ENGINEER - Vol.LVII, No. 02, pp. [57-67], 2024

DOI: https://doi.org/10.4038/engineer.v57i2.7649

Downscaling Future Precipitation over Mi Oya River Basin using Artificial Neural Networks

H.M.S.A. Koswaththa, S.K. Ranasinghe, Imesh Ekanayake, Damayanthi Herath and N.G.P.B. Neluwala

Abstract: Studying future precipitation behaviour in river basins is essential for proper water resources and land-use planning within them, as this will help to reduce the risk and mitigate disasters that can occur in the future. General Circulation Models (GCMs) are used to study future precipitation fluctuations, which simulate large-scale climate variations under the effect of greenhouse gas changes. The GCM runs at a coarse spatial resolution which cannot be directly used for climate impact studies. Therefore, downscaling is required to extract the sub-grid and local scale information. This study examines the use of the Long Short-Term Memory (LSTM) neural network for climate downscaling to the Mi-Oya river basin in Sri Lanka using CNRM-CM5 and HadCM3 GCMs and observed annual data for 35 years. The precipitation data were extracted to cover Sri Lanka. Current downscaling models mostly use Convolutional Neural Networks (CNNs) to downscale GCMs. Out of 42 GCMs, two appropriate GCMs were chosen using the data analysis tool Data Integration and Analysis System (DIAS). The best predictor variables were chosen using the LASSO regression method. In this research, Machine Learning models were implemented using the Google TensorFlow platform. The Nash–Sutcliffe coefficient, Pearson correlation coefficient, and root-mean-square error performance indices were used to evaluate the performances of different downscaling models. Statistical downscaling was performed on the data at RCP 2.6, 4.5, and 8.5 using a LSTM. Subsequently, the changes that would take place by the year 2100 were analysed. The results show that precipitation will be reduced in the 2nd and 3rd decades of the 21st century, and precipitation will increase toward the 22nd century.

Keywords: Climate downscaling, Neural Network, LSTM, GCM, RCP

1. Introduction

Proper water resources and land-use planning within river basins are crucial for mitigating risk and preventing natural disasters [1-3]; therefore, studying future precipitation behavior in these basins is essential. Future precipitation variations are analyzed using general circulation models (GCMs), which forecast large-scale climatic fluctuations resulting from greenhouse gas emissions (GHGs).

GCMs are excellent tools for predicting climate variability and changes in the future. Several previous studies have used GCMs for climate downscaling [4-6]. GCMs are widely used to simulate the Earth's climate and to predict future changes in climate variables such as temperature, precipitation, and wind. They are based on physical equations that describe the Earth's atmosphere, ocean, land, and ice, and they simulate how these components interact.
GCMs typically have a resolution of 100 to 500 km. However, decision-makers who study hydrology, crop production, and species distribution need data at scales between 10 and 50 kilometers. Therefore, numerous techniques have been devised to bridge the gap between GCM data and fine-scale climate data [7, 8]. According to literature, downscaling can also be performed on spatial and temporal aspects [2, 9].

Spatial downscaling extracts high-resolution climatic data from low-resolution GCM outputs [10]. Temporal downscaling refers to the

Eng. H.M.S.A. Koswaththa, AMIE(SL), B.Sc.Eng. (Peradeniya), Dept. of Civil Engineering, University of Peradeniya, Sri Lanka.
Email:anuradhakoswaththa@gmail.com
Eng. S.K. Ranasinghe, AMIE(SL), B.Sc.Eng. (Peradeniya), Dept. of Civil Engineering, University of Peradeniya, Sri Lanka.
Email:sumukavi15@gmail.com
Eng. Imesh Ekanayake, AMIE(SL), B.Sc.Eng. (Peradeniya), Dept. of Computer Engineering, University of Peradeniya, Sri Lanka.
Email:imeshuek@eng.pdn.ac.lk
Eng. (Dr.) Damayanthi Herath, AMIE(SL), B.Sc.Eng. (Peradeniya), D.Eng. (Melbourne), Senior Lecturer, Dept. of Computer Engineering, University of Peradeniya, Sri Lanka.
Email:damayanthiherath@eng.pdn.ac.lk
https://orcid.org/0000-0002-2044-7737
Eng. (Dr.) N.G.P.B. Neluwala, AMIE(SL), B.Sc.Eng. (Peradeniya), M.Eng., D.Eng. (Tokyo), Senior Lecturer, Dept. of Civil Engineering, University of Peradeniya, Sri Lanka. Email:pandukaneluwala@eng.pdn.ac.lk
https://orcid.org/0000-0002-1686-3412

derivation of fine-scale temporal information from coarser-scale temporal GCMs [11].

It is important to note that there are two main types of downscaling techniques with spatial downscaling. The two most prevalent types are statistical and dynamic downscaling. The geographical scale gap between GCM outputs and catchment scale hydroclimatic variables is addressed in statistical downscaling by the creation of empirical statistical correlations between the two sets of data. This is comparable to dynamic downscaling which employs physics-based equations to accomplish the same goal [12].

This study used statistical downscaling to establish a correlation between coarse resolution variables (predictors) in general circulation models and local-scale precipitation data (predictand). When downscaling precipitation data from various sources or complicated data patterns, deep learning, a nonlinear model, may be more effective than traditional statistical approaches [13].

Sachindra et al. [12] used four machine learning models to downscale the precipitation and reported that the performance of relevance vector machine and artificial neural network is better compared to support vector machines and genetic programming. Najafi et al. [14] used adaptive neuro fuzzy interference system, support vector machines and multiple linear regression to downscale precipitation with optimal predictor selection. Their method was successful for monthly and seasonal variation, and multiple linear regression has been recommended as an effective technique. On the other hand, it is argued that the use of conventional machine learning does not provide direct improvements in the downscaling process [15]. Kajbaf et al. [16] used several machine learning algorithms for temporal downscaling precipitation in time series with 3-h intervals. Xu et al. [17] used the Bayesian model average to downscale precipitation and argued that it is better performing compared to conventional global circulation models. Han et al. [18] used the data generated from global circulation models to apply machine learning downscaling to examine the effect of climate change. Furthermore, they observed a significant positive trend in the extreme daily precipitation during 2015-2050. In a study conducted in Indian context, Raje and Mujumdar [19] highlighted that conditional random field and k-nearest neighbours work better compared to support vector machines in downscaling precipitation. A similar study conducted in Iran reported that gradient tree boosting and classification and regression tree performs better in downscaling precipitation compared to support vector machine and random forest [20]. The Long Short-Term Memory (LSTM) artificial neural network architecture was chosen to perform the downscaling of the global precipitation. This study will investigate the variation of future precipitation using LSTM downscaling models for two GCMs under three Representative Concentration Pathway scenarios (RCP 2.6, 4.5, and 8.5).

2. Literature Review

2.1 Neural Networks

Neural networks are the basic machine learning models for deep learning. A neural network is a collection of algorithms used to identify fine relationships in a set of data in a manner similar to how the human brain operates. A neural network consists of algorithms that are implemented to perform specific tasks. These algorithms are designed to analyse data, including text, sounds, and images, represented as vectors of numerical patterns. Neural networks excel at tasks such as pattern recognition, classification, and regression. Their primary function is to discern complex patterns and structures within raw data [21-23]. To accomplish this, it first classifies the input data into groups based on their shared characteristics and then uses the labeled training dataset to classify the resulting unlabeled data. Information processing can be modelled mathematically or computationally with a Neural Network, which is a network of artificial or biological neurons. Neural Networks also automatically adjust to new data, which is a crucial feature. This means that the output criteria can remain unchanged even if the input is modified. Constructed of layers and nodes that are linked together, a neural network is able to perform [5].

When evaluating the performance of a Neural Network, the neuron's connections are represented as weights. A positive weight signifies an excitatory link, whereas a negative weight indicates an inhibitory connection. All inputs are weighted and then added together. This is believed to be a linear combination. A final activation function controls the output's amplitude. It is essential to remember that the output range is often between 0 and 1.

Perceptron, Convolutional Neural Network, Feed Forward Neural Neural Network, Multilayer Perceptron, Radial Basis Function Neural Network, LSTM–Long Short-Term Memory, Recurrent Neural Networks, Sequence to Sequence models, and Modular Neural Networks, etc., are a few examples [24, 25]. While this classic representation still holds in many contexts, it is important to note that recent advancements in neural network architectures have introduced more intricate mechanisms and structures.

2.1.1 Long Short-Term Memory (LSTM)

Long short-term memory is a recurrent neural network architecture. LSTM employs feedback connections in contrast to the feed-forward neural networks. As a result, it can handle individual data points and data sequences. It can determine the significance of the order of events in tasks involving sequence prediction. Complex problem domains, such as speech recognition and machine translation, necessitate this behaviour making LSTM effective in mentioned applications.

For long-range modelling dependencies, LSTM as a particular RNN structure has proven robust and effective for general-purpose sequence modelling. The key innovation of LSTM is its memory cell, which effectively acts as a state information accumulator. Several self-parameterized controlling gates permit access to, write to, and clear the cell. Whenever a new input is received, its data will be gathered in the cell if the input gate is enabled. Additionally, if the forget gate is enabled, the previous cell status may be "lost" during this procedure. The output gate determines whether the latest cell output will be propagated to the final state. Using memory cells and gates to control information flow has the advantage of trapping the gradient within the cell and preventing it from dissipating too rapidly [13].

In the context of each forward pass, the net cell input value is initially determined [26]. The input is then squashed and applied to the function. The result is then multiplied by the activation of the memory block's input gate, which is [27] computed using a logistic squashing function within the interval [0, 1]. The backward pass of the LSTM is an effective combination of error back-propagation (BP) and real-time recurrent learning for weights to cell input, input gates, and forget gates [28].

Since LSTMs are effective at capturing long-term temporal dependencies without the optimisation challenges that afflict simple recurrent networks (SRNs), they have been utilised to advance the state-of-the-art for many applications. This comprises, among others, protein function prediction, handwriting detection and generation, acoustic modelling of voice, language modelling and translation, structure prediction, speech synthesis, and analysis of audio and video data [13].

Referring to the literature, it is evident that a very limited number of studies have considered the LSTM for precipitation prediction. Most studies have focused on comparing different statistical downscaling techniques rather than future predictions. Further, it is identified by many works of literature that the studies are related to one or two RCPs while they are checking for different techniques from them. When it comes to studies related to Sri Lanka, very few studies have been carried out on climate downscaling. In this research, we have developed a statistical downscaling model using the technique targeting the Puttalam meteorological weather station. Future climate predictions were downscaled for RCP 2.6, 4.5, and 8.5 from 2020 to 2100.

3. Methodology

3.1 Study Area and Data

The Mi Oya River basin is located in the Puttalam district, Sri Lanka (Figure 1), and has a catchment area of approximately 1516 km^2 with a total length of about 108 km. Seasonal flooding has a severe impact on the Mi Oya River basin every year as a result of the intense weather conditions during the monsoon seasons [29]. Its catchment area receives approximately 2176 million m^3 of rain per year. To develop the downscaling model, Puttalam meteorological station (8° 02' 1.80" N and 79° 50' 4.19" E) was selected, which had the lowest missing data percentage.

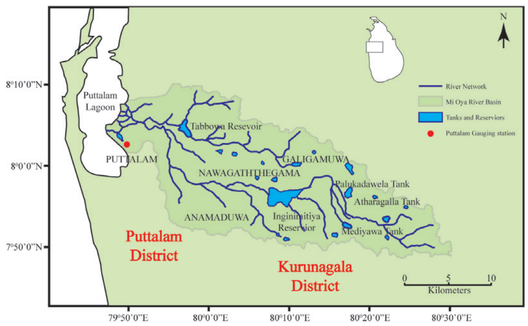

Figure 1 - Map of Mi Oya River Basin

For this study, daily precipitation data spanning from 1970 to 2005 were acquired from the Irrigation Department. These data were then transformed into average monthly precipitation values. To address any missing data points within this dataset, the arithmetic average method was used.

GCM selection test was done with the Data Integration and Analysis System (DIAS) [30], selecting Sri Lanka as the study area. Atmospheric variables were selected for the analysis, and each model was analysed with reference data relevant to the study area. This system comprised a set of tools that provide the easy display and analysis of data from the Coupled Model Intercomparison. Project Phase 5 (CMIP5) has a wide-ranging spatiotemporal resolution. Using JRA55 and other reanalysis data as reference data for comparison with CMIP5 data, the system also has functions for assessing the reproducibility of climate models.

For this research, two GCMs were selected based on the correlation parameters, including the correlation coefficient (Scorr) and root mean square error (RMSE), as well as the data file size. Precipitation datasets were derived from the most updated CMIP5 using two GCMs: HadCM3 and CNRM-CM5. Daily precipitation data were collected at various spatial resolutions for the mentioned GCMs over two distinct timeframes, serving as both training and testing data. GCM outputs consist of gridded data with low spatial resolution (2.5° for HadCM3 and 1.4° for CMIP5). To improve the accuracy of the downscaling process, bilinear interpolation was used as a pre-processing technique to obtain a finer resolution of GCM outputs.

Data were extracted for the atmospheric domain of 7.5 to 10 latitude and 78.75 to 82.5 longitude for each variable in GCMs. The bilinear interpolation method was applied to downscale to the resolution of 2.5 degrees of latitude and 3.75 degrees of longitude before implementing normalisation processes for the training model. Over 35 years (1970–2005) of monthly recorded precipitation was obtained from Puttalam's long-term gauging meteorological station shown in Figure 1.

3.2 Predictor Screening

According to the literature, a unique set of predictors that are most influential on the predictand can provide a more dependable and meaningful insight into the influence of large-scale atmospheric variables on the predictand of interest [5].

As the first step, variables with zero variation were removed. From all 45 variables, surface snow and ice sublimation flux (sbl) were removed as they had zero value throughout the selected period. The remaining 44 variables were advanced to the next step.

The LASSO regression method was used to identify the correlation of predictors and determine the input variable sequence. Correlation coefficients were obtained for each predictor from the test. LASSO regression results showed a mix of negative, positive weights, and zero value weights. Variables that had zero correlation were removed. The remaining variables were ordered according to the magnitude of the weight. From LASSO regression, potential predictors most correlated to the predictand (precipitation) were identified.

The wrapper method [31] was used to select a subset from potential predictors. There are different approaches in the wrapper method, and we used the forward selection approach. Forward selection is an iterative method in which we start with having no feature in the model. In each iteration, we keep adding the feature that best improves our model until adding a new variable does not improve the model's performance.

3.3 Data Scaling

Feature scaling in machine learning is one of the most critical steps during the pre-processing of data before creating a machine learning model. Data scaling removes the units of each predictor and scales the data that are originally in different orders of magnitudes into a single uniform range [5]. Two types of scaling methods have been used in the literature, which are Normalisation and Standardisation. For our study, we used data normalisation. Normalisation is a scaling technique in which values are shifted and rescaled, so that they end up ranging between 0 and 1. Equation 1 shows the mathematical representation of normalization. It is also known as Min-Max scaling.

$$x = \frac{x - x_{min}}{x_{max} - x_{min}} \quad \text{... (1)}$$

Historical GCM data from 1970 to 2005 was separated into three parts: training (1970-1996), validating (1997-1999), and testing (2000-2005). Minimum and maximum values were taken in the training set for each predictor variable. Using values relevant to the training period, each predictor variable was rescaled.

3.4 Model Development

In this study, monthly precipitation over the Mi Oya River basin was downscaled from GCM outputs under RCP 2.6, 4.5, and 8.5 scenarios. The downscaling model was developed and validated using historical data and applied to downscale future climate, as illustrated in Figure 2. CNRM-CM5 GCM provided predictions for all RCP scenarios, whereas HadCM3 only included RCP 4.5.

LSTM is the most popular model in time series analysis, and there are many variants, such as unidirectional LSTM and BLSTM. For our study, the Many-to-One (multiple input and one output) variations of LSTM were used to take the last 24 months' weather parameters and predict the rainfall for the next month. Unidirectional LSTM process data are based only on past information. Bidirectional LSTM utilises the most out of the data by going through time steps in both forward and backward directions. It duplicates the first recurrent network in the architecture to get two layers side by side. Then it passes the input, as it is, to the first layer and provides a reversed copy to the second layer. Although it was traditionally developed for speech recognition, its use has been extended to achieve better performance from LSTM in multiple domains [12].

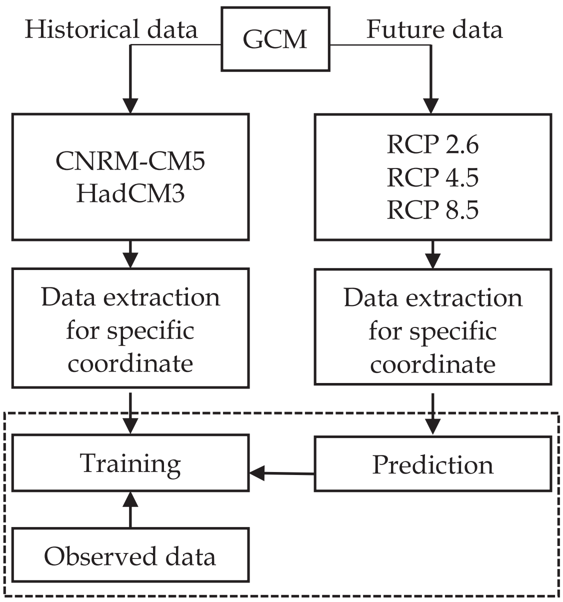

Figure 2 - Flow Chart of the Downscaling Process

The LSTM model was implemented on "google TensorFlow" interface. Hyperparameter tuning was done for the parameters: hidden layers, learning rate, number of hidden nodes in each layer, and dropout rate based on past literature. Rainfall data from the Puttalam gauging station starting from 1970 until 2005 is the dataset considered for the prediction process. This dataset is split into training, validating, and testing datasets. Rainfall data (30 years from 1970 to 1999) is taken as the dataset for training and validating the proposed LSTM-based model. Model trainings were done for two GCMs separately. These trained models were then tested with the dataset 2000 to 2005. The "adam" optimiser and "mean squared error" loss function was used in training the model. Next, the model was fitted to the data; In this case, the model was trained for 200 epochs or iterations over the training data in batches of 32 samples. Different models and parameter setups were explored to determine the best setup for each model. The model architecture is shown in Figure 3. The training models were then evaluated on the testing dataset.

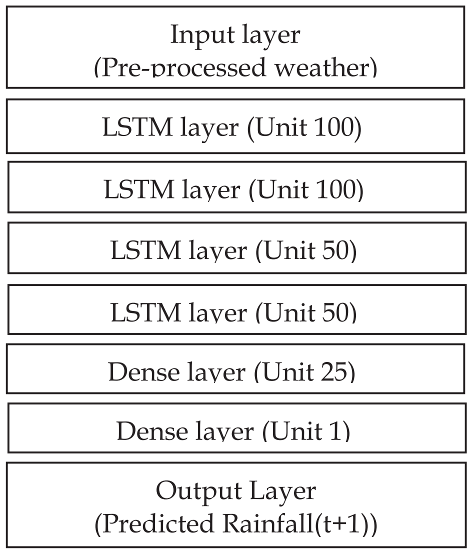

Figure 3 - LSTM Model Architecture

3.5 Evaluation of Downscaling Models

The following metrics were used for evaluation: normalized root mean square error (NRMSE) as shown in Equation 2, which corresponds to the error of the simulated precipitation compared with the observed rainfall data; the correlation coefficient (CC) as shown in Equation 3 and Nash–Sutcliffe efficiency (NSE) as shown in Equation 4, which aim to show the consistency between the predicted rainfall, and the observed rainfall. The metrics are calculated as follows:

$$\text{NRMSE} = \frac{1}{SD}\sqrt{\frac{\sum_{i=1}^{n}\left(x_{obs,i}-x_{model,i}\right)^2}{n}} \quad \dots (2)$$

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{n}(OBS_i - SIM_i)^2}{\sum_{i=1}^{n}(OBS_i - OBS)^2} \quad \dots (3)$$

$$\text{PCC} = \frac{\sum_{i=1}^{n}(OBS_i - \overline{OBS})(SIMi - \overline{SIM})}{\sqrt{(\sum_{i=1}^{n}(OBS_i - OBS)^2 \sum_{i=1}^{n}(SIMi - \overline{SIM})^2)}} \quad \dots (4)$$

4. Results and Discussion

4.1 GCM Selection

HadCM3@r7i1p1 and CNRM-CM5@r1i1p1 GCMS were selected for the study considering the high Scorr and low RMSE values as explained in Section 3.1. HadCM3@r7i1p1 has a Scorr of 0.967 and RMSE of 0.444, while CNRM-CM5@r1i1p1 has a Scorr of 0.917 and RMSE of 0.410.

4.2 Predictor Screening

As mentioned, Lasso regression was used to calculate the correlation of GCM variables with observed precipitation. All variables were ranked according to the correlation weight. Subsets of variables were used as input variables for the LSTM model. Selected variables after many model runs are listed in Table 1. Model performance was evaluated for training, validation, and test data. The model performance for the test data (2000-2005) is shown in Table 2, comparing the performance of two GCMs, CNRM-CM5 and HadCM3, in terms of three metrics: Normalized Root Mean Square Error (NRMSE), Nash-Sutcliffe Efficiency (NSE), and Pearson Correlation Coefficient (CC). In this study, the performance of the two GCMs is evaluated based on their ability to accurately predict a target variable, such as precipitation or temperature, as compared to observations. The NRMSE values show that CNRM-CM5 had a lower error than HadCM3, with a value of 0.61 compared to 0.66. The NSE values indicate that CNRM-CM5 performed better than HadCM3, with a value of 0.62 compared to 0.56. Figure 4 shows the comparison of the predicted from the CNRMCM5 model with the observed rainfall. The coefficient of correlation was 0.644 which gives a good correlation. It is observed that some deviations exist for all predictions despite the correlation. However, higher precipitation values have been accurately predicted compared to lower values. The model consists of both underestimated and overestimated predictions.

The coefficient of correlation between the observed and predicted is 0.623 (Figure 5) which relates to good correlation. The model HadCM3 predicts higher rainfall accurately compared to lower precipitation values. However, the underestimated values have a larger deviation compared to the overestimated precipitation values.

Table 1 - Selected Model Variables

CNRM-CM5	HadCM3
Surface downward eastward stress	Surface upwelling shortwave flux in air
Wind speed	Eastward wind
Water vapor content	Eastward wind @ 850
Surface downwelling shortwave flux in air	Toa outgoing longwave flux
Upwelling shortwave flux in air	Surface upwelling longwave flux in air
Surface upwelling shortwave flux in air	Surface downwelling longwave flux in air
Surface upwelling longwave flux in air	Northward wind@ 850hpa
Relative humidity	Northward wind

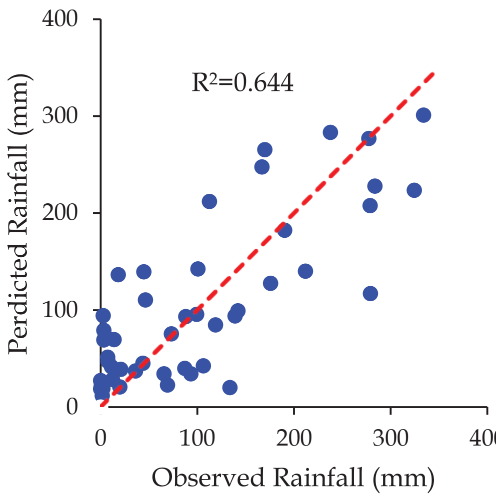

Figure 4 - Variation of Observed and Predicted Precipitation by CNRM-CM5 Model

According to the correlation measurements, model performances for both GCMs were up to a satisfactory level. The testing data correlation using the Pearson correlation test indicates that the correlations obtained in the Puttalam stations oscillate between 70% and 80% for both GCMs.

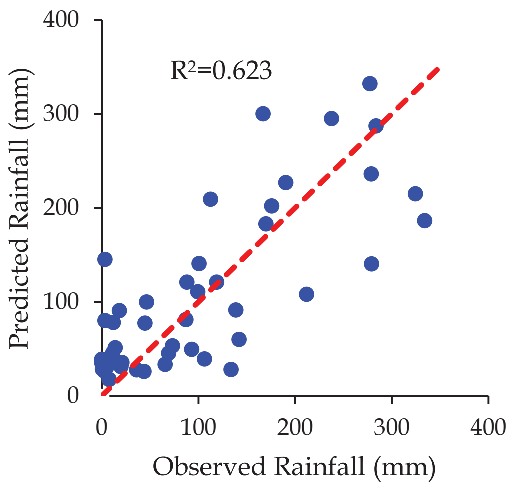

Figure 5 - Variation of Observed and Predicted Precipitation by HadCM3 Model

Table 2 - Evaluation of Downscale Model

Parameter	CNRM-CM5	HadCM3
NRMSE	0.61	0.66
NSE	0.62	0.56
Pearson CC	0.79	0.75

The climate seasons play a crucial role in understanding the regional climate patterns. The climate of Sri Lanka is dominated by the topographical features of the country and the Southwest and Northeast monsoon's regional scale wind regimes. The climate experienced during 12 months period in Sri Lanka can be characterized into 4 climate seasons as follows:

- First Inter-monsoon (March-April),
- Southwest -monsoon (May-September),
- Second Inter-monsoon (October-November),
- Northeast-monsoon (December-February).

The timeline from 2020 to 2100 was divided into two-decade time windows to represent future predictions.

Figure 6(a) which shows the precipitation under RCP 4.5 scenario indicates higher precipitation for First Inter-Monsoon, Southwest Monsoon, and Northeast Monsoon compared to baseline periods in the 20s. The second Inter Monsoon shows lower precipitation compared to the baseline period in the 20s. Figure 6(b), which is related to RCP 8.5, indicates the lower precipitation for all four seasons compared to the baseline period. There is an increasing trend toward the 22nd century for the First Inter-Monsoon season and Southwest Monsoon season. There is a decreasing trend towards the 22nd century for the Second Inter-Monsoon and Northeast Monsoon towards the 22nd century. Figure 6(c) illustrates that RCP 2.6 indicates lower precipitation for all four seasons compared to the baseline period. There is a clear downward trend toward the 22nd century for the Second Inter Monsoon season and Northeast Monsoon season.

The variation trend is visualized using the moving averages method and illustrated in Figure 7. The Mann-Kendall test was used to identify trends in predictions under each RCP scenario, as shown in Table 3.

Table 3 - Mann-Kendall (MK) Results for Trend (CNRM-CM5)

RCP	Z
8.5	6.279
2.6	-0.009
4.5	2.313

From the results of the MK test, RCP 4.5 and 8.5 have an upward trend while RCP 8.5 trend can be identified as significant. RCP 2.6 shows a slight downward trend. RCP 8.5 scenario shows a significant impact on the precipitation trends in the future.

5. Conclusion

This research proposes a method to statistically downscale monthly precipitation obtained from the CMIP5. Precipitation data from two GCMs were statistically downscaled under three scenarios (i.e., RCP2.6, RCP 4.5, and RCP 8.5), supported by gauged data from the meteorological station of Puttalam. In this study, the correlations between observed and predicted values from the LSTM downscaling models during the testing and validating periods were found to be good, as shown in Table 2. Accordingly, the LSTM architecture is shown to be effective for climate downscaling studies.

CNRM-CM5 GCM predicted lower precipitation in the 21st century compared to the baseline period under all three scenarios. HadCM3 predicted higher precipitation for the 3rd and 4th decades of the 21st century. This difference may be due to the selection of different predictor sets for two GCMs, suggesting that the predictor set is highly influenced for the model output.

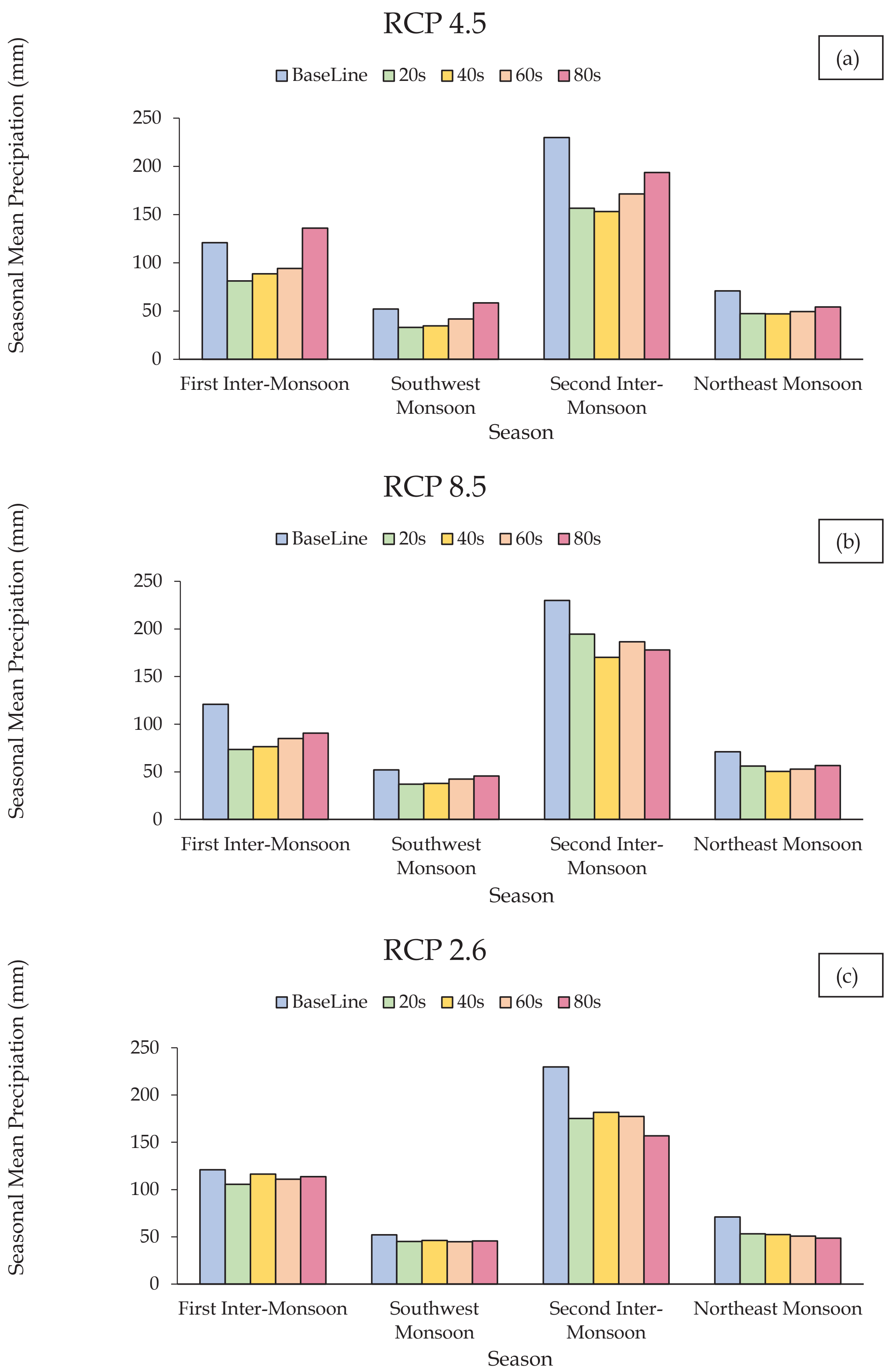

Figure 6 - Variation of Seasonal Mean Precipitation under different RCPs

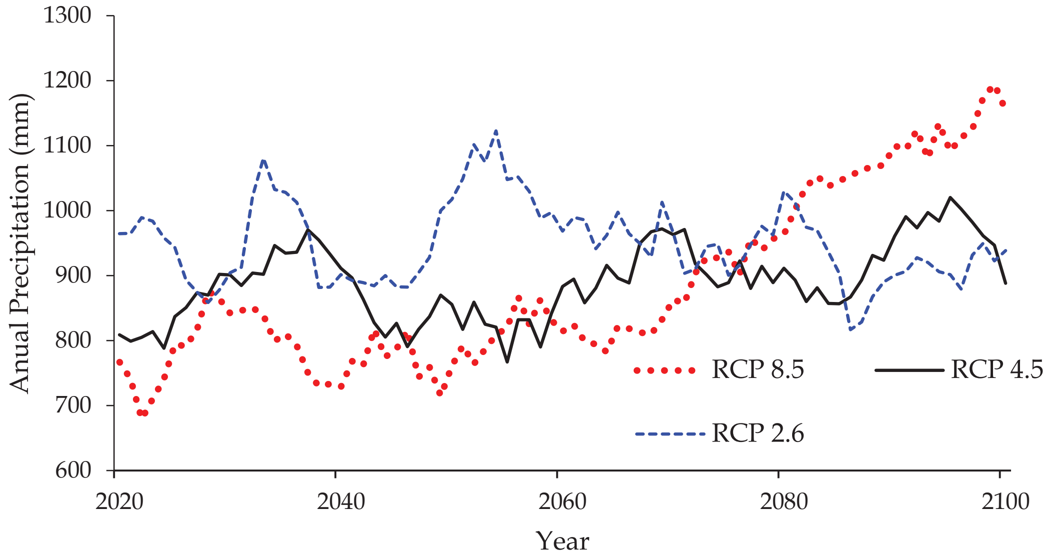

Figure 7 - Trend Variation Under Different RCP(s)

The changes in the trends of precipitation for the 2020-2100 period were well examined using Mann-Kendall analysis. No significant upward or downward trends were detected for the RCP 2.6 scenario. Hence, low greenhouse gas concentration levels will not affect rainfall trend in the future. However, under RCP 4.5, which is a stabilization without overshooting the radiative forcing target scenario, resulted in an upward trend at Puttalam station for the considered period. Moreover, RCP 8.5 demonstrates that an increment of greenhouse gas emissions over time will lead to a significant upward trend in precipitation in the future at Puttalam station. Further work can be done to study the impact of the trends under RCP 8.5. The methods developed in this study can be used to study the climate behaviour of other basins of interest.

Acknowledgement

The authors wish to acknowledge Mr. Kasun Dharmasiri for the guidance on the novelty of this work. The authors would like to acknowledge the Department of Irrigation for providing us with the required data for the research study.

References

1. Hooijer, A., Klijn, F., Pedroli, G.B.M., and Van Os, A.G., "Towards Sustainable Flood Risk Management in the Rhine and Meuse River Basins: Synopsis of the Findings of IRMA-SPONGE", *River Research and Applications,* Vol. 20, No. 3, 2004, pp. 343-357.

2. Sukanya, S., and Joseph, S., "Climate Change Impacts on Water Resources: An Overview", *Visualization Techniques for Climate Change with Machine Learning and Artificial Intelligence*, 2023, pp. 55-76.

3. Zope, P., Eldho, T., and Jothiprakash,V., "Hydrological Impacts of Land Use–Land Cover Change and Detention Basins on Urban Flood Hazard: A Case Study of Poisar River basin, Mumbai, India", *Natural Hazards,* Vol. 87, 2017, pp. 1267-1283.

4. Chen, H., Xu, C.Y., and Guo, S., "Comparison and Evaluation of Multiple GCMs, Statistical Downscaling, and Hydrological Models in the Study of Climate Change Impacts on Runoff," *Journal of Hydrology,* Vol. 434, 2012, pp. 36-45.

5. Khadka, D., and Pathak, D., "Climate Change Projection for the Marsyangdi River Basin, Nepal using Statistical Downscaling of GCM and its Implications in Geodisasters", *Geoenvironmental Disasters,* Vol. 3, No. 1, 2016, pp. 1-15.

6. McSweeney, C., Jones, R., Lee, R.W., and Rowell, D., "Selecting CMIP5 GCMs for Downscaling Over Multiple Regions", *Climate Dynamics,* Vol. 44, 2015, pp. 3237-3260.

7. Sun *et al.*, G., "Forest Hydrology Modeling Tools for Watershed Management: A Review", *Forest Ecology and Management,* Vol. 530, 2023, p. 120755.

8. Stadnyk, T., and Holmes, T., "Large Scale Hydrologic and Tracer Aided Modelling: A Review", *Journal of Hydrology,* 2023, p. 129177.

9. 31, O. M., Sobolowski, S. P., Simon, M.H., Zhang, Z., and Jansen, E., "Sensitivity of Coastal Southern African Climate to Changes in

Coastline Position and Associated Land Extent over the Last Glacial", *Quaternary Science Reviews,* Vol. 300, 2023, p. 107893.

10. Aydin, O., "Downscale Climate Data with Machine Learning | Learn ArcGIS." https://learn.arcgis.com/en/projects/downscale-climate-data-with-machine-learning/, Visited, 14/12/2022.

11. Bhuvandas, N., Timbadiya, P.V., Patel, P.L., and Porey, P.D., "Review of Downscaling Methods in Climate Change and their Role in Hydrological Studies", *World Academy of Science, Engineering and Technology,* Vol. 8, 2014, pp. 660-665.

12. Sachindra, D., Ahmed, K., Rashid, M.M., Shahid, S., and Perera, B., "Statistical Downscaling of Precipitation using Machine Learning Techniques", *Atmospheric Research,* Vol. 212, pp. 240-258, 2018.

13. Tran Anh, D., Van, S.P., Dang, T.D., and Hoang, L.P., "Downscaling Rainfall using Deep Learning Long Short-Term Memory and Feedforward Neural Network", *International Journal of Climatology,* Vol. 39, No. 10, 2019, pp. 4170-4188.

14. Najafi, M.R., Moradkhani, H., and Wherry,S.A., "Statistical Downscaling of Precipitation using Machine Learning with Optimal Predictor Selection", *Journal of Hydrologic Engineering,* Vol. 16, No. 8, 2011, pp. 650-664.

15. Vandal,T., Kodra, E., and Ganguly,A.R., "Intercomparison of Machine Learning Methods for Statistical Downscaling: the Case of Daily and Extreme Precipitation", *Theoretical and Applied Climatology,* Vol. 137, 2019., pp. 557-570.

16. Kajbaf, A.A., Bensi, M., and Brubaker,K.L., "Temporal Downscaling of Precipitation from Climate Model Projections using Machine Learning", *Stochastic Environmental Research and Risk Assessment,* Vol. 36, No. 8, 2022, pp. 2173-2194.

17. Xu,R., Chen,N., Chen,Y., and Chen,Z., "Downscaling and Projection of Multi-cmip5 Precipitation using Machine Learning Methods in the Upper Han River Basin", *Advances in Meteorology,* Vol. 2020, 2020, pp. 1-17.

18. Han,J.-C., Zheng, W., Liu,Z., Zhou,Y., Huang,Y., and Li, B., "Downscaling of Precipitation for Climate Change Projections Using Multiple Machine Learning Techniques: Case Study of Shenzhen City, China", *Journal of Water Resources Planning and Management,* Vol. 148, No. 11, 2022, p. 05022008.

19. Raje, D., and Mujumdar, P., "A Comparison of Three Methods for Downscaling Daily Precipitation in the Punjab Region", *Hydrological Processes,* Vol. 25, No. 23, 2011, pp. 3575-3589.

20. Nakhaei, M., Mohebbi, A., Tafreshi, and Saadi, T., "An Evaluation of Satellite Precipitation Downscaling Models using Machine Learning Algorithms in Hashtgerd Plain, Iran", *Modeling Earth Systems and Environment,* Vol. 9, No. 2, 2023, pp. 2829-2843.

21. Sahastrabuddhe, R., Ghausi, S.A., Joseph, J., and Ghosh, S., "Indian Summer Monsoon Rainfall in a Changing Climate: A Review", *Journal of Water and Climate Change,* Vol. 14, No. 4, 2023, pp. 1061-1088.

22. Kumar, G., and Gupta, R., "Methodologies of Scenario Development for Water Resource Management: A Review", *Modeling and Simulation of Environmental Systems*, 2022, pp. 303-316.

23. Rhymee, H., Ratnayake, U., Abdul Rahman, E.K., and Shams, S., "Application of Normalized Difference Vegetation Index in Agriculture to Estimate Rice Yield", in *AIP Conference Proceedings*, Vol. 2643, 2023.

24. Casasent, D., and Chen, X.-w, "Radial Basis Function Neural Networks for Nonlinear Fisher Discrimination and Neyman–Pearson Classification", *Neural Networks, V*ol. 16, No. 5-6, 2003, pp. 529-535.

25. Zhang,J., Li,C., Yin,Y., Zhang,J., and Grzegorzek,M., "Applications of Artificial Neural Networks in Microorganism Image Analysis: A Comprehensive Review from Conventional Multilayer Perceptron to Popular Convolutional Neural Network and Potential Visual Transformer", *Artificial Intelligence Review,* Vol. 56, No. 2, 2023, pp. 1013-1070.

26. Shibuya, E., and Hotta, K., "Cell Image Segmentation by using Feedback and Convolutional LSTM", *The Visual Computer,* Vol. 38, No. 11, 2022, pp. 3791-3801.

27. Amrutha, K., Patnaik, R., Sandeep, A., and Pattanaik, J.K., "Climate Change Impact on Major River Basins in the Indian Himalayan Region: Risk Assessment and Sustainable Management", *Climate Change Adaptation, Risk Management and Sustainable Practices in the Himalaya*: Springer, 2023, pp. 45-63.

28. Gers, F.A., Schraudolph, N.N., and Schmidhuber, J., "Learning Precise Timing with LSTM Recurrent Networks", *Journal of Machine Learning Research,* Vol. 3, 2002, pp. 115-143.

29. Bandaranayake, G., and Kumara, S., "Modeling for River Basin Management: Its Application to Mi Oya in the Dry Zone of Sri Lanka", *Proceedings of the Fifth International Research*

Conference on Humanities and Social Sciences, University of Sri Jayewardenapura,, 2016, p. 96.

30. Kawasaki, A., Yamamoto, A., Koudelova, P., Acierto, R., Nemoto, T., Kitsuregawa, M., Koike., T., "Data Integration and Analysis System (DIAS) Contributing to Climate Change Analysis and Disaster Risk Reduction", *Data Science Journal,* Vol. 16, 2017, pp. 1-16.

31. Nasseri,M., Tavakol-Davani, H., and Zahraie, B., "Performance Assessment of Different Data Mining Methods in Statistical Downscaling of Daily Precipitation", *Journal of Hydrology,* Vol. 492, 2013, ,pp. 1-14.