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Potential Impacts of Climate Change on Precipitation and Temperature at Jor Dam Lake

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ABSTRACT

Rising global temperatures have threatened the operating conditions of Batang Padang hydropower reservoir system, Malaysia. It is therefore crucial to analyze how such changes in temperature and precipitation will affect water availability in the reservoir in the coming decades. Thus, to predict future climate data, including daily precipitation, and minimum and maximum temperature, a statistical weather generator (LARS-WG) is used as a downscaling model. Observed climate data (1984-2012) were employed to calibrate and validate the model, and to predict future climate data based on SRES A1B, A2, and B1 scenarios simulated by the General Circulation Model's (GCMs) outputs in 50 years. The results show that minimum and maximum temperatures will increase around 0.3-0.7 ºC. Moreover, it is expected that precipitation will be lower in most months. These parameters greatly influence water availability and elevation in the reservoir, which are key factors in hydropower generation potential. In the absence of a suitable strategy for the operation of the hydropower reservoir, which does not consider the effects of climate change, this research could help managers to modify their operation strategy and mitigate such effects.

Keywords: Climate change, precipitation, temperature, global climate models, weather generator, statistical downscaling, LARS-WG

INTRODUCTION

Climate change is defined as a disruption in the statistical distribution of weather patterns that lasts for decades to millions of years. Climate change could involve a change in mean weather conditions or in the time and length of weather variation (i.e. more or fewer

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extreme weather conditions such as floods and droughts). Since the industrial revolution, human activities, especially the burning of fossil fuels for energy production, heating processes and also agricultural activities, deforestation, and changing land uses have been identified as the main sources of climate change and global warming (Carnesale & Chameides, 2011).

In order to investigate past and future climatic conditions, researchers usually use observations and theoretical models. General Circulation Models (GCMs) based on the physical sciences are the most reliable theoretical methods. GCMs use observed data to project future climate models in large scale, and describe the causes and effects of climate change. GCMs have been used by many researchers to predict changes in climate parameters (Biasutti & Giannini, 2006; Hashmi *et al*., 2011). However, these studies have shown that there is a high level of uncertainty in rainfall projection among different GCMs and scenarios. Another significant weakness of GCMs is that their outputs lack sufficient detail to be usable in hydrological models. In order to overcome this limitation, it is essential to transform the country-level predictions of GCMs to the required regional-level information for precipitation and temperature. These methods, which transform the GCM outputs into fine-resolution climate parameters, are called 'downscaling' techniques (Seguí *et al*., 2010; Goyal & Ojha, 2012).

There are different types of downscaling methods, which can be categorised into two main groups: statistical and dynamic downscaling methods. Of the available statistical downscaling techniques, LARS-WG (Long Ashton Research Station Weather Generator) is preferred as it can generate future climate models with less data (Racsko *et al*., 1991; Semenov & Barrow, 1997; Semenov *et al*., 1998). LARS-WG simulates the time series of climate parameters in a daily scale at a single site based on as little as a single year of historical data. This is a well-regarded method that can be used in data-scarce regions like Malaysia. It has therefore been extensively employed in assessing the climate change impact on hydrology, water resources and environmental issues (Vicuña *et al*., 2008; Hashmi *et al*., 2011; Chen *et al*., 2013a). Another advantage of using LARS-WG is that the outputs of 15 GCMs with various emission scenarios could be incorporated into the model to cope with the GCMs uncertainties.

Dibike and Coulibaly (2005) have conducted a comparative study of downscaling models. They found that the LARS-WG method generates a growing trend in mean monthly minimum and maximum temperatures and a small decrement in the variation of temperature for most months. The results also showed that there was no significant change in mean monthly precipitation, or wet and dry spell lengths and the model performance was found to be acceptable. Thus, in this paper, LARS-WG is selected as the downscaling technique.

There is a need to test and evaluate the capability of LARS-WG in downscaling climate parameters like precipitation and temperature in tropical regions like Malaysia. Since these variables are the key weather parameters that directly affect the availability of water in the reservoir, estimating these parameters in the future could help managers and operators predict the potential of the system in generating hydropower and mitigating the effects of climate change by revising the reservoir operation strategy.

As a conclusion, LARS-WG is used as a downscaling model in this study and in order to overcome the uncertainties concerning GCMs, various scenarios are employed to predict the climate parameters under different conditions. Fortunately, simulation of climate change in the 20th century under the special reports on emission's scenario (SRES) is available for most of the sub-models in GCMs (Alexander & Arblaster, 2009). The SRES comprises various storylines that portray the economic, demographic and technology changes in the future. The most common scenarios are namely A1B, A2 and B1, which are used in the present study. A1B portrays a rapid economic and population growth in the future world. New technologies bring out a combination of non-fossil and fossil fuels as greenhouse-gas emissions. The SRES A2 scenario describes a highly heterogeneous world. As a result, economical growth and technological change per capita are slower than in other storylines. SRES B1 scenario depicts a world with a global population growth that peaks mid-century and decreases afterwards. As a result of globalisation, rapid changes in economic structure are projected to occur. This scenario has a positive view for the future, which shows the world with declined material consumption and usage of clean source of technologies.

The main objective of this research is to predict and analyse the changes in future precipitation and temperature using the LARS-WG downscaling model at Jor Reservoir (part of the Batang Padang hydropower system) under SRES B1A, A2 and B1 scenarios generated by one of GCMs model. The results could be a valuable source of information in future water resource planning and management.

RESEARCH METHOD

Study Area and Data Collection

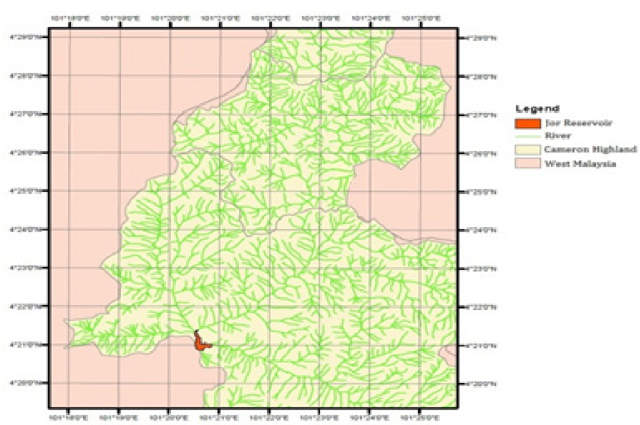

Fig.1: Location of Jor Reservoir in the State of Perak, Malaysia.

This research took place at Jor Reservoir, which is situated in the Tapah Hills Forest Reserve in the state of Perak, Malaysia (Fig.1). Jor Reservoir is part of the Batang Padang hydroelectric scheme (BPHS). The BPHS will impound the discharge from the Sultan Yussuf Power Station together with the waters of the Jor River, Sekam River and Batang Padang River within the Jor Reservoir. From Jor Reservoir, the water will flow 14.5 km through Menglang Tunnel, generating power in the Sultan Idris II underground power station with an installed capacity of 150 KW. The availability of water in the reservoir will, therefore, directly affect power production in the hydropower reservoir system (BPHS). Meanwhile, rising global temperatures and greater climatic variations are significantly influencing water availability. Thus, it is essential to predict and analyse future temperature and precipitation at the Jor Reservoir, as these climate parameters will directly affect water resources. The nearest rainfall and temperature stations in the Jor Reservoir were selected to provide the LARS-WG input for future climate projections in this area (Table 1).

TABLE 1 : Weather Data Used as LARS-WG Input

Station	Climate parameters	Longitude	Latitude	Altitude	Range of data	Source
Empangan Jor	Daily precipitation	101° 20' E	4° 20' N	519.9	1984-2012	Tenaga Nasional Berhad
Cameron Highlands	Daily min and max temperatures	101° 22' E	4° 28' N	1545	1984-2012	Meteorological Department

Procedure of Downscaling by LARS-WG Model

The LARS-WG method was developed by Semenov and Barrow (1997). LARS-WG is extensively used to simulate daily weather data at a single site under present and future conditions (Racsko *et al.*,1991; Semenov & Stratonovitch, 2010). The first step in the weather generation process involves analysing observed daily weather data to calibrate the model. During calibration, LARS-WG analyses observed weather data to determine its statistical characteristics and generate site-specific cumulative probability distributions (*CPDs*) for the climate parameters. LARS-WG employs precipitation, minimum (*Tmin*) and maximum (*Tmax*) temperatures, and solar radiation (or sunshine hours). The process of data analysis involves applying semi-empirical distributions, such as frequency distributions based on the observed data for wet and dry spell lengths, daily precipitation and solar radiation. A Fourier series is used for the maximum and minimum temperatures. The site-specific file is then used in the generation process. Afterwards, the probability distributions of climate variables are used to generate synthetic weather time series of arbitrary lengths by randomly selecting values from the suitable distributions (Chen *et al.*, 2013b). LARS-WG applies a semi-empirical distribution (*SED*), which is specified as the cumulative probability distribution's function (*CPF*), to approximate the probability distribution of dry and wet series of daily precipitation, *Tmin* and *Tmax*. *SED* is divided into 23 intervals for each climate variable. Each climate variable (v) corresponds to the probability of occurrence (P), which is defined as:

$$v_0 = min \{v = P (v_{obs} < v)\} \ i=0,\ldots,n \qquad (1)$$

$$P_0 = 0, \text{ corresponds to } v_0 = min (v_{obs}) \qquad (2)$$

$$P_n = 0, \text{ corresponds to } v_n = max (v_{obs}) \qquad (3)$$

where, P defines the probability of accordance corresponding to (v_{obs}), P_0 and P_n are denoted as 0 and 1 for the climate variable of v_0 and v_n, respectively. To assign the extreme values of climate variables, extremely low values are assigned P values close to 0 and extremely high values are assigned P values close to 1. The other values of P_i are distributed evenly on the probability scale. Since the occurrence probability of low daily precipitation (<1 mm) is high and this low precipitation has no significant effect on the climate model output, Semenov and Stratonovitch (2010) recommended using v_1=0.5 mm and v_2=1 mm for precipitation within the interval [0, 1] with the corresponding probability, which is written as:

$$P_i = P\,(v_{obs} < v) \quad i=1,\,2 \tag{4}$$

In the model, extremely long time series of dry and wet data are considered with two values close to 1, with P_{n-1}=0.99 and P_{n-2}=0.98 in *SEDs*. In addition, in the case of minimum and maximum temperature, two values close to 0 and 1 are assigned for extremely low and high temperatures. For instance P_2=0.01, P_3=0.02, P_{n-1}=0.99, P_{n-2}=0.98 (Hassan *et al*., 2014).

The overall process of generating synthetic weather data by the LARS-WG method can be divided into three steps: calibration, validation and generation of synthetic weather data.

Model calibration. LARS-WG calculates the statistical parameters for each climate variable based on the observed historical data. Once LARS-WG has been calibrated, a series of daily synthetic weather data is generated. A random number generator chooses climate variables from the *CPDs* and as a result, the synthetic weather has the same statistical characteristics as the observed dataset. The generation process requires selecting the number of years to be simulated, as well as a random seed, which controls the stochastic component of the weather generation. Different random seeds generate the same weather statistics, while variables differ on a day-to-day basis (Semenov & Barrow, 2002). In this study, the number of years was taken as 50 and the random seed was chosen as 541.

Model validation. The statistical parameters that were derived from the calibration process were then employed to generate synthetic climate variables with the same statistical characteristics as the original observed weather data. Model validation involved analysing and comparing the statistical characteristics of the observed and synthetic weather data to test the capability of LARS-WG to simulate the precipitation, *Tmax* and *Tmin* at the selected site in order to determine whether or not it is suitable for use. LARS-WG facilitated the validation procedure by employing the *Q*-test option to determine how well it simulated the observed data. LARS-WG, therefore, uses a number of statistical tests such as the Kolmogorov Smirnov, student's *t* test and the *F* test to determine whether the distributions, mean values and standard deviations of the synthetic data were significantly different from the observed data set.

Generation of synthetic weather data. LARS-WG then generated synthetic weather data by synthesising the statistical parameter files derived from the observed weather data in the calibration process with a scenario file containing information about changes in the amount of precipitation, wet and dry series duration, mean temperature, temperature variability and solar radiation. LARS-WG was used to generate daily data based on a particular scenario simulated by GCMs. The scenario file contained the appropriate monthly changes.

Generation of Climate Scenarios

By perturbing the parameters of distributions for a specific site with the predicted climate changes derived from global or regional climate models, a daily climate scenario for the selected site could be generated. In order to generate climate scenarios for a certain future period and an emission scenario at Jor site, the baseline parameters, which were calculated from the observed dataset from 1984-2012, were adjusted by the Δ-changes for the future period based on emission scenarios, which were predicted by the GCM sub-model for each climatic variable. In this research, the local-scale climate scenarios were based on the A1B, A2 and B1 scenarios simulated by one of the GCMs sub-models, which is called the Hadley GCM3 (HadCM3). HadCM3 was proposed by the UK Meteorological Office's research centre. This model is the most popular and mature of the GCMs, which uses 360 days per annum, where each month is 30 days and has a spatial grid with dimensions 2.5° latitude × 3.75° longitude (Toews & Allen, 2009). It is similar to a coupled atmosphere-ocean general circulation model (AOGCM), which used the coupled model to generate the transient projections. HadCM3 has been applied in many studies (Houghton *et al*., 2001; Qian *et al*., 2004; King *et al*., 2009). This model is unique among GCMs models because it does not need flux adjustments to produce a realistic scenario (Collins *et al*., 2001).

Overall, the future weather data in this study are generated by using LARS-WG [V 5.5] for the time periods of 2011-2030 to predict the future precipitation and minimum and maximum temperature change at Jor Reservoir.

RESULTS AND DISCUSSION

Evaluation of LARS-WG Performance for Prediction of Climate Variables at Jor Reservoir Using Statistical Tests

Before running simulations of future climate parameters, the performance of LARS-WG must be evaluated for the selected site (Jor Reservoir). The main purpose of any weather generator is to simulate climate with the same statistical characteristics as the observed data. In this step, the statistical characteristics of the observed data are compared with the generated data. LARS-WG simplifies this procedure by providing the *Q*-test option to determine the equivalence of the generated data with the observed data in terms of the distributions, mean values and standard deviations, using statistical tests such as Kolmogorov Smirnov test, student's *t* test, and *F* test, respectively.

In this study, the observed historical data from 1984-2012 was used to validate the model for the Jor site. In order to discover the capability of LARS-WG, the Kolmogorov Smirnov (*KS*) test was used to evaluate the equivalence of the seasonal distributions of wet and dry series (*W/D*), distributions of the maximum (*D/Tmax*) and minimum daily temperatures (*D/Tmin*) and distributions of daily rainfall *(D/Rain*) between observed historical data and synthetic data. The t test was performed to test the equivalence of the monthly mean rainfall (*M/Rain*) and the monthly means of maximum (*M/Tmax*) and minimum (*M/Tmin*) temperatures. The F test is applied to testing the equivalence of monthly variances of rainfall (MV/Rain) calculated from observed data and synthetic data. The statistical test result is presented in Table 2, where the numbers show how many tests give significant different results at the 5% significance level out of the total number of tests (four wet and four dry seasonally scaled) or 12 (monthly scaled). A large number reveals a poor performance modelling in the generated synthetic data. The KS test results show that LARS-WG perfectly simulated the distributions of (*W/D*), (*D/Tmax*), (*D/Tmin*) and (*D/Rain*) for this site. The number zero reveals the most desired performance outcome in generating the synthetic data. Mean monthly minimum and maximum temperatures are two out of 12, which means there are significant differences between observed and simulated data in two months of the year, while in the majority of months (10 out of 12 months), the model can perfectly simulate the minimum and maximum temperatures. The result was, therefore, acceptable.

TABLE 2 : Statistical Results of Comparing the Equality of Observed and Simulated Data Generated

Site	*W/D* series	*D/Rain*	*D/Tmax*	*D/Tmin*	*M/Rain*	*M/Tmax*	*M/Tmin*	*MV/ Rain*
			KS test			*t* test		*F* test
Jor	0	0	0	0	0	2	2	4
Total tests	8	12	12	12	12	12	12	12

The rainfall results show that although there was a dramatic change in mean monthly rainfall in the tropical region, the LARS-WG could perfectly simulate the monthly mean rainfall (0/12), while it had some difficulty in simulating monthly variances of rainfall (4/12). Thus in four months of the year, there was a significant difference between the variance of observed and simulated data. The months were May, June, July and October, which are months affected by the Southwest monsoon in Malaysia that starts in May. This monsoon causes the drier weather and sporadic rainfall, which significantly affects rainfall variance.

Visual comparison of monthly mean and standard deviation of observed and synthetic rainfall is shown in Fig.2 and Fig.3, respectively. While there were good matches between the monthly means of the observed and simulated rainfall, the performance of the standard deviation was not as good a match; however, the results were still acceptable. The outputs of the model in simulating the monthly mean maximum and minimum temperatures are illustrated in Fig.4 and Fig.5, respectively. It is evident that the model could simulate these parameters extremely well and the synthetic data match very well with the observed historical data in all months.

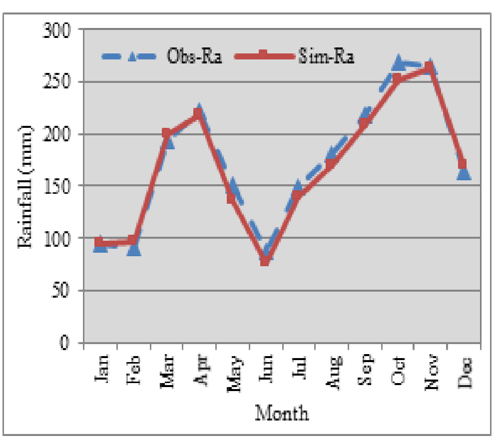

Fig.2: Comparing monthly means of observed and simulated rainfall, 1984-2012

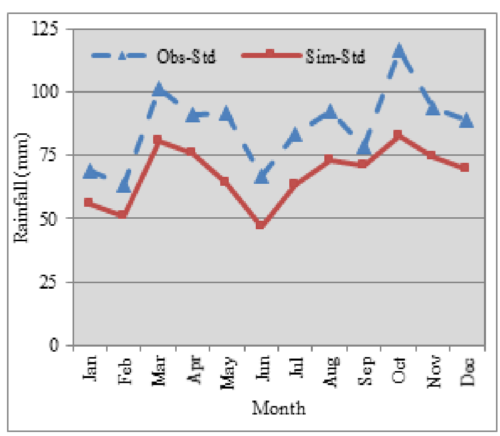

Fig.3: Comparing monthly standard deviations of observed and simulated rainfall, 1984-2012.

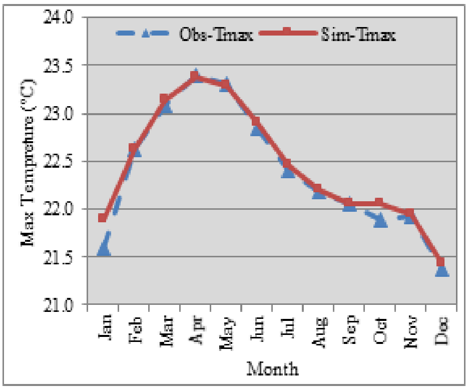

Fig.4: Comparing monthly means of observed and simulated maximum temperatures, 1984-2012.

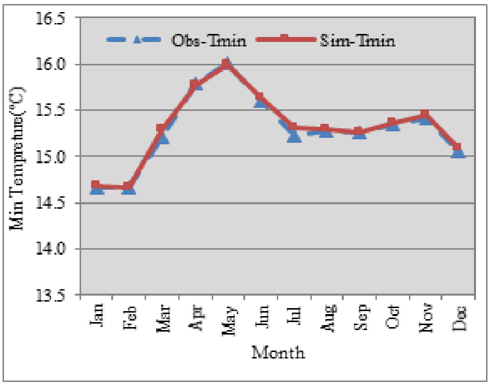

Fig.5: Comparing monthly means of observed and simulated minimum temperatures, 1984-2012.

Change in Temperature

The monthly minimum temperatures in the baseline and future periods are shown in Fig.6. The simulated data were developed for A1B, A2, and B1 scenarios for the 2020s. All scenarios predicted an increment in minimum temperature of around 0.3-0.7 ºC in the next 50 years. The monthly future trends of temperature follow a uniform shape like an observed data trend. The greatest and lowest discrepancies between observed and synthetic data were predicted for March by A1B and September by A2, respectively (Fig.7).

The discrepancy of maximum temperatures in the baseline and future periods is shown in Fig.8, which varies from 21-24 ºC. The maximum temperature will increase by around 0.3 to 0.7ºC in the 2020s (Fig.9). It is evident that the future outputs are highly variable. The greatest discrepancy between future and baseline values will occur in January and March (around 0.7 ºC increments), while the lowest difference will be in September. From the given results, it can be concluded that both *Tmin* and *Tmax* parameters will increase by around 0.3 to 0.7 ºC in the next 50 years. These parameters directly increase the surface evaporation in the reservoir and reduce the available storage at the Jor Lake, which is the key factor in determining hydropower generation. In addition, rising temperatures cause extreme events like droughts or floods, both of which are harmful to power generation. During droughts, the reservoir cannot satisfy the hydropower demand, and during floods, the safety of the reservoir system is threatened.

It is remarkable to note that the main reason for increasing temperature in this area is deforestation. Cameron Highlands is one of the few highland areas with a cool climatic regime that has undergone phenomenal pressures for unplanned development over the last few decades. Development pressures cause more areas to be deforested and cleared. Deforestation is one of the key factors resulting in negative environmental effects, including local climate change. Deforestation is among the human activities that contribute to the spread of carbon dioxide in Cameron Highlands. Deforestation and land-clearing activity for tourism, urbanisation, infrastructure development and agriculture is a major reason for climate change and temperature increment. Deforestation is not the only reason for climate change in this area, but is the major factor of climate change in Cameron Highlands (Hamdan *et al*., 2014).

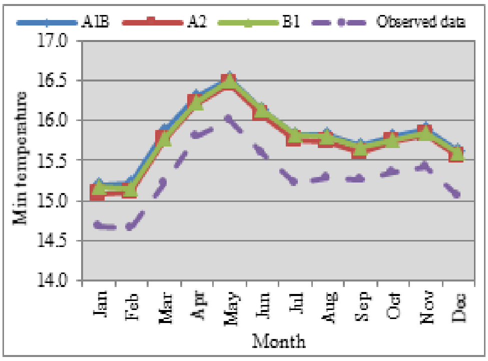

Fig.6: Comparing monthly minimum temperatures between present data and simulated data by A1B, A2, and B1.

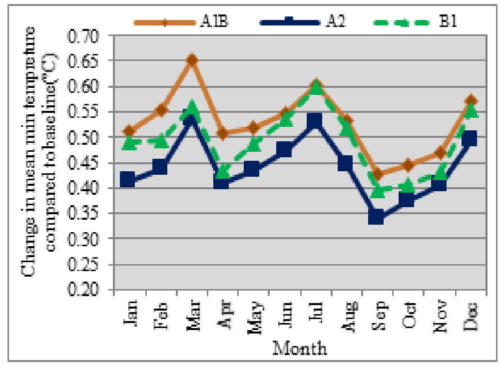

Fig.7: Change in average of monthly minimum temperature.

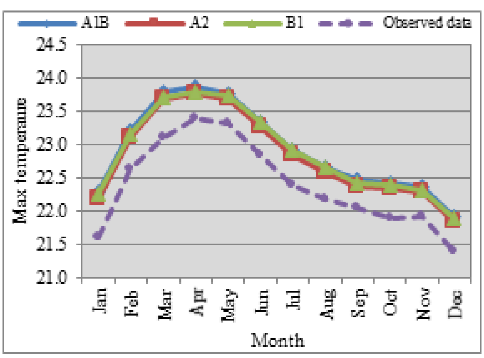

Fig.8: Comparing monthly maximum temperatures between present data and simulated data by A1B, A2, and B1.

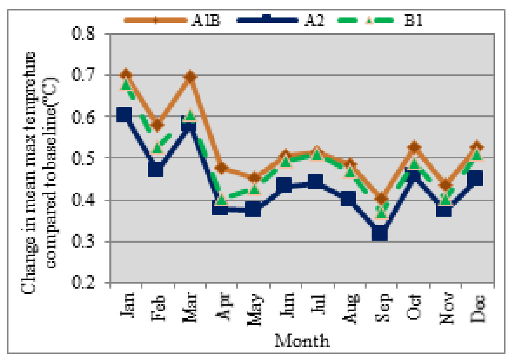

Fig.9: Change in average of monthly maximum temperature.

Change in Precipitation

The monthly amount of observed and simulated rainfall is shown in Fig.10. The given results indicate that in most months, the monthly rainfall will decrease due to global warming in this area. The percentage changes between the simulated and observed values of monthly rainfall were plotted in Fig.11 in 50 years. A positive value indicates an increment and a negative value indicates a decrement in total monthly rainfall. The greatest differences between baseline and future rainfall values among these months are found in February, March and October, which have more than ± 20% variation. Most of the months show a decrement in rainfall, which directly affects the amount of stream flow, water availability and the potential of the reservoir system in producing hydropower. Accordingly, it can be predicted that the potential of hydropower generation will decrease in the future.

The main reason for erratic rainfall in Cameron Highlands is climate change. Climate change is caused by an emission of carbon dioxide in the atmosphere. Greenhouse gases trap electromagnetic radiation form the sun and reflect them back into space. This is the main reason for overall global warming and irregular weather. Besides the negative effects of deforestation in Cameron Highlands, another factor that brings out the greenhouse gas is the installation of rain shelters for some crops, which causes the emission of greenhouse gases. The heat from the sun is supposed to be fully absorbed into the earth; however, by installation of rain shelters in Cameron Highlands, the heat is reflected into space. As a result, more extreme events will occur and the rainfall pattern will change.

In summary, climate change threatens the socio-economic welfare of farmers, the ecology and the environment and also affects the sustainability of agriculture in Cameron Highlands. Since agriculture is a sector that is highly vulnerable to climate change and its production activity considerably depends on natural resources (Alam *et al*., 2012), farmers are also affected by these changes. Among these changes, three principal factors are the rising temperature, deforestation and the considerable numbers of rain shelters that produce uncontrolled greenhouse gases. These changes have negative effects on the two main industries in Cameron Highlands i.e. agriculture and tourism. A number of factors have been distinguished as significant reasons for such changes. The higher cost of living has put pressure on Cameron Highlands' farmers. This is the main factor driving farmers to increase their income somehow. Land clearing is a solution for doubling their productivity and income (Siwar *et al*., 2013). However, it causes a negative effect on the agriculture sector and increases temperature. In addition, the rising trend in temperature will influence the tourism industry as the coolness of Cameron Highlands has always been the principal attraction for tourists. It can be concluded that the Malaysian government needs to develop policies to protect the environment and ecosystem in Cameron Highlands.

CONCLUSION

This research investigates the effects of global warming on key climate parameters such as precipitation and minimum and maximum temperatures in the Batang Padang hydropower reservoir system, Malaysia. These parameters greatly influence the available water in the reservoir, which is the key element of hydropower generation potential. Therefore, the observed climate data on precipitation and minimum and maximum temperatures for 29 years (1984-2012) were employed to prepare the weather generator model and estimate future climate data. In this research, LARS-WG was chosen as a downscaling technique to generate the time series of daily temperature and precipitation under the three climate scenarios of A1B, A2 and B1, simulated by one General Circulation Model's outputs for 50 years in the future. The results indicated that LARS-WG demonstrates good performance in simulating the statistical properties of daily climate data to forecast future climate change. It is estimated that global warming will cause an increase in minimum and maximum temperatures of 0.3-0.7 ºC, which will greatly intensify reservoir surface evaporation. In addition, the overall results demonstrated that the amount of precipitation will experience a decrement in most months under selected scenarios. However, it is expected that the percentage change in mean monthly precipitation will be an increase of +20% or more in February and October. The aforementioned parameters highly influence the availability of water in the reservoir, and thereby, the potential of hydropower generation. This research offers valuable information to managers and operators and implies the need to modify the reservoir system operation in order to mitigate the effects of climate change.

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