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Comparison of MLP-ANN Scheme and SDSM as Tools for Providing Downscaled Precipitation for Impact Studies at Daily Time Scale

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Abstract

Statistical downscaling has become an important part in most of the watershed scale climate change investigations. It is usually performed using multiple regression-based models. Basic working principle of such models is to develop a suitable relationship between the large scale (predictors) and the local climatic parameters called predictands. The development of such relationships using linear regression becomes very challenging when the local parameter to be downscaled is complex in nature such as precipitation. For this reason, use of nonlinear data driven techniques including Artificial Neural Networks (ANNs) is becoming more and more popular. Therefore, an attempt has been made in the study presented here to introduce a new Multi-Layer Perceptron (MLP) ANN-based scheme to develop a robust predictors-predictand relationship to be used as a downscaling model at daily time scale. The efficiency of this model has been compared with a popularly used model called Statistical Down Scaling Model (SDSM), for daily precipitation at the Clutha watershed in New Zealand. The results show that the model developed based on ANN scheme exhibits better performance than the SDSM. Hence, it is concluded that the use of artificial intelligence techniques such as ANN can greatly help in developing more efficient predictor-predictand models for even for precipitation being the toughest climate variable to model

Keywords: Parameters; Hydrological; Neurons; Statistics

Introduction

Global Climate Models (GCMs) are recognized as the most sophisticated tool for producing global scale climate change projections but have limited suitability for regional scale hydrologic impact assessment studies [1,2]. This is because spatial resolution of the GCMs is still too coarse to provide reliable information of local/regional scale climatic variables, especially daily precipitation. Hence, assessing hydrological impacts of climate change requires preprocessing GCM information through the use of a suitable downscaling scheme to generate climate input for the hydrological model being used. There are two broad classes of downscaling that normally appear in literature i.e., statistical and dynamical, and a number of studies provide comprehensive reviews on these two classes such as [1,3-6]. Focusing on statistical downscaling methods, based on their working principle these are of three major types namely; weather generators, weather typing and transfer function or multiple regression [4,7]. Multiple regression based statistical downscaling techniques have been reported to be the most popularly used [8]. These involve the large scale climatic parameters (predictors) and the local variables (predictands; such as temperature and precipitation) and develop a suitable relationship between them, with or without the involvement of principle component analysis (e.g. Schoof and Pryor) and/or the canonical correlation analysis [9] as a data pre-processing technique to simplify the process of regression [10,11]. Owing to its highly stochastic nature, precipitation modelling is always a tough task. Therefore, simplistic, linear regression-based methods may underperform to find an efficient predictor-predictand relationship when the predictand is precipitation. In such situations, soft computing/artificial intelligence techniques have recently shown promise in non-linear regression for developing downscaling models. Artificial Neural Networks (ANNs) is one such option, becoming more and more popular [12-15]. Some more recent studies have presented the application of ANN for downscaling precipitation of a watershed, at monthly time scale [8,16].

The study presented here is an improvement over the existing similar work in multiple ways. Firstly, for downscaling daily precipitation at the Clutha watershed in New Zealand, a new nonlinear multiple regression model developed for this study based on Multi-Layer Perceptron (MLP) ANNs is presented here. Secondly, the modelling time scale of this study is daily which offers more advantage over monthly or seasonal scale that most very recent similar studies work on multilayer perceptron neural network for downscaling rainfall in arid region of Baluchistan [16]. Thirdly, the present study compares MLP-ANNs based model with a popular contemporary method known as Statistical Down Scaling Model (SDSM) in terms of developing a suitable predictor-predictand relationship. In this way, this study will contribute to benchmarking of ANN downscaling models against well-established regression based downscaling models which will help in achieving more efficiency and reliability in precipitation downscaling studies.

Study site and data

The study site for the modelling work presented here is the same as was described [17,18] i.e., the Clutha River watershed at Balclutha (river gauge) in the South Island, New Zealand (Figure 1). The obvious reason for this is availability of the required data to the authors due to their previous published work pertaining to this watershed. Also, as the Clutha River is the largest river by volume and the second longest river in New Zealand, it has a high national socio-economic value and any new scientific exploration for this watershed is considered important [17,18] provide greater details about the study watershed.

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Research Methodology

The structure of ANN used in the study is based on the MLP. The MLP of this specific study has been built up through a network of neurons as its computational elements, interconnected by connection pathways, arranged in a series of layers. In the MLP of this study, there are three neuron layers:

(i) The input layer;

(ii) The output layer; and

(iii) The hidden layer between the input and output layers.

The input layer receives the external input array in a way that each input element is assigned to only one neuron. In this study, the elements of the external input array are the same ten final selected predictors used for constructing a multiple linear regression model using SDSM [17]. This choice of the elements external input array facilitates comparison of like with like to the possible extent between SDSM and ANN. The input neuron conveys its external input without any transformation to each of the hidden layer neurons. Thus, each neuron in this hidden layer has an input array consisting of the outputs of the input layer neurons. Each hidden layer neuron produces only a single output which becomes an element of the input array to each neuron in the subsequent (output) layer. In the present study, as there is only one predictand (precipitation) therefore, the output layer has only one neuron, which produces the final network output in the form of daily precipitation time series. Similar to other studies [19] the optimum number of hidden neurons is found through a trial and error. For this study, it came out to be two (02) neurons beyond which no significant improvement was observed.

As reported by Fernando et al. [19], the process of input-output transformation is transfer function based and is very similar for both hidden and output layer neurons given in Eq. 1. It is basically a "non-linear transformation of the total sum of the products of each of its input array elements with its corresponding weight plus a constant term".

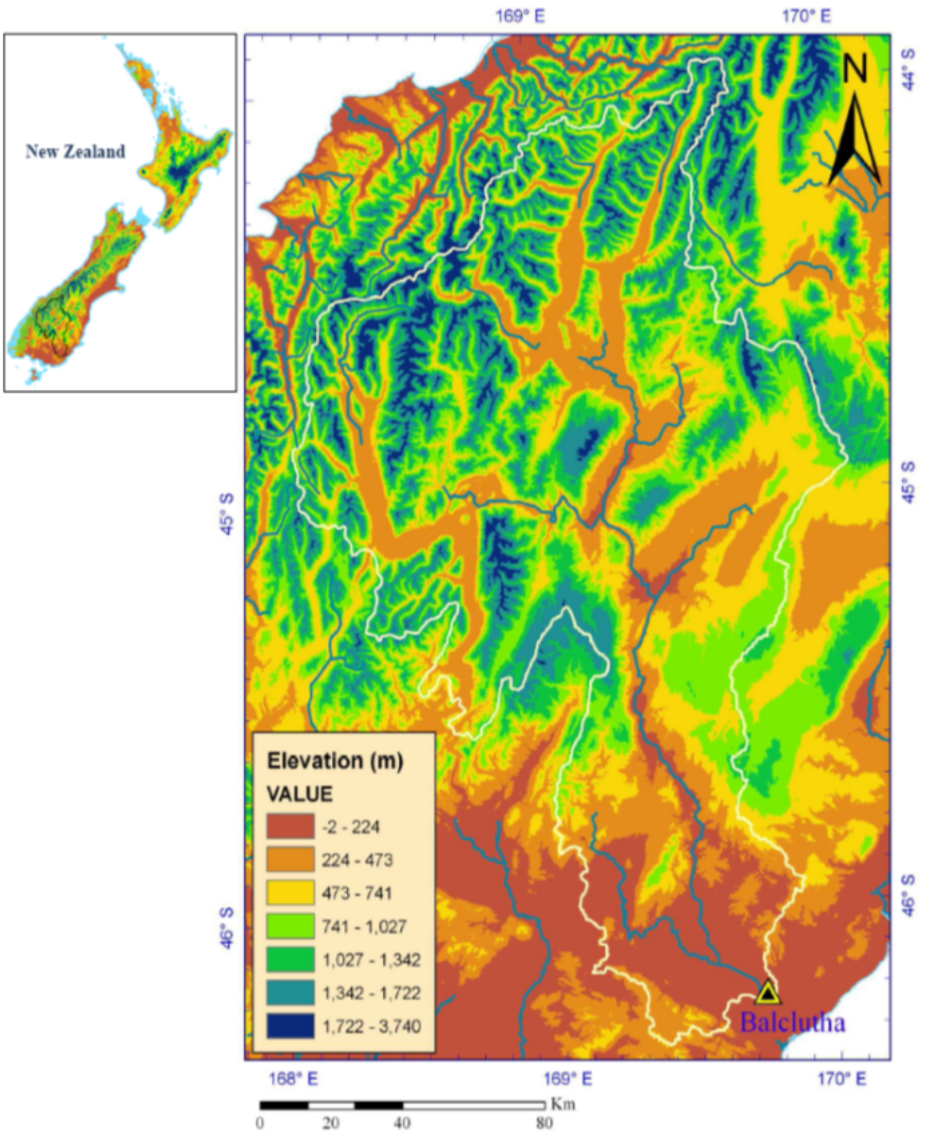

Figure 1: Study area map showing topographic variation [17,18].

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The weights and the threshold values are basically parameters of the network, which are estimated by calibration/training. This calibration process is achieved by minimizing the least squares objective function using non-linear optimization algorithms [19].

As explained in comparison of two data-driven approaches for Daily River flow forecasting [19], the transfer function used in conjunction with neurons in the hidden and the output layers is the hyperbolic tangent function. The function has an 'S' shape and its range varies between -1 and 1, which implies that the estimated network output values are likewise bounded within this range (-1,1). As the actual observed precipitation values are usually outside this range, rescaling of these precipitation values is required in order to compare the actual observed precipitation and the final output time series of the network. In the present study, linear scaling is adopted.

$$R_a = \Phi_2 \sum k = 11 W_{kj} . \Phi_1 \left(\sum j = 15 W_{ji} . X(t) + B_1 \right) + B_2 \qquad (1)$$

where i, j, k = the input, hidden, and output layers, respectively; R_a = the areal rainfall (mm); $\Phi_1(\cdot)$ = the linear sigmoid transfer function of hidden layer; $\Phi_2(\cdot)$ = the linear sigmoid transfer function of output layer; W_{kj} = the connection weights between the hidden and output layers; W_{ji} = the connection weights between the input and hidden layers; X(t) = the time series data of input variables; B_1 = the bias in hidden layer; and B_2 = the bias in output layer.

In line with the similar studies [18], evaluation of the model performance was carried out based on the calculated values of two well-known statistics: (1) Root Mean Square Error (RMSE); and (2) Coefficient of Determination (R^2) between the observed daily precipitation data and the model simulated precipitation data for the training and testing data periods. The period of 1961 to 1990 was termed as model training period, which, in climate impact studies is conventionally taken as the baseline period. Also, such a long training period helps proper learning of the model which is considered essential for efficient working of an artificial intelligence scheme such as ANNs. Hence, after achieving satisfactory level of model training (highest R^2 and lowest RMSE), its efficiency was tested by inputing the data of 1991 to 2000 period (testing period).

To gauge performance of the ANNs based tested/validated model developed for this study, it was compared with the results of a previously published study by Hashmi et al. [17] for the SDSM downscaling model (a well-known and widely used linear regression based downscaling model) in terms of the values of the two statistics used for model performance evaluation (i.e., R^2 and RMSE) and observed versus simulated scatter plots. This is quite in line with the similar studies on introducing new downscaling model published earlier [18], Full details about the SDSM are available in the study of Wilby et al. [4].

Results and Discussion

As mentioned earlier, both the SDSM and the ANNs baed model used the same set of ten (10) large scale predictors in the calibration/training of their final models. Table 1 shows the full list of twenty-six (26) large scale predictors acquired for the study presented by Hashmi et al. [17]. The ten predictors used in the final SDSM model and the ANNs based model are shown in bold text in Table 1. Full description of each of the 26 predictors is available in the study of Hashmi et al. [17].

Model efficiency comparison of the ANNs based model and the SDSM model in terms of the values of RMSE and R2 is shown in Table 2 which reveals that the ANNs based model is more efficient than the SDSM model in both the calibration and the validation periods. It can be seen that the RMSE value obtained from ANNs based model is 5.070 as compared to 5.613 obtained for the SDSM for training/calibration. Likewise, R2 value for ANNs based model is 0.50 as compared to 0.39 for the SDSM for training/calibration. A similar trend has been observed for testing/validation. The higher level of the ANNs based model performance shows that it was able to detect, to a greater extent, the highly non-linear predictor-predictand relationship as compared to the SDSM model.

Figure 2 presents the comparison of the ANNs based model with the SDSM model by showing daily observed vs. daily simulated scatter plots. This figure is a further confirmation and elaboration of what was revealed by the numeric values in Table 2, i.e., better performance of the ANNs based model over the SDSM model. In terms of the overall

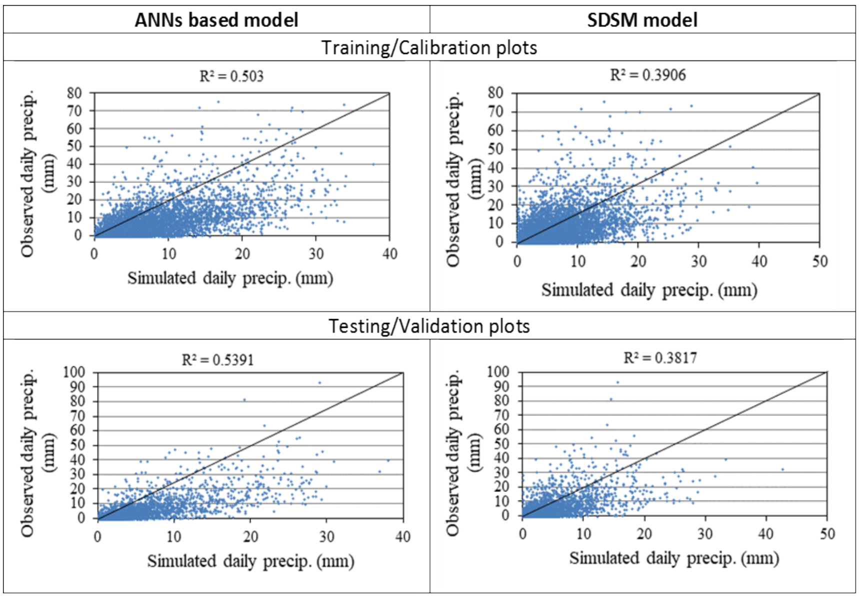

Figure 2: Comparison of ANNs and SDSM in terms of observed vs. simulated scatter plots.

S. No	Predictor Name	S. No	Predictor Name
1	ncepmslpaz	14	ncepp500az
2	ncepp5_faz	15	ncepp850az
3	ncepp5_uaz	16	ncepp__faz
4	ncepp5_vaz	17	ncepp__uaz
5	ncepp5_zaz	18	ncepp__vaz
6	ncepp5thaz	19	ncepp__zaz
7	ncepp5zhaz	20	ncepp_thaz
8	ncepp8_faz	21	ncepp_zhaz
9	ncepp8_uaz	22	ncepr500az
10	ncepp8_vaz	23	ncepr850az
11	ncepp8_zaz	24	nceprhumaz
12	ncepp8thaz	25	ncepshumaz
13	ncepp8zhaz	26	nceptempaz

Table 1: List of the NCEP reanalysis predictors used for model training/calibration [17,18].

Criteria	Simulation type	ANN	SDSM
RMSE	Training /Calibration	5.070	5.613
	Testing /Validation	5.180	6.033
R^2	Training /Calibration	0.50	0.39
	Testing /Validation	0.54	0.38

Table 2: Model efficiency comparison of the ANNs based model and the SDSM model in terms of the values of RMSE and R^2.

spread of obs-vs-sim scatter plots and spread around the diagonal line, the left column of Figure 2 (the ANNs based simulated data) has more agreement between the observed and simulated data than the right column.

Conclusion

The study presented in this paper aimed to explore the use of ANNs as a tool for downscaling daily precipitation for use in climate impact studies by comparing it with a widely used tool called the SDSM. To perform the modelling analysis required in this work, daily precipitation data of the Clutha watershed in New Zealand were used. Similar to previously published studies, the results of the SDSM modelling performed for the study presented [17] were set as a benchmark in order to analyse the performance of the ANNs based model fed with the same set of ten (10) predictor variables as were used in the final SDSM model [17]. Model comparison was performed by calculating and comparing the values of two widely used statistical parameters i.e., R2 and RMSE for the final SDSM and the ANNs based model and also by plotting the observed vs simulated scatter plots for both. Analysis of the results of this study reckons that the MLP-ANNs scheme can be used with confidence for developing a simple yet efficient predictors-predictand non-linear regression model that can be used for downscaling of daily precipitation for a watershed scale hyrological impact assessment study. Furthermore, by virtue of this study, the climate downscaling researchers are invited to broaden the exploration of similar artificial intelligence-soft computing techniques in the persuit of more efficient tools for climate downscaling (including precipitation) than the available lot [20,21].

Acknowledgments

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