Dynamics of potential precipitation under climate change scenarios at Cameron highlands, Malaysia

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Abstract

Precipitation is sensitive to increasing greenhouse gas emission which has a significant impact on environmental sustainability. Rapid change of climate variables is often result into large variation in rainfall characteristics which trigger other forms of hazards such as floods, erosion, and landslides. This study employed multi-model ensembled general circulation models (GCMs) approach to project precipitation into 2050s and 2080s periods under four RCPs emission scenarios. Spatial analysis was performed in ArcGIS10.5 environment using Inverse Distance Weighted (IDW) interpolation and Arc-Hydro extension. The model validation indicated by coefficient of determination, Nash–Sutcliffe efficiency, percent bias, root mean square error, standard error, and mean absolute error are 0.73, 0.27, 20.95, 1.25, 0.37 and 0.15, respectively. The results revealed that the Cameron Highlands will experience higher mean daily precipitations between 5.4 mm in 2050s and 9.6 mm in 2080s under RCP8.5 scenario, respectively. Analysis of precipitation concentration index (PCI) revealed that 75% of the watershed has PCI greater than 20 units which indicates substantial variability of the precipitation. Similarly, there is varied spatial distribution patterns of projected precipitation over the study watershed with the largest annual values ranged between 2900 and 3000 mm, covering 71% of the total area in 2080s under RCP8.5 scenario. Owing to this variability in rainfall magnitudes, appropriate measures for environmental protection are essential and to be strategized to address more vulnerable areas.

Keywords Hydrology · Rainfall erosivity · Soil erosion · Ensemble GCMs · PCI · GHGs emission

1 Introduction

Climate change caused by the greenhouse gas (GHGs) emissions affect both the global hydrological cycle and regional hydrology worldwide, which will continue in future [1–3]. Precipitation is directly influenced by an increase in the global surface temperature that promotes the rate of evapotranspiration, thereby increasing the concentration of water vapor in the atmosphere. Therefore, variability in precipitation is expected in both magnitude and frequency, from one region to another. This variation

will impact the activities of water resources including reservoir storage, flood control, water management, irrigation, energy production, transportation, and recreational activities.

Nowadays, Global Circulation Models (GCMs) are generally regarded as the most popular tools for estimating impacts of climate change on environment [4–7]. The GCMs datasets are obtainable from the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) [8]. Although, the uncertainty inherently possessed by each GCM is significant [9, 10],

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the multi-model ensemble approach is recommended by many existing studies to improve accuracy of climate impact assessments [11–14]. According to IPCC (2013): Summary for Policymakers. In: Climate Change 2013: The Physical Science Basis, the range of precipitation trend varies from negative to positive values up to a thirty percent, indicating that projection of precipitation is highly uncertain over a time and space. This uncertainty increases correspondingly with representative concentration pathways (RCPs) forcing. The use of GCMs has revealed that changes in rainfall patterns will impact soil erosion through several pathways, including changes in rainfall erosivity [15]. The studies conducted by Ratan and Venugopal [16] and Nasidi et al. [17] have shown that the tropical climate has been experiencing highest mean precipitations, followed by other regions farther away from equator. Moreover, examining a spatial and temporal irregularities of precipitation is imperative to establishing a relationship between climate characteristics and soil conservation measures at watershed scale. Thus, it is very vital to interpret extent at which the increasing trend in rainfall amounts and intensities to enable prioritize environmental control measures.

In last two decades, a rapid change in climatic variables have been reported over the Cameron Highlands watershed [18–20]. This changes have been correlated with the high rates of landslides occurrence almost everywhere and at larger scales [17, 20]. Tan and Nying [18] projected that amount of precipitation receive will increase by up to 37% for the next three decades. Similarly Nasidi et al. [17] investigated changes in temporal variation of precipitation in the Cameron highlands watershed due to effect of climate change for the twenty-first century. The results showed considerable increase in the projected precipitation toward the end of the century, particularly under high GHGs emissions. However, existing studies do not report spatial variability of the potential precipitation which is the main concern during strategic planning for environmental protection. Moreover, assessing both spatial and temporal variability for the expected precipitation is prerequisite to establishing soil erosion and sedimentation control best management practices.

Rainfall erosivity is highly likely to increase with increase in rainfall intensities, duration, or frequency to create saturation and ponding [21]. This will eventually increase the capacity soil particles detachment of the raindrops. The most important characteristics of rainfall are intensity, amount, duration, and frequency and often influenced by climate change. Rainfall events with high magnitude are likely to control over rainfall erosivity and possibly increase with higher storm intensities [22]. It was reported that rainfall with higher erosivity combined with slope gradient of 45% will increase the chance of soil erosion and induce landslides in the Cameron Highlands [20]. These

issues are considered the main triggering factors of landslides and soil erosion due to changes in precipitation patterns. The changes in precipitation have been linked to climate change effects on soil erosion because erosivity is expected to change in response to climate variables changes [23]. In a global context, rainfall patterns have varied in time and space over the last century with expected increase in future at the tropical and subtropical areas [24]. This information could help planners and policy makers to implement alternative water management strategies in the future. Thus, an evaluation of the impacts of climate change on potential precipitation is necessary prior to any adoptable plan of conservation policies.

Thus, the purpose of this research was to assess spatial and temporal variability of potential precipitation due to influential of climate change in the Cameron Highlands watershed. In this study, ensembled means of twenty GCMs were employed to project 100-year future precipitations under four RCPs scenarios and two periods as 2050s (2040–2069) and 2080s (2070–2099), respectively. Also, the study applied multiplicative change factor method for downscaling of the climate data to local scale for impact assessment.

2 Materials and methods

2.1 Study location

The Cameron Highlands are located at the main range of Peninsular Malaysia situated on Latitude of 4°28' N, and Longitude of 101°23' E, the average temperatures are 24 °C and 14 °C during the day and night, respectively (Fig. 1). The elevation ranges between 1070 and 1830 m above mean sea level [25–27] and the average annual precipitation is 2660 mm. The region has two peak rainfall periods with wettest from month of October to November every year. The highlands are regarded as vital hill stations for the country which occupied an area of 712.18 square kilometers. Moreover, the Cameron Highland is surrounded by Kelantan and Perak from north and west, respectively, and has a potential of growing a wide variety of vegetables, flowers, and other ornamental plants. Good climatic condition provides opportunity for agricultural activities as the main business in the highlands with many attractive tourism locations [17].

2.2 Global climate data and future scenarios

The global climate data obtained from twenty GCMs under four emission scenarios [13] were used in this study (Table 1). Similarly, selection of models was based on their relative independence and excellent simulation

Fig. 1 The Cameron highlands study watershed

results [28]. The selected models (GCMs) were employed in order to improve degree of accuracy of climate prediction and reduce uncertainty level [12]. The projection was conducted under the emission scenarios; RCP2.6, RCP4.5, RCP6.0, and RCP8.5 obtained from the AR5 of the IPCC which represent low, medium, high, and very high greenhouse gas emission levels, respectively. The GCMs data were downloaded from World Climate Data Center

(<https://cera-ww.dkrz.de/WDCC/ui/cersearch/>). The data source contains 42 GCMs output GCMs of the Coupled Model Intercomparison Project Phase 3 (CMIP3) archive with both historical and future projected climate data on global scale. Thirty years historical data were defined as baseline period for this study (1976–2005). Although, the datasets were made available in NetCDF format, then Matlab software was employed to extract the real data from

Table 1 Global climate models (GCMs) and emission scenarios

S/N	Institution	Country	GCM name	Resolution
1	Commonwealth Scientific and Industrial Research Organization/ Bureau of Meteorology	Australia	ACCESS1-3	1.25° × 1.87°
2	Beijing Climate Center, China Meteorological Administration	China	BCC-CSM1-1	2.78° × 2.81°
3	National Center for Atmospheric Research	USA	CESM1-BGC	0.90° × 1.25°
4	Centro Euro-Mediterraneo sui Cambiamenti Climatici	Italy	CMCC-CMS	1.90° × 1.90°
5	EC-EARTH consortium published at Irish Centre for High-End Computing	Netherlands	EC-EARTH	1.12° × 1.12°
6	NASA/GISS (Goddard Institute for Space Studies)	USA	GISS-E2-R	2.00° × 2.50°
7	Russian Institute for Numerical Mathematics Climate Model	Russia	inmcm4	1.50° × 2.00°
8	Institute Pierre-Simon Laplace	France	IPSL-CM5A-LR	1.89° × 3.75°
9	University of Tokyo), National Institute for environmental Studies, and Japan Agency for Marine-Earth Science and Technology	Japan	MIROC5	1.40° × 1.40°
10	Bjerknes Centre for Climate Research, Norwegian Climate Center	Norway	NorESM1-m	1.89° × 2.50°
11	Canadian Centre for Climate Modeling and Analysis	Canada	CanESM2	2.80° × 2.80°
12	National Center for Atmospheric Research	Canada	CCSM4	1.25° × 0.94°
13	Européen de Recherche et Formation Avancée en Calcul Scientifique	Europe	CNRM-CM5	1.40° × 1.40°
14	Commonwealth Scientific and Industrial Research Organization/Queensland Climate Change Centre of Excellence	Australia	CSIRO	1.80° × 1.80°
15	NOAA Geophysical Fluid Dynamics Laboratory	USA	GFDL-ESM2G	2.05° × 2.00°
16	NOAA Geophysical Fluid Dynamics Laboratory	USA	GFDL-ESM2M	2.50° × 2.00°
17	Met Office Hadley Center	Canada	HadGEM2-CC	1.88° × 1.25°
18	Met Office Hadley Center	Canada	HadGEM2-ES	1.88° × 1.25°
19	Max Planck Institute for Meteorology	Germany	MPI-ESM-LR	1.88° × 1.87°
20	Meteorological Research Institute	Japan	MRI-CGCM3	1.10° × 1.10°

NC format. The change factor downscaling method was used to downscale the GCMs to approximately 1.0 km² resolution local scale on site daily precipitation datasets.

2.3 Meteorological stations and description of observed rainfall data

In this study, eight meteorological stations were considered for observed rainfall data collection as presented in Table 2. The highest mean daily rainfall with magnitude of 6.73 mm has occurred at Tanah Rata sub-watershed, followed by MARDI station with 6.65 mm mean daily rainfall.

Similarly, the highest annual rainfall amount of 2458 mm was recorded at Tanah Rata sub-watershed which corresponds to a station with highest altitude (1502 m). However, the lowest annual rainfall of 1887 m was received at Terrisu station which is located at an elevation of 1075 m. In contrast, the least mean daily rainfall of 5.2 mm occurs at Terrisu sub-basin. The standard deviation for the rainfall series was found highest (12.38) at Telanok station followed by Tana Rata and MARDI sub-catchments with 11.67 and 11.63 deviation, respectively.

Table 2 Observed rainfall series from sub-watershed of the Cameron Highlands

Met. station	Longitude	Latitude	Altitude (m)	Annual Pr (mm)	Mean daily Pr (mm)
Telanok	101.52371	4.35462	543	2313	6.33
Tanah Rata	101.37678	4.47013	1502	2458	6.73
MARDI	101.38520	4.46853	1595	2429	6.65
Terisu	101.48911	4.52413	1075	1886	5.20
Raja	101.40961	4.56639	1667	2310	6.32
Alurmasuk	101.47930	4.51199	1520	2076	5.68
LadangTeh	101.41623	4.51559	1555	2335	6.39
Habu	101.39129	4.43984	1240	2298	6.39

Pr = Precipitation

2.4 GCMs downscaling by change factor method (CFM)

The procedure to calculate multiplicative CFM downscaling technique was followed as extensively described by Matonse et al. [29]. The method involves several steps to estimate the empirical cumulative distribution functions (CDFs) for future GCM (GCMf) and baseline (GCMb) for all the scenarios. In a CFM additive, the arithmetic difference between a GCM variable derived from a current climate simulation and that derived from a future climate scenario at the same GCM grid location is calculated. This difference is then added to the observed local values to produce the future model values. This additive method is typically used for downscaling of temperature assumed that the GCM provides a fair estimate of the complete shift in the variable value irrespective of the precision of the present climate simulation of the GCM. In the same process, a multiplicative change factor (MCF) is calculated except that the ratio of future and present GCM simulations are multiplied rather than the arithmetic difference. For the detail procedure of downscaling using change factor method, the reader may refer to Matonse et al. [29].

2.5 Weighted ensembled means of GCMs

Many recent literatures encourage the use of ensembled means of GCMs for climate projection studies in order to minimize the level of uncertainties inherently possessed by the global models, e.g. [17, 30]. This is because, individual GCM can project various future climate variables, indicating the gross uncertainty associated with each climate model [31]. Thus, it is universally agreed that weighted ensembled means can help to make more stronger projection taking into consideration, the contribution of each model studied. The weight given to the GCM is based on mean deviation between simulated and observed monthly values of precipitation in the baseline period. Therefore, GCMs with greater weights predicted climatic values with more accuracy in the future. The equation for weight determination (Eq. 1) as applied by Abdullah et al. [4] was to climate change scenarios.

$$W_i = \frac{(1/\Delta P_{ij})}{\sum_{j=1}^n (1/\Delta P_{ij})} \quad (1)$$

where, W_i is the weight of each model in month i , and ΔP_{ij} is the difference between average of precipitation simulated j in month i of the baseline period (1976–2005) from the corresponding observed value (1976–2005). To establish climate change scenarios, Eq. 2 is applied to the average precipitation of 30 years from the future period

(2040–2069) and (2070–2099) for each climate model and its simulated baseline period (1976–2005).

$$\Delta P_i = (\bar{P}_{\text{GCM Future}, i} / \bar{P}_{\text{GCM baseline}, i}) \quad (2)$$

where; ΔP_i is the climate change scenarios related precipitation for month i ($1 < i < 12$); $\bar{P}$ is the simulated future and historical average precipitation of 30 years derived from each climate model for month i . To generate weighted ensemble means, Eq. 3 is applied to scenario files within different GCMs and RCPs emission scenarios.

$$E = \sum_{i=1}^n P_{ij} \times W_{ij} \quad (3)$$

where; P_{ij} and W_{ij} are obtained from Eqs. 1 and 2, and n is the number of climate models.

2.6 Precipitation concentration index (PCI)

PCI is an important indicator related to temporal analysis of precipitation concentration in a watershed proposed by Patowary and Sarma [32] as presented in Eq. 4. This index has been applied in several studies to indicated the concentration of rainfall [7, 33–35]. In the PCI tests, values below 10 indicate a uniform distribution of precipitation, values between 11 and 20 reflect seasonality in the distribution of precipitation, and values above 20 correspond to climates with substantial monthly variability.

$$PCI_m(\%) = \frac{\sum_{i=1}^{12} P_i^2}{\left(\sum_{i=1}^{12} P_i\right)^2} \times 100 \quad (4)$$

In addition to the PCI_m , it is normal to use and apply PCIs by referring to their average value correlated with different periods (or seasons) of the year characterizing the climate of a given area. Thus, as the study region has significantly a dry (January–March) and a wet (April–November) period, the supra-seasonal PCI (PCI_{m-ss}) was also evaluated, following the suggestion by de Luis et al. [33] and used in the study conducted by de Mello et al. [7]. It is mathematically stated in Eq. 5.

$$PCI_{m-ss}(\%) = \frac{\sum_{i=1}^{10} P_i^2}{\left(\sum_{i=1}^{10} P_i\right)^2} \times \left(\frac{10}{12}\right) \times 100 \quad (5)$$

where P_i is the precipitation of the month i , in mm, obtained based on the weather simulations.

2.7 Projection of precipitation and spatial modeling in the study watershed

The multi-model ensemble GCMs projected future rainfall variations in two periods of the same length within the twenty-first century. These periods are 2040–2069 and 2070–2099 which are in this study, referred to 2050s and 2080s for simplicity. The historical data collected from each model served as a baseline climate. The literature highlights that the discrepancies between the observed and GCM-simulated precipitations are responsible for the accumulation of errors in model structure, climate forcing, and to a lesser extent, observations [36]. In addition, simulation of hydrological models is highly dependent upon precipitation data of a basin, and thus, such discrepancies are more pronounced when hydrological models use GCMs precipitation simulations with low temporal resolutions. Therefore, for the impact studies implementation of the results, it is advisable to use relative variations through dividing the absolute difference by the actual observation, although mean impacts obtained from application of the different ensemble averaging methods which is conventionally used in recent studies [4, 37, 38].

In this study, a spatial interpolation was employed which is the method of using points of known values to estimate values at other points. In GIS applications, spatial interpolation is typically applied to a raster with estimates made for all cells [39–42]. Spatial interpolation is therefore a means of creating surface data from sampled points. Thus, this study explores the function of GIS to estimate the magnitude of precipitations for all the unknown pixels using the control points. Inverse distance weighted (IDW) method of interpolation was chosen for its high accuracy in estimation of unknown pixels [36, 43]. In IDW interpolation, the estimated value of a point is influenced more by nearby known points than those farther away (Eq. 6).

$$x = \frac{w_1x_1 + w_2x_2 + w_3x_3 + \dots + w_nx_n}{w_1 + w_2 + w_3 + \dots + w_n} \quad (6)$$

where x is the weighted distance, w_n is the weight and x_n is the individual distance before weighting is applied.

2.8 Model validation

There are various indices, which are used to evaluate the performance of climate model. In this research, Nash–Sutcliffe Efficiency (NSE), Percent Bias (PBIAS), Standard Error (SE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) were used to evaluate the model performance [4]. In addition to above indices, Coefficient of Determination

(R^2) was used to evaluate the consistency of simulated and observed data.

2.8.1 Nash–Sutcliffe efficiency (NSE)

NSE is a standardized statistic that specifies the relative magnitude of the residual variance compared to the calculated data variance. The NSE values range from $-\infty$ to 1; in which higher value indicates better performance of the model [4]. The value of unity (100%) indicates a complete match between observed and simulated precipitation. But the value of zero shows the model simulations are close to mean values of observation. Whereas the negative value of NSE statistics indicates that the observed and simulated precipitations are far from each other. In other word, under this condition the residual variance is greater than the observed variance. The NSE was computed using Eq. 7.

$$NSE = 1 - \left[\frac{\sum_{i=1}^n (Y_i^{obs} - Y_i^{sim})^2}{\sum_{i=1}^n (Y_i^{obs} - Y_i^{mean})^2} \right] \quad (7)$$

2.8.2 Percent bias (PBIAS)

PBIAS evaluates the bias in the model calculation (Eq. 8). Positive and negative values of PBIAS demonstrated a model underestimation and overestimation bias, while low-magnitude values suggested better model simulations. The optimal value of PBIAS is considered to be zero [44]. This model accuracy assessment can indicate the deficient performance of any model.

$$PBIAS = \left[\frac{\sum_{i=1}^n (Y_i^{obs} - Y_i^{sim})^2 * 100}{\sum_{i=1}^n Y_i^{obs}} \right] \quad (8)$$

2.8.3 Root mean square error (RMSE)

RMSE is a frequently used measure of differences between values predicted by a model and the actual observation data. RMSE is always non-negative, and a value of zero indicates a perfect fit scenario. In general, a lower RMSE shows better model performance and can be evaluated using Eq. 9 [45].

$$MSE = \sqrt{\frac{\sum (y_{obs} - y_{sim})^2}{n}} \quad (9)$$

2.8.4 Standard error (SE)

SE is a statistical procedure that measures the accuracy with which a sample distribution represents a population by using standard deviation and can be computed using Eq. 10 [46].

$$SE = \sqrt{\frac{\sum (y_{obs} - y_{sim})^2}{n - k - 1}} \quad (10)$$

2.8.5 Mean absolute error (MAE)

MAE is a measure of errors between paired observations expressing the same phenomenon (predicted and actual). This is known as a scale-dependent accuracy measure and can be determined using Eq. 11 [47].

$$MAE = \frac{1}{n} \sum |y_{obs} - y_{sim}| \quad (11)$$

2.8.6 Coefficient of determination R^2

The determination coefficient (R^2), which is defined as the squared value of the Pearson correlation coefficient, ranges from 0 to 1. When the values are close to 1 indicates less error variance, and values greater than 0.5 are commonly deemed acceptable in watershed scales which is computed by using Eq. 12 [4].

$$R^2 = \left(\frac{\sum_{i=1}^n (p_i^{obs} - p_i^{mean})(p_i^{sim} - p_i^{mean})}{\left[\sum_{i=1}^n (p_i^{obs} - p_i^{mean})^2 \sum_{i=1}^n (p_i^{sim} - p_i^{mean})^2 \right]^{0.5}} \right)^2 \quad (12)$$

where Y_{obs} is the observed data, Y_{sim} is the simulated data, Y^{mean} is the mean of the observed data, P is the precipitation, n is the number of recorded data in validation dataset, and k is the number of independent variables in the modeling processes. Note that Y_{obs} and Y_{sim} represent the same variables as y_{obs} and y_{sim} in Eqs. 7–11 in this study.

3 Result and discussion

3.1 Validation of multi-model ensemble rainfall series

Model validation, which is the process of determining the functionality of modeled parameter(s) using observed data, is a crucial step in any modeling operation. In this study, the GCMs simulated precipitation data are compared with another set of the observed precipitation

datasets to ascertain the workability and efficiency of the model. Thus, a set of ten years observed rainfall data (2006–2015) was compared with model output for the same duration (Fig. 2). The result demonstrates that both observed rainfall and simulated rainfall produced approximately the same distribution patterns. Except that, in few cases, variations between modeled and simulated rainfall were observed. For example, in September 2010 and September 2015 the simulated rainfall is found to be high (about 14 mm), while the corresponding observed rainfalls is as low as 4 mm. Similarly, the study detects an inconsistency in simulated and observed rainfalls during January to May annually. However, in a general note, the simulated and observed rainfall are found to have satisfactory distribution patterns which indicates that the ensemble GCMs model can project future rainfall effectively.

Moreover, the parameters used to evaluate the performance indices of the ensemble model are R^2 , NSE, PBIAS, SE, RMSE, and MAE. The analysis of these performance indicators was accomplished on monthly basis. The outcome shows a coefficient of determination is 73% which is a measure of strong agreement between observed and simulated rainfall data. Similarly, PBIAS is computed as 20.94 which is fairly shows a low bias associated with the simulated precipitation. In addition, mean absolute error was calculated as 0.15 and this indicates low computation error in the model parameters and thus is acceptable in hydrology and climate impact studies [5, 48–50]. Similarly, Fig. 3 shows relationship of both simulated and observed datasets and its deviation from 1:1 straight line. This demonstrates a clear closeness and compatibility from each other, and thus, improve the level of model acceptability. Therefore, all the model performance indicators considered in this study found within the acceptable ranges for most climate projection studies and several previous studies used model with similar performances, e.g. [20, 26].

3.2 Temporal variations of precipitations at baseline and future scenarios

3.2.1 Variations of the monthly precipitation

In this study, the weighted ensemble means of 20 GCMs projects monthly average changes of the rainfall amounts in the study watershed (Table 3). The ranges of precipitation under baseline climate are 98 mm in January to 284 mm in November annually. The future precipitations indicated positive changes with largest variation of 80.2% in February under RCP8.5 scenario. Similarly, wider variations in projected precipitation were found in January, March, and December with 55.7%, 51.7%, 53.4% more rainfalls in 2080s under RCP8.5 scenarios, respectively. On other hand, lowest increase in precipitations of 2%, 2.5%,

Fig. 2 Validation of the monthly precipitation datasets

Fig. 3 Observed versus simulated precipitations

3.7% and 4% are found in April, May, July, and August in 2050s projection under RCP2.60 scenario. Previous studies have equally predicted increasing precipitations within the same study watershed. However, their projections are mostly for short durations, do not consider climate changes or not employed high number of GCMs to ascertain the accuracy of projections. For example, Kwan et al.

[38] has projected increase in rainfall amount of 27% more in the Cameron Highlands for the next three decades. Also, Hailegeorgis and Alfredsen [51] analyzed extreme precipitation at Risvollan catchment and found 49% relative difference from reference samples. Generally, the projected rainfall amount has considerably increased from baseline condition for all the scenarios and two projection periods. This can be explained by the fact that; RCP2.6 scenario assumes that stringent measures are applied in the release of greenhouse gases which is a factor responsible for climate variability [8, 12, 46, 52, 53]. This is translated to an increasing trend of potential rainfall erosivity due to climate change [54], and expected to be more severe toward the end of twenty-first century.

3.2.2 Comparisons of future precipitation variability

Figure 4 presents mean daily precipitation in baseline and the projections under the RCPs emissions scenarios. Remarkable changes of daily mean precipitations are observed in both the baseline condition and for each climate scenarios. It is found that 34% increase in precipitation occurred under the RCP8.5 scenarios with maximum daily rainfall of 9.6 mm toward the end of the century. However, the lowest volume of mean daily precipitation is 4.1 mm obtainable under baseline condition. Similarly, noticeable change of projected rainfall occurred

Table 3 Monthly variability of projected precipitation in the study watershed

Month	Precipitation at baseline (mm) (1976–2005)	Increased precipitations relative to baseline (%)							
		2050s (2040–2069)				2080s (2070–2099)			
		RCP2.6	RCP4.5	RCP6.0	RCP8.5	RCP2.6	RCP4.5	RCP6.0	RCP8.5
Jan	98	8.7	17.2	26.1	33.2	9.7	29.8	38.5	55.7
Feb	111	16.0	31.3	46.3	55.7	30.8	44.6	55.2	80.2
Mar	183	7.8	13.3	22.6	31.3	18.9	29.4	43.6	51.7
Apr	232	2.0	4.3	9.0	13.4	6.3	15.1	20.3	25.3
May	211	2.5	2.9	9.5	15.6	8.9	15.4	21.5	27.1
Jun	133	3.7	10.9	20.7	26.5	9.5	24.0	33.0	46.3
Jul	141	3.5	6.3	13.1	20.4	4.0	9.0	17.3	30.4
Aug	153	4.0	8.9	18.6	26.6	4.9	15.1	21.9	32.2
Sep	205	8.0	14.4	19.9	25.0	9.2	21.1	31.0	34.9
Oct	283	4.5	5.7	10.4	13.2	4.1	8.8	15.0	19.6
Nov	284	4.7	8.2	11.7	16.4	5.8	10.0	16.8	24.1
Dec	186	10.5	20.5	30.1	35.0	15.4	27.6	39.3	53.4

Fig. 4 Variation of precipitations relative to baseline climates

under RCP4.5 and RCP6.0 scenarios with corresponding increase of 17.2% and 24.1% relative to baseline condition, respectively. However, the least changing precipitation was observed in RCP2.6 scenario with only 7.1% increase reference to the baseline climate. In general, there is a

progressive increase in mean daily rainfall volume with more concentrated rainfall volume in the study watershed toward the end of the twenty-first century.

3.2.3 Precipitation concentration index (PCI)

In this study, the PCI of each sub-watershed were computed to reveal potentials of rainfall concentration (Table 4). The computed baseline PCI ranged from 9.34% at Kg. Habu (indicating uniform rainfall) to 15.03% at Kg. Raja sub-catchments. Similarly, the various quantities of PCI were projected to 2050s (2040–2069) and 2080s (2070–2099) under RCPs emission scenarios. It is presented that highest projected PCI of 27.66% occurred at Tanah Rata sub-watershed under RCP8.5, indicating precipitation with substantial monthly variability [7]. Similar precipitation with high monthly variability occurred at Ladang Teh and Kg. Raja sub-basin with PCI of 25.42% and 24.43%, respectively. However, the lowest projected PCI were recorded at Kg. Habu and Alurmasuk sub-watersheds with corresponding values of 11.48% and 13.17%,

Table 4 Precipitation concentration index for the projected climate scenarios

Sub-basin	Baseline (1976–2005)	RCP2.6		RCP4.5		RCP6.0		RCP8.5	
		2050s	2080s	2050s	2080s	2050s	2080s	2050s	2080s
Telanok	10.56	11.12	13.02	12.99	15.75	13.88	16.62	14.82	17.30
Tanah Rata	17.42	18.05	20.82	18.99	23.31	20.72	25.01	22.26	27.66
MARDI	15.31	16.43	15.78	18.73	18.31	17.93	20.91	19.26	23.66
Terisu	13.17	14.60	15.08	15.16	17.43	18.07	19.16	20.37	21.62
Kg. Raja	15.03	16.51	17.73	17.04	19.26	19.02	22.71	21.25	24.43
Alurmasuk	11.69	13.50	16.78	14.09	18.38	16.87	20.98	17.30	23.54
Ladang Teh	14.16	16.38	15.67	18.15	19.20	19.69	23.83	20.19	25.42
Kg. Habu	9.34	11.48	14.84	13.06	16.38	14.76	17.97	16.28	18.59

respectively. This therefore, indicates regions in the Cameron Highlands with seasonality in the distribution of precipitation since the PCI values ranged between 10 and 20 [7]. Furthermore, Fig. 5 demonstrates the relative variation of PCI from baseline at each sub-watershed within Cameron Highlands boundary. It shows that largest monthly variation of PCI will occur at Kg. Habu sub-basin with 93% higher than baseline under RCP8.5 scenario. Nevertheless, the lowest change in PCI (2.6%) is found to occur at MARDI sub-catchment 2050s under RCP2.6 scenario. The study shows that all the sub-basins have demonstrated variable PCI depending upon projection period and RCP emission scenario.

3.3 Spatial variability of potential precipitation

3.3.1 Variation precipitation at baseline period (1976–2005)

Spatial analysis of the precipitation shows that amount of rainfall received within the Cameron Highlands varies from one sub-watershed to another in the present climate (Fig. 6). It reveals that the amount of rainfall received by the watershed ranged from 1757 to 2500 mm annually. The highest amount occurs at mountainous regions mostly Tanah Rata, Mardi and Kg Raja sub-watersheds located at southwestern part. However, a low rainfall has been occurring at Terrisu sub-basin with least annual rate of 1750 mm at Habu sub-catchment. The study has found that under present climatic condition, about 67% of the

areas enclosed by the study watershed has been experiencing annual precipitation in the range of 2050 mm to 2200 mm. Previous studies have shown that there has been a continuous rise of climatic condition over the last few decades in the study area. For instant, Tan and Nying [18] forecasted higher amount of precipitation in next thirty years and range from 17 to 36% compared to present state.

3.3.2 Variability of precipitation at 2050s (2040–2069) projection

In this study, the projected annual precipitation in 2050s shows clear spatial distribution patterns over the entire watershed depending upon the climate scenario considered (Fig. 7). The annual rainfall over the watershed indicates increasing rainfall trends from RCP2.6 scenario with about 2000 mm to highest of 3000 mm rainfall under RCP8.5 scenario. Nonetheless, the characteristics of projected precipitation is consistent in the spatial distribution patterns with respect to emission scenarios along the projection line. Although, there is a spatial shift of rainfall volume from one region to another upon the changes of emission scenario in some cases. For example, the low rainfall has been received at Kg. Habu sub-watershed under RCP2.6 and RCP6.0 scenarios but not in the case of RCP4.5 and RCP8.5 scenarios. However, there is a general consistency in annual rainfall distribution in most parts of the study area regardless the climate scenario being selected. Spatial analysis presents that about 76% of the

Fig. 5 Relative variation of PCI from baseline for the sub-watersheds

Fig. 6 Precipitation rates in the study watershed at baseline period (1976–2005)

study watershed will have annual rainfall in the range of 2501–2650 mm under RCP2.6 scenario (Fig. 7(a)). Around 71% will be dominated by annual rainfall volume ranged from 2651 to 2800 mm under RCP4.5 scenario (Fig. 7(b)). Nearly 80% of the catchment will also account for rainfall within the range of 2651 to 2800 mm annually (Fig. 7(c)). Moreover, higher annual rainfall volume of 2801–2950 mm will occupy 69% of the study watershed under RCP8.5 scenario (Fig. 7(d)). It is noted under this scenario that rainfall of more than 2950 mm is found to occur in regions such as Sungai Bertam and Tana Rata sub-catchments. It could also be noted that there is a progressive shift in spatial distribution of high precipitations from Kg. Raja to Tanah Rata. Similarly, there has been a continuous rise of rainfall volume in 2050s occurring at Northwestern part of the study area under both RCP6.0 and RCP8.5 scenarios. This is plausible since both RCP6.0 and RCP8.5 scenarios represent high greenhouse gas emissions and are expected to

produce more variations in climate variables [8, 53]. However, the result shows consistently low erosivity at both Southwestern and Southern parts of the study catchment. Particularly at Alurmasuk where annual precipitation of about 2050 mm has been observed under RCP2.6 scenario.

3.3.3 Variability of precipitation at 2080s (2070–2099) projection

In 2080s projection period, there is more noticeable rainfall variability over the study catchment with higher magnitudes under RCP8.5 emission scenario (Fig. 8). The least amount of precipitation will occur at Habu sub-catchment with annual volume ranged from 2351 to 2500 mm. Unlike 2050s projection, the highest rainfall amount exceeding 3000 mm was observed to occur at southwest regions under higher RCP scenarios. About 56% of the study watershed will receive annual rainfall amount ranged from

Fig. 7 Variability of Potential Precipitations in the study watershed by 2050s **a** RCP2.6, **b** RCP4.5, **c** RCP6.0 and **d** RCP8.5 emission scenarios

2501 to 2650 mm under RCP2.6 scenario (Fig. 8(a)). Similarly, the same magnitude of rainfall is expected to cover about 50% under RCP4.5 scenario with 27% higher rainfall depth of nearly 2800 mm (Fig. 8(b)). Moreover, spatial characteristics of the precipitation indicate considerable rise of rainfall depth from Ladang Teh down to Tanah rata regions which are predominantly high altitudes and hilly areas. Additionally, high variation of rainfall depth reference to the baseline condition was observed under RCP8.5 scenario (Fig. 8(d)). In this situation, 58% of the study

watershed is projected to have rainfall depth ranged from 2951 to 3000 mm annually. It is also noticed that under this emission scenario, about 4% of the catchment area will experience rainfall depth exceeding 3000 mm which is directly translates into high erosivity.

The projection of high precipitations in the Cameron Highlands is found consistent to many previous studies conducted at mountainous regions, especially those located within the tropical areas [55–61]. Amin et al. [62] assessed the impact climate change on hydroclimate

Fig. 8 Variability of Potential Precipitations in the study watershed by 2050s **a** RCP2.5, **b** RCP4.5, **c** RCP6.0 and **d** RCP8.5 emission scenarios

in Peninsular Malaysia and reported an increase in 30-year mean annual precipitation of 17% to 36% from 1970–2000 to 1070–2100 periods. Similarly, de Mello et al. [7] examined the climate impact on precipitation for twenty-first century and arrived at 47% increment relative the baseline condition. The rise in amount of precipitation is responsible for the increased PCI, erosivity and subsequent high soil erosion. Fenta et al. [58] assessed variability of mean annual rainfall of Eastern African regions and found ranged from 300 to 810 mm

in the lowland areas to over 1200 mm in the highlands, respectively. The variability is believed to have influenced by orography of the mountainous regions within the study watershed. Moreover, Nunes et al. [63] analyzed spatial variability and trends in annual precipitation over southern mainland Portugal for the period 1950–2008 where a significant increase in precipitation concentration was found. The study also warned for the rise of potential soil erosion due to the increased erosive rainfall in the study area. Another study by

Amirabadizadeh et al. [64] evaluated the trend of precipitation series over the Langat River Basin, Malaysia. The outcome showed a significant increase in annual precipitation at 95% probability test. Also, the Theil-Sen's slope showed that the rate of increment in the annual precipitation is greater than the seasonal precipitation.

Furthermore, Nasidi et al. [17] examined climate change impact on potential precipitation and resultant erosivity in the Cameron Highlands watershed. It was shown that more rainfall intensity is anticipated to occur in future with high tendencies to caused severe soil erosion in the watershed. In this study, the present maximum monthly rainfall amount is found ranging between 98 mm in January and 284 mm in November annually. Whereas the precipitation projection varies between 2% to maximum of 80.2% increase depending upon the climate scenario and period of projection. This is reasonable considering the pervious study conducted the watershed and in other places with similar tropical climate conditions. It is expected tropical regions will likely to experience growing of extreme events in future due to global climate change impact on the environment [31, 38, 65]. Similarly, Kwan et al. [38] investigated the possibility of changes in future climate extremes over Malaysia based on the SRES A1B emission scenario. The study recorded higher probability of severe rainfall over the west coast of the Malaysian Peninsula during the autumn transitional monsoon season. Additionally, the predicted early monsoon rainfall is found feasible over East Malaysia for some locations. The study also predicted a higher rise in extreme warm temperatures but a smaller drop in cold extremes. Moreover, Gasim et al. [66] analyzed 30-years recurrent floods of Pahang river in Malaysia and found that the flow has been increased due to change of rainfall received by the watershed from 106.66 to 245.01 mm, which represent 129.7% more precipitation.

Furthermore, the application of multi-model ensemble GCMs and statistical downscaling methods are widely accepted by climate scientist globally [17]. However, there are several shortcomings associated with the process which can improve the projection accuracy if addressed. These limitations include large spatial resolutions, uncertainty inherently possessed by GCMs, significant variation of projected data among the GCMs, and the non-specific of downscaling techniques for a particular situation. Moreover, this study did not consider selection of GCM based on their relative importance to the study location, but rather takes their weighted average. However, future work should consider a scale of preference for selection of GCMs based on their spatial resolution, relative importance as well as deploying choosing a suitable downscaling technique for climate projections.

4 Conclusion

This study assessed spatial and temporal variations of potential precipitation due to climate change in the Cameron Highlands catchment. Twenty ensemble GCMs were employed to strengthen the projection capability as recommended in recent literature. The indices used in this study to determine the variability level of potential precipitation have shown considerable rise relative to baseline condition indicated high tendencies to exacerbate soil erosion processes. Similarly, temporal variation revealed more intense precipitation toward the end of the projection period particularly with high GHGs emission scenarios. Spatial variability of potential precipitation revealed that Northwest and western regions will experience concentrated rainfall which spread afterward to east and southeastern parts of the watershed. This is a valuable information because it provides policy makers with idea of where to prioritize management intervention and proper planning. Moreover, effect of environmental disasters such as flooding, soil erosion, landslides and sedimentation could be minimized through preparedness, warning, and initiative-taking measures.

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Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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