outperform simpler bias correction methods that correct only the mean or mean and variance of rainfall series [13–15].

Quantile mapping method is known for seasonal forecasting which has since grown extensively due to its broad use in correcting climatological biases in studies projecting future climate change [5, 16–21]. Among all the quantile mapping algorithms, it was found that those that rely on nonparametric estimates of quantiles tend to outperform those that fit a parametric distribution to data [13]. Quantile mapping (QM) [22–25] also known as distribution mapping adjusts the cumulative distribution of estimated data to the cumulative distribution of rain gauge data using a transfer function. This correction can capture the evolution of the mean and the variability of precipitation while matching all statistical moments [26]. The quantile mapping (QM) method corrects the distribution in rainfall data and thus, attempts to correct the mean, variance, and probability in wet-day [27].

The delta change approach uses observations as a basis and is a stable and robust method that produces future time series with dynamics similar to current conditions [14]. But this also implies that it does not take into account the potential future changes in climate dynamics (e.g., the number of dry vs. wet days does not change) [28]. Another shortcoming is the fact that major events (e.g., heavy rainfall or hot days) will change by the same amount as all other events (e.g. drizzle or cold days) [14]. The delta change method is also called the delta method [29].

Cannon [8] modified the QM method and outlined an approach called the quantile delta mapping (QDM) method. QDM is a break from other typical QM methods whereby it is not constrained by stationary assumptions [30]. In the traditional QM method, a raw modelled value is always corrected by the same value of bias or error that is determined by its respective quantile in the calibration period [30]. On the other hand, QDM multiplies observed values by the ratio of the modelled values (period of interest divided by calibration period) at the same quantiles [30].

Each of the correction techniques has its own characteristics and advantages. Fowler [31] reviewed various bias-correction approaches and concluded that the probabilistic methods seem to be more robust. Gudmundsson [13] analyzed 11 bias-correction methodologies (including distribution-derived transformation, parametric transformation and nonparametric transformation) and found that the two nonparametric-transformation methodologies tested (empirical quantiles and smoothing splines) performed better in reducing the GCM biases for rainfall simulation in Norway [29].

The main objective of this study is to assess different bias correction methods for bias-correcting daily rainfall over Peninsular Malaysia. There are 3 bias correction methods used in this study. Specifically, the nonparametric quantile mapping method, the delta method and the quantile delta method. These 3 bias correction methods were chosen for this study as there have been many researchers who have used these 3 methods in their studies [30, 32–40].

2 Study Area and Data

Peninsular Malaysia is situated in the tropics with Thailand situated in the north and Singapore in the south [41]. Peninsular Malaysia has a latitude of 1.20° north to 6.40° north, and a longitude of 99.35° east to 104.20° east, covering an area of 130,598 km^2 [41]. It is hot and humid and easily influenced by the monsoon winds. The annual rainfall in peninsular Malaysia is about 1933–3080 mm with 150–200 wet days per year [42]. The wet season occurs during the northeast monsoon (November to February, NDJF) while the dry season prevails during the southwest monsoon (May to August, MJJA). In between these two pronounced seasons are the inter-monsoon periods of March and April (MA) and September and October (SO) [43]. The annual rainfall cycles of stations on the west coast of Peninsular Malaysia have two maxima during two inter-monsoon periods that coincide with inter-monsoon periods [44].

The observed daily rainfall data of 15 rainfall stations was obtained from Malaysian Meteorological Department (MMD) for the period of 1985–2005 whereas the General Circulation Model (GCM) data used follows the CNRM-CM5 model. The latitude-longitude coordinates and elevations of the 15 stations are provided in Table 1. The future data used in the study is from the year 2006–2050. In this study, we choose the RCP 4.5 scenario for the GCM data. According to the IPCC, RCP 4.5 assumes that carbon dioxide emissions start declining by approximately 2045 to reach roughly half of the levels of 2050 by 2100.

3 Methodology

3.1 Delta Method

It is assumed that the target model output to adjust is the future-projected model value, denoted as $x_{m,fut}$ with the observed data denoted as y_{obs} [45]. The bias correction procedure is that it transforms (or maps) the target model value $x_{m,fut}$ onto the observation domain using the relationship with the observations and the model value for the base period is denoted as $x_{m,base}$ [45]. The final bias-corrected future model output is denoted as $\hat{y}_{m,fut}$. . Firstly, the future rainfall model value ($x_{m,fut}$) is standardized as

$$z_{m,fut} = \frac{x_{m,fut} - \mu_{m,fut}}{\sigma_{m,fut}} \tag{1}$$

Table 1. The table below shows the latitude-longitude coordinates and elevations of the 15 stations used in this study.

Station Name	Station Number	Latitude	Longitude	Elevation (m)
Alor Setar	48603	6° 12′N	100° 24′E	3.9
Batu Embun	48642	3° 58′N	102° 21′E	59.5
Bayan Lepas	48601	5° 18′N	100° 16′E	2.8
Cameron Highlands	48632	4° 28′N	101° 22′E	1545
Chuping	48604	6° 29′N	100° 16′E	21.7
Ipoh	48625	4° 34′N	101° 06′E	40.1
Kluang	48672	2° 01′N	103° 19′E	88.1
Kota Bharu	48615	6° 10′N	102° 17′E	4.6
Kuala Terengganu	48618	5° 23′N	103° 06′E	5.2
Kuantan	48657	3° 47′N	103° 13′E	15.3
Melaka	48665	2° 16′N	102° 15′E	8.5
Senai	48679	1° 38′N	103° 40′E	37.8
Sitiawan	48620	4° 13′N	100° 42′E	7
Subang	48647	3° 07′N	101° 33′E	16.5
Temerloh	48653	3° 28′N	102° 23′E	39.1

where $\mu_{m,fut}$ and $\sigma_{m,fut}$ are the mean and standard deviation of the future model values respectively [45]. Then, the adjusted mean and standard deviation are applied.

$$\hat{y}_{m,fut} = z_{m,fut}\tilde{\sigma}_{m,fut} + \tilde{\mu}_{m,fut} \tag{2}$$

where

$$\tilde{\sigma}_{\mathrm{m,fut}} = \frac{\sigma_{\mathrm{obs}}}{\sigma_{\mathrm{m,base}}}\sigma_{\mathrm{m,fut}} \tag{3}$$

and

$$\tilde{\mu}_{\mathrm{m,fut}} = \frac{\mu_{\mathrm{obs}}}{\mu_{\mathrm{m,base}}}\mu_{\mathrm{m,fut}} \tag{4}$$

The monthly or seasonal mean and standard deviation are applied to each month or season in consideration of the seasonal cycles of rainfall and temperature [45]. In other words,

$$\hat{y}^{\mathrm{j}}_{\mathrm{m,fut}} = z^{\mathrm{j}}_{\mathrm{m,fut}}\tilde{\sigma}^{\mathrm{j}}_{\mathrm{m,fut}} + \tilde{\mu}^{\mathrm{j}}_{\mathrm{m,fut}} \tag{5}$$

where j denotes a season or month. For example, if the daily rainfall for month j is the target model output, then the mean and standard deviation of daily rainfall are estimated only with the dataset for the j th month [45].

3.2 Quantile Mapping Method

QM allows the probability distribution of the model outputs from GCMs and RCMs (x) to be adjusted to the probability distribution of the observed data (y) by matching the cumulative distribution function (CDF, $F(x; \theta)$ where θ represents the parameter set) values of the two distributions [45]. Through the QM method, the CDF of the GCM output data is transferred to the observed data [45]. The traditional QM method can be defined as

$$\hat{y} = F_o^{-1}(F_{m,base}(x)) \tag{6}$$

where F_o^{-1} represents an inverse function of CDF for the observed data and $F_{m,base}$ is the CDF of the model output from GCM that is fitted to the GCM outputs for the base period [45]. The nonparametric QM can be done by employing formula (7) without any of the assumptions that a parametric distribution has for the observations or for the model data [45]. The general quantile mapping method assumes that only nonzero rainfall values are taken from the daily rainfall data.

$$\hat{F}\left(x_{(i)}\right) = \frac{i}{N+1} \tag{7}$$

where $x_{(i)}$ is the i th increasing-ordered value, and N is the number of data [44].

3.3 Quantile Delta Mapping

Cannon [8] suggested the quantile delta mapping (QDM) method to preserve the relative changes of the model projections. According to Lee [45], for the model projected future series ($x_{m,fut}$), the empirical CDF (ECDF) around the projected period is estimated as

$$\tau_{m,fut} = F_{m,fut}(x_{m,fut}) \tag{8}$$

The relative change in quantiles between the base period and the future projection period [45] is given by

$$\Delta_{m,fut} = \frac{F_{m,fut}^{-1}(x_{m,fut})}{F_{m,base}^{-1}(\tau_{m,fut})} = \frac{x_{m,fut}}{F_{m,base}^{-1}(\tau_{m,fut})} \tag{9}$$

The modeled $\tau_{m,fut}$ quantile can be bias-corrected by applying the inverse ECDF of the observations [45] as

$$\hat{y}_{o,fut} = F_o^{-1}(\tau_{m,fut}) \tag{10}$$

The target future model value can be estimated as follows

$$\hat{y}_{m,fut} = \Delta_{m,fut}\hat{y}_{o,fut} \tag{11}$$

4 Results and Discussion

Figure 1 presents the basic statistics of the monthly mean and standard deviation of the 15 rainfall stations for the year 1985 till the year 2005. The monthly mean rainfall is within a range of approximately 150 mm–250 mm. Station number 48657 has the highest monthly mean of 251 mm while station number 48604 has the lowest monthly mean of 149 mm. The standard deviation of station number 48615 is the highest amounting to 244 mm while station number 48620 has the lowest standard deviation of 86 mm. Figure 2 shows the number of wet days for each station for the year 1985 till the year 2005 for a total of 7670 days. Station number 48632 has the highest number of wet days of 4872 days while station number 48615 has the lowest number of wet days amounting to a total of 3451 days.

Figure 3 shows the results of applying the 3 bias correction methods on the total rainfall amount for each station from the year 1985 to the year 2005. Table 2 shows the total observed rainfall amount before bias correcting it with the total observed rainfall amount after applying each of the 3 bias correction methods. The results for the total amount of rainfall after applying the 3 bias correction methods showed an increase for all

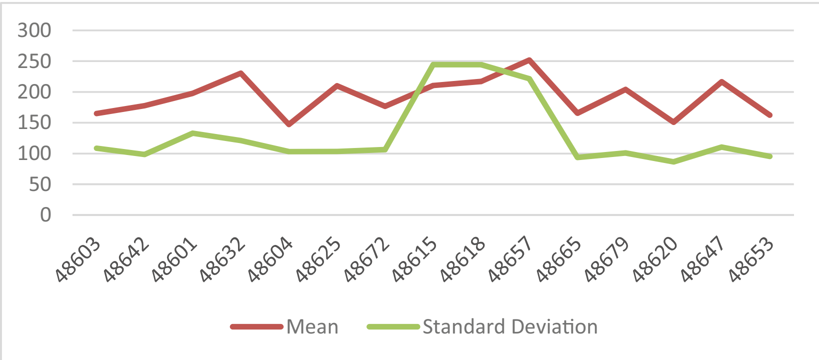


Fig. 1. The figure above shows the monthly mean and standard deviation of the 15 stations.

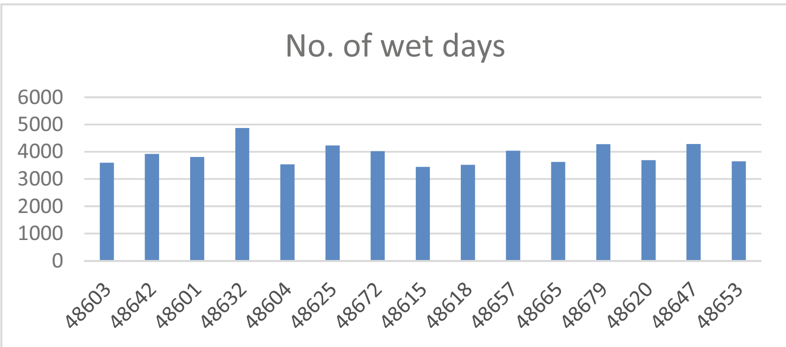
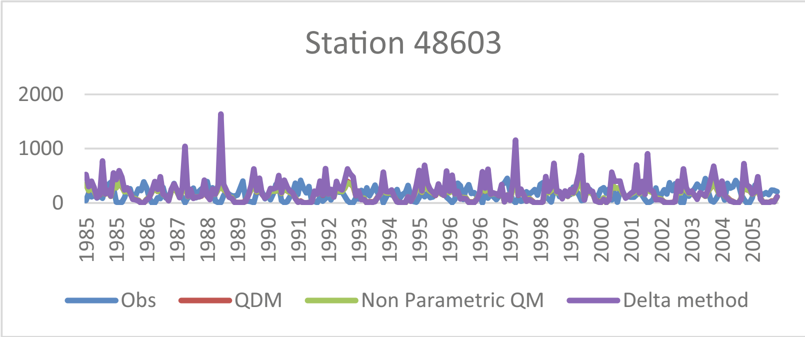
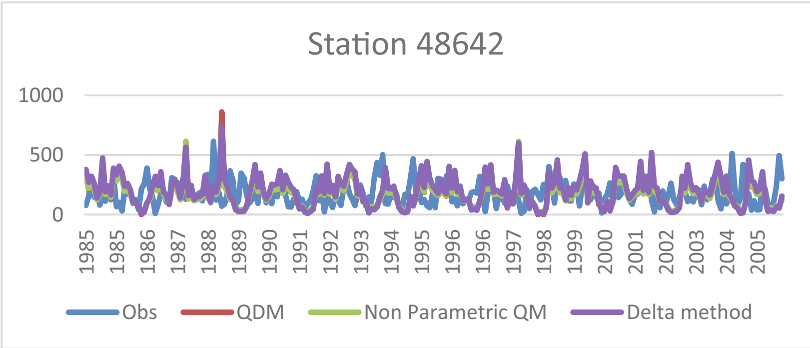


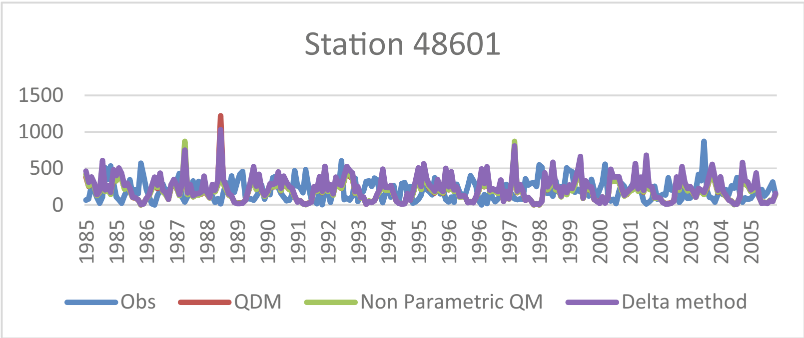
Fig. 2. The figure above shows the number of wet days for each of the 15 stations.



(a)

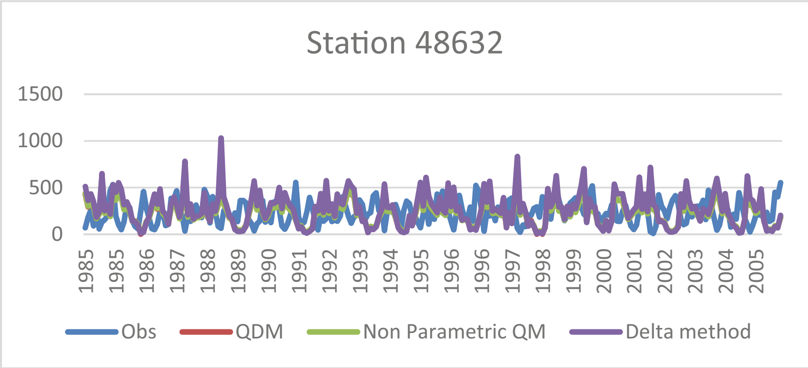


(b)



(c)

Fig. 3. The graphs above (a)–(o) show the results for each method from the year 1985–2005.



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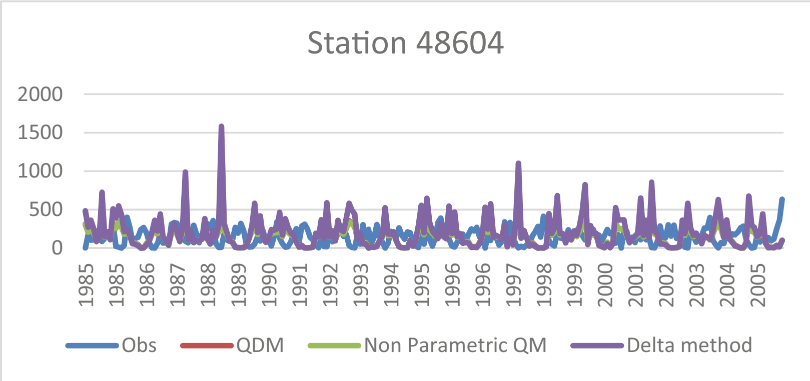

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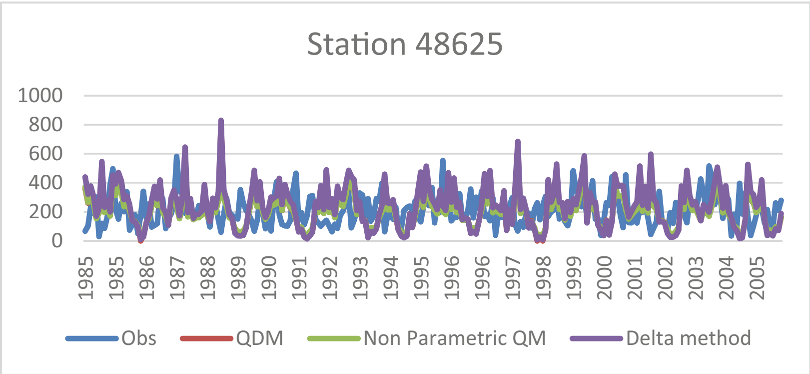
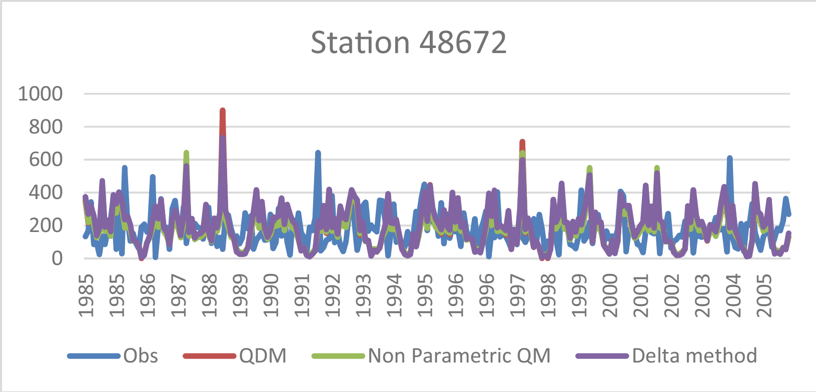
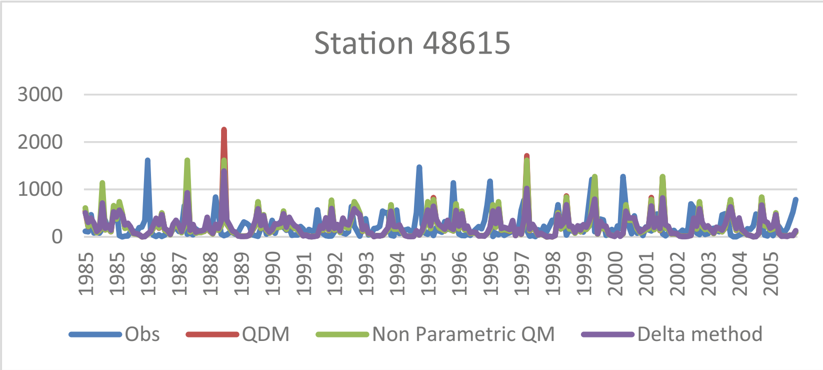


(f)

Fig. 3. (*continued*)



(g)



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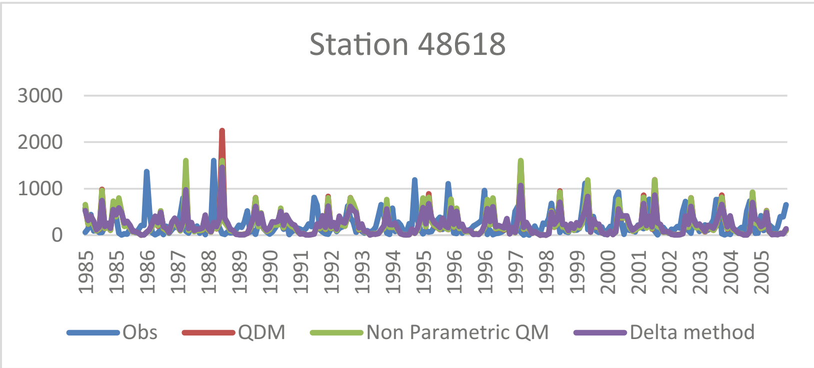
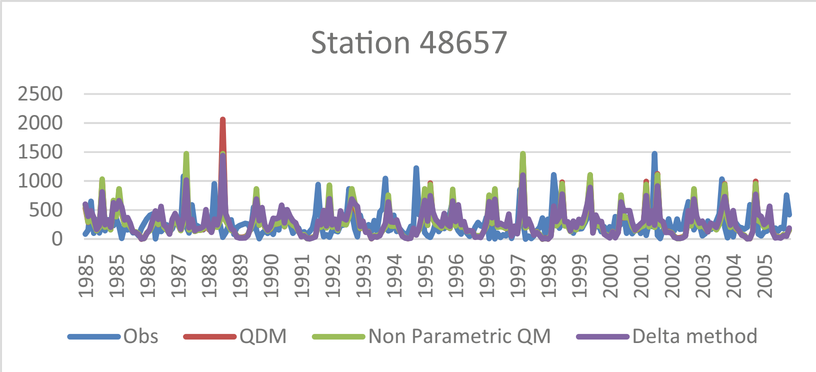
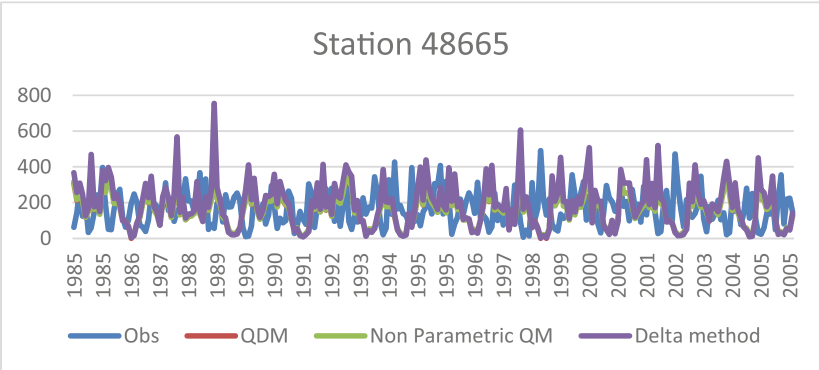


(i)

Fig. 3. (*continued*)



(j)



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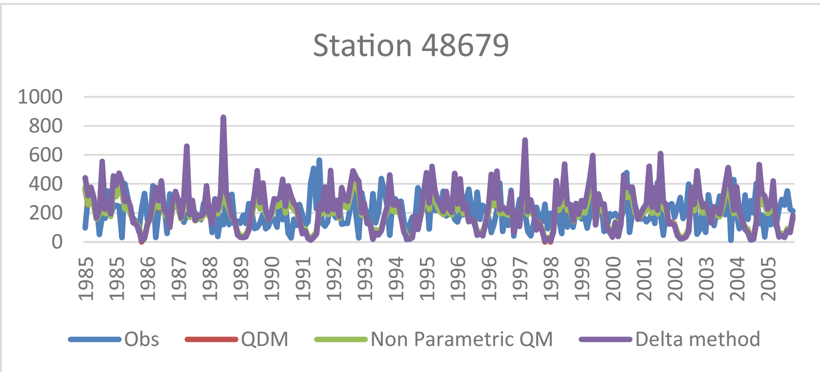
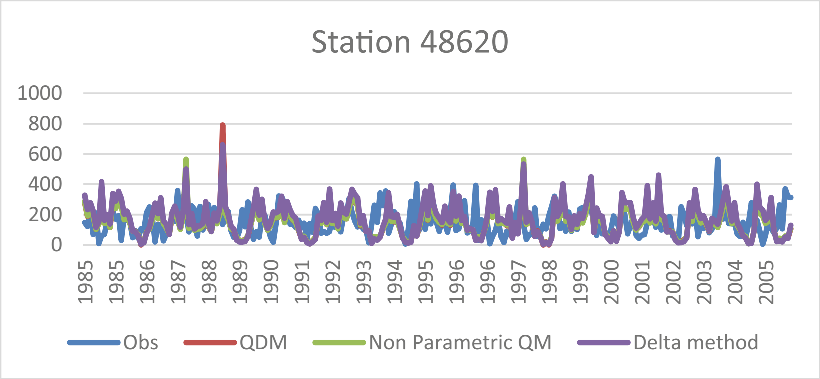
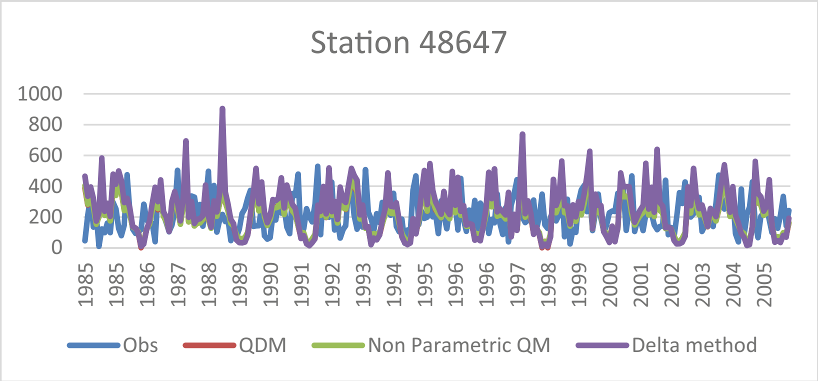


(l)

Fig. 3. (*continued*)



(m)



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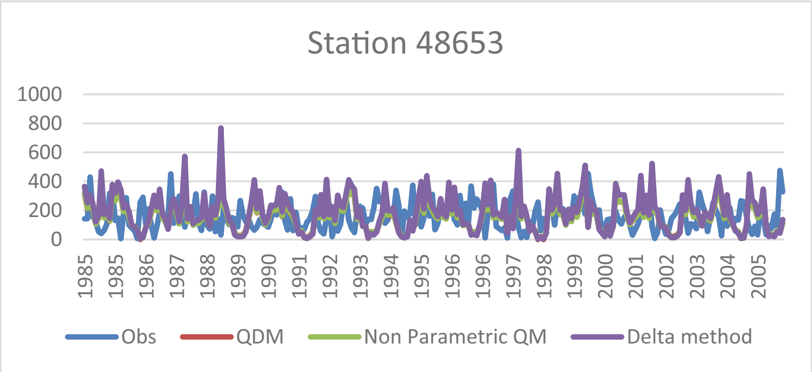

(o)

Fig. 3. (*continued*)

the stations. The total observed rainfall for all the stations is around 37000–63500 mm while the bias-corrected rainfall data using the QM method, the delta method and the QDM method ranges between 38000–67300 mm, 43700–73000 mm and 38300–65640 mm respectively.

Under the QM method, the total rainfall amount after applying the bias correction method has the smallest difference for all the stations whilst comparing it to the total observed rainfall amount before any bias correction method was applied. Station 48657 has the greatest increase of 5.99% of total rainfall amount while station 48679 has the lowest increase of 0.58% under the QM method. The QDM method is able to closely match the total observed rainfall amount (second column of Table 2) for some of the stations only, specifically station 48601, 48615, 48618 and 48657. Station 48618 has the greatest increase of 4.57% while station 48625 has the lowest increase of 0.97% of total rainfall amount under the QDM method. However, the delta method overestimates for all the stations. Under the delta method, station 48604 has the largest increase of 38.58% of total rainfall amount while station 48615 has the smallest increase of 7.8%. Hence, the QM method is the best bias correction method among the three bias correction methods used in this study.

Table 2. The table below shows the total observed rainfall amount before bias correction and the total observed rainfall amount after applying each of the 3 bias correction methods.

Station Number	Total Observed Rainfall (Before) (mm)	Quantile Mapping Method	Delta Method	Quantile Delta Mapping Method (QDM)
48603	41551.53	42148	56865.81	42847.8
48642	44771.2	45399.16	51412.82	45452.52
48601	49858.09	51414.82	58157.16	51122.49
48632	58075.82	58428.9	68151.46	59040.09
48604	37093.55	38038.77	51403.16	38298.09
48625	52924.72	53407.92	60981.82	53437.01
48672	44539.77	45181.15	50768.9	45407.56
48615	53023.34	55805.69	57157.26	55134.07
48618	54723.56	57971.32	59571.46	57226.79
48657	63484.9	67292.04	73085.82	65635.53
48665	41718.99	42301.79	48259.05	42516.81
48679	51441.17	51738.13	60060.87	52192.07
48620	38010.25	38666.25	43765.08	38746.67
48647	54564.32	55146.7	63196.6	55257.47
48653	40900.63	41172.29	47475.31	41701.63

5 Conclusion

There are many bias correction methods available for correcting both current and future GCM simulations. The use of accurate climate data is an important aspect of decision-making in various sectors. In this study, we conclude that the quantile mapping method is the best correction method while comparing it with the delta method and the quantile delta mapping method. In this study, only one GCM model was used. Multiple GCM model should be studied considering that the abilities of different bias correction methods may alternate with different GCM models. As GCM models continue to progress, the research on different bias correction methods applied to correct them becomes more crucial in order to provide a clearer picture of the future climate conditions.

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