Performance Evaluation of an ANN based Bias Correction algorithm in Monthly and Daily Precipitation Time Series of La Farge Station, USA

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Abstract
Understanding the change of future precipitation over long run is highly necessary in climate change impact studies. Mostly, simulated future precipitation series are found to be biased more with the historically observed precipitation series which need to be corrected before use for any impact studies. Many conventional and data-driven methods are available to correct this bias.

In this study, to bias correct the monthly and daily precipitation series, Artificial Neural Network based method is applied and compared with the conventional methods. The normalized root mean squared errors obtained for monthly and daily series are 0.786 and 2.55 respectively. It is found that the performance of ANN-based method is poor in daily series and good only in monthly series. The reason for poor performance in daily series is analysed. In addition, the superiority of ANN based method over conventional method is established in monthly precipitation time series.

Keywords: Artificial neural network, Bias correction, Simulated rainfall series, Climate change, Global circulation model.

Introduction

Owing to increased anthropogenic emission of green house gases, there is a change in the energy balance of earth's climate system which is called as climate change[23]. Rise of sea level, global warming and increase of heavy precipitation events are effectuated because of climate change.

The impact of climate change on various activities can be assessed by the simulated time series. Simulated time series is the output of Global Circulation Models (GCM) or Regional Circulation Models (RCM). Climate models are run based on the various scenarios given by Intergovernmental Panel on Climate Change (IPCC). Already many researchers have assessed the impact of climate change on different activities using simulated time series. For instance, Moriondo et al[14] studied the effect of climate change on the sunflower and wheat using the simulated temperature series. In addition, climate change impact on food, waterborne diseases, water quality, water resources, coast line were studied by various researchers[2,7,18,31]. Williems et al[30] discussed the challenges in assessing the effect of climate change on heavy precipitation.

The simulated series generated by climate models has biases. The under and over estimation of points in a time series or the deviation of the statistical structures such as average, variance, covariance, standard deviation of the simulated time series from the historically measured time series of the particular station are called as biases[26]. Hence, simulated series needs to be bias corrected before its use in any impact studies[4,6,22]. Otherwise, the assessment may have errors[1]. Rojas et al[16] strongly recommended to bias correct the series before its use in impact studies.

Many researches have proposed a new bias correction method. For instance, Pierce et al[15] proposed a new frequency reliant bias correction method to bias correct the simulated temperature and precipitation series of GCM. A new nesting bias correction method was suggested by Johnson and Sharma[10] to correct the biases, especially in the distribution of the series. To maintain physical consistency of series after bias correction, Sippel et al[19] proposed a new bias correction method. Switanek et al[25] proposed a new bias correction method which is conceptually alike the existing quantile delta mapping method. They also pointed out that the assumption of time invariant nature of bias correction values made in quantile mapping method is incorrect. Furthermore, many other works are there on proposing new bias correction algorithm[11,27-29].

Researches tried to improve the existing bias correction method. For example, the performance of an improved quantile mapping method demonstrated in the bias correction of the three different kinds of simulated series by Cannon[3] and Miao et al[12] proposed an innovative method which is a combination of two different type of quantile mapping method.

Lately, researchers started to investigate the success of data driven methods in the bias correction of simulated series. Sonkusare et al[24] bias corrected the output of climate forecast system model using Artificial Neural Network (ANN). Jin et al[9] used both: a machine learning technique and a conventional method to bias correct a simulated dust storm. They reported that the data driven method is best when compared to the conventional method. Moghim and Bras[13] used ANN technique to bias correct temperature and precipitation. In this, skin and air temperature, specific

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humidity and radiations were used to bias correct the temperature of 6 hour time step and previous 4 month data is used to bias correct the monthly precipitation.

Cho et al[5] bias corrected the minimum and maximum air temperature using four methods which included ANN technique also. Saravanan et al[17] developed a simple ANN based bias correction algorithm to bias correct the monthly precipitation time series of two stations located in Australia. They compared the performance of the ANN method with other conventional method and reported that the ANN method is good for the bias correction when compared with other conventional methods.

Sometimes, more than one bias correction methods are applied to bias correct a particular series to arrive at new knowledge by comparison. For example, Pierce et al[15] discussed about how GCM data was altered by various bias correction methods. Hoffmann and Rath[8] proposed a new method to obtain consistent bias corrected series of agricultural model and compared the results with the series bias corrected by conventional quantile mapping method.

Teutschbein and Seibert[26] compared the various bias correction methods such as linear scaling method, local intensity method, power transformation method and the delta-change method to bias correct the temperature and precipitation series. They evaluated the performance of various bias correction method by comparing the bias corrected series with the observed series.

In this study, an ANN based bias correction method proposed in Saravanan et al[17] is used to bias correct both the daily and monthly precipitation time series of La Farge, USA. It is desired to know how well the ANN based method performs for the daily precipitation data, as well as when it is applied to a different catchment. The local intensity method and power transformation method are also applied to bias correct the same series and the best of the three for La Farge monthly and daily series are ascertained.

Study area and data description

The precipitation time series of La Farge, Wisconsin, USA is used in this study. The location of La Farge is shown in figure 1. La Farge is a small town located along the Kickapoo River. Since the vicinity of this town has steep narrow valley, it is highly prone to flood[20]. Usually La Farge is affected by flooding in Kickapoo River.

Hence study of precipitation on this town is very essential. The observed daily and monthly precipitation series from the year 1992 to 2019 for La Farge were taken from NOAA's National Centers for Environmental Information website [https://www.ncdc.noaa.gov/cdo-web/]. The simulated precipitation time series downscaled by a statistical method called Multivariate Adaptive Constructed Analogs is available in climatology lab website [http://www.climatologylab.org/maca.html]. The simulated monthly and daily time series from the year 1992 to 2099 were obtained from there.

Figure 1: Location of the study area

Material and Methods

Conventional Bias Correction Methods: Here, the bias correction procedure by the local intensity scaling method and the power transformation method are briefed. Since the scope of the study is mainly on ANN based bias correction, the details of conventional bias correction methods are briefly given here.

Local intensity scaling method: This method is derived by improving the linear scaling method. This method is able to correct the frequency of wet day and intensity of wet day which is not possible by linear scaling method. In this method, the simulated series is corrected by three steps by assuming a precipitation threshold. A linear scaling factor is also used which is calculated with respect to long term monthly average and the intensity of wet day. The study by Teutschbein and Seibert[26] can be referred for detailed procedure.

Power Transformation method: Power transformation method is mainly intended to correct or adjust the variance of the simulated series. By this method, the variance of the simulated series is corrected by comparing the coefficient of variance of observed series and the coefficient of variance of the simulated series. For detailed procedure, one can follows Hoffmann and Rath[8].

ANN based bias correction method

General note on ANN: This ANN technique is a regression tool which is evolved by the imitation of human brain behavior. ANN has network of neurons which is interconnected by connections. Neurons have tendency to store information. Connections carry numerical data.

In neural network, the architecture is not structured initially. When receiving information from training set of the series, neural network architecture is structured to give the exact output for the corresponding input by observing the statistical pattern and the relation between input and output. The received information is stored at the connections. The trained architecture is tested by testing set of the series and formed the final architecture. The architecture structured after testing is used to predict the output of validation sets of the given time series. One can follow Sivapragasam et al[21] for more clarity.

ANN based bias correction algorithm suggested in Saravanan et al[17]: As per the method suggested in Saravanan et al[17], to obtain the bias corrected series, the simulated series and the corresponding absolute error are kept as input and output to run ANN. Here, absolute error is the magnitude of the difference between the simulated and the corresponding observed value. Hence, the ANN predicts the absolute error in this case. Later, the absolute value is given sign based on the error sign of learning sets. In the observation of learning sets, if more than 50% of error is positive for a particular range of observed data, that range of data will be given as positive sign otherwise negative.

The performance of ANN based bias correction method is measured by normalized root mean squered error (NRMSE) which is the ratio between the root mean square error and average of the corresponding actual values.

Results and Discussion

The monthly and daily precipitation time series of La Farge are bias corrected by local Intensity method, power transformation method and the ANN based method proposed by Saravanan et al [17].

Monthly precipitation time series: Since the ANN model has simulated series as input and the absolute error as output, it has one neuron at input layer and one neuron at output layer. Out of the total data, 50% is used for training, 30% is used for testing and remaining 21% is used for validation purpose. For the selection of number of hidden layer neurons and activation function, sensitivity analysis has been conducted tabulated in table I and table II. As a result of sensitivity analysis, 13 number of hidden layer neurons with Tanh activation function are found as optimal. For both monthly and daily series, the data between 1992 and 2013 are used for learning the pattern (training and testing), the data between 2013 and 2019 are used for evaluating the performance of the various bias correction system.

The comparison of the ANN based method and the conventional methods for the year 2014 is given in figure 2. From the observation of figure 2, it is found that all bias corrected series equally well coincide with the observed time series, except the part of graph between time steps 7 to 10.

Table I
Sensitivity analysis for the selection of Activation function in the monthly bias correction

Trial No.	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
Activation function	Logistic	Tanh	Gaussian	Sine	Tanh15
Validation NRMSE	0.808	0.786	0.796	0.789	0.803

Table II
Sensitivity analysis for the selection of hidden layer neurons in the monthly bias correction

Trial No.	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
No of hidden neurons	7	9	11	13	15
Validation NRMSE	0.797	0.792	0.798	0.786	0.799

In this part of the graph, the observed time series is closely matching with ANN based bias corrected series when compared to local intensity and power transformation method. The time steps from 7 to 10, the values of precipitation obtained by conventional methods are overshoots when compared to the ANN based method. In this location, the value obtained by ANN is captured as the pattern of the observed. This indicates that the ANN based bias correction method is better in the monthly time series for the year 2014. The performance of all the methods in the year 2015 was also evaluated (Figure 3).

From the figure 3, it can be seen that the ANN based bias correction method coincides well with the observed data when comparing with the conventional methods. The performance of both conventional methods is equal, but its precipitation values are over estimated and not close to the observed when compared with the ANN based bias correction method.

Hence, from the figure 2 and figure 3, we can conclude that the ANN based bias corrected method is good when compared with conventional methods in case of monthly time series.

Daily precipitation time series: In daily series also, the ANN model has simulated series as input and the absolute error as output. Out of the total data, 50% is used for training, 30% is used for testing, remaining 21% is used for validation purpose. For the selection of number of hidden layer neurons and activation function, sensitivity analysis was conducted tabulated in table III and table IV. As a result of sensitivity analysis, 72 number of hidden layer neurons with Gaussian comp activation function were found as optimal.

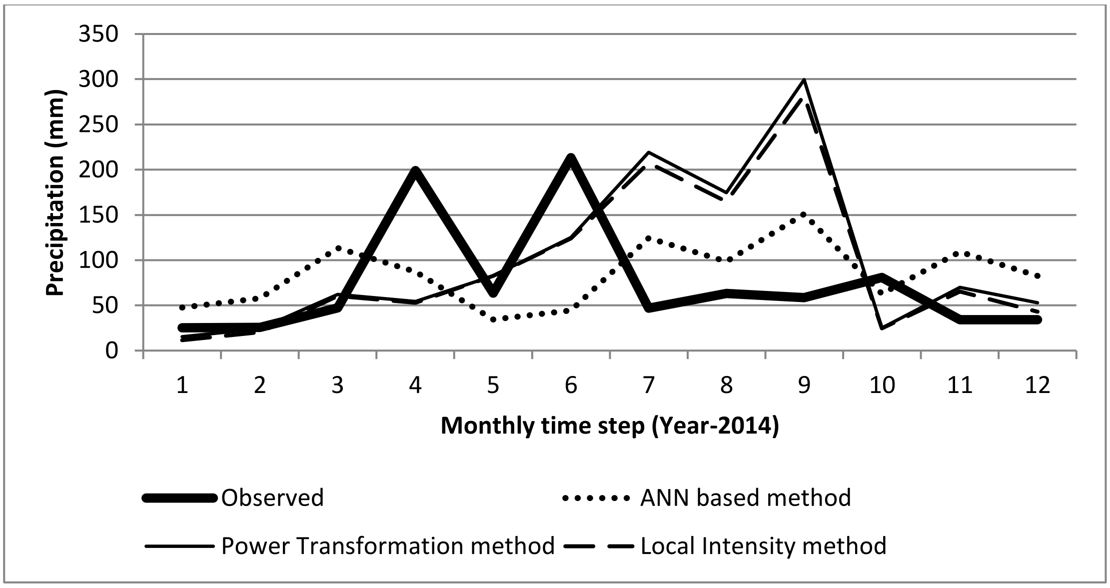

Figure 2: Comparison of various bias correction methods for monthly precipitation time series of the year 2014

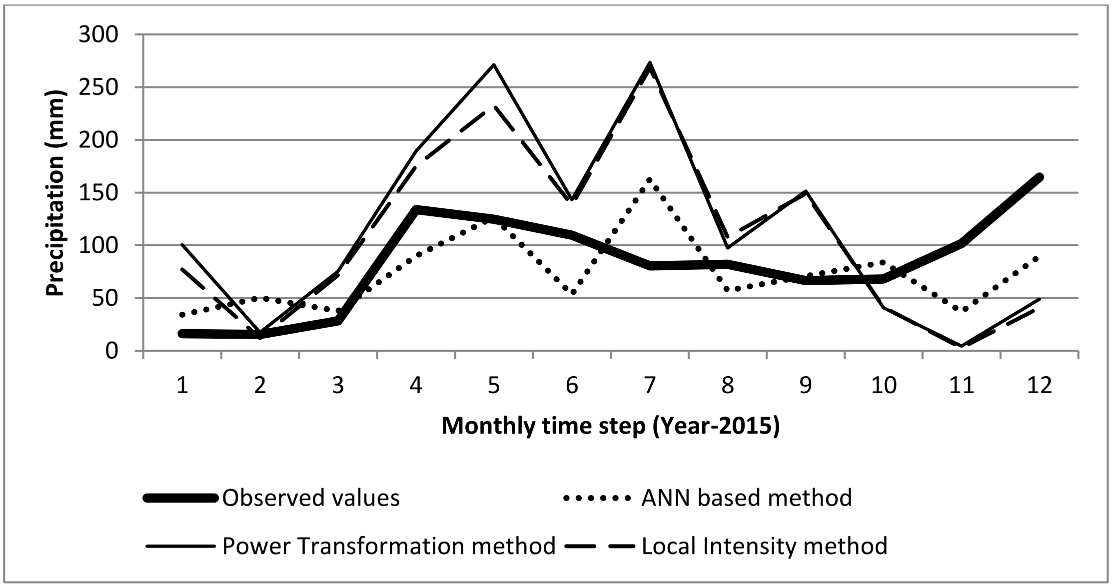

Figure 3: Comparison of various bias correction methods for monthly precipitation time series of the year 2015

Table III
Sensitivity analysis for the selection of Activation function in the daily bias correction

Trial No.	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
Activation function	Logistic	Gaussian comp	Gaussian	Sine	Symmetric logistic
Validation NRMSE	2.5504	2.5500	2.5503	2.5504	2.5505

Table IV
Sensitivity analysis for the selection of hidden layer neurons in the daily bias correction

Trial No.	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
No of hidden neurons	64	68	72	76	80
Validation NRMSE	2.5501	2.5501	2.5500	2.5501	2.5501

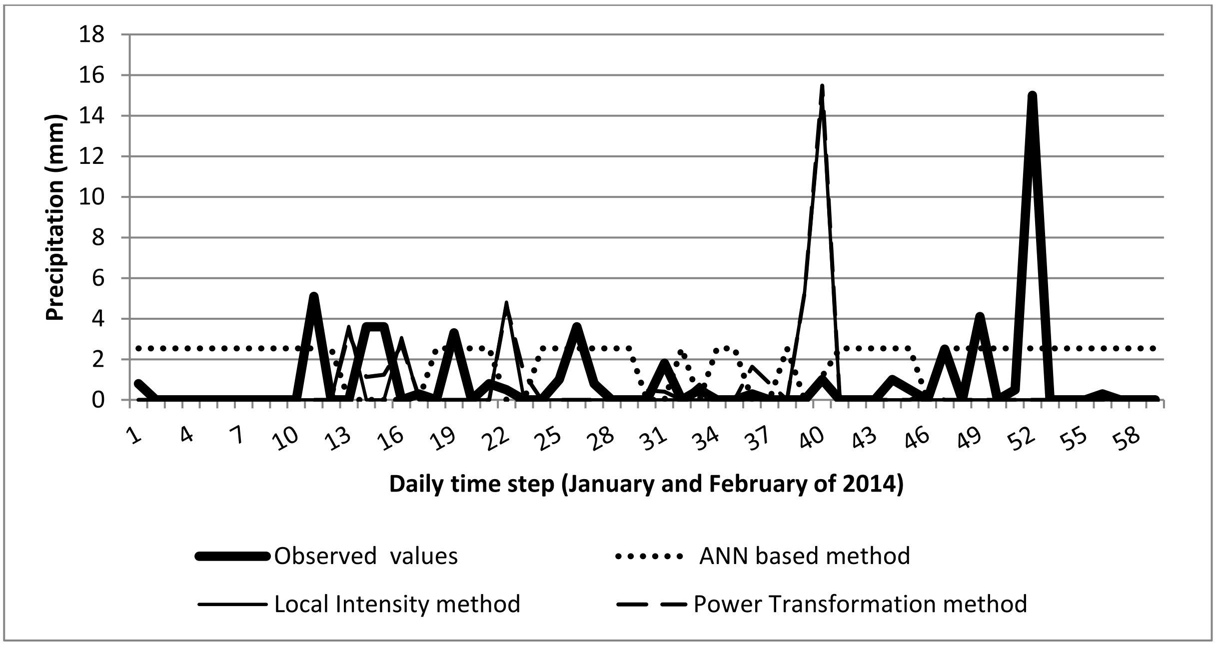

Figure 4: Comparison of various bias correction methods for daily precipitation time series of the January and February in the year 2014

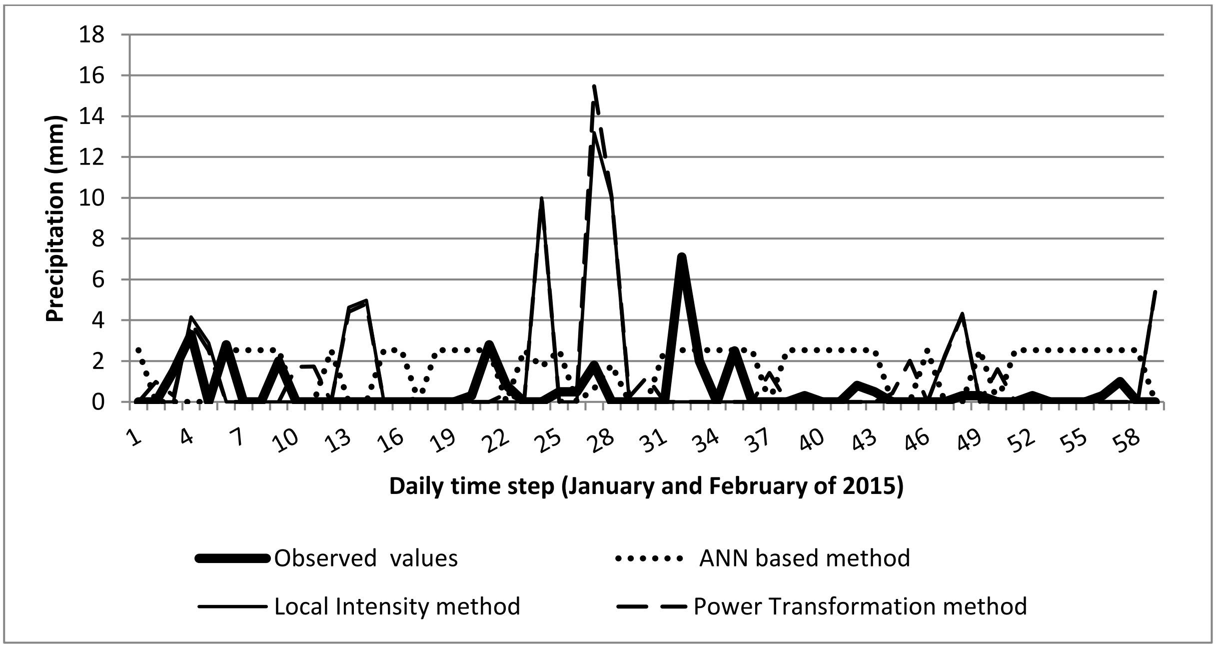

Figure 5: Comparison of various bias correction methods for daily precipitation time series of the January and February in the year 2015

Table V
Comparison of statistical properties of observed series with the series obtained by various bias correction method in daily series

Statistical Property	Various bias correction methods			
	Observed data	ANN based method	Local Intensity method	Power Transformation method
Variance	4205	889	5478	6844
Average	79	74	81	88
Maximum	467	261	575	667
Minimum	2	29	0	0
Range	464	232	575	667

The performance of the various bias correction methods in the daily time step for the first two months (January and February) of the years 2014 and 2015 is given in figure 4 and figure 5 respectively. In the figure 4 (January and February of the year 2014), it is found that the bias corrected value of precipitation through ANN-method is never increasing more than 4 mm which means the variation more than this cannot be identified by this method. Other conventional methods corrected the simulated series by showing proper variation in the bias corrected series. This indicates that the ANN-method failed to bias correct the daily precipitation series.

The performance of all methods in January and February of the year 2015 is shown in figure 5. This also indicates that the performance of ANN-method is poor and not giving values more than 4mm.

To cross verify the poor performance of the ANN-method in daily series, the statistical properties like variance, average, range of various bias corrected series are compared with the observed series which is shown in table V. Though, the average of the observed series is closely matching with the series which is bias corrected by ANN-method, the variance is much less when compared to the observed which means the variation in the series obtained by ANN-method is much lower when compared to the variation of the observed series. This clearly indicates that the ANN-method has failed to bias correct the daily series.

Since, the distribution in the daily precipitation series highly deviates from monthly precipitation series, the model might fail to capture the variations in the daily series. If the number of zero in the input series is more, the ANN may fail due to this because, lots of dry days (Zero precipitation days) are possible, but dry month is very rare.

Conclusion

- The ANN algorithm proposed by Saravanan et al[17] appears to be a be potential method for bias correcting monthly precipitation from La Farge.
- The proposed ANN method is not found to be suitable for bias correcting the daily series.
- The success of an ANN model highly depends on the pattern and distribution in the time series. Hence, an ANN algorithm suggested for one study area cannot be applied for other study area directly.

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