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CLIMATE CHANGE IMPACT PREDICTION IN UPPER MAHAWELI BASIN

H.M.V.V. Herath[1*], R.G.A.B. Dayananda[2] and S.B. Weerakoon[3]

[1]University of Peradeniya, Peradeniya, Sri Lanka
[2]University of Peradeniya, Peradeniya, Sri Lanka
[3]University of Peradeniya, Peradeniya, Sri Lanka
*E-Mail: virajvidura@gmail.com, TP: +94713445745

Abstract: Upper Mahaweli basin is the origination of the main water source of Sri Lanka which is the Mahaweli River. Therefore it is a timely requirement to identify the future climate trends on the basin, to take suitable adaptation strategies. Statistical Downscaling model (SDSM) was used to predict future rainfall patterns of the study area. Observed point rainfall data of ten gauging stations within the study area and Global Climate Model (GCM) data of Hadley Centre Coupled Model, Version 3 (HadCM3) were used for model calibration and validation processes. A representative data set for the study area was generated using Thiessen polygon method from the observed rainfall data of selected gauging stations. Quality of the input data was checked prior to the model calibration. Daily rainfall was forecasted from 1961 to 2099 under A2 (high emission scenario) & B2 (low emission scenario) defined by Intergovernmental Panel on Climate Change (IPCC). Under A2 scenario the total annual rainfall, maximum annual rainfall and annual averaged daily rainfall show an increasing trends and under B2 scenario all the above mentioned parameters show decreasing trends. But the recorded decreasing trends are insignificant.

Keywords: Global Climate Models, Statistical Downscaling model, Emission scenarios

1. Introduction

The climate affects to mankind in a wide variety of ways mainly through precipitation and solar radiation. The climate change phenomenon has become a major concern in modern world due to its adverse effects.Climate change prediction is important to understand accompanied impacts and necessary adaptation to minimize adverse impacts. Simulating the natural atmosphere by using computer models is the main tool that is used for climate prediction.

General Circulation Models or Global Climate Models (GCMs) are mathematical models used to simulate the natural atmosphere. GCM outputs cannot be used directly due to the mismatch in the spatial resolution between GCMs and hydrological models. Then the process of downscaling is required to match those spatial resolutions. In order to understand climate change impacts at basin scale GCMs data are downscaled using standard downscaling methods.

There are two standard downscaling methods namely Dynamical Downscaling (DD) and Statistical Downscaling (SD). Dynamical Downscaling (DD) generates regional scale information using Regional Climate Models (RCM) with coarse GCM data used as boundary conditions and Statistical Downscaling (SD) develops quantitative relationships between large scale atmospheric variables (predictors) and local surface variables (predictands) by using statistical methods [1].

Statistical downscaling methodologies have several practical advantages over dynamical downscaling approaches. In situations where low–cost, rapid assessments of localized climate change impacts are required, statistical downscaling represents the more promising option [2].

Statistical Downscaling model (SDSM) is a combination of Multiple Linear Regression (MLR) and the Stochastic Weather Generator (SWG). Quality control, Transform data, Screen variables, Calibrate model, Weather generator, Summary statics, Frequency analysis, Scenario generator, Compare results and Time series analysis are the key functions of the SDSM model.

SDSM model was used by Dharmarathna [3] to select adaptation measures to sustain rice production in Kurunagala District under the impacts of climate change. Minimum and maximum temperature and rainfall data were downscaled from GCM outputs and the forecasted daily maximum and minimum temperatures showed an increasing trend under both A2 and B2 scenarios while annual rainfall did not show a significant increasing or decreasing trend.

De Silva [4] used the SDSM model to downscale past and future GCM data available at a coarse resolution to the Kelani basin. In this analysis the Kelani basin was divided into two sub basins as lower basin and upper basin. Total annual rainfall was shown an increasing trend for both upper and lower basins under high and low emission scenarios.

2. Study Area and Methodology

The area up to the Polgolla barrage of Mahaweli basin which covers an area of 788 km^2 was selected as the study area. Observed rainfall data of ten gauging stations were used for models calibration and validation. Figure 1 illustrates the study area and selected gauging stations.

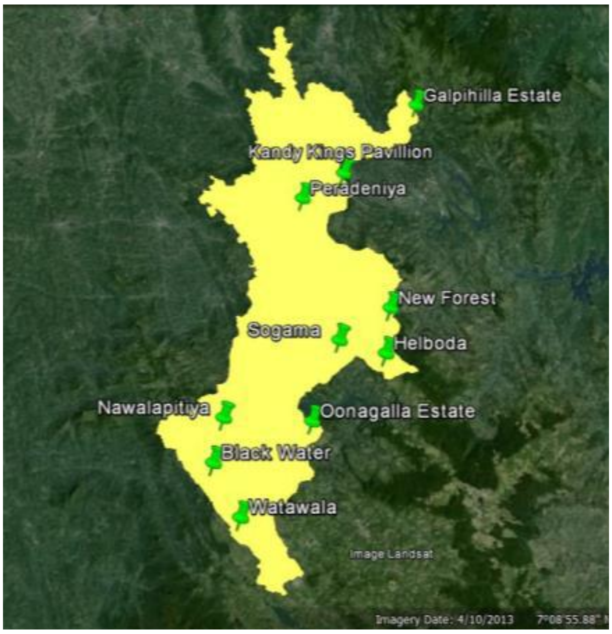

Figure 1: Study area and gauging stations

Observed point rainfall data were spatially distributed over the basin area by Thiessen polygon method and one representative data set for whole study area was generated to feed to the SDSM model.

Statistical Downscaling Model (SDSM) version 4.2.9 was used for climate modelling and rainfall was forecasted up to year 2099 using GCM data**.** GCM data were downloaded from Canadian Climate Scenarios Network [5]. National Centers for Environmental Prediction (NCEP_1961-2001) data set was used to calibrate and validate the model. Then for future rainfall predictions, Hadley Centre Coupled Model, Version 3 (HadCM3) data sets for A2 and B2 scenarios (H3a2a_1961-2099 and H3b2b_1961-2099) were used.

Future forecasts of annual averaged daily rainfall, annual maximum daily rainfall and monthly averaged total precipitations were made under to different emission scenarios namely A2 scenario (high emission case) and B2 scenario (low emission case) of IPCC.

2.1 Model Preparation

Modelling process was set as conditional which assumes an intermediate process between regional forcing and local weather. Forth root transformation was used to convert the skewed rainfall distribution into a normal distribution. The value of variance inflation, which controls the magnitude of variance inflation in downscaled daily weather variables, was set as 18 and the value of bias correction, which compensates for any tendency to over– or under–estimate the mean of conditional processes by the downscaling mode was set as 0.8.

2.2 Model Calibration

Rainfall data from 1971 to 1986 were used for model calibration. The Screening Variable option was used in the choice of appropriate downscaling predictor variables for model calibration. Table 1 illustrates the selected predictor variables among the available 26 variables in SDSM model for the Upper Mahaweli basin.

Table 1: Selected predictor variables for model calibration

Predictor Variable	Description
ncepp_fas.dat	Surface airflow strength
ncepp_zhas.dat	Surface vorticity
ncepp5_fas.dat	500 hPa airflow strength
ncepp5_uas.dat	500 hPa zonal velocity
ncep5_zas.dat	500 hPa vorticity
ncepr850as.dat	850 hPa geopotential height
nceprhumas.dat	Near surface relative humidity
ncepshmas.dat	Surface specific humidity

The simulated values of annual averaged daily rainfall, annual maximum daily rainfall and monthly averaged total precipitations were used to compare with observed rainfall data. Further, the number of dry days of simulated and observed were compared for the above time period. Figure 2 illustrates the comparison done for annual averaged daily rainfall.

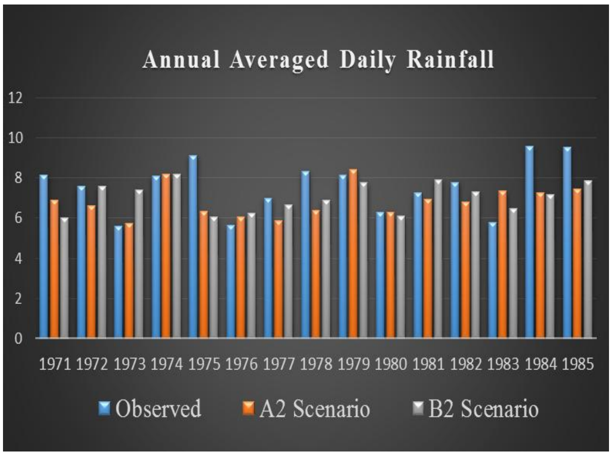

Figure 2: Variation of annual average daily rainfall

The Mean Model Error Percentages (MME %) were calculated to compare the simulated (SR) and observed (OR) rainfall values.

$$MME\ \% = (SR - OR) / OR\ x\ 100\ \% \qquad (1)$$

Figure 3 illustrates the calculated MME percentages for annual averaged daily rainfall under two emission scenarios.

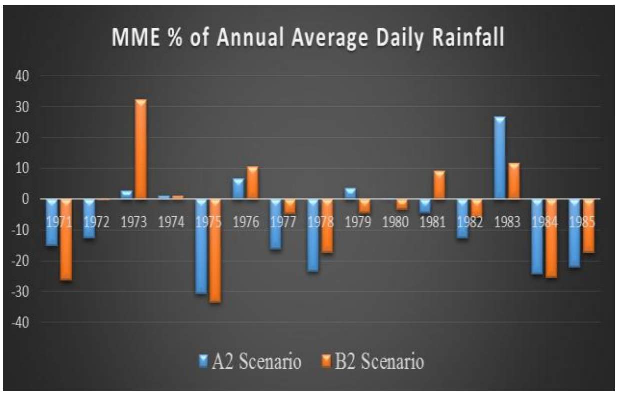

Figure 3: MME% for annual averaged daily rainfall

When calibration period is considered averaged mean model error % values were 13, 13 and 18 for averaged annual daily rainfall, monthly rainfall and number of dry days respectively under A2 emission scenario. Under B2 scenario respective values were 12, 13 and 15.

3.3 Model Validation

Observed rainfall data from year 1986 to 1993 (8 years) were used to validate the model by keeping the same values for variance inflation and bias correction which were used in model calibration stage. Figure 4 shows the comparison between observed and simulated rainfall values for validation period.

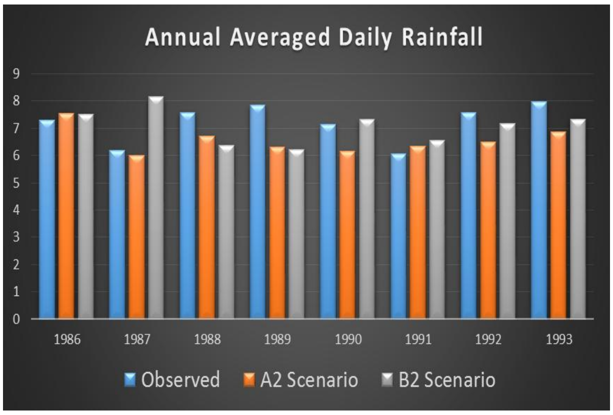

Figure 4: Model validation – Annual averaged daily rainfall

When validation period is considered averaged MME % values were 10, 17 and 10 for averaged annual daily rainfall, monthly rainfall and number of dry days respectively under A2 emission scenario. Under B2 scenario respective values were 12, 13 and 8.

3. Results and Discussion

Calibrated model was used to forecast daily rainfall from 1961 to 2099 under both A2 and B2 scenarios. Following figures illustrate the Time Series Graphs (TSG) derived for annual average daily rainfall, annual total rainfall and annual maximum rainfall under both A2 and B2 scenarios for the study area.

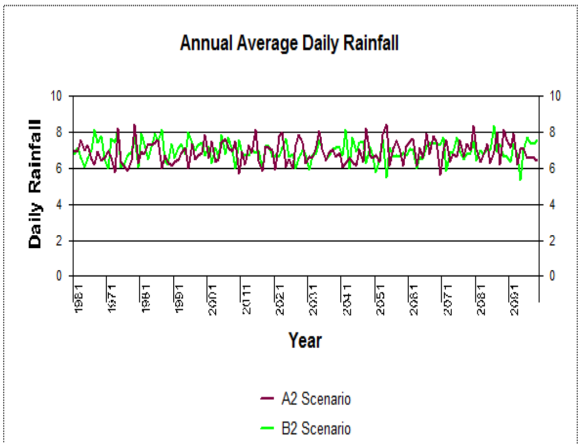

Figure 5: TSG of annual average daily rainfall

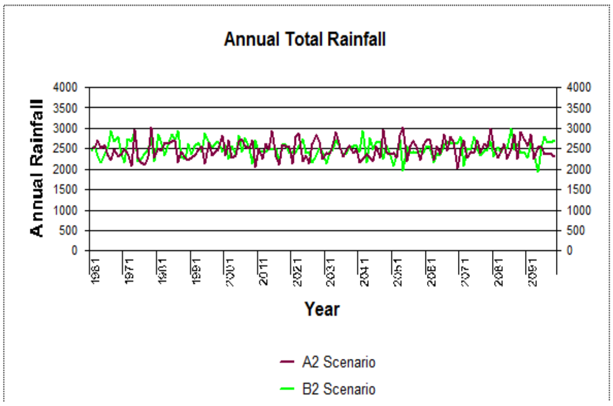

Figure 6: TSG of annual total rainfall

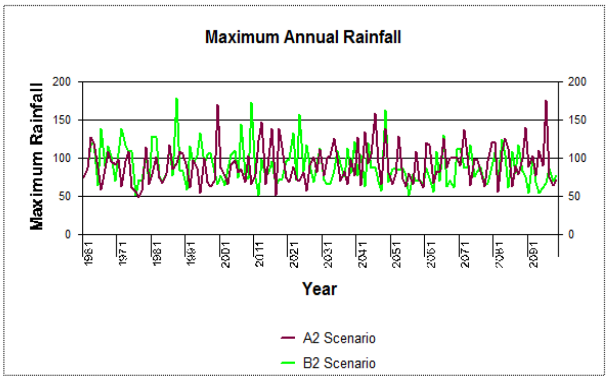

Figure 7: TSG of maximum annual rainfall

Best fit lines for each time series plot under both A2 and B2 scenarios were generated to identify the trend of each variation. Figure 8 and Figure 9 illustrate the best fit lines generated for annual total precipitation under A2 & B2 scenarios.

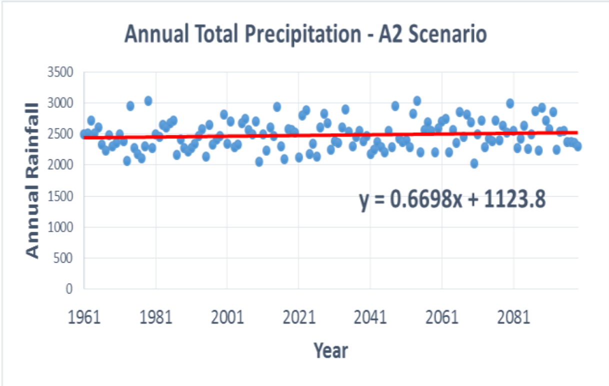

Figure 8: Best fit line for annual total precipitation under A2 scenario

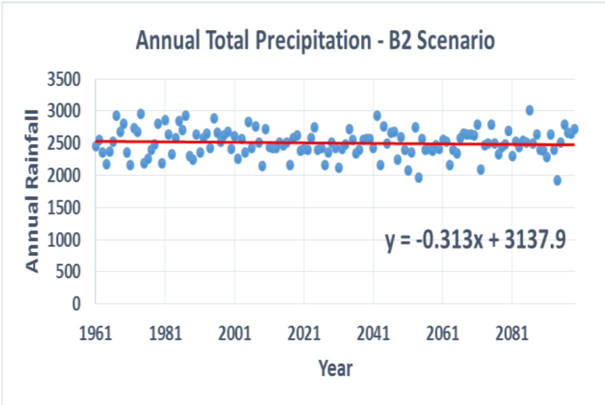

Figure 9: Best fit line for annual total precipitation under B2 scenario

Annual total precipitation, maximum annual rainfall and annual averaged daily rainfall show an increasing trends of 0.7 mm per year, 0.1 mm per year and 0.002 mm per year respectively under A2 scenario. Under B2 scenario all above mentioned parameters illustrate decreasing trends of 0.3 mm per year, 0.15 mm per year and 0.001 mm per year respectively.

4. Conclusions

Annual total precipitation, maximum annual rainfall and annual averaged daily rainfall show increasing trends under A2 scenario and decreasing trends under B2 scenario. But the recorded decreasing trends are insignificant.

References

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