Abdellatif, M, Atherton, W and Alkhaddar, R

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A Hybrid Generalised Linear & Levenberg-Marquardt Artificial Neural Network Approach for Downscaling Future Rainfall in North Western England

M.Abdellatif[1], W. Atherton[1] and R. Alkhaddar[1]

[1] Liverpool John Moores University, School of the Built Environment, The Peter Jost Centre, Byrom Street, Liverpool, L3 3AF, UK;

Correspondence: M.Abdellatif ; email:**m.e.abdellatif@2010.ljmu.ac.uk**

T: +44 (0)1512314149; F: +44 (0)151 231 2815

Abstract

This paper describes a novel technique for downscaling daily rainfall which uses a combination of a Generalised Linear Model (GLM) and Artificial Neural Network (ANN) to downscale rainfall. A two–stage process is applied, an occurrence process which uses the GLM model and an amount process which uses an ANN model trained with a Levenberg-Marquardt approach. The GLM-ANN was compared with other three downscaling models, the traditional neural network (ANN), multiple linear regression (MLR) and Possion regression (PR). The models are applied for downscaling daily rainfall at three locations in North West of England during the winter and summer. Model performances with respect to reproduction of various statistics such as correlation coefficient, autocorrelation, root mean square errors (RMSE), standard deviation and the mean rainfall are examined. It is found that the GLM-ANN model performs better than the other three models in reproducing most daily rainfall statistics, with slight difficulties in predicting extremes rainfall event in summer. The GLM-ANN model is then used to project future rainfall at the three locations employing three different GCMs for SRES scenarios A2 & B2. The study projects significant increases in mean daily rainfall at most locations for winter and decrease in summer.

Keywords: Artificial Neural Network, Climate change, Downscaling, Generalised Linear Model, Levenberg-Marguardt algorithm.

Introduction

Statistical downscaling is the most widely used tool in downscaling climate variables from GCMs, which relates large- scale climate variables (predictors) to regional and local variables (predictands). Then the large-scale output of GCM simulation is fed into this statistical model to estimate the corresponding local and regional climate characteristic (Wilby et al., 2004).

Several alternative approaches have emerged, including regression- based techniques, weather pattern classification and weather generators. Downscaling through these methods depends heavily on the validity of the host GCM. It should also be noted that statistical downscaling often requires extensive observational data sets for training and significant amounts of pre-processing for the GCM outputs (Greg et al., 2005). The results of the downscaled models are highly sensitive to the statistical transfer function as well as the choice of predictor variables which are considered the most challenging aspects of the entire downscaling procedure (Winkler et al., 1997).

The statistical methods assume that the derived relationships between the observed predictors (climate variables) and predictand (i.e. rainfall) will remain constant under conditions of climate change and that the relationships are time-invariant (Yarnal et al., 2001and Fowler et al., 2007). One of the primary advantages of these techniques is that they are computationally inexpensive and thus can be easily applied to outputs from different GCM experiments (Wilby et al., 2004).

Linear and nonlinear regression methods have been used extensively to downscale precipitation with different capabilities of each method. Beuchat et al., (2012) ; Fealy and Sweeney, (2007) have used Generalized linear models (GLMs) to downscale rainfall in Switzerland and Ireland, respectively. The GLM downscaling models developed were found to perform well in reproducing historical rainfall statistics. Muluye (2012) employed the hybrid (SDSM), ANN, and nearest neighbor-based approaches (KNN) to downscale rainfall in Canada and found that ANN models have greater skills to reproduce historical rainfall. Another study carried by Hassan and Harun (2012) showed that SDSM model can be well acceptable in regards to its performance in the downscaling of daily and annual rainfall in Malaysia. Results from three downscaling methods (multiple linear regressions, multiple non-linear regression, and stochastic weather generator) have been used by Hashmi et al., (2012) as inputs to obtain improved historical and future rainfall predictions. The results obtained are found very encouraging for any future attempts to combine results of multiple statistical downscaling methods. Other examples of recent studies, which used linear regression, are (Busuioc et al., 2008; Goubanova et al., 2010), and those which used nonparametric regression based on splines and generalized additive models are (Vrac et al., 2007; Salameh et al., 2009).

Numerous studies found in literature have considered other methods of downscaling which are not counted as regression and have good results. An example of such studies is the work of Goyal and Ojha, (2012) which used rule induction and tree algorithms, namely Single Conjunctive Rule Learner, Decision Table, M5 Model Tree, Decision Stump and REP Tree for downscaling mean monthly precipitation on a lake basin in India. M5 Model Tree algorithm was found to yield better performance among all other learning techniques explored in the present study. Another example is the study by Olsson et al., (2012) which used a stochastic model for downscaling short-term precipitation from RCM grid in Sweden. The study derived IDF-curves and it was found that the IDF-curves may be effectively reproduced by the model.

The Artificial Neural Network (ANN) is an example of the nonlinear regression statistical downscaling method and has been used widely in downscaling of rainfall. ANNs have potential for complex, nonlinear, and time varying input-output mapping. Although the weights of an ANN are similar to nonlinear regression coefficients, the unique structure of the network and the nonlinear transfer function associated with each hidden and output node allows ANNs to approximate highly nonlinear relationships. Therefore the interest in ANNs is nowadays increasing (Coulibaly and Dibike, 2004).

The application of ANNs and utility of downscaling applications are dominant in several recent studies. Samadi et al., (2012) used ANNs to determine how future stream flow may change in a semi-arid catchment. Hoai et al., (2011) used a feed-forward multilayer perceptron (MLP) neural network for downscaling precipitation in India and later used the downscaled precipitations as inputs to a runoff model for flood prediction. Moreover, Ojha et al., (2010); Fistikoglu and Okkan, (2011) found that ANNs have good performance in downscaling monthly precipitation in India and Turkey, respectively. The finding in the later study was obtained earlier by Schoof and Pryor (2001) when ANNs model has failed to

simulate the daily precipitation at Indianapolis in USA and resulted in correlation coefficient of less than 0.5 between the observed and simulated precipitation. However, it performed slightly better for simulating monthly total precipitation with correlation coefficient of 0.65. Later, Ramirez and Ferreira, (2006) have compared the ANN and MLR approaches to downscale rainfall in Eta region of Brazil. They concluded that ANN has tendency to forecast moderate and high rainfall with greater accuracy during the austral summer and was superior to multiple linear regression (MLR).
A review study by Fowler et al., (2007) linking the climate change modelling to impact studies, found that, downscaling of rainfall by Wilby and Wigley (1997), using Weather Generators (WGs) were more skilful in comparison with ANNs. Indeed, ANNs have been shown repeatedly to perform poorly in the simulation of daily precipitation, particularly for wet-day occurrence (Wilby and Wigley, 1997; Wilby et al., 1998; Zorita and Von, 1999; Khan et al., 2006 a and Haylock et al., 2006) due to a simplistic treatment of non rain days, although they have been found to perform adequately for monthly precipitation as mentioned above. Moreover most ANN studies overcome this by explicitly modelling both processes (occurrence and amount) separately. Harpham and Wilby (2005) addressed this by using a variant of ANNs which, analogous to weather generation methods, treat the occurrence and amount of precipitation separately. They found ANNs overestimate the inter-site correlations of daily rainfall amount due to the deterministic forcing of the amount (Fowler et al., 2007).

Hybrid approaches (i.e. marriage between two or more approaches) have been used broadly in hydrology to improve modeling results for downscaling climate variables or flood forecasting purposes. Statistical downscaling model (SDSM) (Wilby & Dawson, 2001) is an example of hybrid approaches as it combines a stochastic weather generator with linear regression approaches. SDSM has been applied by Wilby et al., (2003) on multisite downscaling in NWAand SE of England. Later SDSM was successfully used as a downscaling tool in different part of the world (e.g. Ebrahim et al., (2012) in Ethiopia, Adab and Amirahmadi., (2012) in Iran , Hashmi et al, (2011) in New Zealand, Khan et al, (2006 b) in Canada, Dibike, and Coulibaly, (2005) in Canada). New hybrid time series neural network model is proposed by Jain and Kumar, (2006), which is capable of exploiting the strengths of traditional time series approaches and ANNs and provides a robust modeling framework. Cawely et al., (2003) employed ANN, which trained with hybrid Bernoulli/Gamma data to downscale daily precipitation across NW of England. The hybrid trained ANN has outperformed the traditionally trained ANN. Another example of improvement in results brought by use of hybrid approaches is the model used by Mishra et al., (2007). They combined a linear stochastic model and a nonlinear ANN model to forecast drought in a river basin in India. The model was found to forecast droughts with greater accuracy than any of the single approaches used. Recently, Kim (2011) used a combination of different relationships of measuring pan evaporation (PE) to predict the alfalfa reference evapotranspiration (ET_r).

Therefore this paper comes in the context of using hybrid approaches to improve model results in the area of rainfall downscaling. It introduce**s** a hybrid Generalised Linear Model (GLM) and an Artificial Neural Network (ANN) novel approaches to downscale the coarse resolution of global climate model to the finer spatial scales. The reason for combining the two techniques is that ANNs when traditionally used in downscaling rainfall was found to be inadequate in reproducing daily observed rainfall as previously outlined. This weakness is circumvented here by using GLM to simulate the rainfall occurrence and then employing the occurrence model to resample the observed rainfall before using the ANN, which is trained with the Levenberg-Marquardt algorithm, to model rainfall amounts. The Levenberg-

Marquardt algorithm is considered more efficient and more skilful than the usual feed forward neural network training algorithm of steeper decent (MATLAB User guide, 2010).
GLM has been previously applied to model climatic variable series in a number of studies for the modelling of rainfall occurrence and was found to have a satisfactory performance (e.g. Chandler and Wheater, 2002; Fealy and Sweeny, 2007; Kenabatho et al., 2008; Chun, 2010). Performance of the hybrid GLM-ANN introduced in this paper was then examined and compared with traditional ANN and other two regression methods of downscaling to explore its usefulness.

Study Area & Data Collection

The study selected three stations in the North West of England (NW) which represent various climatic regions (the north, middle, and the south), as shown in Figure 1. The exposure of the NW region to westerly maritime air masses and the presence of extensive areas of high ground mean that the region is considered as one of the wettest places in the UK. The average annual rainfall in the highest parts of the Lakes District is over 3200mm, in contrast to Manchester where the average annual rainfall is only 860mm (Met office web site, 2010). Two principal data sets were employed during the calibration and validation of the daily precipitation models. Firstly, the observed daily rainfall data set, collected from three stations in the North West of England (see Figure 1), was obtained from the Environment Agency for England & Wales, for the period 1961–2001. Secondly, the large-scale observed climatic predictors data set was obtained from the National Centre for Environment Predictions (NCEP/NCAR). Originally at resolution of 2.5^0x2.5^0 degrees, this data was regridded to confirm to output of the GCM models. The two sets of data were needed to build the downscaling model for each station.

GCM data were obtained from the Canadian Climate Impacts Scenarios Group website, for three different GCM models: Hadley Centre (HadCM3) model, Canadian Centre for Climate Modelling and Analysis (CCCma) (CGCM2) model and Commonwealth Scientific and Industrial Research Organization (CSIRO Mark2) model for A2 and B2 emissions scenarios. All the modelled datasets exist on a common grid resolution, total of 2.5^0x 3.75^0 degrees, and were obtained for the two grids boxes (Scottish Border, SB, and North Wales, NW) representing the studied catchments in the GCM domain.

Methodology

In the GLM-ANN model the methodology broadly follows a two staged approach, which are relating to occurrence**s** and amount**s** of rain associated with wet days, to model daily rainfall. First, in this model is screening for rainfall predictors from very large NCEP climate variables at grid points. Second, is building the downscale models for rainfall occurrence and amount (including resampling scheme) using the GLM and ANN techniques, respectively (see Figure 2).

In the coming paragraphs, brief descriptions for how each step in the above mentioned methodology was implemented in this study for GLM-ANN.

Predictors Screening

For the downscaling predictand, the selection of appropriate predictors is one of the most important steps in a down-scaling exercise. It would generally not be useful to include all of the potential predictors in a final model. This is because the predictor variables are almost

always mutually correlated, so that the full set of potential predictors contains redundant information (Wilks, 1995).
The predictors - rainfall relations in this research are formed based on correlation coefficients between them. The predictors, which come from NCEP data, are then selected from a range of candidate predictors based on the significance and strength of their correlation with the predictand.

Stepwise regression is applied for the selection process as it yields the most powerful and parsimonious model as has been shown by previous studies (Huth, 1999; Harpham and Wilby, 2005). The stepwise regression is the most sophisticated of the statistical methods used for predictor selection. Each variable is entered in sequence and its value assessed. If adding the variable contributes to the model then it is retained, but all other variables in the model are then re-tested to see if they are still contributing to the success of the model. If they no longer contribute significantly they are removed. Thus, this method should ensure the smallest possible set of predictor variables is included in the resulting model (Al-Subaihi, 2002; Goyal and Ojha, 2010).

The screening process was achieved by forming a stepwise regression between the rainfall occurrence series and predictors. In order to remove any inconsistencies associated with the presence of small rainfall values, a threshold of 0.3mm was applied to the data as rainfall values less than this threshold are considered to be dry days and represented with zero. Those equal to or greater than the threshold were considered wet days and represented with one to form a series of binary values for the occurrence of rainfall. The threshold of 0.3 mm/day to treat trace rain days as dry days and that due to the heavy rainfall was recommended by many studies in the North West, for example Wilby et al., (2003).

The pool of predictors used in this study were daily values of 26 variables comprising surface pressure, temperature and humidity as well as upper air measures of wind speed and direction, vorticity, divergence, humidity, temperature and geo-potential height.

Rainfall Occurrence Model
Logistic regression is one of a large class of generalised linear models (McCullagh and Nelder, 1989) with an error distribution belonging to an exponential family. It is often used to model the probability of rainfall occurrence as a function of predictors (atmospheric variables) in statistical downscaling applications.

In the present study logistic regression has been employed to model wet and dry sequences of rainfall at a single site. The description of logistic regression below is given by Chandler and Wheater (2002).

Let p_i denote the probability of rain for the ith case in the data set, conditional on the covariate vector X_i' ; then the model is given by

$$\ln\left(\frac{P_i}{1-P_i}\right) = X_i'\beta \qquad (1)$$

This can be rewritten in terms of odds rather than log odds as,

$$\left(\frac{P_i}{1-P_i}\right) = e^{X_i'\beta} \qquad (2)$$

where,

e = base of the natural logarithms
β = coefficients estimated from the data
As a general result of the properties of the exponential family distribution, the maximum likelihood estimator of GLMs can be found robustly using the Newton-Raphson algorithm (Chun, 2010).
The reason for using the GLM to model the rainfall occurrence is that the logistic regression approach offers a significant improvement over the general multiple linear regressions as the distribution of errors is normally distributed, and additionally, the predicted values can be interpreted as probabilities which ensures that p_i lies in the interval between 0 and 1 (Fealy and Sweeny, 2007 and Annette and Barnett, 2008). To test the performance of the occurrence model, the Percent Correct (PC) and Heidke Skill Score (HSS) indices proposed by Wilks (1995) are used as a check for the Bias (B). These indices can be obtained from a 2x2 contingency table (Table 1) derived from the observed and modelled outcomes of the rainfall binary series (Weather Forecasting On-Line, 2010) as,

$$\mathrm{PC} = (\mathrm{a} + \mathrm{d})/\mathrm{n} \tag{3}$$

PC ranges from zero (0) for no correct forecasts to one (1) when all forecasts are correct.

$$\mathrm{HSS} = 2(\mathrm{ad} - \mathrm{bc})/[(\mathrm{a} + \mathrm{c})(\mathrm{c} + \mathrm{d}) + (\mathrm{a} + \mathrm{b})(\mathrm{b} + \mathrm{d})] \tag{4}$$

HSS = 1 for a perfect forecast; HSS = 0 shows no skill. If HSS < 0, the forecast is worse.

$$\mathrm{B} = (\mathrm{a} + \mathrm{b})/(\mathrm{a} + \mathrm{c}) \tag{5}$$

If B =1 (unbiased), if B >1 (over forecast), if B <1 (under forecast).

Where a, b, c, and d as defined in Table 1.

Rainfall Amount Model
A multi-layer feed forward artificial neural network (MLF-ANN) model was used to build a non-linear relation between the observed rainfall amount series and the same selected set of climatic variables (predictors) used for the rainfall occurrence model. The rainfall series used to calibrate this model was re-sampled using the derived occurrence model, some of which may return zero amounts despite the fact that the original series of rainfall indicate a wet day.

Figure 3 shows a representation of the neural network diagram with inputs X_1 to X_8 and outputs Y_1 that are used in the present study.

The number of neurons in the input and output layers is determined by the number of elements in the external input array and output array of the network, respectively. Determination of the appropriate number of neurons in the hidden layer is important for the success of the neural network model and the best strategy for selecting the appropriate number is by trial and error (Hammerstorm, 1993). The network learns by applying a back-propagation algorithm, which compares the neural network simulated output values to the actual values and calculates a prediction error. The error is then back propagated through the network and weights are adjusted as the network attempts to decrease the prediction error by optimising the weights that contribute most to the error. One problem with neural network training is that, if the network over learns the training data, it is more difficult for the network to generalise a data set that was not seen by the network during training. Therefore, it is common practice to divide the data set into a learning data set which is used to train the network, a test data set that is used after the training terminates, and a validation data set that is used to test network performance.

This training process would take longer if the usual back-propagation algorithm of conjugate gradient is used. To avoid this, the 10 to 100 times faster back-propagation algorithm of Levenberg-Marquardt (Yadav et al., 2010) was used, which was designed to speed up the training process.

To highlight the differences between the improved hybrid model developed in this study and the traditional ANN model, another rainfall model for traditional ANN is built for each station. One staged approach is usually adopted, includes screening for rainfall predictors from very large NCEP climate variables and building the rainfall amount model using the ANN technique (no resampling scheme is employed here). Additionally, multiple linear regressions (MLR) and Poisson Regression (PR) models have also been developed using the same steps followed in developing the traditional ANN model. Results from the three different modelling techniques are then compared with the hybrid GLM-ANN to explore the modelling capabilities of the GLM-ANN.

In the present study, MATLAB 7.11 software has been utilised to model all the methods. The model which performed better was then used to project future rainfall at three stations for winter and summer seasons.

Future Model

The developed hybrid GLM-ANN was then used to simulate seasonal future rainfall for corresponding wet days obtained from the occurrence model using a set of input variables generated by global circulation models (for a specific scenario emission) as predictors (this set corresponds to the NCEP predictors used in building the downscaling model).

To avoid bias that may occur from using GCM variables to simulate future rainfall, correction for future rainfall (Rcf) is usally required. The correction is proposed here to be carried out by multiplying the furture rainfall produced by the hybrid GLM-ANN model $\mathrm{Rsim}_{\mathrm{fut}}$ for A2 and B2 scenarios with a ratio of the mean observed rainfall ($\mathrm{Mean}_{\mathrm{ob}}$) and the mean simulated rainfal ($\mathrm{Mean}_{\mathrm{sim.control\ run}}$) of the control period (1961-1990). This method of correcting future rainfall is called the Scaling (or Direct Approch) Method (Maraun et al., 2010). It can be expressed in mathematical terms as:

$$\mathrm{Rcf} = \mathrm{Rsim}_{\mathrm{fut}} * (\mathrm{Mean}_{\mathrm{ob}} / \mathrm{Mean}_{\mathrm{sim.control\ run}}) \qquad (6)$$

The scaling method used here assumes that bias ratio of the control period is the same as that in the future.

Results and Discussion

Calibration and Performance of Downscaling Models

Table 2 shows the set of predictors which have been selected, based on the strength of their correlation with rainfall, for winter and summer seasons in each of the three catchments. Definitions of each of the predictors that appear in Table 2 are given in Table 3. It can be observed from the data in Table 2 that the lag forward and exponential transformations were used in some predictors because they produced better correlation with the observed rainfall.

The most dominant predictors for the rainfall in all stations, for both seasons, are relative humidity (rhum), vorticity (p_z) at surfaces, 500hp and 850hp levels, and surface meridional velocity (p_v). The vorticity (p_z at different levels) tends to be the most important predictor (judged by its strong correlation with rainfall in all stations). This is consistent with findings of studies carried out in this region by Harpham and Wilby (2005) and in Conway et al. (1996). Zonal velocity (p-u) at 850hp and mean sea level (msl) are ranked second in terms of dominance for both seasons. Surface air flow strength (p_f) at 500hp and 850hp level predictors are associated with Tower Wood (TW) and Worleston(WR) stations only. **S**urface divergence (p_zh) has been selected for TW and Worthington (WN) but not for WR, as no significant correlation was found. Near surface specific humidity (shum) and geopotential hight (p_gh) at 500hp and 850hp appear to be dominant at Worthington and WR in the winter season only. Generally, 8 predictors have been found more suitable in predicting rainfall occurrence and amount at all stations, as dictated by the correlation coefficient of the stepwise regression model.

The seasonal occurrence model for each station has been calibrated and validated using daily rainfall data for a 27 year (1961-1987) period and a 14 year (1988-2001) period, respectively. Daily data of selected predictors and predictand (occurrence binary series) for these periods were used to build the occurrence model employing a generalised linear modelling technique. An occurrence binary series is a series of 0 and 1 values. The value 1 is used if the day is wet (i.e. rainfall depth >= 0.3 mm/day); and a value of 0 is used if the day is dry (i.e. rainfall depth < 0.3 mm/day).

Table 4 shows the performance of the models in terms of the Heidke Skill Score (HSS) and Percent Correct (PC) indices, as well as their Bias (B). The indices results in Table 4 suggest that both of the TW seasonal models are more accurate than seasonal models of the other two stations. This is attributed to the nature of rainfall in the Lakes District as it is more frequent with high intensity. Longer rainfall series with higher intensity would usually result in a better calibrated occurrence model. However, this is not the case for the WN and WR stations as they are classified as relatively drier areas than the Lakes District. Results in Table 4 also confirm that all developed occurrence models are capable of predicting rainfall occurrence with sufficient accuracy as dictated by higher values of PC (> 70%) in both calibration and verification periods.

The resampled rainfall series produced by the occurrence models, developed in the previous step, and the predictors of Table 2, were used to build seasonal hybrid GLM-ANN models for the three stations. Concurrently, seasonal traditional ANN, MLR and PR models were developed for all stations. Rainfall values, in all set**s** of the developed models, were transformed by taking their forth root to normalise the distribution of the rainfall series and make it less skewed to low rainfall values. The whole wet days data set (1961-2001) has then been divided into three sets comprising training, validation and verification sets. Records in each set have been chosen randomly by the MATLAB fitting tool after setting the data percentage in each set.

The structure**s** of the neural networks used in building the models are shown in Table 5. It can be deduced from the network structures of Table 5 that the hybrid modelling approach employs a larger number of neurons in the hidden layer than the traditional modelling approach. This larger number of neurons in the hidden layer generally contributes to the accuracy of the model. This increased accuracy is brought to the hybrid approach by the use of a re-sampled rainfall series, as the number of wet days are increased in this case. In contrast, the traditional modelling approach network uses smaller numbers of neurons in the

hidden layer, and sometimes two hidden layers (as in the summer model, because one layer failed to give best fit for the model) and hence it leads to a less accurate model. The transfer functions used for both approaches were log-sigmoid for the hidden layer and linear transfer function in the output layer.
The efficiency and ability of each model to predict rainfall amount that best matched the observed rainfall are expressed here in terms of their correlation coefficient (R) and root mean square error (RMSE) and are presented in Figures 4 (a &b) and Figures 5(a &b). The higher values of R and lower values of RMSE obtained by models built using the hybrid GLM-ANN approach indicate that this modelling approach outperforms the traditional ANN model as well as the MLR and PR in downscaling the rainfall amount. The GLM-ANN and traditional ANN modelling approaches performed better in the winter than in the summer for all stations. The main reason for the difference in performance between the hybrid and the other models is the inclusion of the rainfall occurrence process with resampling scheme when building the hybrid GLM-ANN model and hence it becomes superior to the traditional ANN. MLR and PR models show poor performance in terms of R values, which is below 0.5 for some location.

Figures 6 to 8 (a, b) show the inter-annual variability for the three stations, between the observed and simulated series for winter and summer for the period 1961-2001 (calibration and verification periods). The average yearly values would appear to have been adequately captured by the GLM-ANN model better than the other three models with the PR model tends to be also better for TW and WN. Therefore these results demonstrate that the hybrid model is more reliable in reproducing the observed rainfall which is an important requirement when assessing climate impacts on hydrological systems.

A standard two-sample z-test (for a large sample) on the differences in seasonal mean of the simulated rainfall between the hybrid, the traditional ANN, MLR and PR models shows that the discrepancy in the mean was statistically significant at the 5% level of significance for winter and summer at all stations.

Another demonstration of the hybrid approach in terms of superiority over the traditional ANN and the other two approaches is the comparison for their closeness of variability in simulated rainfall to the observed variability. Figures 9a and 9b show comparative plots of the standard deviations of the observed and simulated daily rainfall amount obtained by the winter and summer models, respectively. All models underestimate the variability in the observed rainfall (judged here by the falling of all markers below the straight diagonal line) for winter and summer.

In the plots for the winter and summer models (see Figures 9a & b), it can be seen that results for winter are better than in summer. The hybrid model appears to capture the standard deviation (and hence the variability) of the observed rainfall better than the other three models for both seasons (judged here by the closer proximity of the diamond markers from the straight diagonal line than the square ones).

The seasonal biases in standard deviations of observed and simulated daily rainfall amounts were up to 50%, 58% and 61% for the traditional ANN models, compared with 37%, 27% and 32% for the GLM-ANN model in winter for TW, WN and WR stations respectively. In summer the traditional ANN returned biases of 47%, 65% and 62% compared with 36%, 47% and 55% for GLM-ANN at the three stations. For MLR and PR models the bias is relatively close to the traditional ANN model.

Figures 10a and 10b also compare the lag-1 autocorrelations for which the traditional ANN and hybrid GLM-ANN models show consistent over-estimation, which is attributed here to the explicit autoregressive mechanism associated with ANNs (Harpham and Wilby, 2005). The MLR and PR models show less performance with overestimating the lag-1 autocorrelations. In comparison the GLM-ANN model provides better skills due to the stochastic component of the simulated rainfall amounts when the re-sampling scheme is used.

Another diagnostic test for reproduction of rainfall values, is a plot of quantiles of observed versus simulated values as can be seen in Figures 11a, 11b, 11c, 11d, 11e and 11f. The figures show the quantile-quantile plot at all locations for years 1961-2001 (calibration and verification periods). At all locations, it can be observed that the GLM-ANN model follows the 45^0 line better than the other three models for all rainfall values in winter and summer, suggesting that the GLM-ANN model is closer to the observed rainfall distribution. A winter extreme rainfall is better represented by the GLM-ANN model. For the summer, there are some outliers for extremes amounts obtained by the GLM-ANN model; however, the model still has good performance compared to the other three models. In general the low rainfall amounts are better simulated than the extreme values by the GLM-ANN model.

Anticipated Future Rainfall Changes in North West of England

Having calibrated the seasonal models for daily rainfall in the three rainfall stations, the derived GLM-ANN models were then used to produce scenarios of changes in rainfall based on scenarios A2 and B2 obtained from outputs of three GCMs models for three future periods (the 2020s, 2050s, and 2080s). While uncertainties arising from the derived models were not accounted for, GCM and emissions uncertainties could be tentatively approached by employing a number of GCMs. The results also highlight the importance of using multiple GCMs when conducting climate change research, as the magnitude of change can be vastly different between GCMs and in some cases even different in direction.

The results depicted in Figures 12 to 14 (a, b, c) are comparisons of the seasonal change in rainfall amount obtained by the hybrid model. The percentage change at each station is represented as the difference between the future time period of interest and the model control period for different GCMs. The downscaled data from HadCM3, CGCM2 and CSIRO GCMs suggest that there could be an increase or decrease in winter rainfall at these stations. In winter, TW is expected an increase by the 2020s as predicted by CGCM2 and CSIRO with a very slight decrease as predicted by HadCM3 for scenarios A2 and B2. In the 2050s TW is projected to have an increase in winter rainfall as predicted by all GCMs for both scenarios A2 and B2. However, in the 2080s, an increase is predicted for scenario B2 by all GCMs and for scenario A2 by the HadCM3 only. For WN there would be an increase in winter rainfall as predicted by the CGCM2 and CSIRO GCMs for all future periods under scenarios A2 and B2, except the predictions by HadCM3 which indicate a decrease in rainfall in the 2020s and 2050s under scenario B2. Results for WR stations show that winters will be wetter in the future as projected by the HadCM3 and CSIRO GCMs, but there would be a significant drop in rainfall during summers, especially under scenario B2.

The summer months are the only period in which all GCM models agree that there will be a decrease in rainfall, but the magnitude of this decrease varies among the GCMs.

Conclusion

This paper presents initial findings from a research programme investigating the downscaling of future rainfall amounts from GCMs under scenarios A2 and B2 which can be summarised in the following paragraphs.

Building the downscaling models - this included screening for suitable predictors from NCEP data to develop the occurrence and amount models. A hybrid GLM-ANN modelling approach was used to develop the seasonal rainfall downscaling models which utilised daily rainfall data from three stations in the north-west region of England.

The developed hybrid models performance and predictability were compared to those of other models developed for the stations with same data, but with the use of a traditional ANN, MLR and PR. The results demonstrated that the hybrid approach was found to be more efficient than the traditional ANN in modeling the rainfall amount (model efficiencies are 7 – 29% higher) and more capable of predicting rainfall series matching well with the observed data. It is also compared with other two models (MLR and PR) and the same outcomes have been obtained.

It is noted that the projected rainfall in the three stations have showed disagreements between different GCMs, which represent a significant source of uncertainty. Therefore, over-reliance on a single GCM is not appropriate for planning adaptation responses. Thus, future decision making should be based on use of multiple GCMs and scenarios to incorporate the underlying GCM and scenario, uncertainties.

The predicted future (for three periods, the 2020s, 2050s, and 2080s) change of seasonal rainfall for winter and summer in these periods were compared to those of the control or base period (1961-1990). Comparison of results has indicated that impacts of climate change on rainfall amounts are very significant in the studied region. Results show some increase in winter rainfall and a decrease in summer rainfall in some locations and that depend on the GCMs used and future period considered. The greatest increase in winter rainfall is 63%, which is predicted to occur at WN under scenario A2 and the maximum decrease in summer rainfall is 44% and is predicted to occur at WR under scenario B2. Both extreme predictions were obtained from the CGCM2 GCM in the 2050s.

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Table 1. Contingency table for possible outcomes of the occurrence model

		Observed		
		Yes	No	
Forecast	Yes	a	b	a+b
	No	c	d	c+d
		a+c	b+d	n = a+b+c+d

This table looks at four possible outcomes:

- Number of events which are forecasted and actually occurred (a)
- Number of events which are forecasted but not occurred (b)
- Number of events which are not forecasted but occurred (c)
- Number of events which are not forecasted and not occurred (d)

Table 2. Selected large-scale climate variables for winter & summer seasons at each station

Station	**Climate variable (predictor)**								
	P_u	P_z	mslp	rhum	P_f	P_v	P_zh	P_gh	shum
Tower wood winter	850(0)	(+1)	(exp)	(+1), 500(0)	850(+1)	(0), (+1)			
Tower wood summer		850(+1)	(+1)	(+1), 500(0), 850(0)	500 (+1)	(0)	(+1)		
Worthington winter	850(0)	(+1)		500(0)		(0), (+1)		850(+1) 850(0), 500(+1)	
Worthington summer		850(+1)	(exp)	(+1), 500(0), 850(+1)		(+1)	(0) (+1)		
Worleston winter	850(+1)	(+1)	(+1)	850(0), 500(0)	500 (+1)	(+1)			(0)
Worleston summer	850(0)	500(+1), 500(0), 850(+1)		(+1), 500(0), 850(0)		(+1)			

(+1) =Lagged forward, (exp) =exponential, (0) = no transformation

Table 3. Predictors definition

Code	**Variable**
p_u	zonal velocity
p_z	surface vorticity
mslp	Mean sea level pressure
rhum	Near surface relative humidity
p_f	Surface airflow strength
p_v	Surface meridional velocity
p_zh	Surface divergence
p_gh	Geopotential height
shum	Near surface specific humidity

Table 4. Percent correct (PC), Heidke skill scores (HSS) and Bias for the winter-summer rainfall occurrence models for both calibration (1961–1987) and verification (1988–2001) periods for Hybrid model.

Station	**PC**		**HSS**		**Bias**	
	Calibration	Verification	Calibration	Verification	Calibration	Verification
Tower Wood winter	0.83	0.86	0.66	0.69	1.03	1.01
Tower Wood summer	0.80	0.81	0.61	0.97	1.00	1.00
Worthington winter	0.81	0.81	0.60	0.61	1.00	1.06
Worthington summer	0.78	0.77	0.56	0.54	1.0	1.08
Worleston winter	0.77	0.78	0.55	0.56	1.01	1.14
Worleston summer	0.78	0.80	0.54	0.58	0.94	0.97

Table 5. Structure of ANN used in Hybird & TraditionalANN Model

Model	**Hybrid (GLM-ANN)**	**Traditional (ANN)**
Tower Wood winter	8-29-1	8-6-1
Tower Wood summer	8-34-1	8-6-1
Worthington winter	8-30-1	8-9-1
Worthington summer	8-30-1	8- 4,3-1
Worleston winter	8-37-1	8-7-1
Worleston summer	8-17-1	8-13,3-1

Table 6. Functions of MATLAB Rb2010.V.11used in the four downscaling methods

Model	**Code or Function**
Hybrid (GLM-ANN):	
GLM	glmfit(binomial), glmval (logit)
ANN	Trainlm
Traditional (ANN)	Trainlm
MLR	regstats
Poisson	glmfit(Poisson), glmval (log)

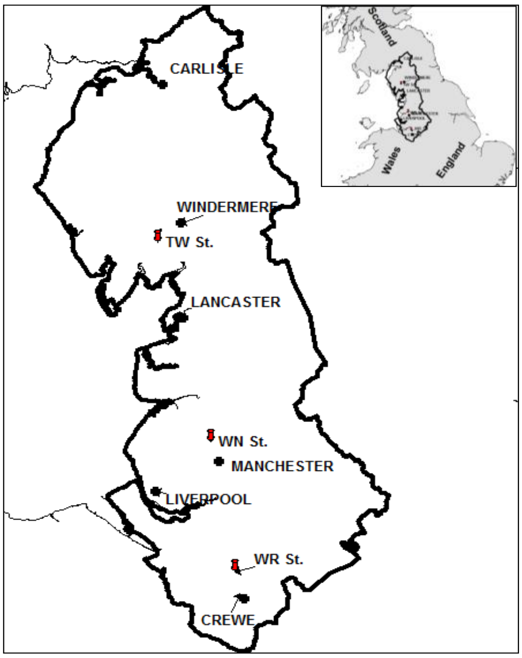


Figure 1 Three Rainfall gauges in the Study Area in North West of England.TW (Tower Wood), WN (Worthington), WR (Worleston)

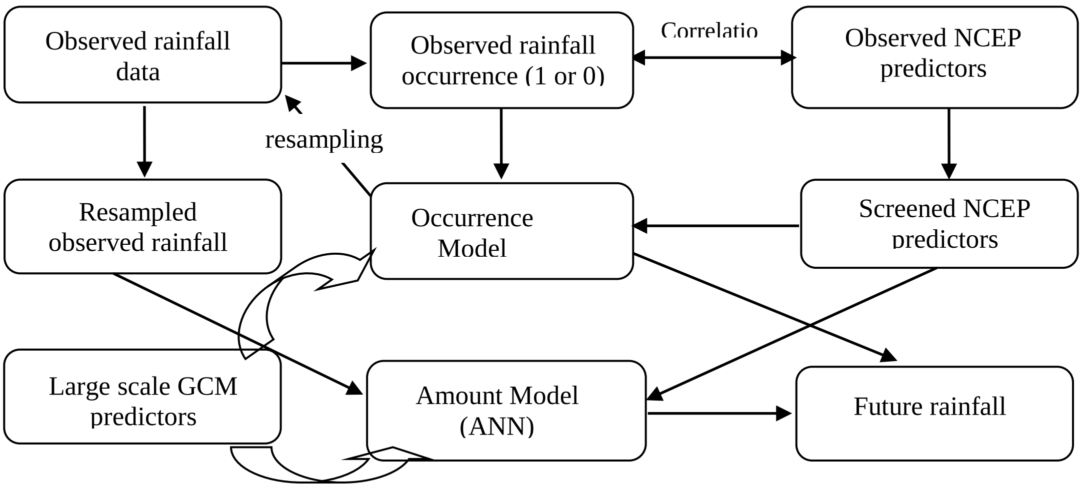


Figure 2 A flow chart illustrating the downscaling procedure with Hybrid GLM-ANN

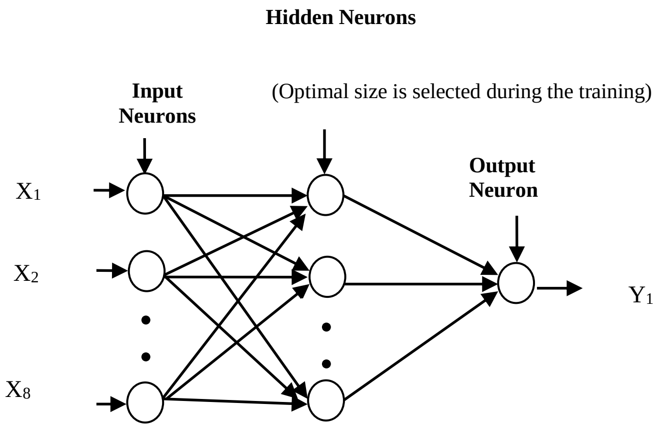
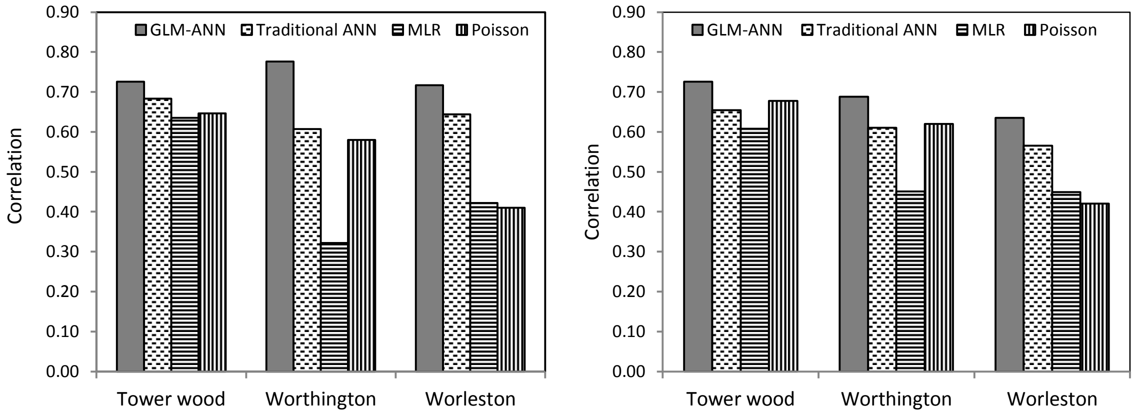
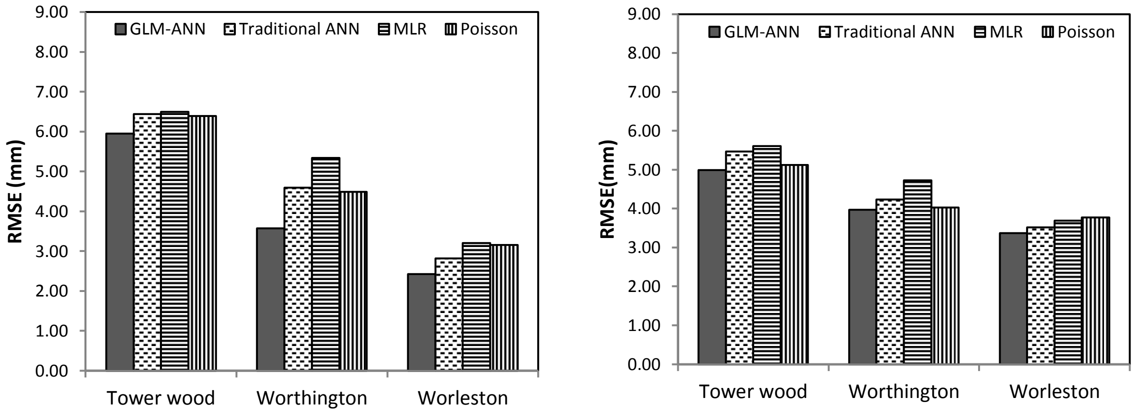


Figure 3 Feed forward neural network model



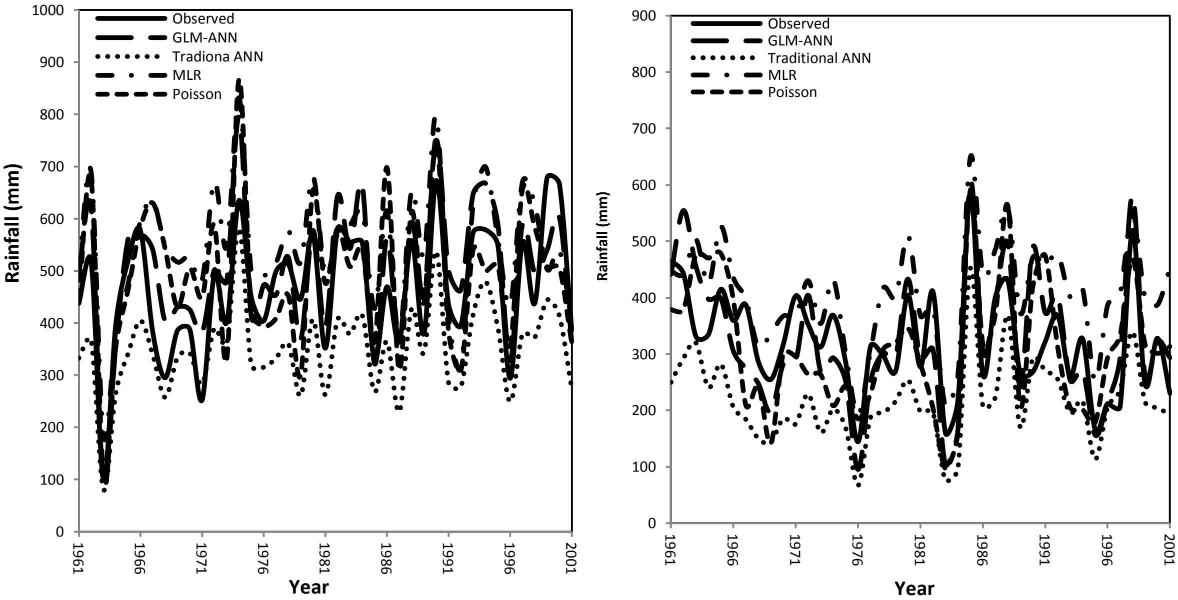
(a) **(b)**

Figure 4 Correlation coefficients between observed and simulated rainfall amount modeled by the four downscaling methods during calibration and verification periods (1961-2001) at the three stations for winter (a) and summer (b)



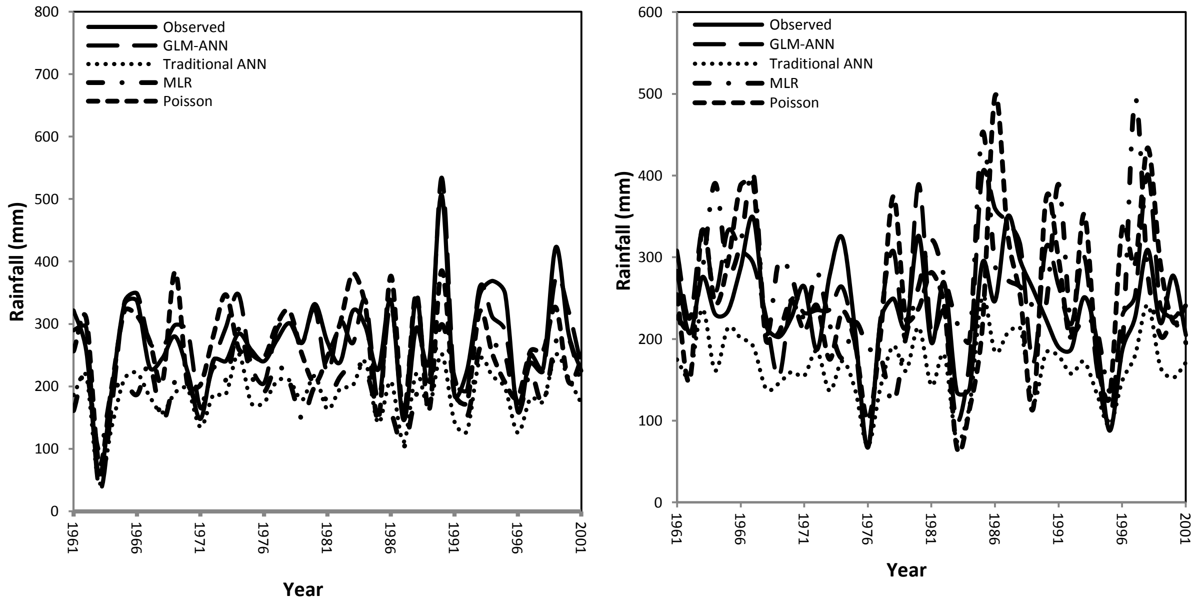
(a) **(b)**

Figure 5 Root Mean Square Error (RMSE) of rainfall amount model by the four downscaling methods during calibration and verification periods (1961-2001) at the three stations in winter (a) and summer (b)



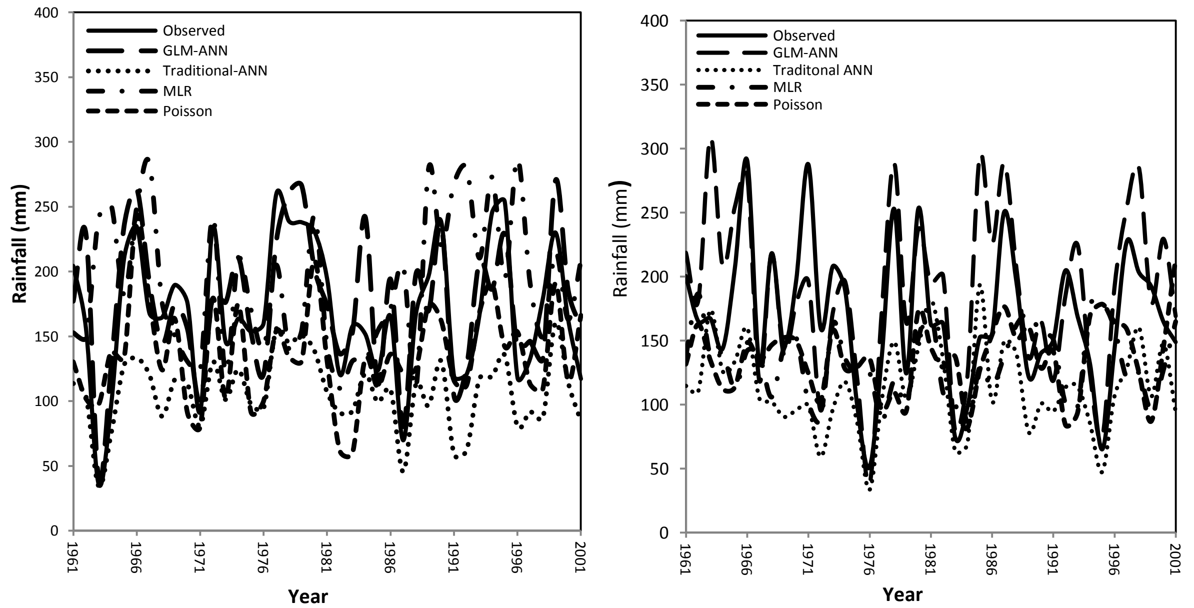
(a) **(b)**

Figure 6 Inter-annual variability for observed and modeled winter (a) and summer (b) rainfall for the four methods for TW during calibration and verification periods (1961-2001)



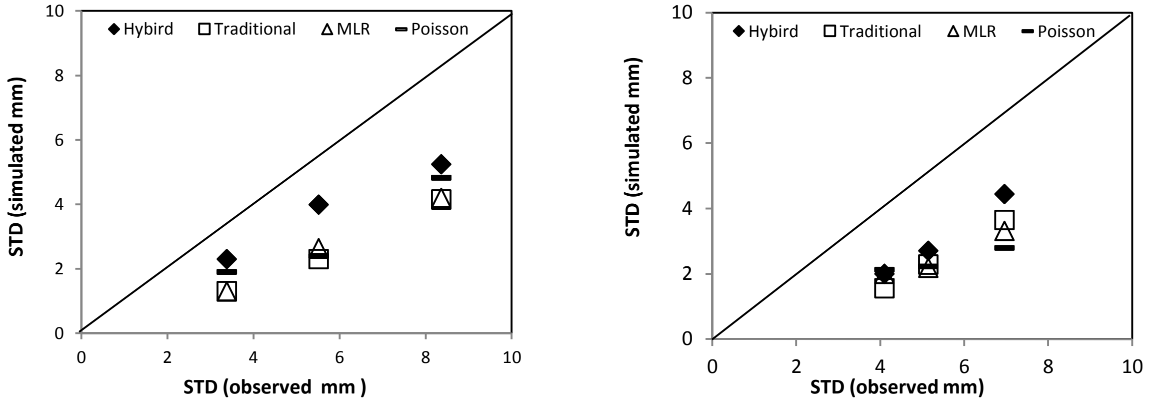
(a) **(b)**

Figure 7 Inter-annual variability for observed and modeled winter (a) and summer (b) rainfall for the four methods for WN during calibration and verification periods (1961-2001)



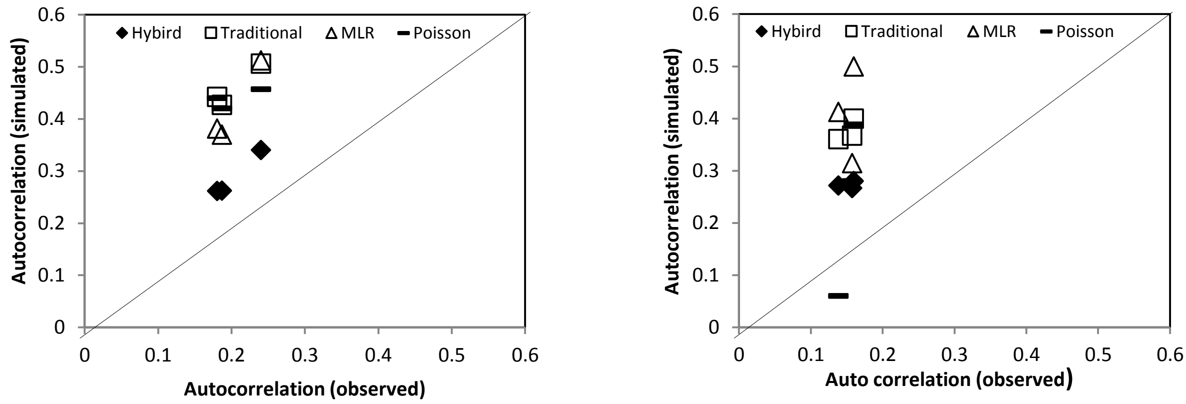
(a) **(b)**

Figure 8 Inter-annual variability for observed and modeled winter (a) and summer (b) rainfall for the four methods for WR during calibration and verification periods (1961-2001)



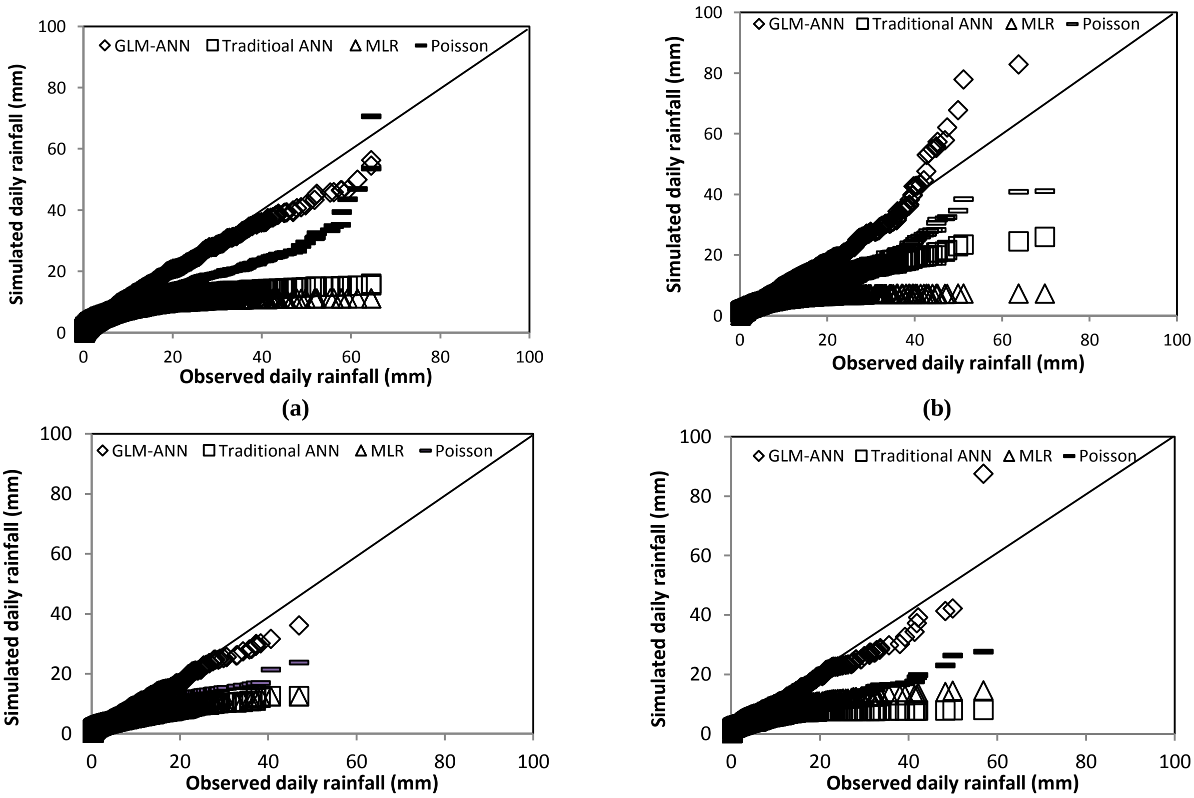
(a) (b)

Figure 9 Standard deviation for the three stations in the winter (a) &summer (b) seasons during calibration and verification periods (1961-2001)

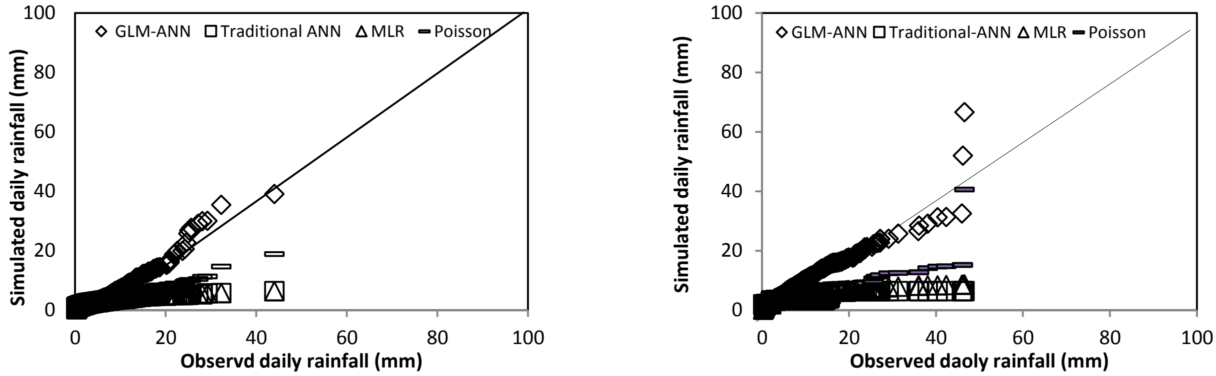


(a) (b)

Figure 10 Autocorrelation for the three stations in the winter (a) &summer (b) seasons during calibration and verification periods (1961-2001)

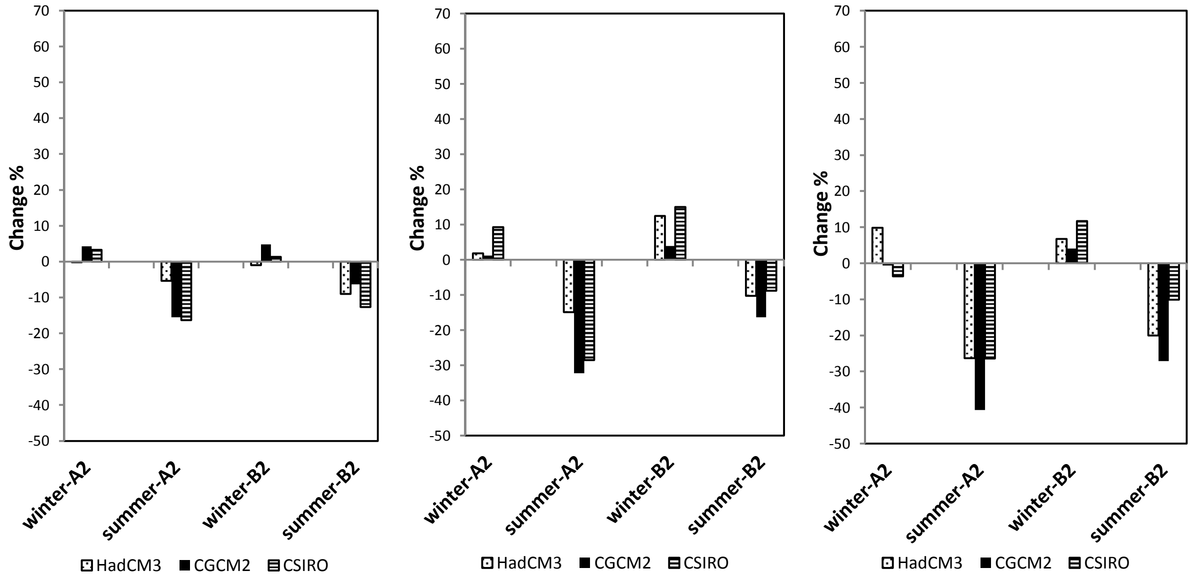


(c) (d)



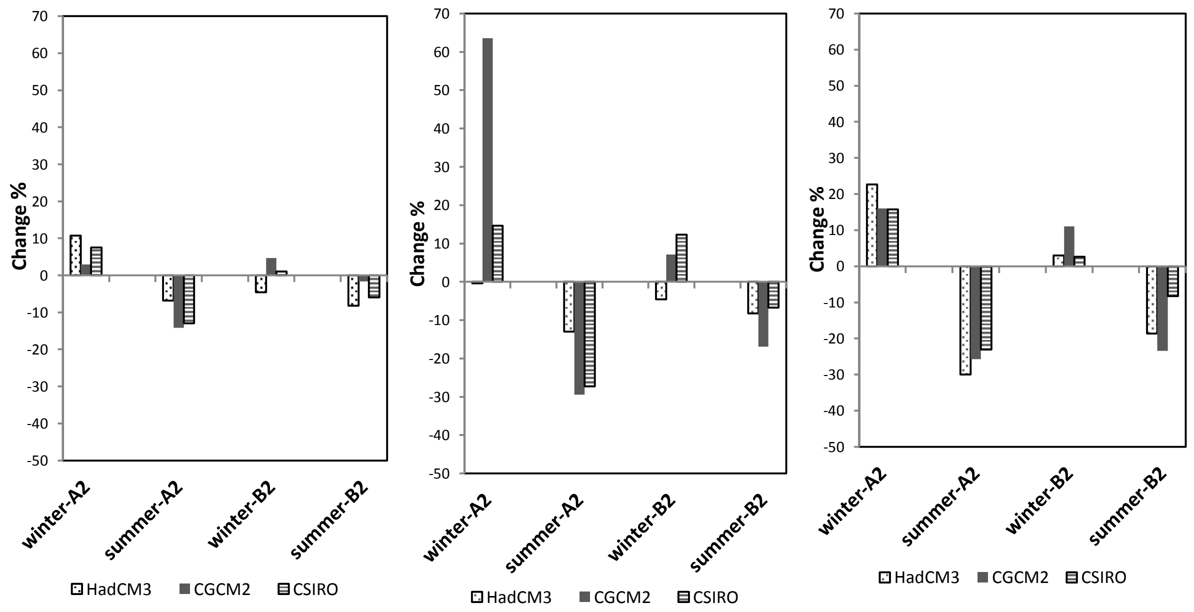
(e) (f)

Figure 11 Quantile – Quantile plot of daily rainfall for year 1961-2001 (calibration and verification periods) using the four downscaling methods for TW winter &summer (a and b), WN winter&summer (c and d) and WR winter& summer (e and f)



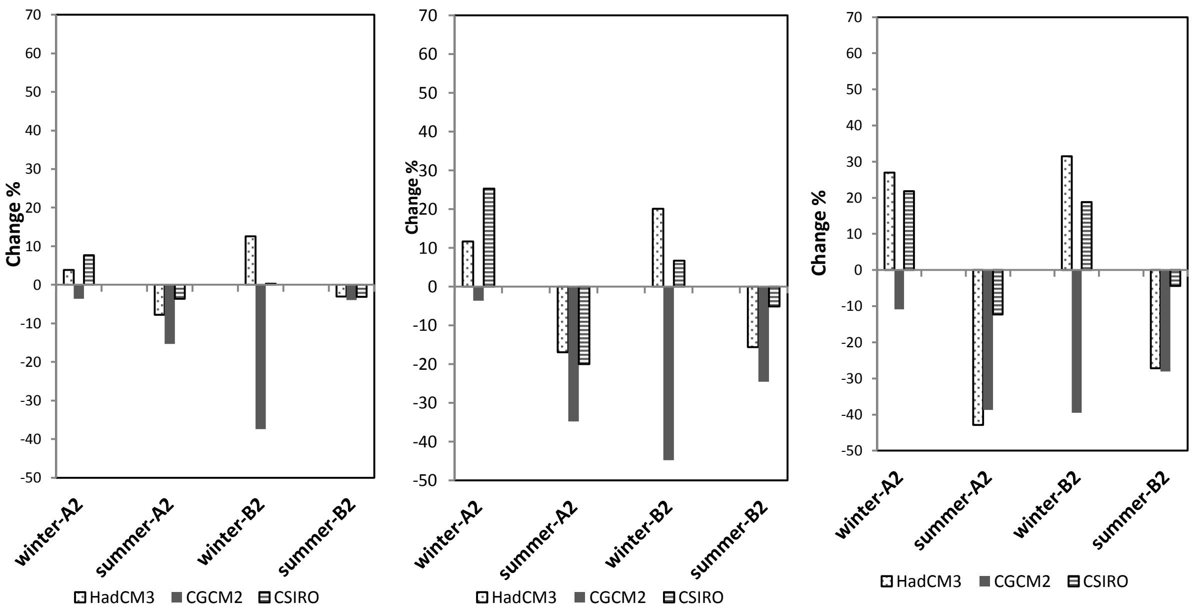
(a) (b) (c)

Figure 12 Seasonal rainfall changes for future period 2020s (a), 2050s (b) and 2080s(c) relative to 1961– 1990 years for A2 & B2 emission scenarios (TW)



(a) (b) (c)

Figure 13 Seasonal rainfall changes for future period 2020s (a), 2050s (b) and 2080s(c) relative to 1961– 1990 years for A2 & B2 emission scenarios (WN)



(a) **(b)** **(c)**

Figure 14 Seasonal rainfall changes for future period 2020s (a), 2050s (b) and 2080s(c) relative to 1961– 1990 years for A2 & B2 emission scenarios (WR)