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Future Temperature for Drought Prediction in Bukit Merah, Perak by Using SDSM Modelling

Dharshilan A/L Murugan, Nuramidah Hamidon^{a)}, Nur Suhana Abdul Manap, Nur Aini Mohd Arish, Nor Maizzaty Abdullah, Mariah Awang, Alia Farhana Malik, Nor Hazren Abdul Hamid, Hasnida Harun, Norshuhaila Mohamed Sunar, Mimi Suliza Muhamad and Roslinda Ali

Department of Civil Engineering Technology, Faculty of Engineering Technology, Universiti Tun Hussein Onn Malaysia, 84600 Pagoh, Johor, Malaysia.

^{a)}Corresponding Author: nuramidah@uthm.edu.my

Abstract. Climate change is a worldwide phenomenon that can cause many sudden changes, especially to water resources. Malaysia has experienced warming and rainfall abnormalities, especially in the last two decades, and therefore estimates of climate change in Malaysia receive a lot of attention. Global climate research is increasingly focused on severe temperature changes due to severe climatic phenomena like droughts and heat waves globally. This research aims to forecast maximum and minimum temperatures in Bukit Merah, Perak, for the years 2020-2050 and 2050-2080. This project predicted the magnitude of drought over the next 60 years, and the data collected is aid hydrologic modelling in the Bukit Merah, Perak. The findings analysed and addressed to estimate the future drought that may occur in the next 60 years. SDSM has been widely used for downscaling climate variables such as precipitation, rainfall, and temperature among statistical downscaling methods. Statistical downscaling provides local scale statistics, which is useful in climate change analysis. It involves the use of past weather data for a longer time to collect large-scale variables. Therefore, it was necessary to utilize the Root mean Square error (RSME) and the coefficient R^2 to evaluate the performance of historical and simulated data from the model during the calibration and validation periods. The coefficient of determination (R^2) during calibration and validation for maximum temperature were 0.89 and 0.67, while for minimum temperature, the value for calibration and validation is 0.83 and 0.85. Therefore, the drought forecasting is an early warning system that the most crucial stages for drought management that will arise in the future.

INTRODUCTION

Climate change is an unavoidable, pervasive, and chronic global issue that creates trouble for the world's water supply and freshwater ecosystems. This remarkable increase was related to growing greenhouse gas (GHG) levels in the atmosphere, directly caused by deforestation, open burning, and human activities. Climate change has also become a global environmental concern that has dominated the world agenda and is one of humanity's challenges [1]. Changes in land surface features drove the most significant changes in the radiative balance and climate, followed by those caused by large amounts of soot and chemicals released into the atmosphere [2]. In addition, human emission sources at the same time, has produce certain climate-related chemicals and others that might influence air pollution, and influence both atmospheric chemistry and climate science. Malaysia, in particular, has shifted from an agriculture to an industrial economy during the previous four decades, resulting in a rise in GHG emissions from autos, factories, and power plants [3,4].

Based on the Malaysian Meteorological Department (MMD), during South West Monsoon since 1951, Malaysia recorded at least 12 times extreme heat [5]. Drought has recently been a significant concern in peninsular Malaysia because of the extreme shortfall of rain, leading to water crisis difficulties. Most of the countries of Malaysia Peninsular have had severe historical drought events, which have substantial environmental, economic and social [6],

[7]. Moreover, it creates disastrous implications in a more globalized world for regional water supplies, agriculture, the economy, the environment, and land desertification. In addition, El Nino events may have affected recent drought, rising global temperatures and change the pattern of precipitation. Therefore, it also increases the probability of drought variations and severity in that region. In 2014, drought-affected many states in western and coastal Peninsular Malaysia, leading all major dams to reach critical water levels due to the El Nino event [8]. Therefore, General Circulation Models (CGMs) nowadays are widely used to predict and estimate the consequences of global climate change. Hence, there are essential tools for mitigating the problems through the climate variables. For example, temperature and rainfall data frequently used in CGMs to forecast the future climate. There are two methods in downscaling, which are dynamical downscaling (DD) and statistical downscaling (SD) [9], [10]. For instance, Statistical Downscaling Model (SDSM) is a statistical methodology use for downscaling climatic variables such as precipitation, rainfall, and temperature that has been widely used. Moreover, statistical downscaling creates data at the local level that may be used to analyze climate change. SDSM provides acceptable downscaled temperature and precipitation data when using predictors representing the observed further categorized in weather type and future climatic effect in that place [2,11]

MATERIALS AND METHODS

Study Area

The catchment in Kerian, Perak, was chosen for this study since it is located in the north of Peninsular Malaysia [12] as illustrated in Figure 1. In 1900, it was the first manmade reservoir, located in the region of Kerian in northern Perak state [13]. The basin is drained by two major rivers, the Kurau and Kerian. The reservoir receives water from two major catchment areas: the Kurau River Basin and the Merah River Basin. Two subsystems are located upstream of the reservoir: Kurau and the Merah River, which flow from swelling to steep terrains [14]. The Bukit Merah Reservoir is separated into the northern and southern portions by a 4 km railway line built across the reservoir for economic objectives. Bukit Merah reservoir land usage consisted primarily of natural and main forests (46.29 %). According to Talib [14], the primary aim of this basin is to provide potable water for the double yearly harvesting of paddy over 24,000 hectares of rice paddy [15] under the Kerian Sungai Manik project.



FIGURE 1. Bukit Merah reservoir location

Study Data

Temperature data from Ipoh Perak were utilised to do statistical downscaling in our study. SDSM. Ipoh Perak was chosen as the location for the station due to the nearest meteorology station in Bukit Merah, Perak. The data get from meteorology data were used to calibrate the statistical downscaling model. Thus, we assume that Bukit Merah is the same temperature as the dam in Ipoh Perak in this study. Therefore, the temperature is used as a predictor, as stated in Table 1.

TABLE 1. Detail meteorology station (Temperature)

ID of station	Name of station	Year	Location	
			latitude	longitude
48625	Ipoh, Perak	2010-2019	4°34'01"	101°06'00"

Statistical Downscaling Method

Statistical downscaling methods are used by the hydrologist to obtain the local scale of data as input to the hydrological model [9]. According to Tahir [16], SDSM is subdivided into three sub-models: yearly, seasonal, and monthly. Each model is connected to a regression equation. In SDSM 4.2, the spatial data of GCM will be downscaled of daily predictor-predictand relationships using the multiple linear regression techniques [17]. SDSM 4.2's newest version of the programme determines the essential variables by performing a linear correlation analysis, partial correlation analysis, and scatter plots between the predictor and predictand variables [18]. Based on previous study, Tahir [16], N.Hamidon [19], Hassan [17], Ismail [20] and Wilby [21], have compared dynamical and statistical downscaling methods. Most of them stated that statistical methods are more feasible to use and provided local scale climate output.

N.Hamidon [18] studied the future temperature climate change for rainfall in the Upper Kurau River basin, Perak, using the SDSM model. The study analyzed large-scale atmospheric factors using data from the National Centres for Environmental Prediction (NCEP). In addition, Huang [22] studies that most researchers in China mostly use statistical downscaling methods, mainly focused on maximum and minimum temperature assessment due to its general applicability and free software availability. Wilby [21] has outlined seven critical steps for the most effective implementation of multi-linear regression equations for downscaling, including quality control and data transformation such as predictor variable screening, weather calibration generation, statistical analysis and scenario generation.

Selection of Predictors

Screening predictor is the most crucial step in SDSM where most relevant atmospheric parameters are chosen [16]. According to Dawson and Wilby [21], different atmospheric predictors can control different local variables and result in the outcome of predictand. The selected predictors produced the monthly weather series under given atmospheric predictors' variables. In addition, this study generated future data under two scenario emissions: RCP 4.5 and RCP 8.5. RCP 4.5 medium-low scenario while RCP 8.5 represented a higher scenario and the RCP 2.6 scenario was not included in this study. The final selections of the NCEP variables for Ipoh station shown in Table 2 for the maximum and minimum temperatures. Predictand correlation between maximum and minimum temperature is significant between the maximum and minimum temperature. The most relevant atmospheric parameters were selected using the MLR model based on P-values, Scatter plots, correlation matrix, and partial correlation. A correlation matrix was the best way to look at the relationship between predictand and CanESM2 predictors during this study. In the case of maximum and minimum temperature, the significantly-connected predictor parameter has the lowest possible minimum P-value. In addition, the computation time and efficiency of downscaling can be improved if select of the smaller number of predictors [23].

TABLE 2. Summary selection of GCM variables

Max temperature	Min temperature
Nceptempgl.dat (mean temperature at 2m)	Ncepp8_zgl.dat (850hpa vorticity)
Ncepshumgl.dat (surface specific humidity)	Nceps500gl.dat (specific humidity at 500hpa)
Nceps500gl.dat (specific humidity at 500hpa)	Nceps850gl.dat (specific humidity at 850hpa)
Ncepp8_zgl.dat (850hpa vorticity)	Ncepshumgl.dat (surface specific humidity)
Ncepp500gl.dat (500hpa geopotential height)	Nceptempgl.dat (mean temperature at 2m)

Calibration and Validation

Calibration is accomplished by using output from NCEP reanalysis data [24] in which predictive factors have been identified. The historical data for this station is separated into two periods: (2010–2015) for calibration and (2016–2019) for validation. Following the calibration procedure, a validation procedure is required. During this procedure, the input file for calibration was utilised to generate synthetic current day weather data. Due to the relative importance of the deterministic and stochastic components of the regression model, the validation result may change between the calibration model and each ensemble of validation. Thus, SDSM performed significantly better during validation with seasonal and monthly time series findings than with daily time series [25]. The model will be evaluated only for mean daily maximum and minimum temperature during calibration and validation of the SDSM [24]. Two standard evaluation indices applied in the climate simulation, as determination coefficient of determination (R^2) and mean standard error (RMSE) [18], is used to qualify the difference between values predicted by a model

Downscaling Temperature Under Future Emission

The SDSM software derived historical and future temperature data under each scenario. The future maximum and minimum temperatures at Bukit Merah, Perak have been downscaled for 2020-2050 and 2050-2080 using SDSM output for RCP 4.5 and RCP 8.5 scenarios. The forecasted data has been compared with the modelled data for the possible changes in the future maximum and minimum temperature. The result between observed and modelled temperature corresponds to the selected NCEP predictors [18]. The statistical data generated are presented in monthly mean, maximum, minimum and sum forms.

RESULTS AND DISCUSSION

Calibration and Validation of SDSM

The performance of calibrated and validated results presented in Table 3 consists of coefficient of determination (R^2), coefficient of correlation (R), and root mean square error (RSME). Further analysis can refer to Appendix A. According to the findings, the R^2 value was associated with more excellent performance during validation, with $R^2 \geq 0.30$ and $RSME \geq 0.66$. Therefore, it was necessary to utilise the Root mean Square error (RSME) and the coefficient R^2 to evaluate the performance of historical and simulated data from the model during the calibration and validation periods [16]. The coefficient of determination (R^2) during calibration and validation for maximum temperature were 0.89 and 0.67, while for minimum temperature, the value for calibration and validation is 0.83 and 0.85. Moreover, the RSME values are minimal for both maximum and minimum temperature analyses. For maximum temperature, the value of RSME for calibration and validation is 0.006 and 0.002. Meanwhile, the value for calibration and validation is 0.008 and 0.007 for minimum temperature. The closest the RSME number is to zero, the good the model's performance, and an R^2 value between 0.6 and 0.8 indicates moderate to high performance, with a value of 1 indicating a good fit [18], [24]. As a result, it may be concluded that the calibrated and validated values were in satisfactory correlation with historical data.

TABLE 3. Performance of calibration and validation of temperature using SDSM

Evaluation Indices	Maximum Temperature		Minimum Temperature	
	Calibration	Validation	Calibration	Validation
R^2	0.89	0.67	0.83	0.85
R	0.94	0.82	0.91	0.92
RSME	0.006	0.002	0.008	0.007

Downscaling for Future Emission RCP 4.5 and RCP 8.5

The temperature output in terms of minimum and maximum for the period 2020-2100 is illustrated in Figures 2 and 3 respectively. The mean monthly temperature in the findings represents every interval year period 2020 - 2050 (2045s) and 2050 - 2080 (the 2075s). The result shows that the overall maximum and minimum temperature for Bukit

Merah, Perak will increase for 2020 -2050 and 2050- 2080 compared with the base period. It has been predicted that the variation of maximum and minimum temperature will be slightly different between the two scenarios RCP 4.5 and RCP 8.5.

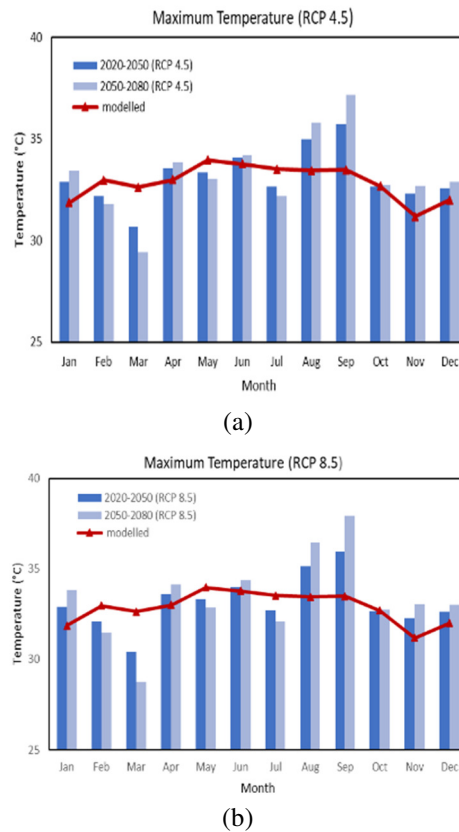
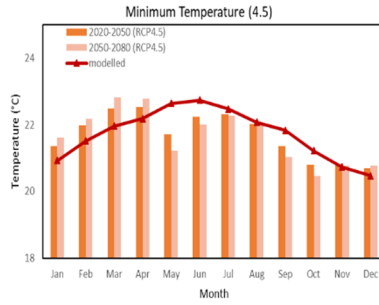


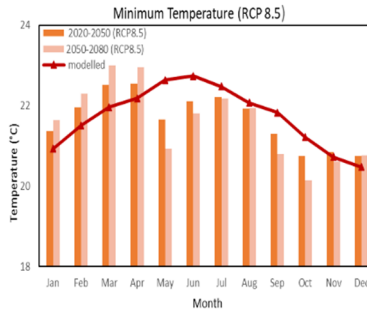
FIGURE 2. Projection future maximum temperature trend for (a) RCP 4.5 and (b) RCP 8.5

The temperature result shows the increment in the maximum temperature for RCP 4.5 and RCP 8.5. Based on Figure 2(a), Figure 2(b) and Figure 3 and 4 shows a higher temperature predicted to occur in January, April, June, August, September, November and December may be affected by the interchange of the northeast monsoon (October - March) and the southwest monsoon (April- September). Over the study period 2020-2050, the maximum temperature under RCP 4.5 in August and September is 35.01°C and 35.75°C while, for period 2050-2080, the temperature in August and September is higher, which is 35.81°C and 37.16°C respectively as shown in Figure 2(a). Meanwhile, under RCP 8.5, the temperature predicted was higher compared to RCP 4.5. By referring in Figure 2(b), for period 2020-2050 in August and September, the temperature is 35.15°C and 35.97°C compared to period 2050-2080 in August and September, the temperature rises to 36.47°C and 37.94°C. Furthermore, by comparing to the historical data, the graph shows the temperature trend under both carbon emissions were increasing. Therefore, it indicates that high chance drought events will happen for the next 60 years during this month.

As the temperature rises, it may stimulate the loss of soil moisture volume and increase the evapotranspiration rate, particularly in paddy crops in the surrounding state of Perak. Besides, it also may affect the water catchment in Bukit Merah reservoir. Apart from these factors, the increasing average temperature in August and September for both the RCP (4.5 and the 8.5) values, it will significantly influence agriculture. It is due to increase evapotranspiration associated with a lack of precipitation, which could severely affect the paddy crop, solely due to a lack of water for irrigation throughout drought seasons.



(a)



(b)

FIGURE 3. Projection future minimum temperature trend for a) RCP 4.5 and b) RCP 8.5

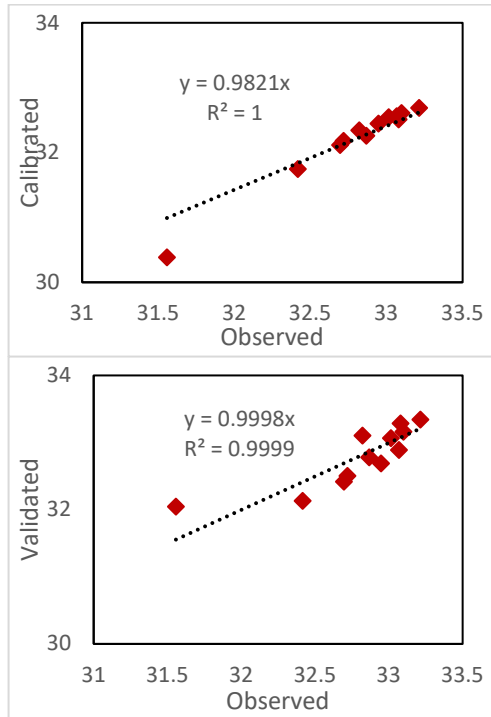


FIGURE 4. Graph R^2 for maximum temperature analysis using SDSM

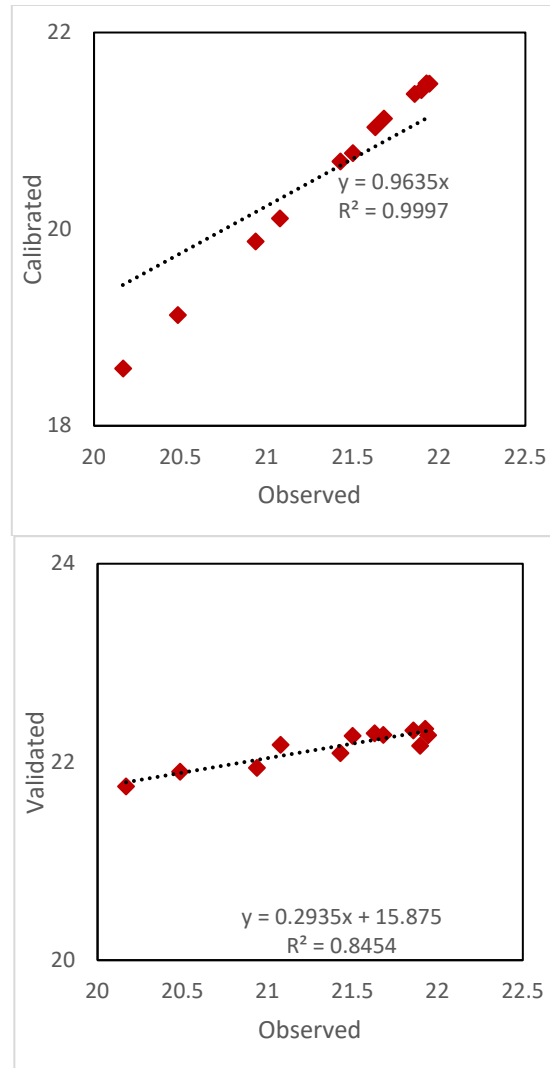


FIGURE 5. Graph R^2 for minimum temperature analysis using SDSM

Furthermore, in period 2020-2050 for minimum temperature, the increasing temperature under RCP 4.5 is in month of Mar and April, which is 22.50°C and 22.53°C while, for the period 2050-2080, the temperature in Mar and April is higher, which is 22.82°C and 22.77°C respectively as shown in Figure 3 (a). Meanwhile, under RCP 8.5, the temperature predicted was higher compared to RCP 4.5. By referring to Figure 3 (b), for period 2020-2050 in Mar and April, the temperature is 22.51°C and 22.55°C compared to period 2050-2080 which the temperature rises to 23.00°C and 22.95°C. Further, compared to the historical data, the graph shows the temperature trend under both carbon emissions were increasing for projected minimum temperature. Therefore, temperature patterns found between 2020 and 2050 and 2050 and 2080 indicate that the country's climate is changing in future, with a long-term warming trend interspersed with more frequent and prolonged high-temperature occurrences. Moreover, it demonstrated that the trend toward higher annual temperatures would be followed by a fall in annual rainfall. On top of that, from previous study, global warming has increased the temperature especially in peninsular Malaysia and other parts of the world. [25].

Drought Indices Analysis

Drought is classified as a disaster because it has a significant impact on the earth's ecosystem, comparable to that of flooding and because it occurs more frequently as floods. Based on Figure 3 and Figure 2, at the 12-month scale, it was observed that both scenarios RCP 4.5 and RCP 8.5 had significant increasing trends in monthly temperature. The

temperature rise appeared in January, April, June, August, September, November, and December for both scenarios. For periods 2020-2050 and 2050-2080, it is clear that trends will be similar, and the research region will face drier conditions as a result. Moreover, drought episodes are predicted to occur in 20% of the following 60 years for Bukit Merah station, indicating a significant likelihood of drought occurring at least twice in the station's lifetime. Meanwhile, the RCP8.5 models generated more frequent high temperatures over the next 60 years. Therefore, in the future, predicting a long-term drought in the region can be used as a substantial data input to optimise water management while also reducing risk and expense.

Nevertheless, in some country studies by [26], using CanESM2, there would be mild drought monthly, seasonally, and annually under all scenarios on a time scale (2000-2017) in Cambodia. Besides, a study from [27] states that Brunei is predicted to experience more warming and less precipitation in the next 60 years. This shows that Southeast Asia countries may experience drought events for the next century. Moreover, the high temperature stimulates evapotranspiration (ET) activities, which has a negative impact on the efficiency of water consumption in the environment. Consequently, it affects the electricity demand, a source of hydropower's energy output to power machinery and electricity production [28].

CONCLUSION

In conclusion, The Global Climate Models (GCMs) play a primary role in simulating the current climate and the future of climate change. Climate change has increased the frequency extreme weather events, such as tropical cyclone activity, hot temperatures, hot nights, and heatwaves, as well as the amount of precipitation. Therefore, this study's findings provide crucial information on the monthly trend of meteorological indicators in Bukit Merah, Perak. For the maximum temperature, RCP 4.5 has the highest average temperature of nearly 37.16°C during 2050-2080, while for minimum temperature, RCP 8.5 indicates the highest temperature of nearly 23°C during 2050-2080. Hence, Bukit Merah, Perak will experience maximum temperature in August and September during the southeast monsoon and maximum temperature in January and April during the northeast monsoon. As a result, the monthly maximum and minimum temperature variations are slightly different for both RCP.

In conclusion, despite inherent limitations in statistical downscaling, it is believed to be an effective technique to downscale the future temperature under global climate change. Therefore, it is likely that the study area is expected to experience warmer weather, and drought might happen for the next 60 years. With early year detection of a drought event, drought preparedness particularly related to fire hazards and other disaster mitigation could be implemented. Hence, by improving the drought early warning system it may help to prepare immediate action plans in the future

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