# Generation of multi-site stochastic daily rainfall with four weather generators: a case study of Gloucester catchment in Australia

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**Abstract**

Four weather generator models, i.e., **R**-package version of the **G**eneralised **Li**near **M**odel for daily **Clim**ate time series (RGLIMCLIM), Stochastic Climate Library (SCL), R-package multi-site precipitation generator (RGENERATRPREC), and R-package Multi-site Auto-regressive Weather GENerator (RMAWGEN), were used to generate multi-sites stochastic daily rainfall for a small catchment in Australia. The results show: 1) All four models produced reasonable results in terms of annual, monthly and daily rainfall occurrence and amount, as well as daily extreme, multi-day extremes and dry/wet spell length. However, they also simulated a large range of variability, which not only demonstrates the advantages of multiple weather generators rather than a single model, but also is more suitable for climate change and variability impact studies; 2) Every model has its own advantages and disadvantages due to their different theories and principals. This enhances the benefits of using multiple models; 3) The models can be further calibrated/improved to have a "better" performance in comparison with observations. However, it was chosen not to do so in this case study for two reasons: to obtain a full ranges of climate variability and to acknowledge the uncertainties associated with observation data, which are interpolated from limited stations and therefore have high pairwise correlations — ranging from 0.693 to 0.989 with a median and mean value of 0.873 and 0.877 for daily rainfall.

**Keywords**: Australia, RGENERATRPREC, RGLIMCLIM, RMAWGEN, SCL, Stochastic weather generator

## 1. INTRODUCTION

Stochastic weather generators are statistical models that can relatively easily simulate realistic or plausible random sequences of atmospheric variables such as temperature and rainfall (e.g., Wilks and Wilby 1999). The stochastic weather generators attempt to reproduce the spatial and temporal dynamics and correlation structures of the variables of interest (Ailliot et al 2015). These synthetic sequences provide a set of alternate realisations that can be used for risk and reliability assessment in the design and operation of agricultural, water resource and environmental systems (Mehrotra et al 2006).

Wilks and Wilby (1999) presents a review of the historical development of stochastic weather models, from simple analyses of runs of consecutive rainy and dry days at single sites, through to multisite models of daily precipitation. They also describe models that have been developed specifically for applications in agriculture, ecology, hydrology and simulations of regional climate change. There are literally thousands of papers on the development and applications of stochastic weather generators, and some of the recent key reviews of the relative merits of the different methods include blah blah blah blah blah.

The aim of this paper is to describe the application of four weather generators to simulate multi-site daily rainfall in a 4,000? $km^2$ region in south-eastern Australia. The ability of these models to simulate the different rainfall characteristics is presented and the relative merits of the models, as well as the advantages of using multiple models, are discussed.

The stochastic rainfall data is generated here to assess the cumulative impact of coal resource development in the context of climate variability and climate change. Hydrological modelling with the stochastic rainfall data will assess the influence of natural climate variability on the severity and timing of water resource and environmental impact from coal development, and the relative contribution and combined impact from coal resource development and climate change.

## 2. DATA AND METHODS

### 2.1 Study Catchment

The study region is the Gloucester catchment, located about 250 km north of Sydney (see Figure 1). The Gloucester subregion is part of the Northern Sydney Basin Bioregion, one of the Bioregional Assessment region where the cumulative impact of coal resource development is being assessed by the Australian Government (main reference to BA or BA method, and the Gloucester report). The region has a temperate climate and mean annual rainfall of about 1100 mm, dominated by summer rainfall.

The study region in about 4,000 $km^2$, and is modelled hydrologically as 156 $0.05^o$ grid cells. However, to reduce computational time and to realistically model the spatial rainfall correlations, stochastic daily rainfall is generated for 21 points (see Figure 1), which can then be interpolated to provide stochastic rainfall inputs at the 156 grid cells for hydrological modelling.

### 2.2 Rainfall Data

Daily rainfall data, from 1923 to 2013, from the Bureau of Meteorology (BoM) of Australia 0.05$^{o}$ gridded rainfall data product, is used in this study (http://www.csiro.au/awap/). The BoM gridded rainfall product is obtained by interpolating rainfall observed at gauging stations across Australia. The interpolation method uses a two-step process (Beesley et al 2009): interpolation of monthly rainfall climatology using a thin plate smoothed spline; and interpolation of anomalies of daily rainfall (expressed as a percentage of the climatological rainfall) using Barnes' successive correction method.

## 2.3 Weather Generator Models

### *2.3.1 RGLIMCLIM*

Rglimclim is a multivariate, multisite weather generator based on generalised linear models (GLMs). It is an update R-package version of the Glimclim (**G**eneralised **Li**near **M**odel for daily **Clim**ate time series) software package that has been widely used for univariate weather generation in the UK, Australia, China, South Africa and elsewhere (Chandler and Wheater 2002; Yang et al. 2005; Yan et al. 2006; Frost et al. 2011; Liu et al 2013; Ambrosino et al 2014), and has also been updated to allow for the simultaneous generation of multiple weather variables. Details on the theory can be found in the developers' papers (Chandler 2002: Chandler and Wheater 2002; Yang et al., 2005) and the user's manual (Chandler, 2015).

Briefly, precipitation in Rglimclim is modeled in two parts: occurrence and amount. The rainfall occurrence is modelled by using logistic regression and rainfall amounts using a gamma distribution with a common dispersion parameter. The logistic regression can be described as follows (Chandler 2002):

$$\ln \frac{pi}{1-pi} = x_i^{'}\beta \qquad (1)$$

where $pi$ is the rainfall probability for the $i$th case in the dataset conditional on a covariate vector $x_i$ with coefficient vector $\beta$. The rainfall amount for $i$th wet month has, conditional on a covariate vctor $\xi_i^{'}$ and coefficient vector $\gamma$, a gamma distribution with mean $\mu_i$, where

$$\ln(\mu_i) = \xi_i^{'}\gamma \qquad (2)$$

The shape parameter of the gamma distribution ($\nu$) is assumed constant for all observations. To describe the climatology of the region, other covariates representing spatial dependence, seasonal variation, interactions terms and persistence are also included in the occurrence and amount models in GLIMCLIM.

*2.3.2 SCL*

The Stochastic Climate Library (SCL) is a library of stochastic models for generating climate data. It has eight models for generating rainfall and climate data, i.e, single site rainfall at sub-daily, daily, monthly and annual timescales, single site climate (rainfall, evaporation and maximum temperature) at daily, monthly and annual timescales, and multi-sites daily rainfall (Srikanthan et al. 2007). The models in SCL have been tested using data from many sites across Australia.

A multi-site two-part model is used in SCL to generate daily rainfall at multi-sites. The model has two parts: rainfall occurrence and the rainfall amounts. A first-order two-state Markov chain is used to determine the occurrence of rainfall. For each site *k*, the Markov chain has the two transition probabilities: $p_{10}^{k}$, the conditional probability of a wet day given that the previous day was dry; $p_{11}^{k}$, the conditional probability of a wet day given that the previous day was wet. The unconditional probability of a wet day for the site *k*, can be derived as

$$\pi^k = \frac{p_{10}^k}{1+p_{10}^k - p_{11}^k} \qquad (3)$$

Given a network of *N* locations, there are *N(N - 1)/2* pair wise correlations that should be maintained in the generated rainfall occurrences. This is achieved by using correlated uniform random numbers $(u_t)$ in simulating the occurrence process. The uniform variates $u_t(k)$ can be derived from standard Gaussian variates $w_t(k)$ through the transformation. Details on the theory can be found in the SCL user's manual (Srikanthan et al. 2007).

### *2.3.3 RGENERATEPREC*

RGENERATEPREC is an R multi-site rainfall generator (Cordano 2014). It generates precipitation occurrence in several sites using logit regression (GLM as RGLIMCLIM) and DS Wilk's approach (Wilk 1998). The daily precipitation occurrence model used in RGENERATEPREC is the familiar chain-dependent process, comprised of a first-order, two-state Markov process governing daily precipitation occurrence, with serially independent precipitation amounts on wet days (Wilk 1998).

Nonzero precipitation amounts $r_t(k)$ are simulated here using the mixed exponential distribution, which has been widely used in the literature. This is a probability mixture of two one-parameter exponential distributions, with probability density function (Wilk 1998):

$$f[r(k)] = \frac{\alpha(k)}{\beta_1(k)} \exp\left[\frac{-r(k)}{\beta_1(k)}\right] + \frac{1-\alpha(k)}{\beta_2(k)} \exp\,[\frac{-r(k)}{\beta_2(k)}] \qquad (4)$$

$$\beta_1(k) \geq \beta_{2(k)} > 0, \qquad 0 < \alpha(k) \leq 1$$

Here *α(k)* is the mixing probability for location *k,* which determines the frequencies with which the exponential distribution with the larger ($\beta$1) or smaller ($\beta$2) mean will be used to generate the next value in the $r_t(k)$ series.

The basic idea to extend the single-station stochastic model to multiple locations is then to drive this collection of individual station models with *vectors* of uniform [0,1] variates **u**1, and **v**1 whose elements ($u_t(k)$ and $v_t(k)$, respectively) are correlated so that Corr$[u_t(k), u_t(\ell)] \neq 0$ and Corr$[v_t(k), v_t(\ell)] \neq 0$, but which are mutually and serially independent so that $Coxx[u_t(k), v_t(\ell)] = Coxx[u_t(k), u_{t+1}(\ell)] = Coxx[v_t(k), v_{t+1}(\ell)] = 0$. "Nonzero correlations among the elements of **u**1, and **v**1 result in interstation correlations between the resulting synthetic precipitation series, while the fact that the marginal distributions of the variates $u_t(k)$ and $v_t(k)$ are uniform and independent ensures that each local stochastic process behaves in the same way as if it alone were being simulated in the conventional way" (Wilk 1998).

*2.3.4 RMAWGEN*

R Multi-site Auto-regressive Weather GENerator (RMAWGEN) is built to generate daily temperature and precipitation time series in several sites by using the theory of vectorial autoregressive models (VAR). The VAR model is used because it is able to maintain the temporal and spatial correlations among the several series (Cordano and Eccel 2012).
A set of $K$ random variables can be described by a Vector Auto-Regressive Model (VAR($K$,$p$)) as follows (Cordano and Eccel 2012):

$$x_t = A_1 \cdot x_{t-1} + \cdots + A_p \cdot x_{t-p} + C \cdot d_t + u_t \qquad (5)$$

where $x_t$ is a $K$-dimensional vector representing the set of weather variables generated at day $t$ by the model, called "endogenous" variables, $A_i$ is a coefficient matrix K×K for $i = 1, \ldots, p$ and u$t$ is a $K$-dimensional stochastic process. $x_t$ and $u_t$ are usually normalized to have a null mean. $u_t$ is a Standard White Noise (Luetkepohl, 2007), i.e. a continuous random process with zero mean and $u_t$, $u_s$ independent for each t≠s, consequently it has a time-invariant non-singular covariance matrix. The VAR models work correctly if the variable $x_t$ is normally distributed, which requires a normalization procedure of the meteorological variables (Cordano and Eccel 2012).

The structure of the RMAWGEN consists in functions that transform precipitation and temperature time series into Gaussian-distributed random variables through deseasonalization and Principal Component Analysis (PCA). Then a VAR model is calibrated on transformed time series. The time series generated by VAR are then inversely re transformed into precipitation and/or temperature series (Cordano 2015).

How do you parameterise the models?

Then used to generate 100 stochastic replicates.

## 3. RESULTS AND DISCUSSION

### 3.1 Rainfall Occurrence

#### *3.1.1 Annual*

The box plots in Figure 2 show the range of the annual rainfall occurrence (number of days with rainfall above 1 mm/day) in the observations (1923–2013) at the 21 points, and the means from 100 stochastic replicates from the four weather generation models for the 21 points.

Both RGLIMCLIM and RGENERATEPREC produce a similar annual rainfall occurrence as observations, but the SCL results slightly underestimate the rainfall occurrence and the RMAWGEN slightly overestimate the rainfall occurrence. For example, the mean and median annual rainfall occurrence across the 21 grids are 0.339 and 0.335, respectively, from observations, and they are 0.341 and 0.337, and 0.339 and 0.334 from RGLIMCLIM and RGENERATEPREC respectively. However, they are 0.326 and 0.321 from SCL, about 4% underestimation, and 0.367 and 0.332 from RMAWGEN, about 8% overestimation.

The rainfall occurrence ranges of both RGLIMCLIM and RGENERATEPREC are also close to observations: 0.308 – 0.392 from observation, and 0.288 – 0.395 from RGLIMCLIM and 0.294 – 0.404 from RGENERATEPREC.

It needs to point out that the SCL model does not have a function to set a threshold, so it treats any non-zero rainfall amount as a wet day, while other three models do have a function to set the threshold value (1.00 mm/day in our case). Therefore, SCL would significantly underestimate the annual rainfall occurrence, because the rainfall data used were interpolated from nearby stations. That is to say, if anyone of stations receives rainfall in one day, it will result in an amount of rainfall. As a result, 27.0% (22.4–33.9% from cell to cell) of days in the last 90 years (1923 – 2012) has a daily rainfall amount of between 0.00 mm and 1.00 mm.

In order to solve this problem, a 3-step method (Fu et al 2013) was implemented: 1) All the days with daily rainfall below 1.00 mm were set to 0; 2) The discontinuous time series of daily rainfall with 0 mm and >1.00 mm from Step 1 are inappropriate for daily rainfall amount model, so we minus 0.99 mm from all wet days. It makes the continuous daily rainfall amount, which is suitable for the SCL modelling; 3) After we obtain the model simulation results, a 0.99 mm was added back to all wet days. This method has been proved as an effective method to deal with the threshold issues and to improve the model performances.

*3.1.2 Monthly*

The box plots in Figure 3 show the range of rainfall occurrence (number of days with rainfall above 1 mm/day) in the observations (1923–2013) at the 21 points in each of the 12 months, and the means from 100 stochastic replicates from the four weather generation models for the 21 points.

It seems all models can reproduce the annual cycle (monthly distribution) of rainfall occurrence: a wet summer and a dry winter (Figure 3). However, slightly differences do exist: Overall, RGENERATEPREC performs the best and the median values of 100 simulations exactly match the observed monthly rainfall occurrence, while it is not surprised that majority months of SCL/RMAWGEN underestimate/overestimate the rainfall occurrence due to their respective annual performances (Figure 2).

It needs to point out that the models can be further improved to have a "better" fit with observations in term of annual cycle. For example, However, RGLIMCLIM has a parameter to control every single month rainfall occurrence (monthly effects, Code 11–22, Table 1, Chandler 2015). It then can simulate exact rainfall occurrence for every single month. However, we chose not to do so in this study because monthly shift is one aspect of climate change and variability and our objective is to obtain a wide range scenarios of climate change and variability and to explore its impacts on water resources. For example, Potter et al (2010) have identified that decreased autumn (southern hemisphere) rainfall in recent years relative to other seasons is one of the reasons resulting in the larger than expected runoff decrease in the Murray–Darling Basin.

RGCLIM and RGENPREC perform best.

SCL okay, slight underestimation (you already accounted for occurrence = rainfall > 1mm?).

RMAWGEN overestimate.

Are there reasons for this? – relate to model structure and/or parameterisation.

All four models capture the relative rainfall occurrence in the different months over the year.

[But occurrence is not of key importance here, days < 1 mm do not generate runoff, of more importance is days > 5mm or consecutive totals over multi-days].

## 3.2 Annual Rainfall Amounts and Variability

The annual mean, standard deviation (SD), the coefficient of variation (CV), and the ratio of maximum and minimum annual rainfall provide a summary of whether a model can reproduce long term hydro-climatic characteristics, e.g. water availability and drought.

The overall long-term mean annual rainfall are generally simulated with acceptable results, although RGLIMCLIM overestimates it by 22.5% and RGENERATEPREC underestimate it by -16.4% (Figure 4). It is interesting to note that SCL produced the best results not only in term of relative errors (1.8%) but also spatial patterns ($r$=0.986), while RGLIMCLIM produced the poorest results. It may partly be because SCL fixes the pairwise correlation among all grid cells from observations, while RGLIMCLIM uses the correlation-based dependence structures, which allow the dependence to vary with distance. In general, it is better to fit a correlation model than to use the empirical correlations themselves. This issue will be further explored in Section 3.5 of spatial distributions.

Figure 5 shows that the ratio of maximum and minimum annual rainfall, standard deviations and the coefficient of variations of annual rainfall from the four model simulations. Among the four models, SCL seems the best one to simulate the variability of annual rainfall, while RGENERATEPREC is the worst, and RGLIMCLIM and RWAMGEN fall in between. For example, the ratios of the maximum and minimum annual rainfall from 1923 to 2012 from the observation is about 3.4 averaging over the 21 grid cells (with a range of 2.8–3.6). That is to say the maximum annual rainfall is about 3.4 times of the minimum annual rainfall during the last 90 years, while the mean and median values of 100 simulations across the 21 grids are 3.2 and 3.1, respectively. In contrast, the mean and median values are 2.4 and 2.4, 2.3 and 2.3, and 2.7 and 2.7, for RGLIMCLIM, RGENERATEPREC and RWAMGEN, respectively. In term of standard deviations of annual rainfall, the observed standard deviations of annual rainfall is about 257.5 mm averaging across the 21 grid cells (range of 224.4–294.7mm, median 260.8mm), while the mean and median values of SCL 100 simulations across the 21 cells are 257.6 and 256.6 mm. RGENERATEPREC significantly underestimate the standard deviations of annual rainfall with mean and median values of 156.2 and 155.8mm, which are -30.4% and -47.1% in comparison with observations. Since the coefficient of variation (CV) is the ratio of standard deviations and mean of annual rainfall, it is not surprised that its simulation results fall in between these two (Figure 5).

Annual rainfall

SCL performs best (at all sites, therefore spatial correlations also) (can also show pair-wise correlation, but probably not, too may plots already).

RMAWGEN, ‘error’s in sites’ but no overall bias.

RGLIMCLIM overestimates annual rainfall, RGENRATEPREC underestimates annual rainfall. This is a problem. Why is this happening here but not with SCL? Can constrain to annual rainfall, then nest this in monthly rainfall, etc… [I suspect SCL is doing this, hence reproducing the annual and monthly totals].

SCL also best reproduces the inter-annual variability.

The three other methods underestimate the variability, therefore potentially underestimating multi-year dry sequences

3.3 Monthly Rainfall

For hydrological applications, it is essential that simulations can reproduce the monthly distribution and intra-annual variability of rainfall. The results show that all the four models can catch the annual cycle (monthly distribution) of rainfall amount: a wet summer and a dry winter (Figure 6). Therefore, it is not surprised that the annual cycle of rainfall occurrence (Figure 3) is well simulated.

However, there are difference among the models: 1) SCL performs the best in terms of rainfall amount as well as rainfall percentage (monthly rainfall over annual rainfall in percentage term); 2) Both RGENERATEPREC and RMAWGEN performed much better in rainfall percentage rather than rainfall amounts. It is because their annual rainfall is underestimated/overestimated by about -16.4%/+5.7% (Figure 4), but their annual cycle are almost perfectly simulated; 3) RGLIMCLIM's simulations are relatively poor among the four models used, but they are still well simulated. For example, the mean and median values of correlation coefficients between simulated and observed monthly rainfalls (i.e., a sample size of 12) of 100 simulations are 0.960 and 0.961 respectively. The minimum correlation coefficient of 100 simulations is 0.892 (Figure 6). As it is stated in the previous section, the

RGLIMCLIM has a parameter to control every single month rainfall occurrence, and it then could simulate exact rainfall occurrence for every single month. However, we chose not to do so in this study because monthly shift is one aspect of climate change and variability and our objective is to obtain a wide range scenarios of climate change and variability and to explore its hydrological impacts.

Besides rainfall occurrence, the rainfall amount models are also a source of uncertainties. Ideally, rainfall amount parameters should vary from season to season (Frost et al. 2011; Liu et al 2013) to catch the different relationship and physical rainfall processes between rainfall amount and rainfall occurrence. However, it is out scope of current study.

Overall, the annual cycle (monthly distribution) of rainfall amount is well simulated by four models used in this study, and the ranges of 100 simulations from each model also present a reasonable wide range of variability (boxplot of every month of Figure 6). These ranges are useful for climate change and variability impact studies.

All methods can reproduce the monthly distribution through the year. Expect this?, Because they are ‘parameterised monthly?

Can also see the underestimation in the monthly (and annual) rainfall in RGLIMCLIM and overestimation in RGENRATEPREC.

3.4 Daily statistics

Daily rainfall characteristics, such as daily rainfall distribution, extremes (e.g. daily maximum, 99$^{th}$ and 95$^{th}$ percentiles), dry/wet spell length and spatial correlations are critical for hydrological modelling.

### *3.4.1 Probability Density*

The probability density is explored by two methods in this study: quantile-quantile (q-q) plot and cumulative density functions. The q-q plot is a graphical technique for determining if two data sets (i.e., observed and modelled daily rainfall) come from populations with a common distribution. A 45-degree reference line is also plotted. If the two sets come from a population with the same distribution, the points should fall approximately along this reference line. The greater the departure from this reference line, the greater the evidence for the conclusion that the two data sets have come from populations with different distributions, i.e., the model results have larger differences with observations. The results indicate (Figure 7) that the RGLIMCLIM produced the best fit with observations except just one extreme outliers, while the RGENERATEPREC significantly underestimated the extreme daily rainfall, especially 99% percentile or larger — the three vertical lines are 90$^{th}$, 95$^{th}$ and 99$^{th}$ percentiles. For example, when the observed daily rainfall reached 150 mm/day, their corresponding percentage simulated daily rainfall were only about 100 mm/day. On the other side, SCL slightly overestimated the extreme daily rainfall of 99% percentile or larger and RMAWGEN seems significantly overestimated the extreme daily rainfall of 99% percentile or larger. For example, when the observed daily rainfall reached 150 mm/day, their corresponding percentage simulated daily rainfall were about 200 mm/day.

Given the large amount of the data points (for each model simulations result, 21grids*100simulations* 90years (1923–2012)*365/366days = 68844300), the q-q plot might be focus on too extreme values. For example, 90% of daily rainfall are smaller than 8.7 mm/day, i.e., below the first vertical lines (Figure 7).

The cumulative density functions, or just distribution function, evaluated at *x*, is the probability that a real-valued random variable. The empirical distribution function estimates the cumulative distribution function underlying of the points in the sample and converges with probability 1 according to the Glivenko–Cantelli theorem. Therefore, it avoids the disadvantages of q-q plot to focus on extreme values, and it is a different point of view to visual inspection of modelled results in comparison with observation. The results (Figure 8) shows overall all four models produce good results, but the RGLIMCLIM overestimated the daily rainfall amount for the 80–97 percentiles, which cannot be seen by a its q-q plot. It is why its q-q plot shows the best fit (Figure 7), but its annual rainfall is about 22.5% overestimations. It also shows the RGENERATEPREC underestimates the daily rainfall for the 95–99 percentiles, while SCL underestimated daily rainfall for 70-90 percentiles but slightly overestimated for 95-99 percentiles. RMAWGEN seems to have a perfect match with observations, which probably is the main reason why its annual rainfall is best simulated – although its extreme daily rainfall was significantly overestimated (Figure 7).

One significant difference between the cumulative density functions plot and q-q plot is that maximum daily rainfall from the cumulative density functions plot is only up to 100mm/day (Figure 8), which is less than half of q-q plot (Figure 7). It is because the 100mm/day is equivalent to 99.935% percentile of observed daily rainfall. The corresponding percentiles of 100mm/day from four models are 99.919%, 99.891%, 99.991% and 99.875% for RGLIMCLIM, SCL, RGENERATEGEN and RMAWGEN, respectively.

### 3.4.2 Extreme Daily Rainfall

Figure 9 shows the extreme daily rainfall, including maximum daily rainfall and 99$^{th}$ and 95$^{th}$ percentiles of daily rainfall, simulated by four models. Overall, they are replicated reasonable results in comparison with observations. However, differences do exist between models and statistics: 1) The RGLIMCLIM performs the best in simulating the daily maximum rainfall, But its 99th and 95th percentile daily rainfalls were overestimated about 16.2% and 29.4% averaging 100 simulations and 21 grid cells. This is consistent with CDF plot (Figure 8) where the daily rainfall within 80–97 percentiles are overestimated; 2) SCI overestimated the daily maximum rainfall and 99th percentile daily rainfall, for about 16.0% and 16.9%, but it is the best model to simulate 95th percentile daily rainfall. In addition, it has the second largest variations among 100 simulations behind RMAWGEN (Figure 9); 3) The RGENERATEGEN underestimated the daily extreme daily rainfall, especially for daily maximum rainfall and 99th percentile daily rainfall. Its underestimation magnitudes of daily maximum rainfall are the largest among the four models: -28.3% for the daily maximum rainfall average 100 simulations and 21 grid cells. However, its 95th percentile of daily rainfall is well simulated (Figure 8); 4) The mean values of extreme daily rainfall from 100 simulations produced by RMAWGEN seem close to the observation, especially for 99th and 95th percentile daily rainfalls. Their relative errors are 6.1% and -1.2%, respectively. But it has the largest variations among 100 simulations.

In general, multi-day extreme rainfall are simulated as well as daily statistics (Figure 10), except RGENERATEPREC model.  That is to say the simulation results still are at an acceptable level except RGENERATEPREC. A few interesting observations can be noted: 1) The 3-day extreme rainfall (maximum 3-day rainfall and 99th and 95th percentiles of 3-day rainfall) are generally underestimated even with the models of overestimation of daily extremes (Figure 9). It is understandable as a stochastic model usually cannot simulate consecutive extreme daily rainfall, but it can happen in realty; 2) The RMAWGEN model produced the best results:  The relative errors of mean values of 100 simulations are -1.8%, -0.5% and 0.4% for 3-day maximum rainfall, 3-day 99th and 95th percentile daily rainfalls, respectively. These values are the smallest magnitudes among four models in every statistics. However, as the daily extremes, it also has the largest variations among 100 simulations

(Figure 10); 2) As the same for the daily extremes, the RGENERATEPREC is the worst model to simulate the 3-day extreme rainfalls, but with a larger magnitudes of relative errors: -35.3% for the 3-day maximum rainfall average 100 simulations and 21 grid cells, -30.3% for the 3-day 99$^{th}$ percentile rainfall, and -15.8% for the 3-day 95$^{th}$ percentile rainfall. These are worse than the daily extremes of -28.2%, -23.5% and -12.3%. Therefore, these simulation result might be acceptable for the researches of the impacts of climate change and variability on water resources, but cannot be used for the extreme rainfall and flooding relevant studies; 3) The simulation results of RGLIMCLIM and SCL fall in between with an underestimation of 3-day maximum rainfall (-12.3 – -13.3%) and 3-day 99$^{th}$ percentile rainfall (-2.6 – -6.2%), but an overestimation of 3-day 95$^{th}$ percentile rainfall, 19.6% for RGLIMCLIM and 7.3% for SCL.

### 3.4.3 Wet spell and dry spell

The wet spell and dry spell have important hydrological implications: the consecutive rainfall generally result in flood as earlier rainfalls saturate soil moisture and later rainfalls convert into runoff and streamflow, and the consecutive non-rain days are usually associated with drought events.

In general, both RGLIMCLIM and RGENERATEPREC generate similar results as observations in term of lengths of wet spell and dry spell. For example, for the 99$^{th}$ percentile lengths of wet spell, the mean and median lengths among 21 grid cells are 11.0 and 11.0 days, while the RGLIMCLIM and RGRNERATEPREC simulate 10.6 and 11.0 days, and 10.7 and 11.0, respectively. On the other hand, for the 99$^{th}$ percentile lengths of dry spell, the mean and median lengths among 21 grid cells are 25.2 and 25.0 days, while the RGLIMCLIM and RGRNERATEPREC simulated 23.5 and 24.0 days, and 22.9 and 23.0, respectively.

SCL significantly overestimates the dry spell lengths, especially for the maximum and 99$^{th}$ percentile of dry spell length (Figure 11). The mean and median values of the observed maximum and 99$^{th}$ percentile of dry spell lengths are 58.1 and 57.0 days, and 25.2 and 25.0 days, respectively, while their respective values for SCL are 95.6 and 95.0 days, and 36.8 and 36.9 days. These are about 65% and 47% overestimations for the maximum and 99$^{th}$ percentile of dry spell lengths, respectively.

The RMAWGEN significantly underestimated lengths of wet spell, especially for 99$^{th}$ and 95$^{th}$ percentiles, as well as median lengths of wet-spell (Figure 11). For example, for the 99$^{th}$ and 95$^{th}$ percentile lengths of wet spell, the mean and median lengths of wet spell among 21 grid cells are 11.0 and 11.0 days, and 6.8 and 7.0 days, respectively. But the RMAWGEN simulated the corresponding values are 8.9 and 9 days, 5.7 and 6 days, respectively, about 15-20% underestimations (Figure 11).

It is not surprised that model results generally have a wide range than observations. It is because the boxplot of observation only comprises 21 grid values, while that of model results have 2100 values — 21 grid cells * 100 simulations. For the same reason, boxplots of model results usually have "outliers" (Figure 11).

3.5 Spatial distribution (Occurrence and amount)

Figures 12–14 show that the pairwise correlation coefficients of rainfall occurrence (Figure 12), daily rainfall amount (Figure 13) and annual rainfall (Figure 14) from observations and four model results. Overall, the models produced reasonable results with underestimations. Part of reason is that the area of study catchment is relatively small and the grid rainfall were interpolated from limited numbers of meteorological stations, which make the rainfall among grid cells highly correlated. For example, the pairwise correlation coefficients of daily rainfall among these 21 grid cells (sample size $n$=21×20/2=210) range from 0.693 to 0.989 with a mean value of 0.873 and a median value of 0.877.

It is not surprised that rainfall occurrence (Figure 12) was better simulated than rainfall amount (Figures 13–14), as three (RGLIMCLIM, SCL and RGENERATEPREC) out of four models used fitted a rainfall occurrence model at first step, and then a separate rainfall amount is followed.

It is also not surprised that annual rainfall correlation is generally better simulated than daily rainfall (Figures 13–14), as annual rainfall sums the daily rainfall in a specific year. For example, the mean and medians of 21000 pairwise correlation coefficients (210 pairwise for 21 grid cells with 100 simulations) are 0.399 and 0.400 from RGENERATEPREC for daily rainfall (Figure 13), and improved into 0.586 and 0.592 for annual rainfall (Figure 14). But their difference are relatively small for RGLIMCLIM and SCL. For example, the mean and medians of 21000 pairwise correlation coefficients are 0.579 and 0.579 from RGLIMCLIM for daily rainfall, and 0.626 and 0.630 for annual rainfall. The corresponding values for SCL are 0.660 and 0.667 (daily rainfall), and 0.668 and 0.693 (annual rainfall), respectively.

It is interesting to note that the RGRNERATEPREC perform the best to simulate the rainfall occurrence and its pairwise correlation coefficients are almost perfect matched with observations (Figure 12). However its pairwise correlation coefficients of rainfall amount is the worst among the four models. It implies that the rainfall amount of RGENERATEPREC may not be suitable for the study catchment. Our early study (Fu et al 2010) shows that the root transform might be a better model for rainfall amount for the Australia and it has potential to improve the performance of RGENERATEPREC, but it is out of scope of the current study.

It is also interesting to note that the RGLIMCLIM seems to produce an overall high-pairwise correlation coefficients of rainfall occurrence (mean and median values of 0.692 and 0.692, the closest to observations of 0.732 and 0.717), but does not correspond to each individual value (Figure 12). It is because a correlation-based dependence structures is used, instead of holding empirical pairwise correlation coefficients, which are used by other three models. The RGLIMCLIM does have an option to hold the pairwise correlation coefficients, but it is generally better to fit a correlation model than to use the empirical correlations themselves for two reasons (Chandler, personal communication): 1) the empirical correlations are not guaranteed to be mutually compatible because they are calculated pairwise; and 2) it cannot be used to simulate at an ungauged location if empirical correlations are unknown. In addition, we want to explore a wide range of climate variability.

## 4. CONCLUSIONS

I suggest we shorten Section 3, and call the section “Results”.

Then, have a Section 4 Discussion and Section 5 Conclusion, or just Section 4 Discussion and Conclusion. I prefer the former, better but more difficult to write, but can be okay with just a very short Conclusion then.

We need to summarise the four models – how they perform; why, relating to the method, setup and parameterisation; and implications on the hydrological modelling for this context.

See attached table I made up (speculatively).

Then discussion of this.

I challenge the statement of ‘multiple models have advantages over a single weather generator’.

Yes, because they allow us to represent the range of uncertainty and plausibility, but only if they are not clearly inadequate.

Four weather generators models (RGLIMCLIM, SCL, RGENERATEPREC and RMAWGEM) were used in this study to generate multi-sites daily rainfall for a small catchment in Australia. The results showed they all produced reasonable results in term of annual, monthly and daily rainfall occurrence and amount, as well as daily extreme, multi-day extremes and dry/wet spell length. However, they also simulated a large range of variability, which not only demonstrates the advantages of multiple weather generators rather than a single model, but also is more suitable for climate change and variability impact studies. These simulation results will be used for climate change and variability impacts on hydrological and water resources in the study catchment, and for comparisons with impacts of coal seam gas and coal mining on water resources.

Since weather generators are based on different theory and principals, so every model has its own advantages and disadvantages. For example, the RGRNERATEPREC performed the best to simulate the spatial correlation of rainfall occurrence and its pairwise correlation coefficients are almost perfect matched with observations (Figure 12). However its pairwise correlation coefficients of rainfall amount is the worst among the four models (Figures 13 and 14); The RGLIMCLIM is the best model to simulate daily rainfall, especially for extreme daily rainfall over 99$^{th}$ percentile (Figure 7), but it annual rainfall is overestimated (Figure 4); SCL can accurately simulate daily, monthly and annual rainfall amounts as well as annual variability and extreme daily rainfall (Figure 4-10), but its dry-spell length was significantly overestimated (Figure 11). This again enhances our conclusion that multiple models do have advantages over a single weather generator.

It needs to point out that models can be further calibrated/improved to have a "better" performance in comparison with observation. For example, the RGLIMCLIM does have a parameter to control every single month rainfall occurrence, and it then could simulate exact rainfall occurrence for every single month to have a perfect match with observations. However, we choose not to do so in this study for two reasons: 1) to get a full ranges of variability. For example, monthly rainfall shifts from GCMs have been identified (Fu et al 2013) and it does have hydrological implications, and extreme rainfall is expected to enhance in the climate scenarios; 2) there are uncertainties associated with observation data, which are interpolated from limited stations to produce a high pairwise correlations and many tiny rainfall – 27.0% (22.4–33.9% from cell to cell) of days in the last 90 years (1923 – 2012) has a daily rainfall amount of between 0 and 1.0 mm.

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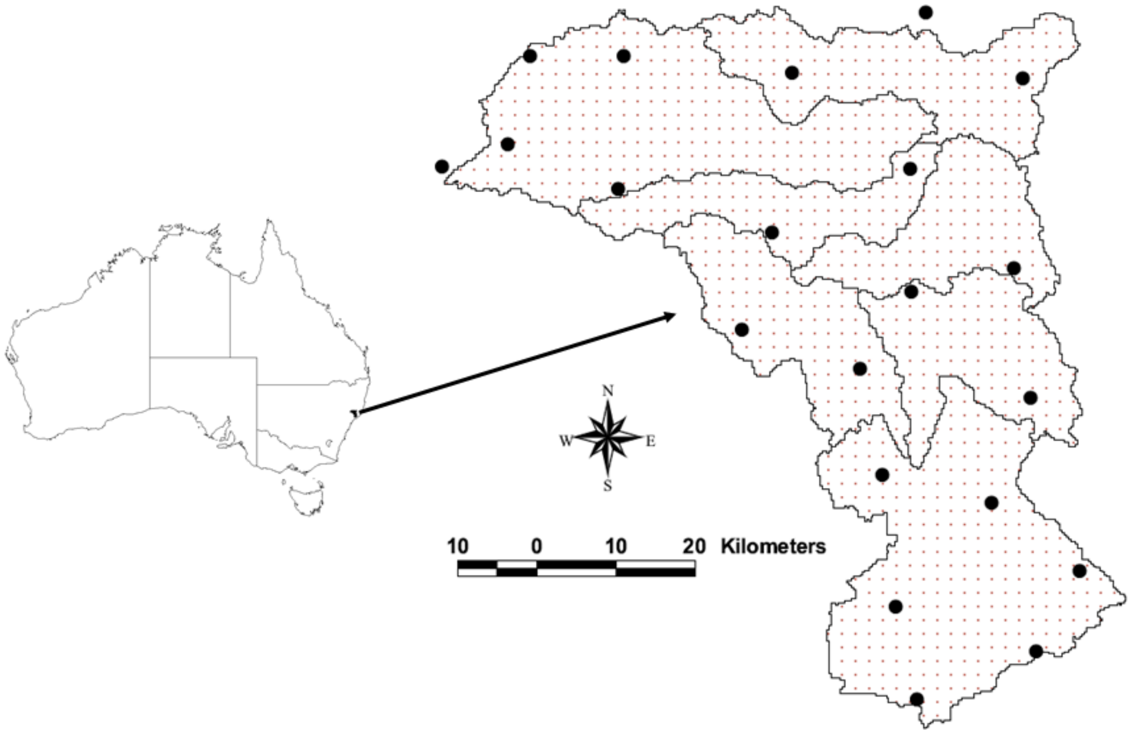


Figure 1 Location of study area and rainfall sites

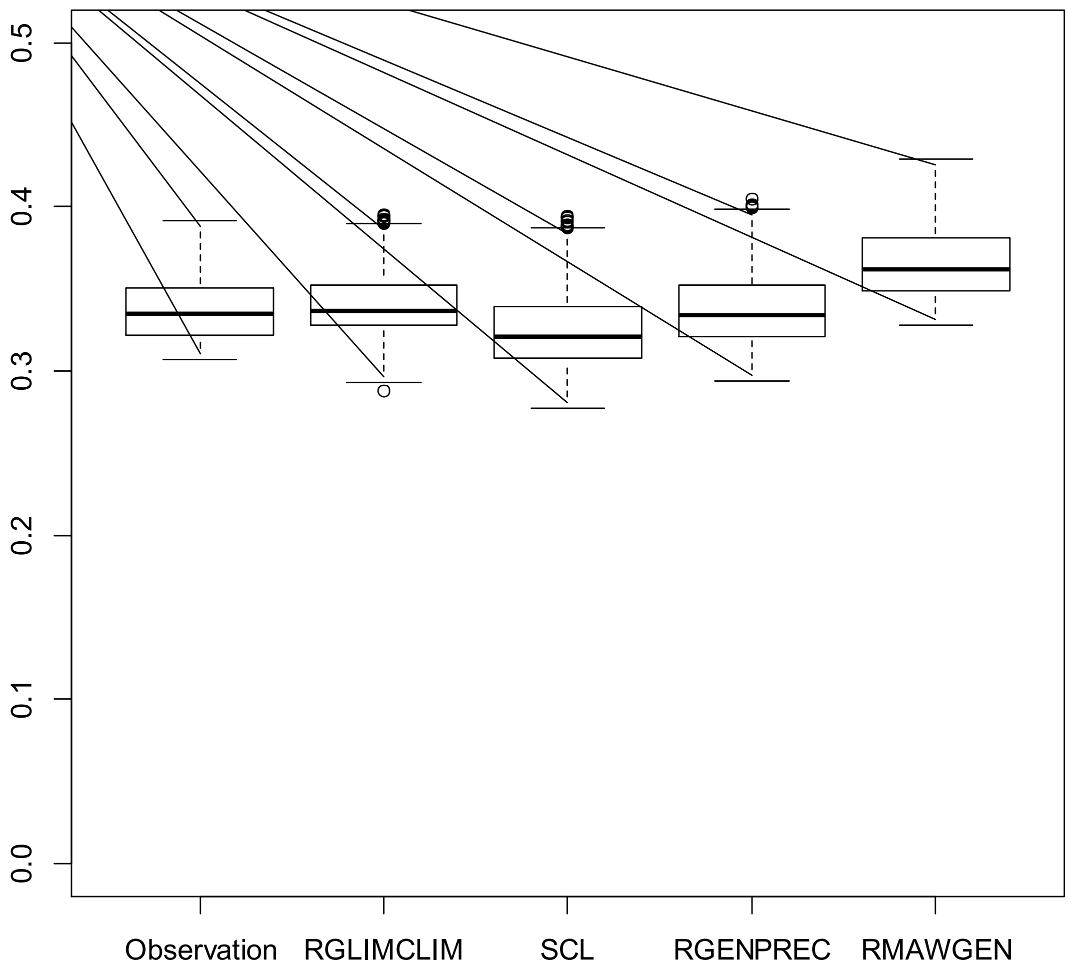


Figure 2 Rainfall occurrence (>=1.0mm/day) from observations and model results

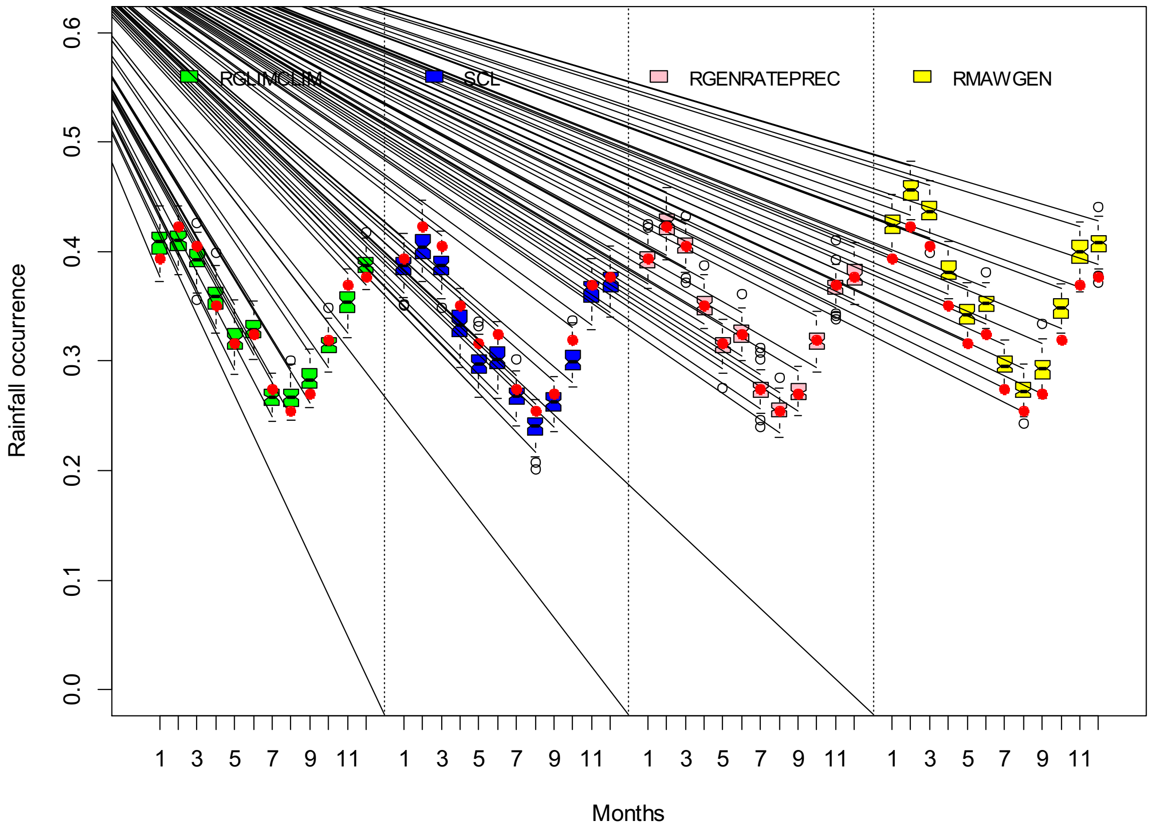


Figure 3 Rainfall occurrence by month from four models (red solid dots are observed values)

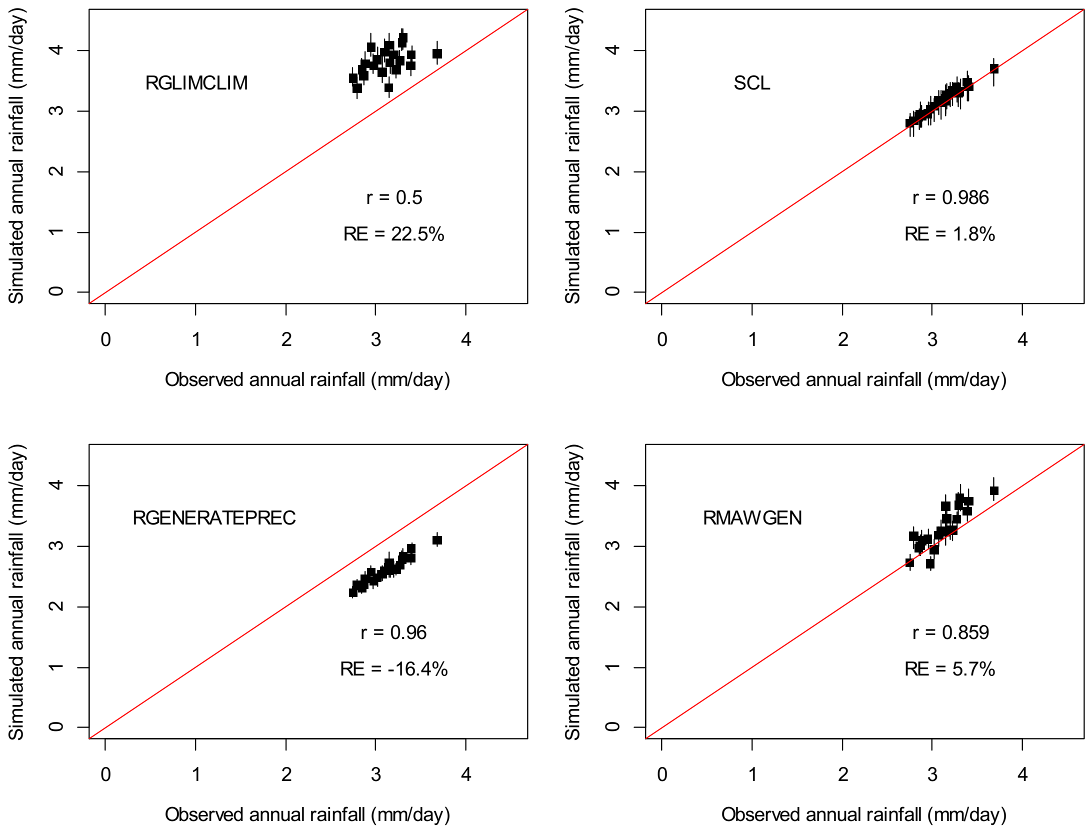


Figure 4 Observed and simulated annual rainfall (mm/day)

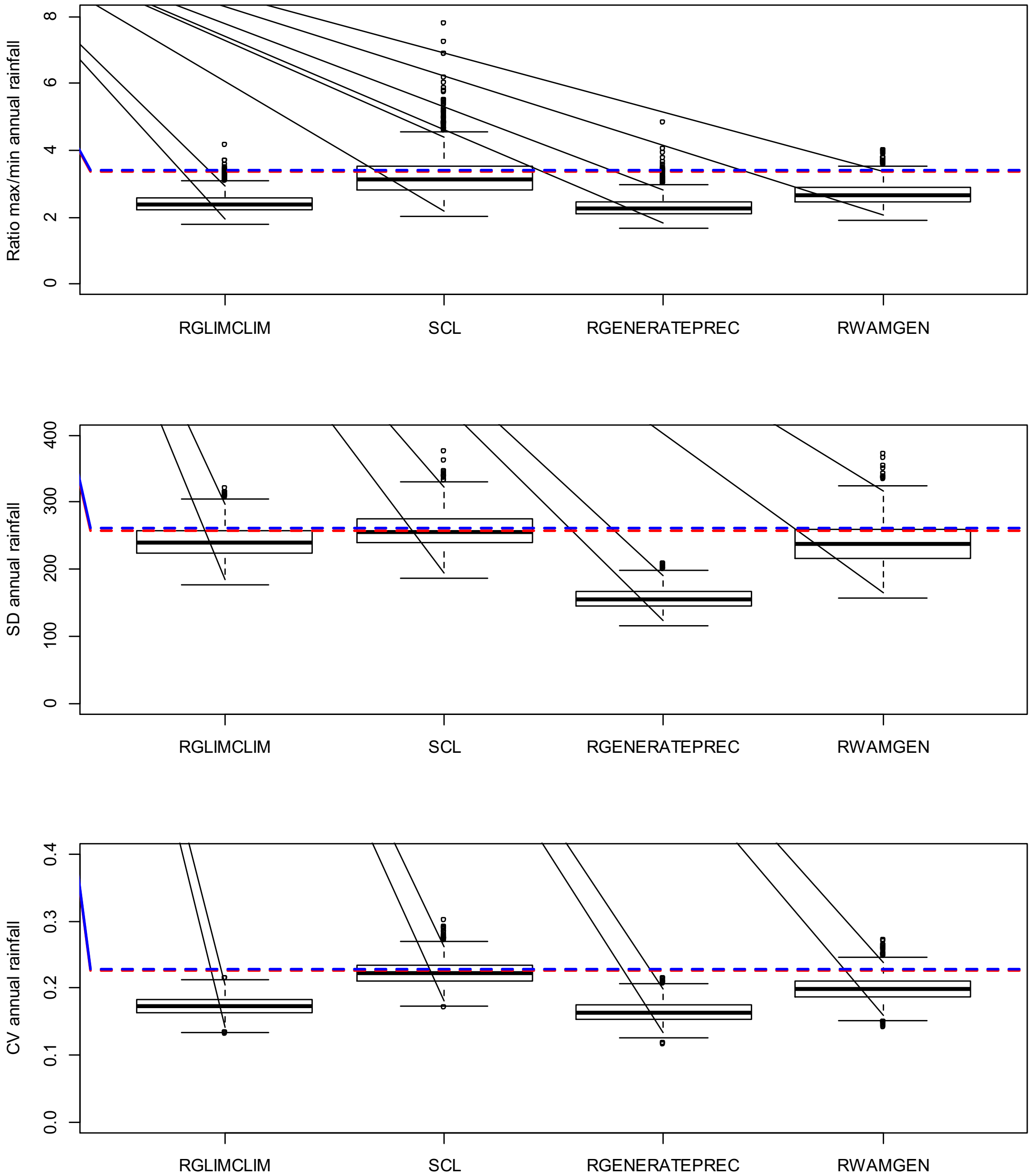


Figure 5 Variability of annual rainfall (red dash-line is the mean values of 21 grid cells and the blue dash-line is the median of 21 grid cells)

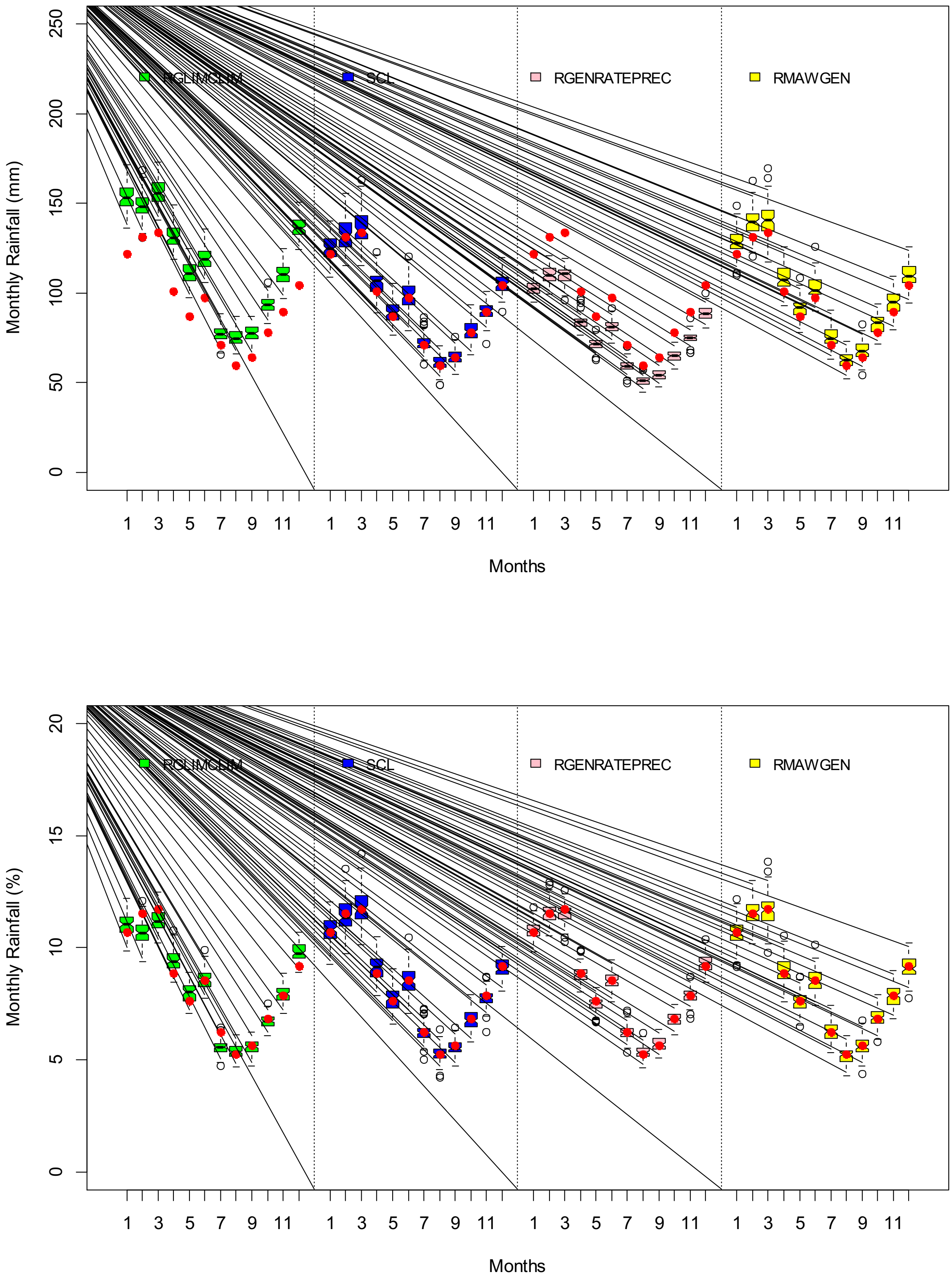


Figure 6 Monthly distributions of rainfall and its percentage of annual rainfall

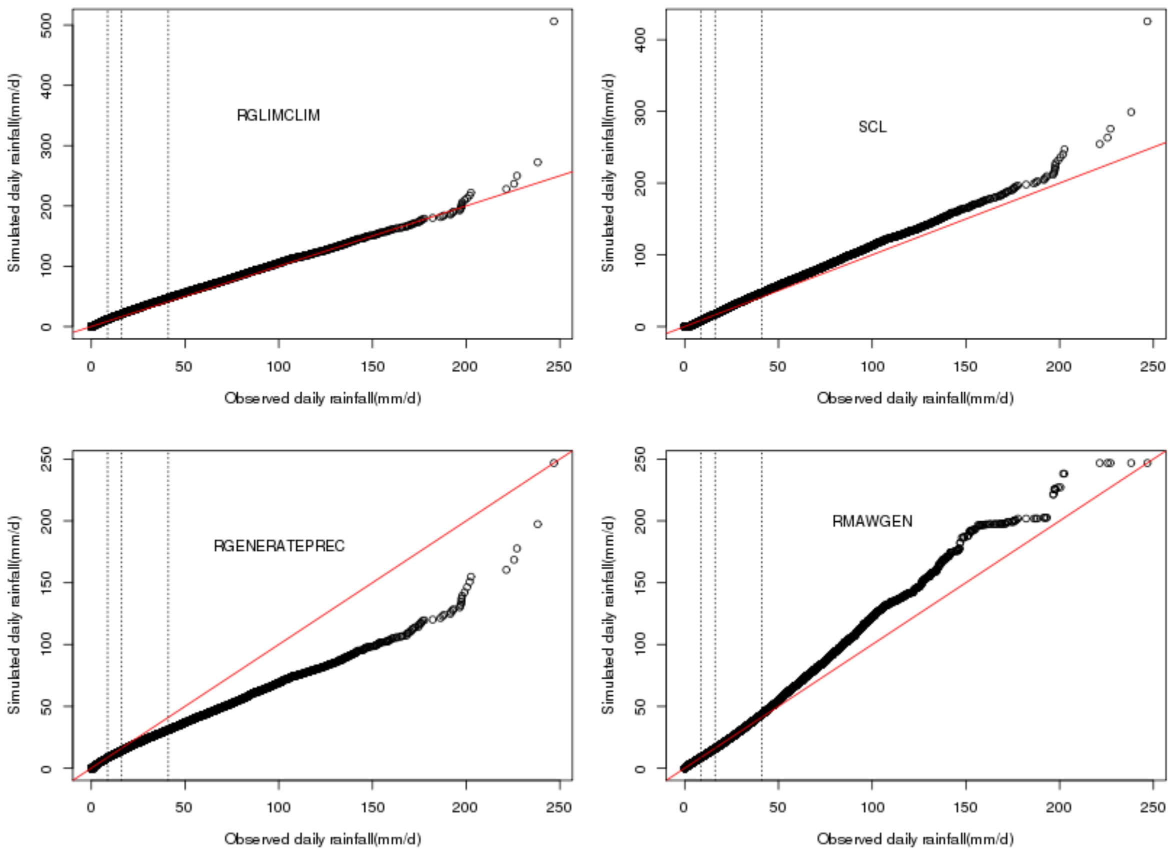


Figure 7 Q-Q plot of observed and simulated daily rainfall (Three vertical lines are 90%, 95% and 99% percentiles of daily rainfall)

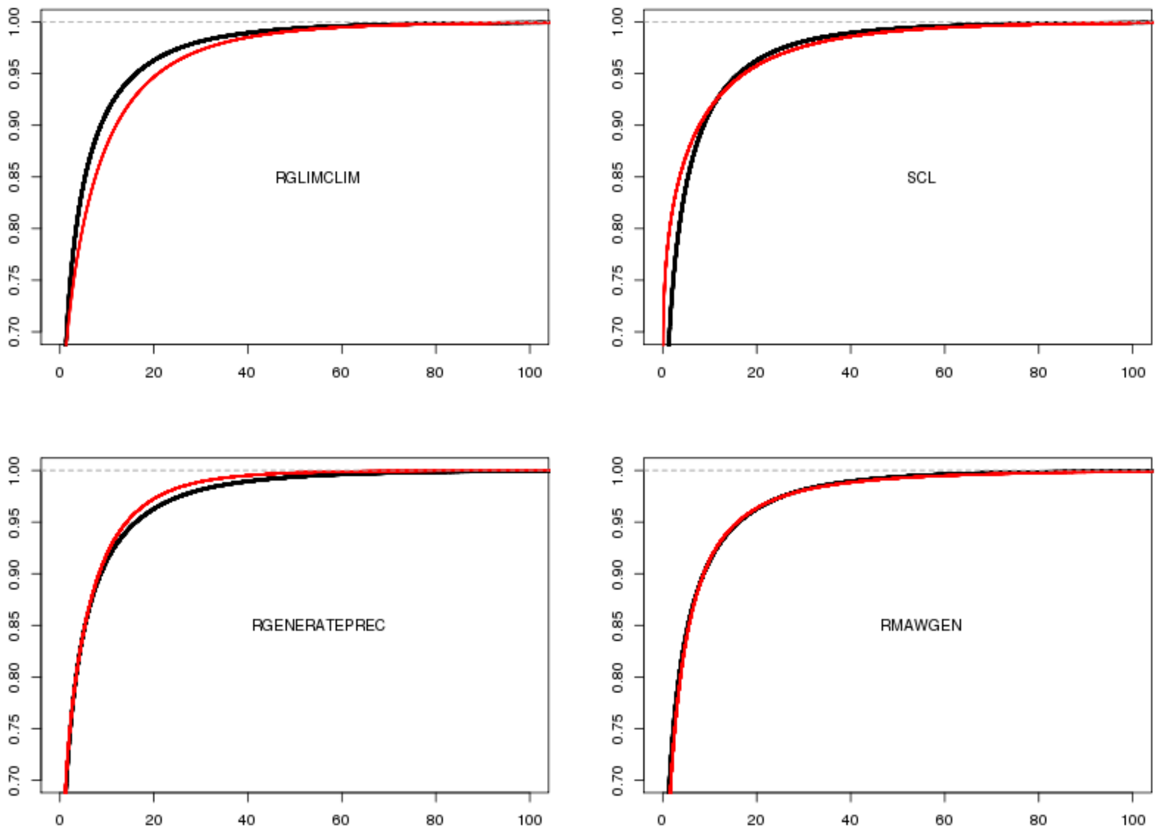


Figure 8 The empirical cumulative density function of daily rainfall (Observation are plot in black and model results are plotted in red)

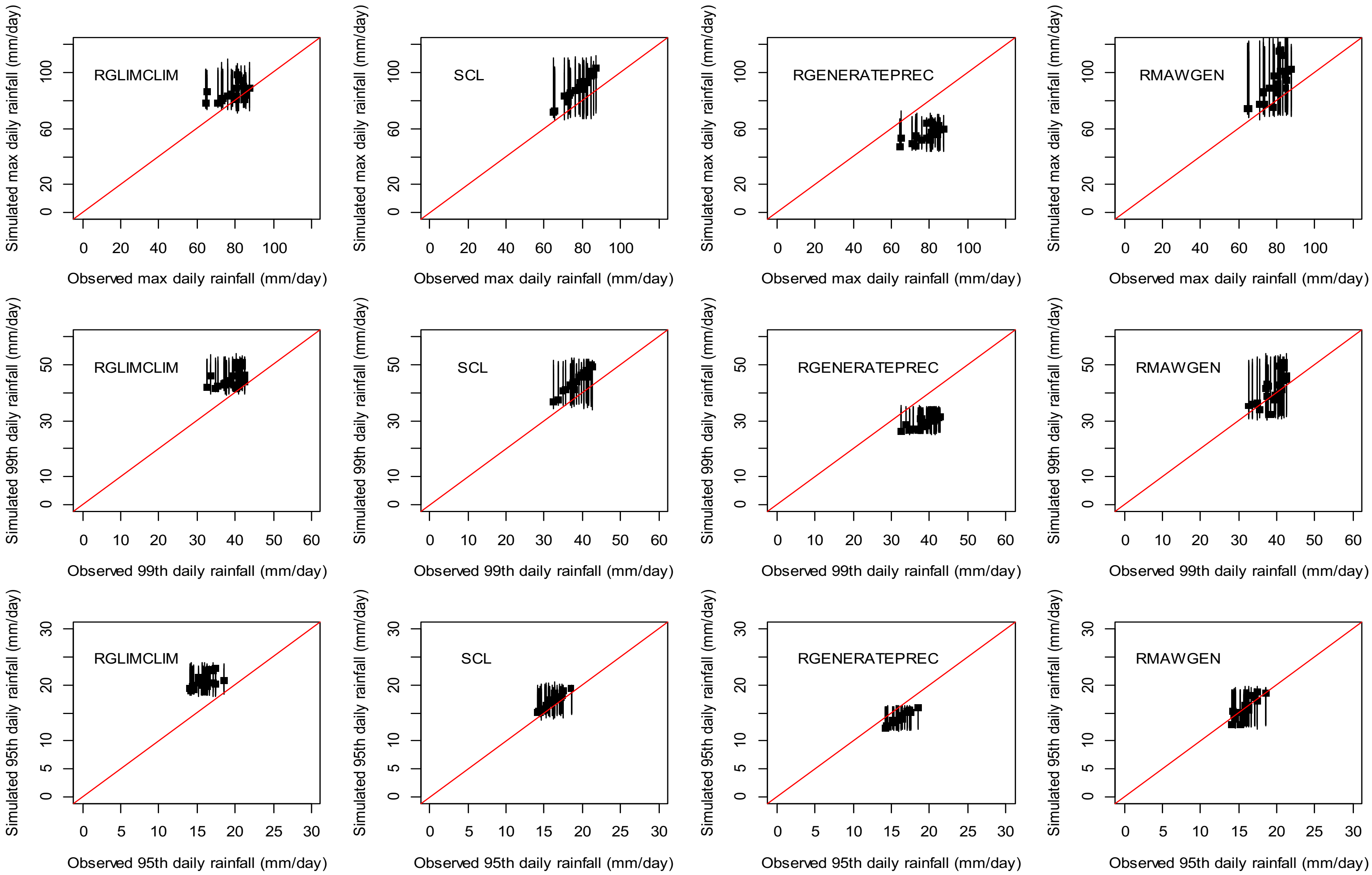


Figure 9 Simulations of extreme daily rainfall (maximum daily, 99th and 95th percentiles) from four models in comparison with observations

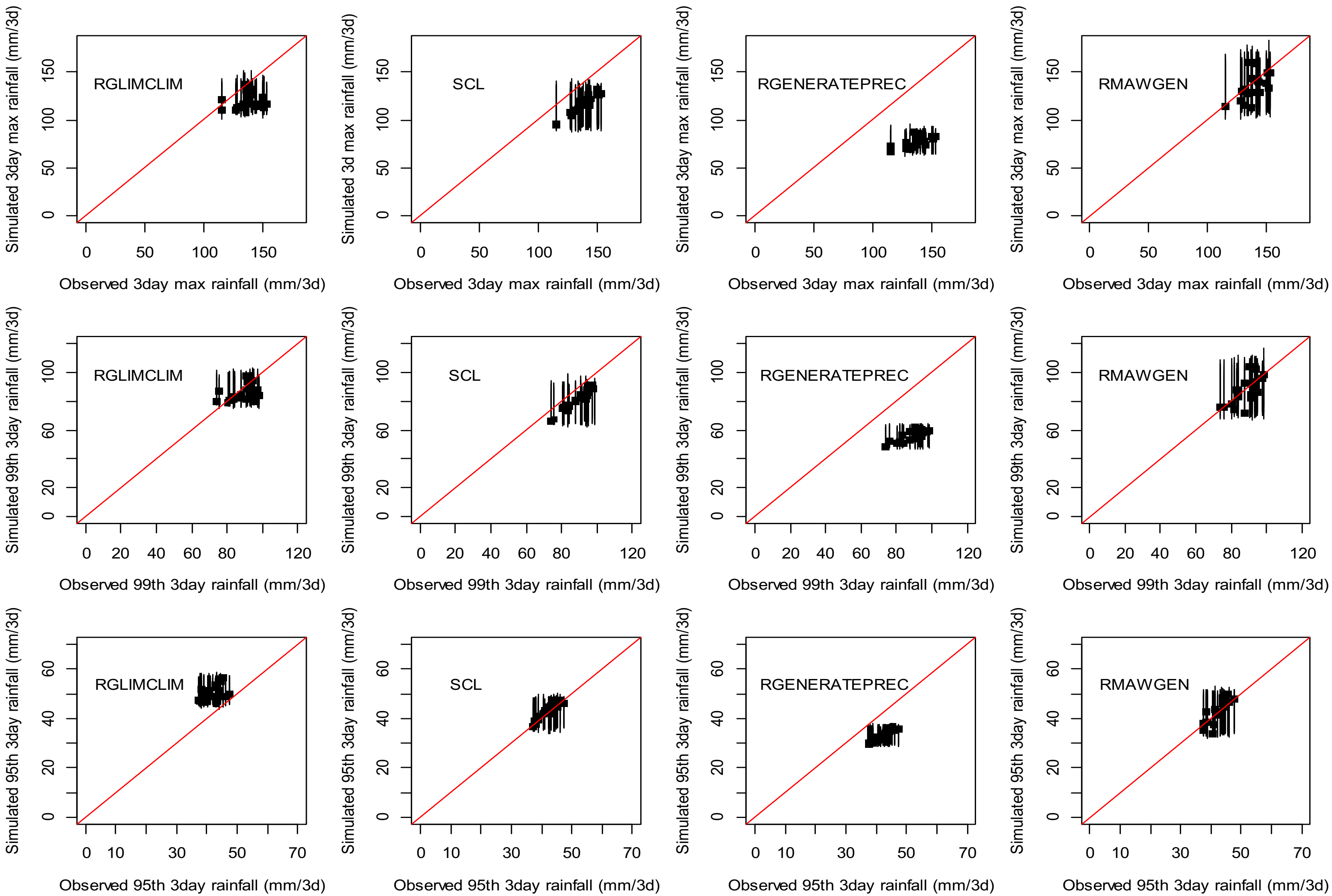


Figure 10 Simulations of extreme 3-day rainfall (maximum daily, 99th and 95th percentiles) from four models in comparison with observations

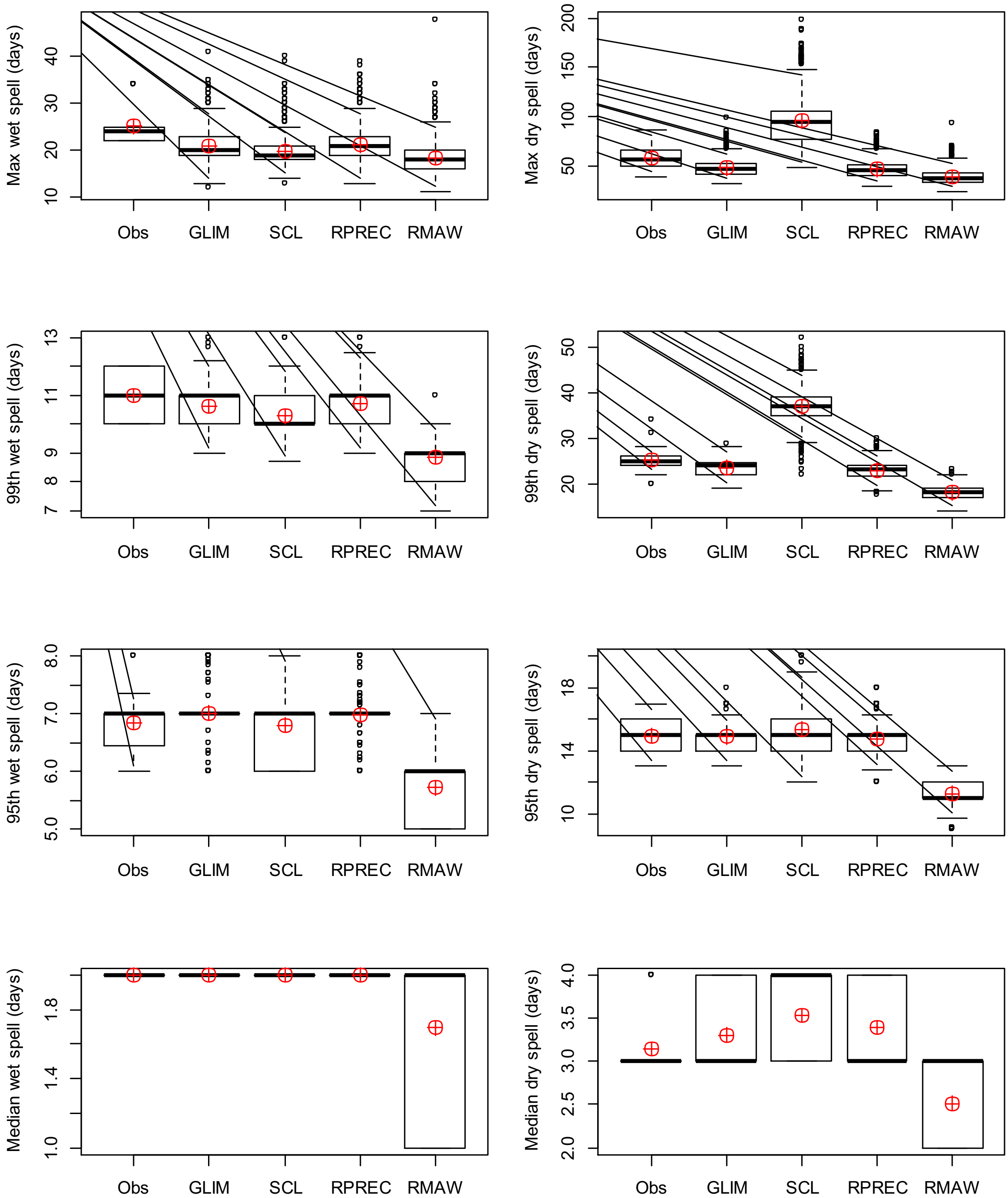


Figure 11 The maximum, 99th and 95th percentiles, and median of wet spell and dry spell from observations and four model simulations

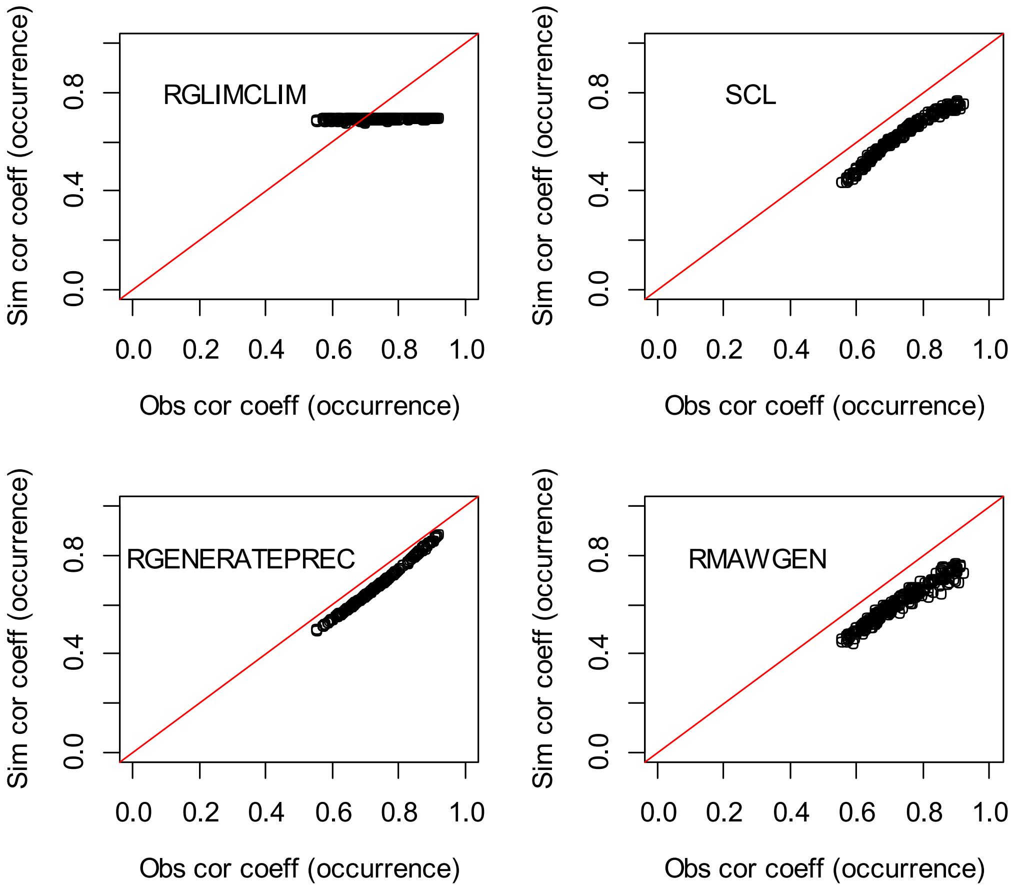


Figure 12 Pairwise correlation coefficients of rainfall occurrence from observations and model results

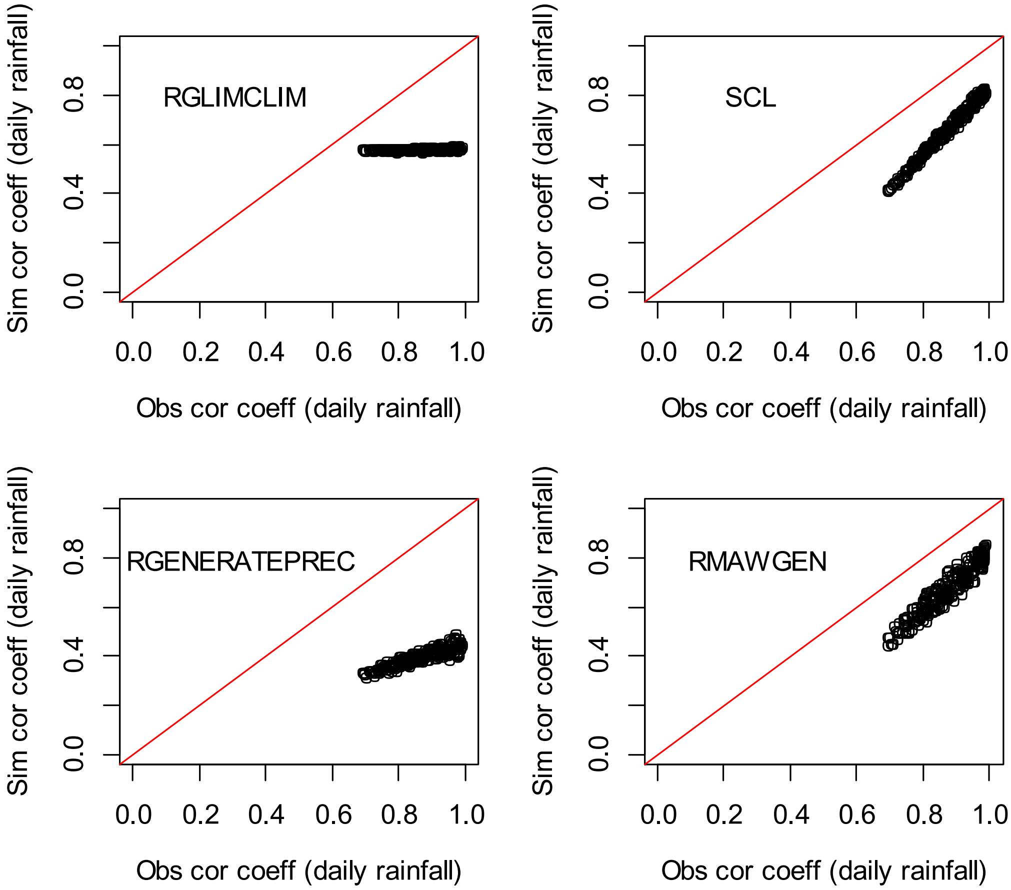


Figure 13 Pairwise correlation coefficients of daily rainfall amount from observations and model results

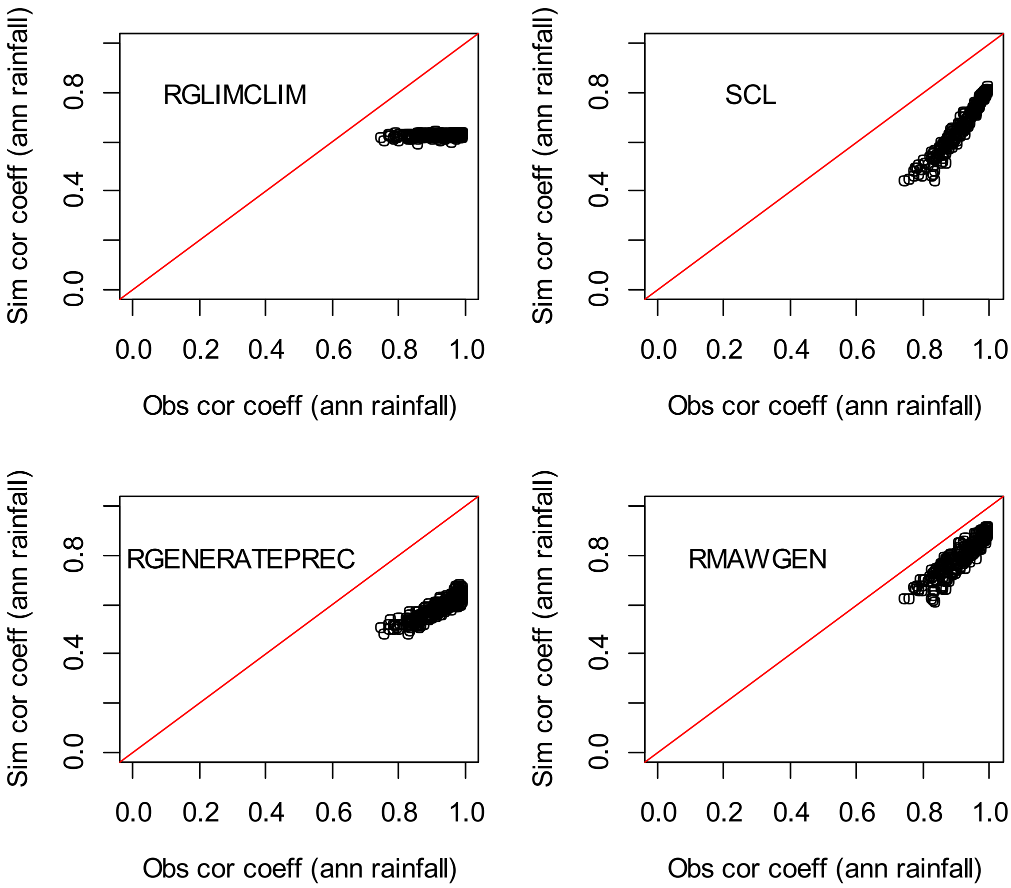


Figure 14 Pairwise correlation coefficients of annual rainfall from observations and model results