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Climate change impact under CanESM2 on future rainfall in the state of Kelantan using Artificial Neural Network

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Abstract. Kelantan is a state in Peninsular Malaysia that is highly vulnerable to extreme events such as drought and floods which are becoming worse because of climate change due to global warming that is caused by human activities. This study aims to evaluate the potential impacts of climate change on the future of rainfall in Kelantan using Artificial Neural Network. CanESM2 under three Representative Concentration Pathways (RCPs), namely RCPs 2.6, 4.5, and 8.5 for 2011-2100 are incorporated with the ANN model and are used to compare the baseline period (1972 to 2018). In general, the simulated rainfall that downscaled by using the ANN model approximates the observed rainfall (during the calibration and validation periods) reasonably well. The study also shows that the ANN model anticipates a major increase in annual rainfall in the 2080s for the RCP 8.5 scenario.

1. Introduction

The state of Kelantan is frequently affected by extreme events such as monsoons, floods, and droughts during the wet (November - January) and dry (March - May) seasons. For instance, a massive flood occurred in 2004 that resulted in the evacuation of more than 10000 people and 12 deaths. It is also reported by Irwan *et al.* [1] that the amount of rainfall had increased significantly from 1985 to 2014 and it is believed that these events could be more severe in the future. Therefore, evaluation of future water resources including rainfall under climate change is important to develop better water management systems and climate adaptation strategies in Kelantan.

General Circulation Models (GCMs) which are computer based-models determine the greenhouse gases and aerosols in the atmosphere by simulating the present and the future climate outputs [2]. The Representative Concentration Pathways (RCPs) developed from the collaboration of terrestrial ecosystem modellers, climate modellers and experts in emission inventory are introduced in the IPCC's [3] Fifth Assessment Report (AR5). These emission pathways represent the atmospheric composition forcing and classified by following the radiative forcing values (i.e. 2.6 to 8.5 W/m^2) until the end of 2100. In this context, new-generation of GCMs are produced from the framework of Climate Model Inter-comparison Project Phase 5 (CMIP5) under different RCPs which utilized to define the potential future scenarios. However, the outputs of the GCMs cannot directly be applied to the hydrological assessment in a small catchment due to their coarse spatial resolution characteristics. Therefore, the statistical downscaling (SD) method was applied in this study to downscale the coarse spatial of the

GCMs into a finer output. This method is one of the most widely used methods for climate and hydrological assessments [4]. The SD method was applied to identify time-series patterns such as temperature, rainfall, and rainfall-runoff. The concept of SD is effective as it defines the variables in a regional climate that are conditioned by the large-scale predictors and local variables [5]. The predictors from the GCMs were commonly used and applied in the SD method.

To incorporate the GCMs and SD, the Artificial Neural Network (ANN) was applied. The ANN model is considered to be a powerful tool as it has the ability to predict the pattern of linear or non-linear relationships between variables [6]. The ANN model has a superior technique whereby it has parallel processing capabilities to train large-scale samples. However, despite these advantages of the ANN model, a systematic procedure and model development needs to be considered to achieve the best performance. For example, regarding the present study, appropriate data sets were attained such as the type and size of the data while considering the data accuracy, inputs data, processing functions, criteria of validation, and output techniques. Therefore, a proper technique was incorporated to improve and develop a robust model for the study, thus, improving the output patterns and giving accurate results from the trained ANN model.

The objective of this study is to downscale the GCMs using the SD method for future rainfall. The concept will be embedded in the ANN model. The inputs of data, architecture, ability, and performances of the model are also discussed.

2. Materials and methods

2.1. Study area

Kelantan experiences a tropical climate in which the temperature ranges from 21 to 32 °C and receives an abundance of rainfall throughout the year (from about 2000 to 4000 mm/year) [7]. Kelantan is one of the states in Malaysia that is frequently affected by floods and drought. For instance, several major droughts occurred in 1997, 1998, 2002, 2003, 2005, 2006, 2007, 2009, and 2010.

The Gua Musang rainfall station (5006021) that is located at lat 5.0180N and long 100.650E is situated at the upstream of Galas River at Dabong, the Lebir River at Tualang and the Kelantan River as shown in figure 1. According to Ismail *et al.* [8], three days (21st to the 23rd of December, 2014) of continuous heavy rainfall that occurred in Gua Musang exacerbated the condition of floods that occurred

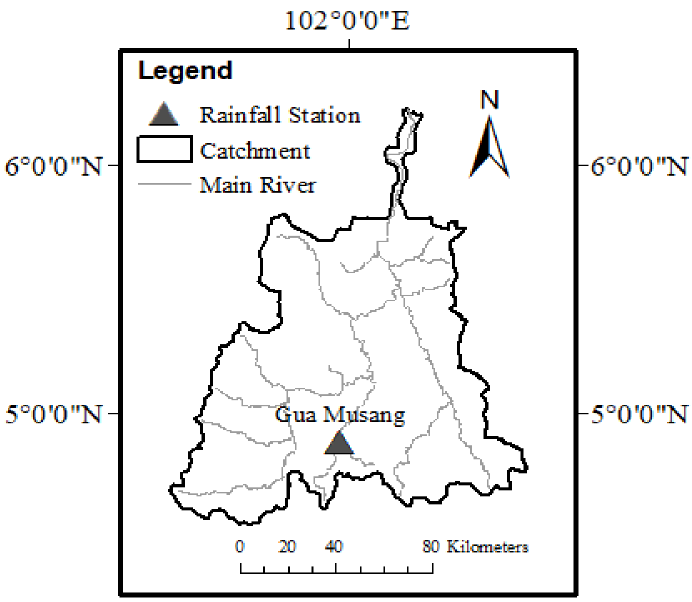

Figure 1. Map of the Kelantan catchment with the Gua Musang rainfall station.

at the time. They further explain that the recorded rainfall was approximately 1,295 mm which is equivalent to the amount of rainfall in a span of 64 days. The event was caused by ascending water levels to a dangerous level in all the three major rivers. This tragedy was the worst flood that occurred in Kelantan since 1967. It is for this reason that the Gua Musang Rainfall Station is chosen as a case study as it is located at the upstream and will affect the three (3) main rivers if any significant event were to happen in Gua Musang. The Gua Musang Station will represent the effects of climate change in the upper basins.

2.2. The General Circulation Model (GCM)

The second-generation version of the Canadian Earth System Model (CanESM2) is utilized as the studied GCM data throughout the study. The CanESM2 was established by the Canadian Centre for Climate Modelling and Analysis (CCCma) [9,10]. The CanESM2 is one of the models used in the CMIP5 that aims to develop the ensemble of daily predictors through the climate simulation process. The Canadians performed this project as a contribution to the fifth assessment report of the IPCC (AR5). As a result, the daily scale of 26 basic predictor variables was established in the project. They are described in 128x64 grid boxes in longitude and latitude direction and can be downloaded at the Canadian Climate Impacts Scenarios (CCIS) website. In the present study, the data used from the CanESM2 are re-analysed data predictors of the National Center of Environmental Prediction (NCEP) and the Representative Concentration Pathways scenarios (RCP 2.6, RCP 4.5 and RCP 8.5) from grid box of 37x 34y. The RCP 2.6 is a very low forcing level scenario, the RCP 4.5 is the stabilizes radiative forcing (represent the intermediate scenario) and the RCP 8.5 corresponds to the possible highest forcing level scenario. Therefore, RCP 2.6, RCP 4.5 and RCP 8.5 have been chosen as these three scenarios will exhibit a complete range of potential impacts. The data provided for the NCEP are from the years 1961 to 2005 while 2006 to 2100 are for the RCPs scenarios.

The correlation coefficient (R) was used to determine the relationship between the rainfall and potential predictors from the GCMs. The R can be defined as:

$$R = \frac{\sum(x-\bar{x}).(y-\bar{y})}{\sqrt{\sum(x-\bar{y})^2.(x-\bar{y})^2}} \tag{1}$$

whereby x is the observed rainfall value, y is the predictor value, $\bar{x}$ is the mean observed rainfall value, and $\bar{y}$ is the mean predictor value. The higher R values to 1 represent a strong relationship between the observed rainfall and predictors [11].

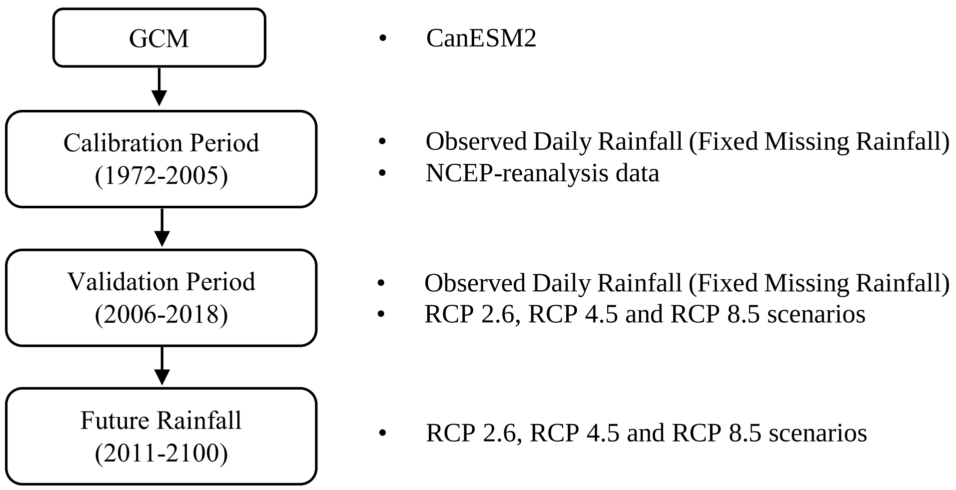

Figure 2. Flow design of the study.

2.3. Implementation of the Artificial Neural Network (ANN) as the GCM Downscale

The Artificial Neural Network (ANN) was utilized when downscaling the GCM for the current and future rainfall. Some steps need to be executed to implement the ANN model such as (1) determine the appropriate ANN architecture (2) use suitable training algorithm and (3) have the proper ANN model training procedures. The type of algorithm of the ANN model used in this study is the multilayer perceptron (MLP). This algorithm is the easy, effective and most frequent topology employed in a data-driven prediction model [12]. The model and algorithm composed a set of nodes that act as connecting links, activation function, and bias. The input data of the MLP model were datasets of predictands (daily rainfall time series) and predictors from the NCEP and the RCPs. The flow design of the study is illustrated in figure 2 and a detailed algorithm for the ANN model can be referred to in Hassan *et al.* [13].

3. Results and discussion

3.1. Screening of the GCMs variables

Future climate can be determined by having a robust relationship between large-scale predictors and the observed local scale predictands as defined in the statistical downscaling technique [14]. Before performing the calibration process, screening the appropriate predictor variables was conducted as shown in table 1. It can be seen that the total precipitation (prpgl) and specific humidity at 500 hPa (s500gl), 850 hPa (s850gl), and 1000 hPa (shumgl) displayed a robust correlation (R) with the rainfall in the Gua Musang Station, in which the R in the range of 0.1331 to 0.223. Additionally, the list of the predictors as listed in the table is in line with the suggested factors by Hassan *et al.* [15] and Gutierrez-Lopez *et al.* [16], in which they reported that factors such as monsoon mechanisms, ambient temperatures, maritime influence, and the interplay of wind components from the South China Sea and the Indian Ocean played a huge influence in the occurrence of rainfall in Malaysia.

Table 1. Correlation between daily NCEP-reanalysis with observed daily rainfall.

Predictors (Code)	Correlation value, R
Total precipitation (prpgl)	0.2225
500 hPa Specific humidity (s500gl)	0.1703
850 hPa Specific humidity (s850gl)	0.1746
1000 hPa Specific humidity (shumgl)	0.1331

3.2. Development of the ANN model during the calibration and validation periods

The rainfall (predictands) and the potential predictors will be separated into two-period groups; 1972-2005 and 2006-2018; the former for model calibration and the latter for model validation. For the calibration, the parameters of the ANN model were developed with the NCEP/NCAR data and were determined by a visual comparison between simulated rainfall and observed rainfall. For the validation, the performance of the calibrated ANN model was checked using three sets of RCP scenarios, namely RCP 2.6, 4.5 and 8.5 from CanESM2.

As shown in figure 3 and figure 4, the ANN model shows a good agreement in downscaling the observed rainfall during the calibration period, in which the model was able to simulate well in terms of the mean rainfall and wet day. However, the performance of the ANN model decreased during the validation period as compared to the performance of the model during the calibration. The high differences are shown from October until December, in which the differences between the observed and simulated mean rainfall is in the range of 2 mm. This reduction in the performance of the ANN model may be because the ANN model was calibrated with NCEP data and the built parameters have a bias when the model was driven by the RCPs data [17].

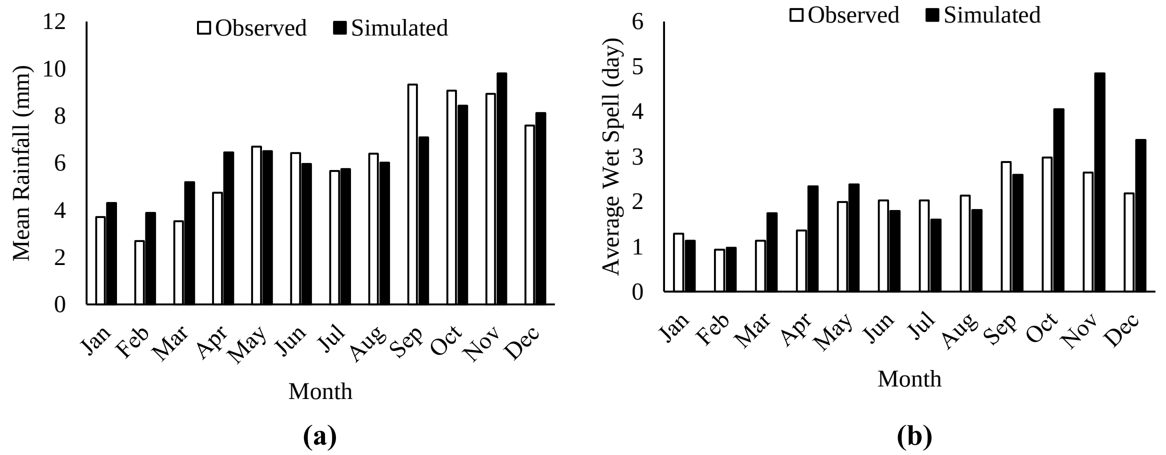

Figure 3. Calibration results for the (a) mean rainfall and (b) average wet spell of the ANN model.

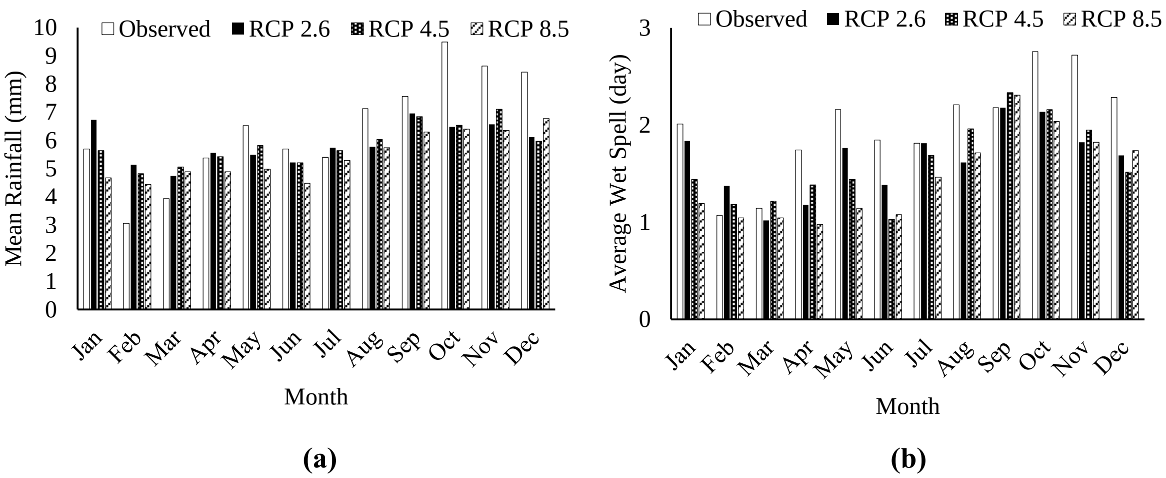

Figure 4. Validation results for the (a) mean rainfall and (b) average wet spell of the ANN model.

3.3. Projection of Future Rainfall under the RCPs scenarios using the calibrated ANN model

The downscaling of future rainfall under the RCPs scenario is displayed in table 2. The possibilities of future rainfall are grouped into three periods, namely 2020s (2011–2040), 2050s (2041–2070) and 2080s (2071–2100). As detailed in the table, the trend of change anomalies in the mean daily rainfall against the observed period shows a similar trend, in which an increasing trend is shown in the daily rainfall from January until April (up to 4.4 mm) and a decreasing trend from May until December (up to -3 mm). This trend is slightly different from the study by Toriman *et al.* [18] in which they found that the increase of monthly rainfall was during the wet season (May until December) over the Kelantan River catchment.

Figure 5 shows the trend of annual rainfall corresponding to the RCP 2.6, 4.5 and 8.5 scenarios. The trend shows a fluctuated trend of annual rainfall through all periods with the range from the minimum (1565 mm at the year 2037) to the maximum (3464 mm at the year 2095). A decrease in the average annual rainfall depth in the future period until the 2080s was projected based on the RCP 2.6 and 4.5 scenarios as compared to the average of annual observed rainfall which is 2282 mm. Meanwhile, the RCP 8.5 projected a higher average annual rainfall throughout the years. In particular, the recorded average annual rainfall depth projected for the three RCPs is 2152 mm (RCP 2.6), 2097 mm (RCP 4.5) and 2306 mm (RCP 8.5). From the results, preparedness for flood events will also need to be taken accordingly to correspond to the increase of annual rainfall that has been projected from RCP 8.5 in the

2080s. This trend is similar to the study by Tan *et al.* [19], in which they also found that there is an increase in annual rainfall in Kelantan in the 2080s.

Table 2. Change anomalies in mean daily rainfall corresponding to three RCPs.

Month	RCP 2.6 (mm)			RCP 4.5 (mm)			RCP 8.5 (mm)		
	2020s	2050s	2080s	2020s	2050s	2080s	2020s	2050s	2080s
Jan	2.64	1.39	2.15	1.53	1.53	1.67	2.27	1.77	1.79
Feb	2.04	2.87	2.53	1.73	1.73	2.42	2.32	2.49	1.8
Mar	1.12	1.81	1.89	1.34	1.34	1.49	1.87	1.53	1.65
Apr	0.86	0.72	1.37	1.16	1.16	0.55	0.96	0.5	1.78
May	-0.96	-1.03	-1.15	-1.45	-1.45	-1.45	-1.4	-1.61	0.36
Jun	-1.45	-1.46	-1.24	-1.21	-1.21	-1.73	-1.39	-1.43	0.29
Jul	-0.24	-0.22	-0.63	-0.28	-0.28	-0.33	-0.19	-0.24	3.22
Aug	-0.63	-0.67	-0.57	-0.8	-0.8	-0.57	-0.39	-0.09	4.42
Sep	-2.79	-2.66	-3.06	-2.69	-2.69	-2.58	-2.61	-2.23	1.37
Oct	-2.26	-2.14	-1.84	-2.26	-2.26	-2.05	-2.23	-2.03	-0.86
Nov	-1.78	-2.04	-1.79	-1.89	-1.89	-2.16	-2.07	-2	-2.31
Dec	-1.15	-1.08	-0.83	-1.62	-1.62	-0.47	-1.34	-1.88	-1.35

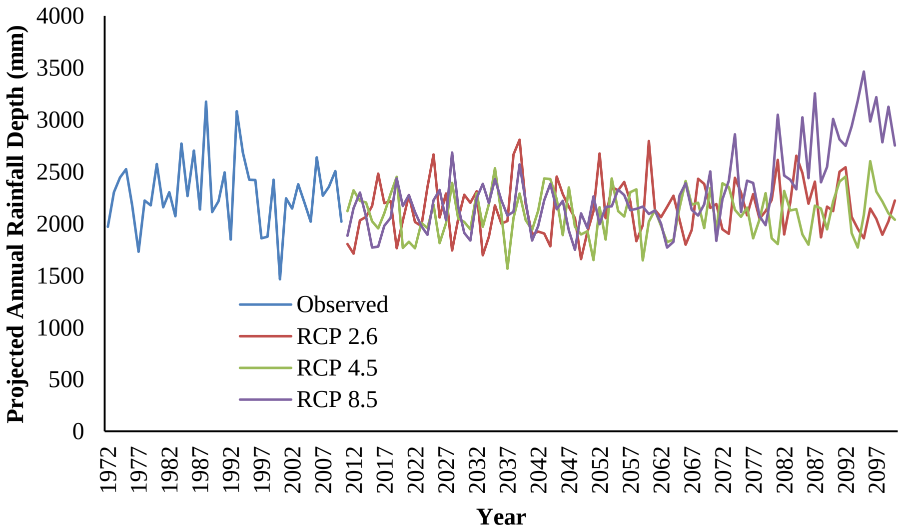

Figure 5. The trend of annual rainfall corresponding to the GCMs.

4. Conclusion

Overall, the proposed methodology with the ANN model can downscale the GCM and project future rainfall with satisfied performance. It reveals that the calibrated ANN model is satisfactory to downscale the observed rainfall. In terms of future rainfall, the changes in climates could result in a shifting trend of daily rainfall in the area of Gua Musang in which there is decreasing in monthly rainfall during the wet season and vice-versa for another season. Also, there will be a significant change in the increase of daily rainfall in the 2080s.

This study provides preliminary results of climate change impacts using a single rainfall station. Therefore, for generalization of results, further research must be performed to evaluate the comprehensive effects of climate change impact toward the Kelantan River catchment.

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