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FUTURE ASSESSMENT OF RAINFALL EROSIVITY (R-FACTOR) IN WEST RAPTI BASIN, NEPAL BASED ON RUSLE AND CMIP5 CLIMATE MODELS

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This paper assesses the projected impacts of climate change on rainfall erosivity (R-factor) in west rapti basin (WRB), Nepal. Rainfall is one of the principal drivers of soil erosion. Anticipated changes in rainfall intensities, patterns, and amounts greatly affect the erosive power of rainfall. This study evaluates R-factor of Revised Universal Soil Loss Equation (RUSLE) for historical time (1970-2005), future time1 (F1: 2020-2059 or 40's), and future time2 (F2: 2060-2099 or 80's). Six selected climate models (CMs) of the fifth phase of the Coupled Model Intercomparison Project (CMIP5) under two representative concentration pathways (RCP 4.5 and RCP 8.5) were used for projected analysis. This study provides a synopsis of R-factor (past and projections) in WRB, Nepal. The magnitude of changes varies, depending on the CMs and warming scenarios. Based on an average of CMs we found that the annual R-factors are expected to increase by 10% in the higher region, and 16.7% in the lower region of the study area during 80's under RCP 8.5 with reference to historical time. The study displays pictures of soil erosion in the future based on just the effects of the R-factor.

Key Words : *climate model, climate change, R-factor, westrapti basin*

1. INTRODUCTION

Intergovernmental Panel on Climate Change (IPCC) unequivocally states that climate change is occurring. Climate variables such as rainfall, temperatures, solar radiation, and others are expected to change significantly. Soil erosion will have impacts via multiple pathways, one of which is the change in the erosive power of rainfall[1)]. The erosive power of rainfall has a direct effect on soil erosion. R-factor is one of the main factors of soil loss, which quantifies kinetic energy of raindrop impact and rate of subsequent surface runoff.

A precise computation of R-factor for RUSLE needs a long term higher temporal resolution rainfall data (< 15 min interval), which is rarely available. Few heavy rainfall events often result in a huge soil loss, these events cannot be detected from rainfall data with low temporal resolution. In addition, current CMs do not provide such sub-hourly rainfall information under climate change. Many researchers[2),3)] use the relationship between monthly or annual rainfall and the R-factor, or some researchers[4),5)] even use daily rainfall; so that the output of CMs can directly be used. These empirical relationships based on rainfall (daily/monthly/annual) are location specific[3] and should be applied with careful attention by confirming with locally available rainfall data.

Even though some studies[6),7),8),9)] on estimations of R-factor and soil erosion at local/regional/country level have been conducted for Nepal, future assessment of R-factors in a changing climate has not been studied. Therefore, the objective of this paper is to estimate R-factor in the future (F1: 2020-2059 or 40's, and F2: 2060-2099 or 80's), discuss the anticipated change with respect to (wrt) historical time (1970-2005). We used six selected CMIP5 CMs under two greenhouse gas emissions scenarios, RCP 4.5 and RCP 8.5. Linear scaling (LS) method of bias correction was used to correct the raw historical rainfall CMs data. This study used sub-hourly rainfall data to develop the relation of R-factor based on daily rainfall and the established relation was used to assess the future scenario. The outcomes of this study are expected to be beneficial for decision-makers while planning soil conservation to adapt climate change.

2. STUDY AREA

Geographically west rapti basin (WRB), located in the lower mid-west region of Nepal, extends from 27°56'50'' to 28°2'30'' N lat and 81°45'0'' to 83°40'0'' E lon (**Fig. 1**). The elevation ranges from 100 m asl (above sea level) to 3600 m asl. The study area is divided into 4 elevation bands; EB1 (0 – 500 m asl), EB2 (500-1000 m asl), EB3 (1000-2000 m asl), and EB4 (>2000 m asl). The temperature reaches >45°C in summer in the lower part of WRB and falls <2°C during winter in the upper part of WRB.

3. DATA AND METHOD

(1) Rainfall data

Department of Hydrology and Meteorology (DHM) operates both manual (24 hr. accumulated rainfall, hereinafter termed as daily, at 8:45 AM Nepal local time) and automatic rain gauges (every 5 min). There are 8 automatic and 24 manual rain gauges in the study area (shown in **Fig. 1** and metadata of automatic rain gauges in **Table 1**). Manual stations were used for bias correction of CMIP5 CMs, whereas automatic stations were used for developing an R-factor estimation model based on daily rainfall. Automatic rain gauges were started in WRB since 2011. This study used 5 years of automatic rainfall data (2011-2015). 5 min interval rainfall data were used to compute R-factor. Same rainfall data were aggregated to daily at 8:45 Nepal local time.

R-factor estimation based on daily rainfall was applied to daily rainfall data of CMs. The selected CMs are individual members of the Conformal-Cubic Atmospheric Model (CCAM), one of the popular Coordinated Regional Climate Downscaling Experiment (CORDEX) south Asia regional CMs downscaled using global CM (GCM) forcings (**Table 2**) at a horizontal resolution of 0.44° (~50 km). The CMs data were downloaded from Center for Climate Change Research, Indian Institute of Tropical Meteorology (CCCR-IITM, a nodal agency for coordinating CORDEX modeling activity in South Asia).

Biases in CMs can be reduced using correction methods by comparing with observation data[10]. The correlation coefficient (R^2) and percent bias (PBIAS) were computed to check the performance. To employ the LS method of bias correction, at first correction factor (CF) between monthly observed and historical time series of CM were calculated. These monthly CFs were then applied to obtain the bias-corrected rainfall.

(2) Calculation of R-factor

Soil erosion is estimated based on RUSLE (eqn 1).

$$A = R \times K \times LS \times C \times P \qquad (1)$$

where A is average soil loss per unit area (tons ha^{-1} yr^{-1}), R is R-factor (MJ mm ha^{-1} h^{-1} yr^{-1}), K is soil erodibility factor (tons h MJ^{-1} mm^{-1}), LS is combined slope length and slope steepness factor, C is cover management factor, and P is conservation support practice factor. The methods used to determine the R-factor are documented in Wischmeier and Smith (1978)[11], and in the RUSLE user guide[12].

Mathematically, R-factor is the sum of the product of the storm total kinetic energy, E (MJ ha^{-1}) and the maximum rain intensity recorded within consecutive 30 mins, I_{30} (mm h^{-1}), mean annual R-factor can be estimated using eqn. 2.

$$R = \frac{1}{N}\sum_{j=1}^{N}\left[\sum_{k=1}^{mj}(EI_{30})_k\right]_j \qquad (2)$$

where N is number of years of records, and mj is number of erosive events of a year j.

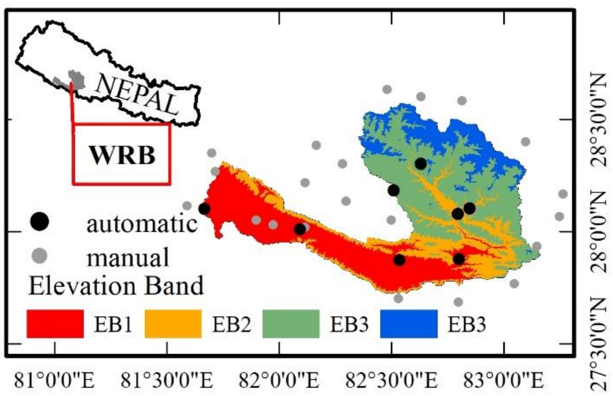

Fig. 1 Location of the study area and rainfall stations used in this study. The topography of WRB is divided into 4 EBs: EB1 (0 – 500 m asl), EB2 (500-1000 m asl), EB3 (1000-2000 m asl), and EB4 (>2000 m asl).

Table 1 Automatic rainfall stations used in this study

SN	Station Name	lat (deg)	lon (deg)	elevation (m asl)	SN	Station Name	lat (deg)	lon (deg)	elevation (m asl)
1	Kusum	28.01	82.09	199.19	5	Nayagaon	28.08	82.8	520
2	Bijuwartar	28.1	82.85	808	6	Nepalgunj	28.1	81.67	145.8
3	Lamahi	27.87	82.54	237.2	7	Sulichour	28.18	82.5	1828
4	Libang gaon	28.3	82.63	1270	8	Bagasoti	27.88	82.8	321

Table 2 Detail of selected CMIP5 climate models

CMIP5 Model	Institute	Country	GCM Resolution
ACCESS1-0	Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM)	Australia	1.25° x 1.875°
CCSM4	National Center for Atmospheric Research (NCAR)	USA	0.94° x 1.25°
CNRM-CM5	Centre National de Recherches Me´te´orologiques (CNRM)	France	1.4° x 1.4°
GFDL-CM3	National Oceanic and Atmospheric Administration (NOAA), Geophysical Fluid Dynamics Laboratory (GFDL)	USA	2° x 2.5°
MPI-ESM-LR	Max-Planck-Institut für Meteorologie /Max Planck Institute for Meteorology (MPI-M)	Germany	1.865° x 1.875°
NorESM1-M	Norwegian Climate Centre (NCC)	Norway	1.895° x 2.5°

I_{30} can be obtained directly from the rainfall record. Brown and Foster (1987)[13]'s approach was used for calculating storm kinetic energy. The criteria for an erosive event are: a) cumulative rainfall > 12.7 mm, b) at least one peak > 6.35 mm in 15 min and c) a rainfall-period < 1.27 mm in 6 h is used to divide a longer rainfall period into two storm events[12].

At first, automatic rain gauge data of WRB were employed with the above-mentioned approach for estimating R-factor. Daily rainfall data are available for more stations and even longer time span. Therefore, estimating R-factor from daily rainfall is extremely demanding. In addition, future CMs lack the sub-hourly rainfall information needed to compute R-factor. This study employed Loureiro and Coutinho, (2001)[14]'s approach for estimating R-factor based on daily rainfall data and the performance was checked with R-factor derived using automatic rain gauge data on a monthly scale with careful parameterization. This model has been applied in many regions. A threshold value of daily rainfall (10 mm) has been assumed for determination of erosive event[14].

$$R = \frac{1}{N}\sum_{i=1}^{N}\sum_{m=1}^{12}(\gamma_1 * r_{10} - \gamma_2 * d_{10})_{i,m} \qquad (3)$$

where r_{10} is monthly rainfall for days ≥ 10 mm, d_{10} is monthly number of days with rainfall ≥ 10 mm, and γ_1 = 6.7, and γ_2 = 84.2 (calibrated for WRB with performance check). Then onwards, the R-factor estimation model was applied for historical and future scenarios using CMs. This paper highlights the anticipated changes in future R-factors wrt historical.

(3) Assessment of soil erosion

Though the focus of the paper is R-factor, we attempted to estimate mean annual soil loss by evaluating other factors mentioned in eqn. 1. We used soil and terrain database (SOTER) and values of K-factor were assigned average values of Koirala et al. (2019)[8] and Uddin et al. (2018)[9]. LS-factor was determined using 30 m resolution ASTER GDEM employing Wischmeier and Smith, (1978)[11]'s method. The values of C-factor for different landuse/landcover (LULC) for the year 2010 prepared by ICIMOD were allocated in accordance with Koirala et al. (2019)[8]. The values of P-factor for different LULC, slope, and cropping pattern were assigned (Refer Ban et al. (2016)[8] for detail information).

4. RESULTS AND DISCUSSIONS

(1) Rainfall

The performance of individual selected CMs and a multimodel mean (MMM) of all selected CMs are checked with observed data during the historical time for both raw and bias-corrected. **Fig. 2 a** and **b** show the comparisons of MMM with observed data (mean monthly and annual). They clearly show bias-corrected data have better agreement with observed data.

On comparisons of observed with individual CMs for raw and bias-corrected, it is found that R^2 varying from 0.48 to 0.62 improved to R^2 = >0.7 after bias correction. And for MMM R^2 reached to 0.86 after bias correction indicating a good correlation with observed and bias-corrected data series.

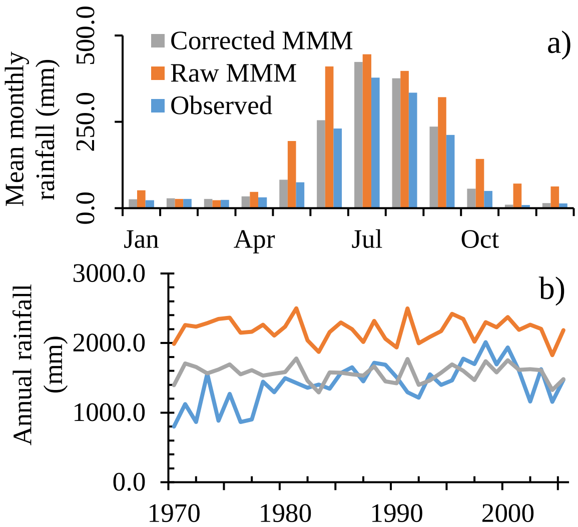

Fig. 2 Comparisons of observed, raw MMM and bias corrected MMM for historical time period : a) mean monthly rainfall, and b) annual rainfall

The bias-corrected rainfall data were then used for further analysis. Hereinafter, simply rainfall means bias-corrected rainfall. **Fig. 3** shows deviation of mean monthly rainfall for different future scenarios wrt historical based on MMM. In general, greater positive deviations wrt historical are found during Feb - May. A mixed pattern of positive and negative deviations wrt historical is observed during Jun - Oct. Negative deviations wrt historical are found during Nov – Dec. Both warming scenarios (RCPs) and both future time periods (F1and F2) show an almost similar tendency of deviations wrt historical at most of the months. A slightly different tendency of deviations is found in Jan, May, Jul, and Oct. Higher deviations are found in F2 compared to F1 and similarly, during RCP 8.5 compared to RCP 4.5.

On annual scale, the MMM shows that annual rainfall is expected to decrease by 4.5% during 40's under RCP 4.5 while is expected to increase by 3.55% under RCP 8.5. Similarly, during 80's it is expected to increase by >5.5% under both warming scenarios.

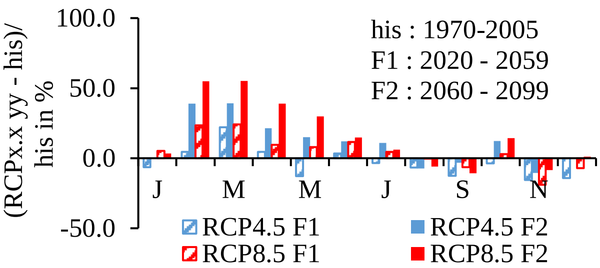

Fig. 3 Deviation of mean monthly rainfall (expressed in %) for different future scenarios wrt historical. RCPx.x means different RCP scenarios, yy means different future scenarios and his represents historical.

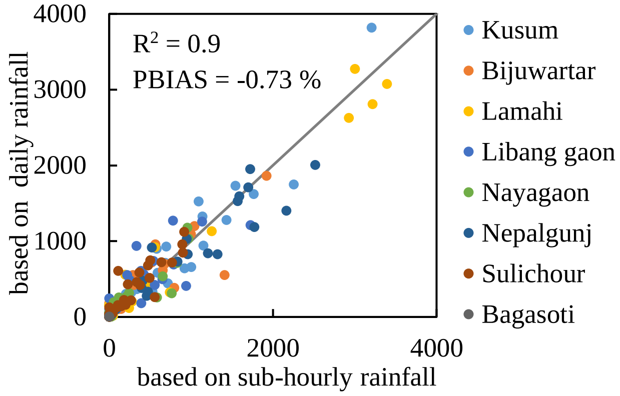

Fig. 4 Performance check of monthly R-factor estimation model based on daily rainfall wrt sub-hourly rainfall (2011 – 2015)

(2) R-factor

Fig. 4 shows the performance check of R-factor estimation model based on daily rainfall wrt sub-hourly rainfall on a monthly scale computed for 8 automatic stations for the time period of 2011 – 2015. Values of R^2 = 0.9 (close to 1) and PBIAS = -0.73% (close to 0) represent the good agreement for the estimation of monthly R-factor. Importantly, the model estimation is equally good for less erosive months. With this agreeability, the daily rainfall of different CMs at different time periods under different warming scenarios are then inputted for further analysis.

Fig. 5 shows the spatial distributions of annual R-factors for historical and future scenarios driven by different CMs. The spatial patterns are more or less similar in all cases with some fluctuations. Lower values of annual R-factors are observed in EB1 and EB2 (i.e. river valleys and lowlands). **Fig. 6** shows mean annual R-factors for historical and future scenarios of WRB driven by different individual CMs and an average of them. The variabilities of CNRM-CM5 is the lowest compared to others. GFDL-CM3 shows bigger values under RCP 4.5 whereas CCSM4 shows bigger values under RCP 8.5. The higher value of annual R-factor in historical time is observed for CNRM-CM5 (i.e. 3279.11 MJ mm ha^{-1} h^{-1} yr^{-1}) followed by MPI-ESM-LR (i.e. 3270.79 MJ mm ha^{-1} h^{-1} yr^{-1}). In summary, the magnitude varies, depending on the CMs, time periods, and warming scenarios.

Based on the average, the historical values and deviation of mean monthly and annual R-factors wrt to historical were determined (shown in **Table 3**). It shows that it is expected to increase the annual R-factor (historical = 3228.2 MJ mm ha^{-1} h^{-1} yr^{-1}) by about 10% during 40's and by about 14% during 80's. Our result shows slightly greater increment under RCP 4.5 than RCP 8.5. The possible reason might be the consideration of only rainfall as a driving factor. Our future work includes consideration of projected temperature along with rainfall for estimation of soil loss.

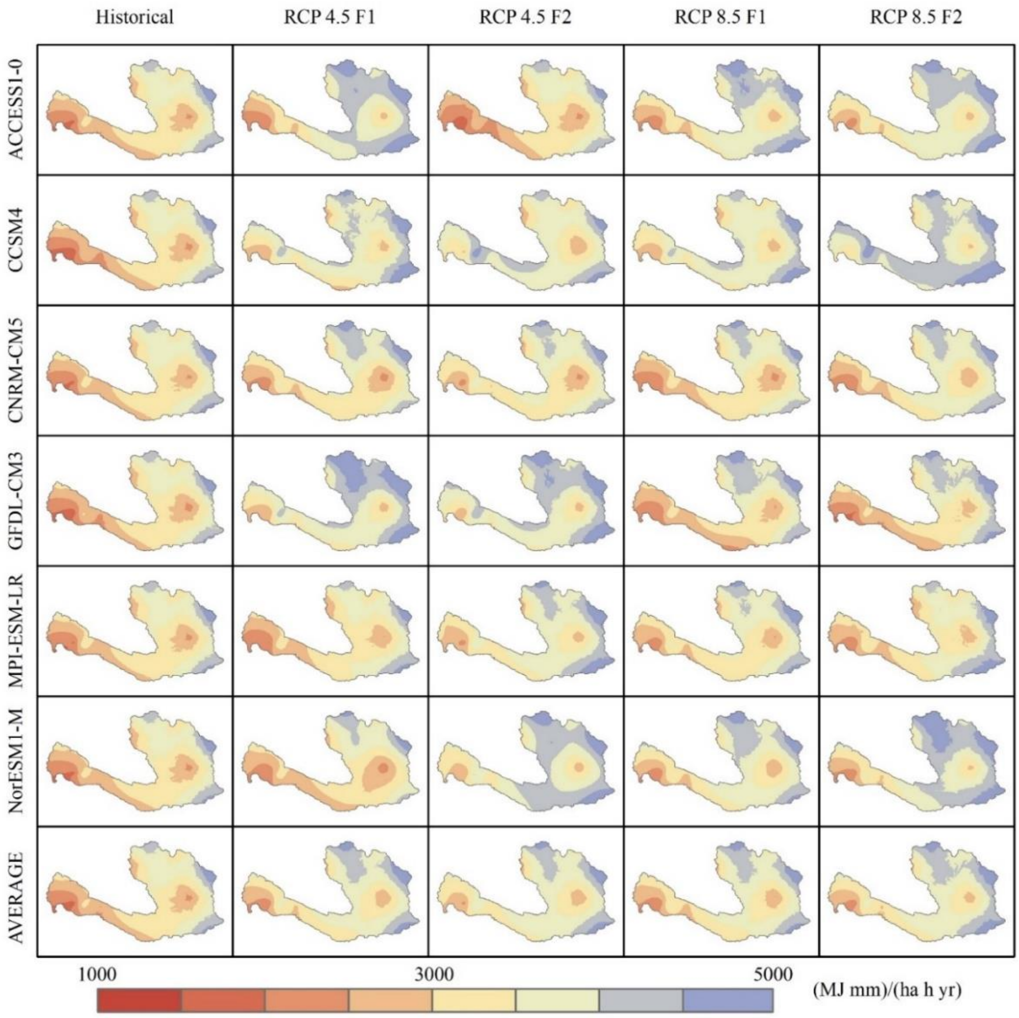

Fig. 5 Spatial distribution of mean annual R-factors for historical and future driven by different CMs and average

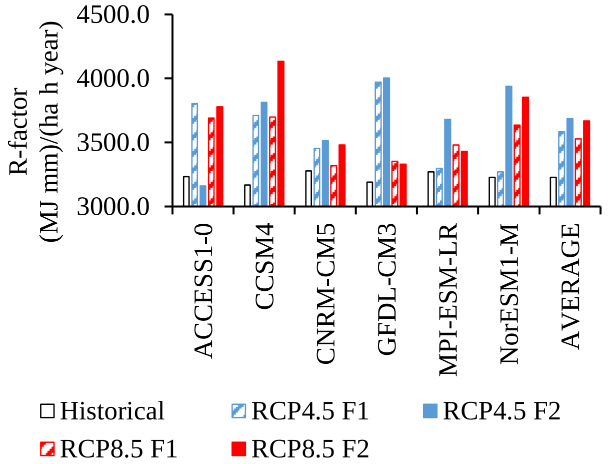

Fig. 6 Mean annual R-factor for historical time and different future scenarios based on individual CMs and average of selected 6 CMs.

Fig. 7 shows a sample of deviations of mean monthly R-factors of RCP during 80's wrt to historical in different EBs of the study area. It is expected to have a higher deviation in lower EBs compared to higher EBs (not shown for other scenarios). Higher deviations (expressed in %) are found in non-monsoon season compared to monsoon season. On an annual scale, the annual R-factors are expected to increase by 10% in the higher region, and 16.7% in the lower region under RCP 8.5 during 80's.

Table 3 Historical values and deviation of R-factors wrt to historical (in %) generated by average of CMs

Historical	MJ mm /(ha h yr)	3228.2
Change in R-factor wrt historical (%)	RCP4.5 F1	11.0
	RCP4.5 F2	14.1
	RCP8.5 F1	9.3
	RCP8.5 F2	13.6

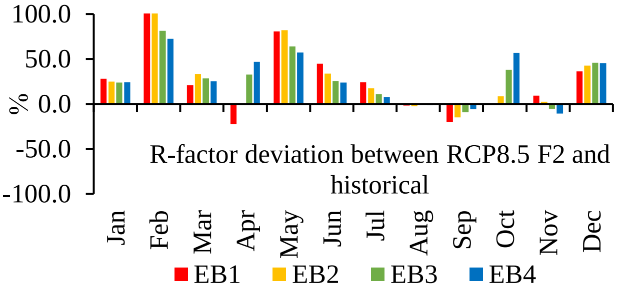

Fig. 7 Deviation of mean monthly R-factor (expressed in %) of RCP 8.5 F2 wrt to historical in different EBs of WRB

Table 4 Mean annual soil erosion for historical, future scenarios and deviation expressed in % wrt to historical for future scenarios in different EBs and WRB. The bold values represent the highest deviation in future scenarios wrt to historical.

		Mean soil erosion (tons/ha/yr)					% Deviation wrt to historical			
Elevation Band	Area in %	Histor-ical	RCP4 .5 F1	RCP4.5 F2	RCP8.5 F1	RCP8.5 F2	RCP4.5 F1	RCP4.5 F2	RCP8.5 F1	RCP8.5 F2
EB1	31.6	2.94	3.16	3.31	3.12	3.29	7.48	**12.59**	6.12	11.90
EB2	20.1	14.30	15.25	15.46	15.09	15.95	6.64	8.11	5.52	**11.54**
EB3	35.4	31.57	34.27	33.97	33.89	35.06	8.55	7.60	7.35	**11.05**
EB4	12.9	17.52	19.45	19.00	19.09	19.42	**11.02**	8.45	8.96	10.84
WRB		8.19	10.02	10.04	9.83	10.24	22.34	22.59	20.02	**25.03**

(3) Soil erosion

Table 4 shows the mean annual soil erosion for historical, future scenarios in different EBs and WRB. In general, the mean soil erosion is higher in EB3 followed by EB4. Even though R-factor is expected to increase in a larger rate in the lower region, the multiple effects of rainfall, topography, and landuse have slightly different results in overall projected deviation of mean annual soil erosion under different future scenarios. The mean annual soil erosion is estimated to be 8.19 tons ha^{-1} yr^{-1}, which is projected to increase by 25% under RCP 8.5 during 80’s. Our results are based on just the effects of R-factor variation under climate change. In reality, other factors are also highly dynamic and significantly affected by climate change. Therefore, in the future, we would conduct an intensive study on each factor. Notably, soil erosion is local in both space and time. But this paper applies the CMs, which have larger spatial scales and daily temporal resolution.

5. CONCLUSION

This study used selected CMIP5 CMs to estimate R-factors for the future time period. The variabilities of CNRM-CM5 is lower compared to other CMs. A MMM shows that during 80’s annual rainfall is expected to increase by >5.5% under both warming scenarios. This study provides an overview of anticipated changes in R-factor. It is expected to increase annual R-factor (historical = 3228.2 MJ mm ha^{-1} h^{-1} yr^{-1}) by about 10% during 40’s and by about 14% during 80’s. Our results show a slightly greater increment under RCP 4.5 than RCP 8.5. A general pattern of higher positive deviations in the lower region is found compared to the higher region of the study area. This study indicates the scenario of climate change will increase soil erosion.

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