SPATIAL DISTRIBUTION AND TEMPORAL CHANGE OF EXTREME PRECIPITATION EVENTS ON THE KOSHI BASIN OF NEPAL

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KEYWORDS

Koshi Basin, Extreme precipitation events, Climate change, Inverse distance weighting, Kriging interpolation

ABSTRACT

Climate change, particularly at South Asia region is having a huge impact on precipitation patterns, its intensity and extremeness. Mountainous area is much sensitive to these extreme events, hence having adverse effect on environment as well as people in term of fluctuation in water supply as well as frequent extreme weather events such as flood, landslide etc. So, prediction of extreme precipitation is imperative for proper management. The objective of this study was to assess the spatial distribution and temporal change of extreme precipitation events on Koshi basin of Nepal during 1980-2010. Five indicators (R1day, R5day, R > 25.4 mm, SDII and CDD) were chosen for 41 meteorological stations to test the extreme events. Inverse distance weighting and kriging interpolation technique was used to interpolate the spatial patterns. Result showed that most extreme precipitation events increased up to mountain regions from low river valley; and then it decreased subsequently up to Himalayan regions (south to north direction). However, there is high value of indices for lowland Terai valley also. Most of the indices have hotspot with higher value at north western and southern part of the study area. For temporal change, most of the extreme precipitation indices showed increasing trend within 30 years' period. The spatial distribution of temporal change in indices suggests that there is increasing trend in lowland area and decreasing trend in mountainous and Himalayan area. So, adaptive measure should be adopted through proper land use planning, especially at those hotspot areas and their tributaries; to reduce adverse effect of extreme precipitation events.

1. INTRODUCTION

South Asia region is particularly vulnerable to climate change (IPCC, 2014). Mostly, global warming is having effect on many components of hydrological systems such as precipitation patterns, its intensity and extreme event (Agarwal, Babel, & Maskey, 2014). This is likely to manifest through increased precipitation and more frequent extreme weather event, such as floods, particularly in vulnerable areas like coasts and river basins. There is a raising concern on issues such as drought and erosive rainfall that causes risk of land degradation and desertification(Costa, Durão, Soares, & Pereira, 2008).

Mountainous area is more sensitive to these environmental change, hence affect the important environmental services it offers such as drinking water supply, irrigation etc (Agarwal et al., 2014). In addition, they are characterized by steep slopes and small drainage basins, so heavy rainfall can trigger rapid and unexpected flash flood events, landslides, debris flow and soil erosions, especially at non forested area (Pereira, Oliva, & Baltrenaite, 2010). As extreme rainfall events have important impact on mountain area, it is particularly important to understand the spatial and temporal distribution of extreme rainfall to have knowledge of and to predict impact of these events and identify higher vulnerable areas. (Pereira et al., 2010; Pereira, Oliva, & Misiune, 2016). But, distribution of rain gauge stations in mountainous area is generally sparse. Additionally, there is quick change in precipitation pattern within small distance. So better prediction with higher value of extreme precipitation is necessary for better land use planning and minimizing the effect of flood, landslides and soil erosion(Pereira et al., 2010).

The objectives of this study were i) to identify spatial patterns of the extreme precipitation indicators; and ii) to analyse the temporal change and their spatial distribution of each extreme precipitation indicators.

2. STUDY AREA

This study was conducted in the Koshi river basin, in Nepal. This is the largest river basin, covering 18 districts (administrative units in Nepal) and nearly 30,000 km^2 of land from Himalayas to the lowland of terai region. This basin consists of seven major sub-basins, namely Sun Koshi, Indrawati, Dudh Koshi, Tama Koshi, Likhu, Arun and Tamor. The basin area lies within 26^{0}51' N and 29^{0}79' N latitudes and 85^{0}24' Eand 88^{0}57' E longitudes, with elevation ranging from 65 mamsl (meters above mean sea level) in low valley (terai region) to over 8000 mamsl in high Himalayas. The majority of area in Koshi basin falls under the mountains, followed by hills, himalayas, high mountains, terai plane and low river valleys (Agarwal et al., 2014).

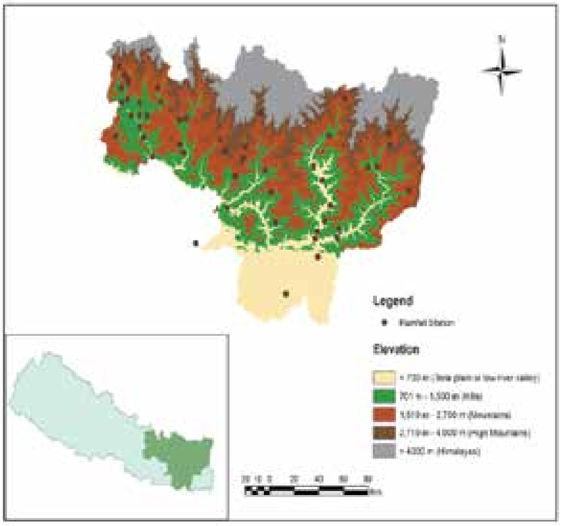

Figure 1: Study area with elevation range and precipitation station

3. DATA AND METHODS

3.1 Data

Time series data of daily precipitation, which were used to calculate precipitation extreme, recorded at 48 meteorological stations on the Koshi basin were collected for this study from 1980 and 2010. This data was provided by Department of Hydrology and Meteorology, Nepal.

Basic assumption was made (Pereira et al., 2016), where meteorological station with more than 10% of missing values were not considered.

Indicator of Extreme Climate Events

Five indicators on extreme precipitation index [from over 50 in the list defined by CCI/ CLIVAR/JCOMM Expert Team on Climate Change Detection and Indices (ETCCDI)] were used. Of the five extreme precipitation indices, four of them related to “wetness” (R1day, R5day, R25.4, SDII) while one of them related to “dryness” [consecutive dry days (CDD)], described in table 1.

Only 42 stations were used for calculating the extreme precipitation index, after filtering out the station for basic assumption made. For each indicator, two value were extracted, one for duration of 1980-1982 and another for duration of 2008-2010. This was done by averaging each value for that duration.

Indicators	Definition	Unit
R1d	Intense precipitation event: Maximum 1 day precipitation	mm
R5d	Intense precipitation event: Maximum 5-day precipitation total	mm
R > 25.4	Heavy precipitation days: Number of days with precipitation >=25.4 mm day^{-1} (1 inch)	Days
SDII	Simple daily intensity index: Annual total precipitation/ number of Rday >= 1 mm day^{-1}	mm
CDD	Consecutive dry days: Maximum number of CDD (Rday < 1mm)	days

Table 1: Extreme precipitation indicators

3.2 Methodology

3.2.1 Exploratory Data Analysis: Descriptive and Bivariate Analysis

Some descriptive statistics of all variables were performed, mean (m), median (md), standard deviation(SD), coefficient of variation (CV%), minimum (min), maximum (max), quartile (Q1), 3rd Quartile (Q3), skewness (Sk) and kurtosis (kur). Also, Pearson’s correlation between each variable with longitude, latitude and elevation was also performed to test the relation of each variable with geographic and terrain characteristics so that decision can be made for kriging interpolation.

3.2.2 Exploratory Spatial Data Analysis

Various ESDA tools such as data posting, regional histogram, voronoi maps, local and global moron’s I statistics, contour lines and moving window statistics were applied to every indicator to know about its spatial behavior in study area. This is an essential step prior to interpolation.

3.2.3 Interpolation

Establishment of spatial representation of precipitation is based upon the principle of ordinary kriging and inverse distance weighting (Borges, Franke, Anunciação, Weiss, & Bernhofer, 2015). Current studies (Borges et al., 2015; Griffiths & Bradley, 2007) make use of terrain characteristics such as elevation, geographic position to describe spatial representation of precipitation using co-kriging techniques.

Inverse distance weighting is a deterministic method whose estimation is based on the weighted average which is proportional to the inverse of distance between point to be interpolated and measured points (Borges et al., 2015). IDW is performed with power value as 2 to create an interpolated surface as it is mostly used in interpolating precipitation value.

Geostatistical method, kriging interpolation takes consideration of both the distance as well as degree of variation between the measured points(Pereira et al., 2010). The main advantage of kriging is that it gives statistically unbiased estimates of surface value from a set of observations at sampled location. This is done by fitting mathematical semi variogram model (inverse function of spatial and temporal covariance) on experimental variogram, representing variability of spatial and temporal pattern of physical phenomena (Costa et al., 2008). Several types of models are available such as ordinary, simple, and universal kriging. The parameter of variogram model such as sill, range and nugget are used to assign weight for spatial prediction.

Here, we used omnidirectional variogram as there is no sign of anisotropy in all variables. Here, we used exponential model which captures spatial characteristics of each sample in study area subjectively to model experimental semi-variogram considering the physical knowledge of the area and phenomenon (Costa et al., 2008).

It is being said that spatial heterogeneity of precipitation distribution varies with topography as well as spatial position where co-kriging can act (Pereira et al., 2016). But, as there is poor linear relationships (assessed through Pearson's correlation coefficients) between five indices and topographical variable as elevation and spatial position (longitude and latitude), we preferred ordinary kriging over co-kriging.

Experimental space time semi-variograms were calculated for the two-time period, between 1980-1982 and 2008-2010, for each extreme precipitation indices. For those indices, whose semi variogram could not be modelled; interpolation surface resulted from inverse distance weighting is considered for spatial analysis. For rest, comparison between IDW and kriging is done to assess the appropriate interpolation technique and surface is generated which has high accuracy.

3.2.4 Assessment Criteria for Interpolation Techniques

Interpolation techniques such as inverse distance weighting and ordinary kriging were tested for determining most appropriate interpolation technique for every indicator. Every assessment criteria are based on error produced by each model i.e. observed value – predicted value. Leave one out cross validation method was used to assess the error associated with each model, which based on the principle that is achieved by taking each sampled point and estimating it from the other remaining values. The error produced for each model allowed us to calculate mean error (ME) and root mean square error (RMSE), as per following formula and is used extensively to assess the accuracy of interpolation methods.

$$ME = \frac{1}{N}\sum\nolimits_{i=1}^{n}\{z(xi) - \hat{z}\,(xi)\} \qquad (1)$$

$$RMSE = \sqrt{\frac{1}{N}\sum\nolimits_{i=1}^{n}\{z(xi) - z\widehat{(xi)}]\}^2} \qquad (2)$$

Where (xi) is sampled observed value and z(xi) is predicted and N is number of data points. The best model is the method with lower value of ME and RMSE.

4. RESULT AND DISCUSSION

4.1 Descriptive and Bivariate Analysis

The table 2 shows the basic statistics of five extreme precipitation indices and elevation of meteorological station. On average, the meteorological stations were located at 1370 m and ranged from 85m to 2625 m, with standard deviation of 715.1. In koshi basin, there are on average 90.8 mm of maximum precipitation in one day per year; 174.2 mm of maximum precipitation in consecutive 5 days per year, 21 days per year with R >= 25.4mm, 15.1 mm of average value of wet days and 54.5 consecutive dry days per year, with standard deviation of 27.1, 69.3, 12.6, 15.1 and 54.4 respectively. We can see that for all indices, mean is somehow greater in amount. So, we can say that distribution of all variables is positively skewed. This may be due to the presence of extreme values, possibly an outlier.

	R1 Day (mm)	R5 day (mm)	R25.4 mm (days)	SDII (mm)	CDD (days)	Elevation (m)
Mean	90.8	174.2	21.0	15.1	54.4	1370.2
Standard Error	4.2	10.7	1.9	0.6	1.2	110.3
Median	85.1	159.6	19.0	14.2	52.0	1507

Standard Deviation	27.1	69.3	12.6	4.0	7.4	715.1
Sample Variance	735.1	4797.8	158.7	16.3	55.1	511295.7
Kurtosis	4.1	0.6	2.2	1.1	-1.4	-0.6
Skewness	1.6	0.7	1.4	1.2	0.4	-0.2
Range	138.3	318.9	59.0	17.7	20.0	2540
Minimum	56.5	43.0	3.0	9.4	45.0	85
Maximum	194.8	361.9	62.0	27.1	65.0	2625
Sum	3812.7	7315.1	883.0	618.3	2231	57550
Count	41	41	41	41	41	41

Table 2: Descriptive statistics for extreme precipitation indicator and elevation of respective stations

The result from Pearson's correlation suggests that almost all precipitation indices shows low correlation with elevation and geographic position (longitude and latitude). However, there is somehow positive correlation between R > 25.4 mm index and elevation with latitude.

4.2 Exploratory Spatial Data Analysis

Regional histogram of all five indices reveals that there is two possible suspect of spatial/data outliers/spatial regime, one at the north-western part and one at the northern part of the study area. But the points at the north-western parts spread throughout the histogram, thus there is no suspect of spatial regime at this area. But, one point at northern part is still highly different (large value) from neighbouring points. As there is no local characteristic of that point to favour that extremity, we considered it as data outlier and remove before preceding other exploratory spatial data analysis.

Data posting of precipitation index in relation with elevation shows that there is increase in precipitation index (R1day, R5day, R > 25.4 and SDII) with elevation up to mountain regions; and then it decreased subsequently, analogous with conclusion drawn form (Ichiyanagi, Yamanaka, Muraji, & Vaidya, 2007). But for indices like R1day, R5day and SDII, there is also a high value in lowland valley. This may be due to the reason that, most of heavy rainfall in Nepal is due to humid wind from Bay of Bengal, which enters through south east part of Nepal (Lal & Shrestha, 2012).

Several exploratory spatial data analysis of five extreme precipitation indices reveals that there is oversampled area at north western part or near eastern part of the study area, whereas under sampled area lies at high land (mountains and upper mountain). There is no sample point located at Himalaya region. No spatial outliers, global trend or anisotropic pattern were seen for all indices. Proportional effect is seen in some indices, but as it is so less in area, we can interpolate whole study area at once. Global Moran I index for all indices shows that spatial distribution of high values and low values in the dataset is more spatially clustered than would be expected if underlying spatial processes were random.

4.3 Interpolation

Index	Period	Nugget	Major Range	Partial Sill	Lag Size	No of Lags
R1 Day	1980-1982	40	46100	415	20220.4	10
R5 Day	1980-1982	0	41500	4150	3728.6	10
SDII	1980-1982	0	32675	17	3559.5	10
CDD	1980-1982	0	41000	65.57	3925.8	10

Table 3: Parameters for semi-variogram model

Experimental space time semi-variograms for the two-time period, between 1980-1982 and 2008-2010 were calculated for each extreme precipitation indices. In some cases, distribution of experimental semi-variogram is random, so semi-variogram model cannot be modelled well. In addition, in some case, though semi-variogram is well distributed to model but major range for this is so less that it cannot contain sufficient measured data due to sparse sample data. As an output, interpolated surface is not smooth.

Taking this into consideration, for only four indices, namely R1day for 1980-1982, R5day for 1980-1982 and SDII for 2008-2010, CDD for 2008-2010, exponential semi-variogram models is fitted keeping in mind that the spatial component is isotropic as suggested by exploratory spatial data analysis. Parameters for selected indices are shown in table 3.

4.4 Interpolation Method Accuracy

Index	Period	Method	ME	RMSE
R1Day	1980-1982	IDW	-2.654	28.989
		Ordinary Kriging	**-0.812**	**18.794**
	2008-2010	**IDW**	**-0.136**	**31.919**
R5Day	1980-1982	IDW	-2.534	51.622
		Ordinary Kriging	**1.00**	**47.733**
	2008-2010	**IDW**	**-1.753**	**60.951**
R > 25.4 mm	1980-1982	**IDW**	**-0.168**	**9.607**
	2008-2010	**IDW**	**-1.486**	**13.551**
SDII	1980-1982	IDW	-0.069	3.19
		Ordinary Kriging	**-0.028**	**3.340**
	2008-2010	**IDW**	**1.897**	**25.311**
CDD	1980-1982	IDW	0.292	7.765
		Ordinary Kriging	**0.142**	**7.768**
	2008-2010	**IDW**	**0.308**	**5.432**

Table 4: Comparison of IDW and Kriging for extreme precipitation index

The ME ad RMSE calculated from the residuals obtained from each model are presented in table 4. For all tested model, Ordinary kriging is the most accurate method to interpolate surface.

4.5 Spatial Distribution

4.5.1 Spatial Pattern of Extreme Precipitation Indicators

R >= 25.4 mm (number of days with precipitation >=25.4 mm day^{-1}) (figure 2E and 2F) shows clear increasing trend of index low land valley up to Himalayas ranging from 5 days to 69 days. R5day (maximum 5-day precipitation) index (figure 2C and 2D) showed similar spatial distribution except it has high value at lowland valley too. It has maximum value as 334.5 mm at north west corner and southern part of study area and minimum value as 46 mm at middle part of study area but maximum study area is covered by high values.

The hotspot area for R1day index (ranges from 57.32 mm to 142.95 mm) (figure 2A and 2B) and SDII Index (ranges from 144.48 mm to 144.48 mm) (Figure 3G and 3H) is same as that of R5day index with the highest values in north western part and southern part of the study area, but overall trend is not similar with previous index. Other parts is characterized by less value of these index.

CDD index (figure 2I and 2J) ranged from 45.3 to 65 days with the smallest values in the northern and eastern part and greatest value in the south and south western part. This implies, the low land and hills are more severely affected by drought than other regions, with more intense value of CDD falls under this reason.

Maximum intense precipitation index has high value at northwestern and southern part (lowland) part of study area; basin of tributaries lying in this part should be taken into greater priority to avoid flood, landslide, and soil erosion events.

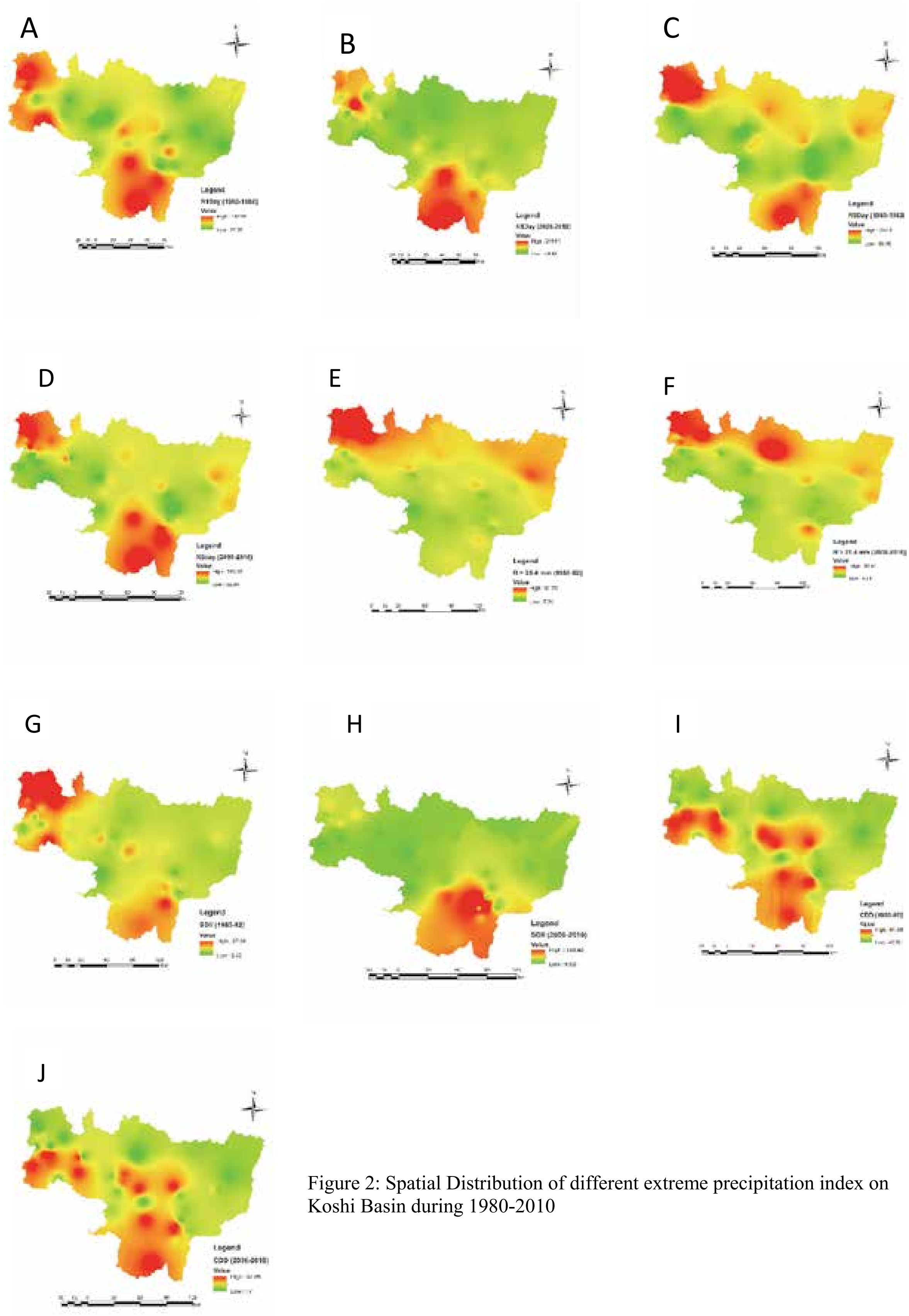

Figure 2: Spatial Distribution of different extreme precipitation index on Koshi Basin during 1980-2010

4.5.2 Spatial Pattern of Temporal Change of Extreme Precipitation Indicators

Table 5 shows the maximum and minimum value of change of each extreme precipitation indices with mean overall change in the period of 30 years. R5day, R > 25.4 mm and SDII indices shows overall increasing trend, while R1day shows overall decreasing trend and CDD is somehow constant. For R1day index, though there is overall decrease in trend, there is increasing trend in area where intensity of this index is high (i.e. north western and southern part of study area). This symbolizes the situation is getting worse in that area with increasing maximum precipitation per year. For R5day index, there is increasing trend in hill and lowland area and decreasing trend in mountains, high mountains and himalayas. For SDII index, lowland area faced increasing trend and there is decreasing trend in hill, mountains and high mountains. Since CDD is somehow constant over thirty years, there is no serious increasing threat on drought over the study area.

Overall, almost all extreme precipitation indices are in increasing trend in lowland area, whereas there is decreasing trend in mountain, high mountain and himalayan area. Hilly area showed random pattern.

Index	Period	Positive Extreme of change	Negative Extreme of change	Mean Increase	Mean Decrease
R1 Day	1980-2010	114.49 mm	-83.47 mm		7.614
R5 day	1980-2010	128.79 mm	-67.9 mm	2.387	
R >25.4 mm	1980-2010	47.992 day	-13.39 day	4.173	
SDII	1980-2010	123.12 mm	-6.5 mm	5.124	
CDD	1980-2010	3.8 day	-5.4 day		0.08

Table 5: Temporal change of precipitation indices showing maximum positive, maximum negative and mean change.

5. LIMITATIONS

In this study, interpolation for some of the indicator is not performed; as mathematical semi variogram model (inverse function of spatial and temporal covariance) couldn't be fitted on experimental variogram. This is because there is very sparse network of meteorological stations, especially at high elevated regions. So, we can't model semi-variogram to represent variability of spatial and temporal pattern of physical phenomena. The situation may got worsen due to orographic effect in mountainous area. Also, due to sparse network, major range cannot accommodate sufficient data point; as a result resultant surface is very poor. So, we only used IDW (though not very good) for that indicator where semi-variogram model cannot be fitted.

6. CONCLUSION AND RECOMMENDATION

Daily precipitations at 41 meteorological stations on the Koshi basin during 1980-2010 were used to analyze the spatial distribution and temporal change of extreme precipitation indicators. The spatial distribution of most of precipitation index shows that there is increase in extreme precipitation index with elevation up to mountain regions; and then it decreased subsequently for Himalayan regions. However, there is high value of indices for lowland terai valley. For most of the indices, there is a hotspot with higher value at north western and southern part of the study area. Most of the extreme precipitation indices showed increasing trend within 30 years' time period. The spatial distribution of temporal change in indices suggests that there is increasing trend in lowland area and decreasing trend in mountain and himalayan area.

The abovementioned spatial distribution and temporal change of extreme precipitation indices suggest that there is increasing possibility of soil loss, landslides and flood. Special care should be given to the hotspot area and its tributaries and proper land use planning should be adopted.

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