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Research Article

A Novel Appraisal Protocol for Spatiotemporal Patterns of Rainfall by Reconnaissance the Precipitation Concentration Index (PCI) with Global Warming Context

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In global warming contexts, continuous increment in temperature triggers several environmental, economic, and ecological challenges. Its impacts have severe effects on energy, agriculture, and socioeconomic structure. Moreover, the strong correlation between temperature and dynamic changing of rainfall patterns greatly influences the natural cycles of water resources. Therefore, it is necessary to examine the spatiotemporal variation of precipitation to improve precipitation monitoring systems. Thereby, it helps to make future planning for flood control and water resource management. Considering the importance of the spatiotemporal assessment of precipitation, the current study provides a new method: regional contextual precipitation concentration index (RCPCI) to analyze spatial-temporal patterns of annual rainfall intensities by reconnaissance the precipitation concentration index (PCI) in the global warming context. The current study modifies the existing version of PCI by propagating the role of temperature as auxiliary information. Further, based on spatial and nonspatial correlation analysis, the current study compares the performance of RCPCI and PCI for 45 meteorological stations of Pakistan. Tjøstheim's coefficient and the modified *t*-test are used for testing and estimating the spatial correlation between both indices. In addition, the Poisson log-normal spatial model is used to assess the spatial distribution of each rainfall pattern. Outcomes associated with the current analysis show that the proposed method is a good and efficient substitute for PCI in the global warming scenario in the presence of temperature data. Therefore, to make accurate and precise climate and precipitation mitigation policies, the proposed method may incorporate uncovering the yearly pattern of rainfall.

1. Introduction

Climate variability is a change in the statistical distribution of weather patterns. The climate of a region is defined by assessing the variation in humidity, temperature, wind, atmospheric pressure, and precipitation. In recent decades, climatological changes, the temperature, variation in precipitation, increase in the intensity of some extreme weather phenomena, rise in sea levels, etc., negatively impact the natural and human systems worldwide [1]. Certain climatic variables like temperature, precipitation, wind pattern, and solar radiation mainly describe the distinctive features of the climatic system [2]; however, the precipitation and temperature are the most significant and conventional climatic variables which change in time and space and affect hydrological cycle, irrigation schedules, agriculture, and other human activities. Additionally, the change in the intensity and amount of rainfall may lead to extraordinary weather events (e.g., floods, rainstorms, and droughts) [3, 4], which can cause economic and environmental damages and increased in mortality rate [5, 6]. However, by considering these issues, the understanding of the spatiotemporal variability of precipitation is very important for agricultural and flood control planning, hydrological processes, water resources management, assessing and understanding climate change impacts, and other environmental assessments [7]. Many researchers have been providing various techniques in their publications for investigating spatial and temporal characteristics of precipitation [7–9]. According to the literature, different methods, including frequency analysis, probabilistic based analysis, and homogeneity of precipitation, have been utilized to investigate the spatiotemporal variation of precipitation [10]. Several precipitation indices have been proposed to examine the spatial and temporal variability of rainfall at daily, annual, and seasonal scales, such as the concentration index and the seasonal precipitation concentration index [3, 4, 11], coefficient of variation, standardized precipitation index [12]; principal component analysis [13], and precipitation concentration index (PCI) [14, 15]. PCI [14] is the simplest and most used indicator of precipitation concentration. This indicator considers only monthly precipitation data to analyze the annual rainfall distribution, which is insufficient for analyzing precipitation variability.

Further, PCI does not involve several meteorological variables such as wind, temperature, and speed. Therefore, the current study proposes a new index, the regional contextual precipitation concentration index (RCPCI), which is an extension of PCI. RCPCI employs a regression estimator to improve the annual mean precipitation by using extreme temperature as an auxiliary variable. Moreover, 45 meteorological stations of Pakistan from the period of 1952–2017 are considered for the computation of PCI [16] and RCPCI. The modified t-test and Tjøstheim's coefficient are employed for comparative analysis. In addition, the Poisson log-normal spatial model is utilized to assess the spatial distribution of each rainfall pattern.

2. Methodologies

2.1. Precipitation Concentration Index (PCI). Precipitation concentration index (PCI) is suggested by Oliver [14] and developed by De Luis et al. [16]. It is used for analyzing precipitation variability at an annual time scale and defined (see equations (1)–(3)).

$$\text{PCI} = 100 \times \frac{\sum_{I=1}^{12} p_i^2}{\left(\sum_{i=1}^{12} p_i\right)^2}, \tag{1}$$

$$\sum_{i=1}^{12} p_i = 12 \times \overline{p}, \tag{2}$$

$$\text{PCI} = 100 \times \frac{\sum_{I=1}^{12} p_i^2}{(12 \times \overline{p})^2}, \tag{3}$$

where p_i represents the monthly precipitation amount in the ith month and $\overline{p}$ is the average annual precipitation. The quantitative values (Table 1) of PCI are classified according to [14].

Table 1: Classification criteria for PCI.

PCI	Class
<10	A uniform pattern of precipitation
11 to 15	Moderate concentration of precipitation
16 to 20	The irregular pattern of precipitation
>20	High precipitation concentration (strong irregularity)

2.2. The Regional Contextual Precipitation Concentration Index (RCPCI). Oliver [14] developed PCI which has been used to analyze the yearly pattern of rainfall distribution. In PCI, the monthly precipitation amount is used for 12 months to determine the regional distribution of precipitation. Moreover, Oliver [14] had not described the prolonged behavior of precipitation and the size of the catchment area for estimation of mean temperature. At the same time, many other meteorological factors such as temperature, wind, speed, and runoff were neglected in the earlier PCI. Therefore, the current study proposes a new precipitation index: RCPCI, which presents a novel methodology for defining various patterns of precipitation intensity. The configuration of temperature as an auxiliary variable is an important factor of RCPCI development for estimating regional precipitation and reducing the gap between observed and actual values of precipitation. The current study uses maximum temperature as auxiliary information using the regression estimator [17]:

$$\overline{p_r} = \overline{p} + b(\overline{T} + \overline{t}), \tag{4}$$

where $\overline{T}$ = overall mean of the maximum temperature, $\overline{t}$ = annual mean of maximum temperature, $\overline{p}$ = average annual precipitation, and

$$b = \frac{\sum_{i=1}^{12} (p_i - \overline{p})(t_i - \overline{t})}{\sum_{i=1}^{12} (t_i - \overline{t})^2}. \tag{5}$$

In equation (5), b is the estimate of the change in precipitation when the temperature is increased by one unit. Now the proposed method is given in the following equation:

$$\text{RCPCI} = 100 \times \frac{\sum_{I=1}^{12} p_i^2}{(12 \times \overline{p_r})^2}, \tag{6}$$

where $\overline{p_r}$ the indicating mean of precipitation estimates, which is improved now by incorporating the regional effect of temperature using the regression estimator.

2.3. Tjøstheim's Coefficient and the Modified T-test. Tjostheimâs coefficient was presented by Tjøstheim [18] and Hubert and Golledge [19] to describe the correlation between two variables or between two spatial sequences. A general form of the Tjøstheim's index is given (see equations (7) and (8)),

$$\Lambda_{OBS} = \sum_{i=1}^{n} d(l_F(i), l_G(i)), \tag{7}$$

$$d(l_F(i), l_G(i)) = \left(x_{F_i} x_{G_i} + y_{F_i} y_{G_i}\right), \tag{8}$$

where the location $(l_F(i))$ is represented by two coordinates (x_{F_i}, y_{F_i}) and $(l_G(i))$ by (x_{G_i}, y_{G_i}). Λ_{OBS} designates the degree to which homogeneous rank values on two variables F and G occupy geographical locations. G defines by the untied ranks from 1 to n; the location of rank i on F is denoted by $(l_F(i))$ and i on G is $(l_G(i))$, $1 \le i \le n$.

In the present study, Tj ϕ stheim's coefficient [18] and the modified t-test [20] are applied to investigate the spatial correlation with patterns of each category. SpatialPack [21] R package is used for testing and estimating the spatial correlation.

2.4. Poisson Log-Normal Spatial Model. The Poisson log-normal spatial model proposed in [22] is the most useful generalized linear spatial model for spatial count data. It has the conditional distribution of each response variable Y_i and logarithm link function is Poisson. The complete specification of the Poisson log-normal spatial model is given in equations (9)–(11):

$$Y_i|S(x_i) \sim \text{Poisson}(\mu_i), \tag{9}$$

$$\mu_i = \exp\{S(x_i)\}, \tag{10}$$

$$S = (S(x_1), \ldots..S(x_n)) \sim MVN(D\beta, \Sigma), \tag{11}$$

where $Y_i: i = 1, 2, 3 \ldots, n$ is response variable and conditionally independent and $S = (S(x_1) \ldots\ldots S(x_n))$ is a stationary Gaussian process with mean $D\beta$ and covariance Σ.

$\beta = (\beta_1, \ldots, \beta_p)$ is coefficient vector and $D' = (d_1, \ldots, d_n)$ is a known $p \times n$ co-variate matrix related to locations and assumed of full rank. In the present study, Geo-count [23] and geoRglm [24] R packages are used for implementation of the Poisson log-normal spatial model using Monto Carlo Markov chain algorithms.

3. Application

3.1. Study Area and Data. Pakistan lies in the domain of 2339N–37°01N and 60°49E–77°40E with a total area of 796, 096 km^2 (see Figure 1). Due to domain variability, it experiences tropical in subtropical types of climates. Usually, two major climatic phenomena, i.e., South Asian summer monsoon and western disturbances, cause rainfall in Pakistan during the summer and winter seasons. These rainfall systems report almost 45 and 31 percent of the annual rainfall during the monsoon and winter seasons, and the average temperature ranges from 12 to 20°C and 19 to 35°C during winter and summer correspondingly. The study of this research is based on province-wise (Punjab, Sindh, Baluchistan, KPK, GB, and AJK) annually climatic data on precipitation (mm) and maximum temperature from 45 meteorological stations of Pakistan covering the long-term period 1971–2017. For calculating precipitation indices, 47 years of data was obtained from Pakistan Meteorological Department, Islamabad.

4. Results and Discussion

4.1. Spatiotemporal Regional Description of Precipitation Patterns under PCI and RCPCI. The data of 45 stations from 1971 to 2017 is processed for analysis. The precipitation and temperature of the varying selected stations are used for analysis. The precipitation observed in Faisalabad for the selected period is presented in Figure 2. Similarly, the precipitation of other selected stations can be observed accordingly. To avert the multiple figures, the behavior of the one station is presented. Further, the behavior of the temperature in Faisalabad can be observed in Figure 3. The behavior of temperature for other stations can be presented accordingly. Further, the current study shows that extreme temperature has a significant role; consequently, the proposed method provides quite different estimates from simple mean precipitation. Figure 4 shows the temporal deviation between the estimated values of PCI and RCPCI for Larkana, Quetta, and Kotli stations. It is found that there is a significant variation between the quantitative values of PCI and RCPCI. Therefore, for regional studies to assess and evaluate the effect of temperature on the mean estimation, the analysis is expanded for 45 meteorological stations of Pakistan. Based on PCI and RCPCI the outcomes of each count from 1971 to 2017 of selected stations are given in Table 2. Outcomes show the significant deviations in the counts of annual variability patterns determined by PCI and RCPCI. However, both methods behave in the same way at some homogeneous climatic stations. Moreover, the summary statistics of PCI and RCPCI also calculated for 45 meteorological stations from 1971 to 2017 are given in Table 3. The results associated with this descriptive analysis showed that the frequencies of all precipitation categories deviate from both indices. For instance, the two indices give homogeneous results from the uniform pattern at the minimum and median level, and slight variation is found at the maximum level for the uniform pattern, while slight variation is found at the median and maximum level for moderate, irregular, and strongly irregular (Str irr.) patterns. This exploratory analysis shows that both indices behaved identical to some patterns of precipitation classes, and some showed slight variation. Therefore, spatial decision and plotting techniques are necessary for internal comparison between each index.

4.2. Spatial Comparative Analysis. The results of the spatial comparative analysis are based on Tjøstheim's coefficient index [18] and the modified t-test [20]. Tjøstheim's coefficient and the modified t-test measure the correlation between two stochastic processes observed over space. In this research, spatiotemporal regional spatial count data is used for the analysis. SpatialPack [21] R package is used to estimate and test the spatial correlation among PCI and RCPCI with their respective scales. Table 4 provides the summary statistics of Tjøstheim's coefficient and the modified t-test. The results for Tjøstheim's coefficient show that there is a high spatial correlation between PCI and

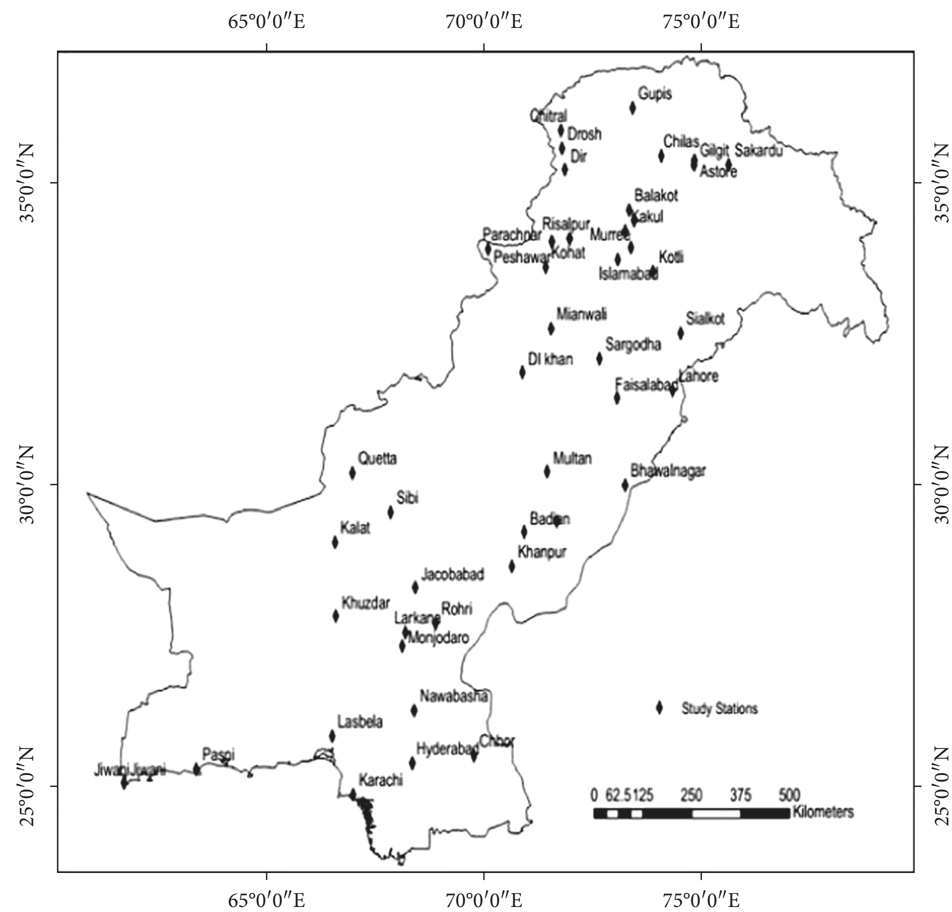

FIGURE 1: The location of Pakistan along with studied stations.

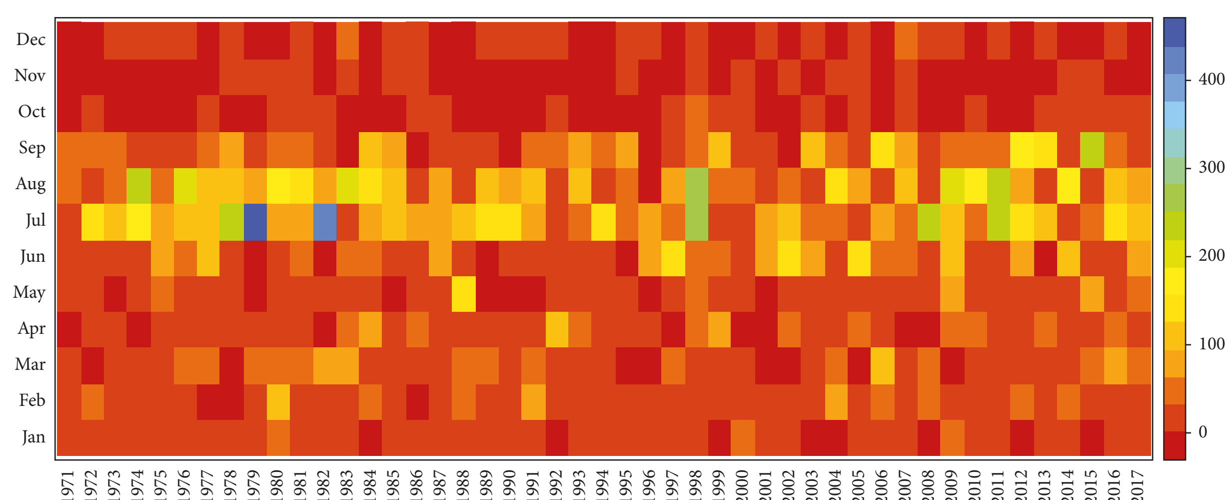

FIGURE 2: The precipitation observed in selected period is presented.

RCPCI for all patterns except uniform pattern $r = 0.4939$. For testing of hypothesis, there is also a significant correlation between both indices for all p values.

4.3. Spatial Predictive Distribution. In this study, the Poisson log-normal spatial model is employed to examine the spatial distribution of each pattern of rainfall. The use of the Poisson

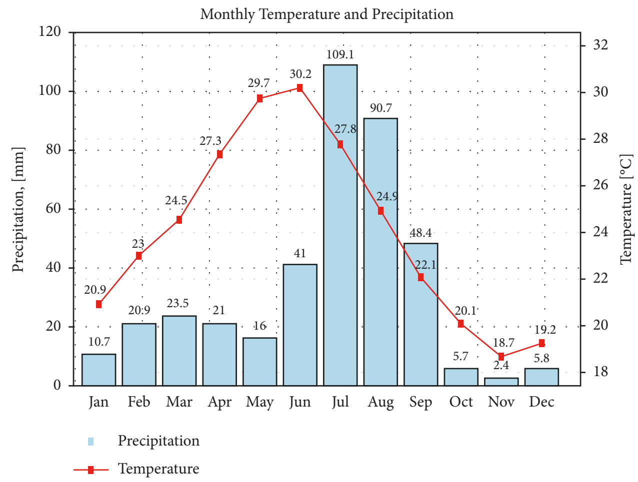

Figure 3: The monthly precipitation and temperature are presented for Faisalabad.

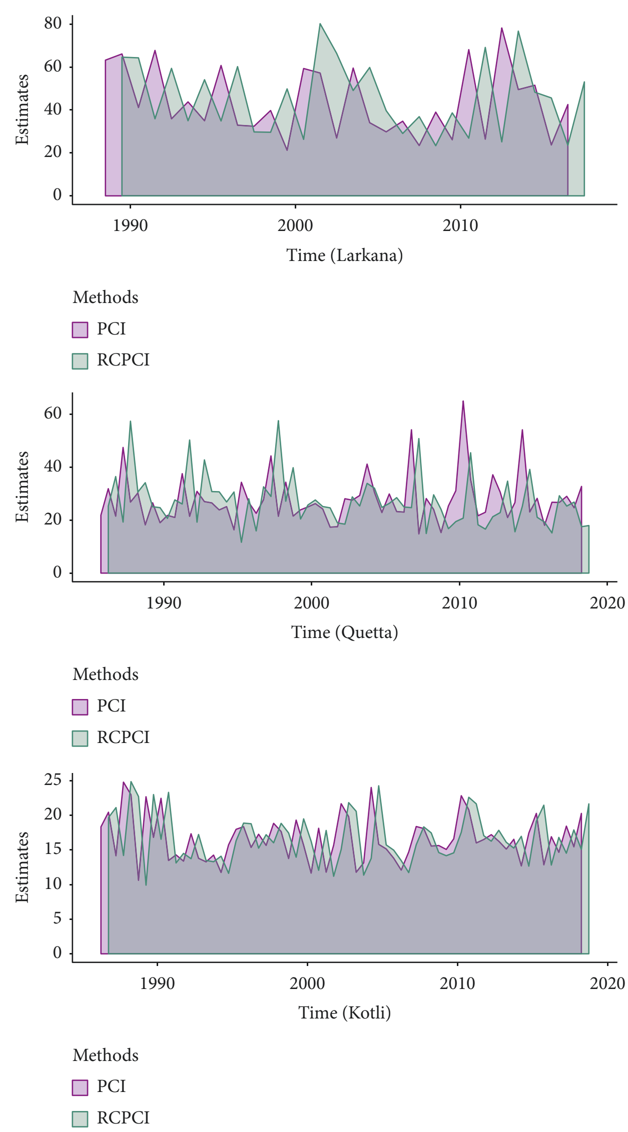

Figure 4: Temporal deviation between PCI and RCPCI.

Table 2: Total counts for PCI and RCPCI of uniform, moderate, irregular, and strongly irregular patterns.

	PCI				RCPCI			
	Uniform	Moderate	Irregular	Str irr	Uniform	Moderate	Irregular	Str irr
Stations								
Islamabad	0	21	21	5	0	23	21	3
Barkhan	0	7	17	23	1	5	18	23
Dir	1	38	8	0	1	40	6	0
Multan	0	0	6	41	0	0	8	39
Khuzdar	0	3	16	28	0	3	16	28
Chitral	0	8	23	16	0	7	25	15
Bahawalnagar	0	0	6	41	0	0	10	37
Mianwali	0	7	21	19	0	6	21	20
Balakot	0	32	13	2	0	29	16	2
Karachi Masroor	0	21	21	5	0	23	21	3
Sargodha	0	5	14	28	0	9	7	31
Garhi Dopatta	1	39	6	1	1	36	9	1
Gupis	0	5	18	24	0	6	16	25
Muzaffarabad	1	28	16	2	2	28	15	2
Nawabshah	0	0	0	47	2	0	0	45
Kohat	0	21	15	11	0	20	16	11
Astor	0	18	20	9	0	18	20	9
Risalpur	0	13	18	16	0	14	17	16
Bunji	0	7	17	23	0	7	18	22
Chilas	0	6	16	25	0	6	16	25
Lahore ap	0	0	14	33	0	0	12	35
Kakul	0	34	13	0	0	35	12	0
Hyderabad	0	0	0	47	0	1	1	45
Khanpur	0	0	2	45	0	1	1	45
Kotli	0	11	30	6	0	14	26	7
Skardu	0	7	21	19	1	10	22	14
Kalat	1	0	5	41	2	2	3	40
Jacobabad	0	0	1	46	0	0	1	46
Jhelum	0	1	22	24	0	6	15	26
Karachi ap	1	1	0	45	1	1	0	45
Lahore Pbo	0	21	21	5	0	23	21	3
Rafique PAF	0	21	21	5	0	23	21	3
Murree	0	33	13	1	0	30	15	2
Padidan	0	0	0	47	0	0	1	46
Panjgur	0	0	3	44	0	0	5	42
Parachinar	0	42	3	2	1	41	3	2
Pasni	1	0	0	46	2	2	3	40
Peshawar	0	13	21	13	0	15	20	12
Quetta	0	1	4	42	0	1	12	34
Gilgit	0	5	18	24	0	5	20	22
Chhor	0	0	1	46	0	0	1	46
Zhob	0	7	20	20	0	7	20	20
Sialkot	0	3	10	34	0	3	9	35
Sibbi	1	3	5	38	1	3	5	38
Bahawalpur	0	1	8	38	0	1	8	38

Table 3: Summary statistics of PCI and RCPCI at 45 meteorological stations of Pakistan.

	Statistics	Uniform	Moderate	Irregular	Strongly irregular
PCI	Minimum	0	0	0	0
	Median	0	5	13	24.5
	Maximum	1	42	30	47
RCPCI	Minimum	0	0	0	0
	Median	0	6	12	25.5
	Maximum	3	41	27	47

Table 4: Summary statistics of Tjøstheim's coefficient and the modified t-test.

Index		Patterns	Spatial corr.	F-statistics	P value
PCI	RCPCI	Uniform	0.4939	17.78	0.000147
		Moderate	0.9917	3086.2	0.00001
		Irregular	0.9643	688.96	0.0001
		Strongly irregular	0.9933	3793.5	0.0001

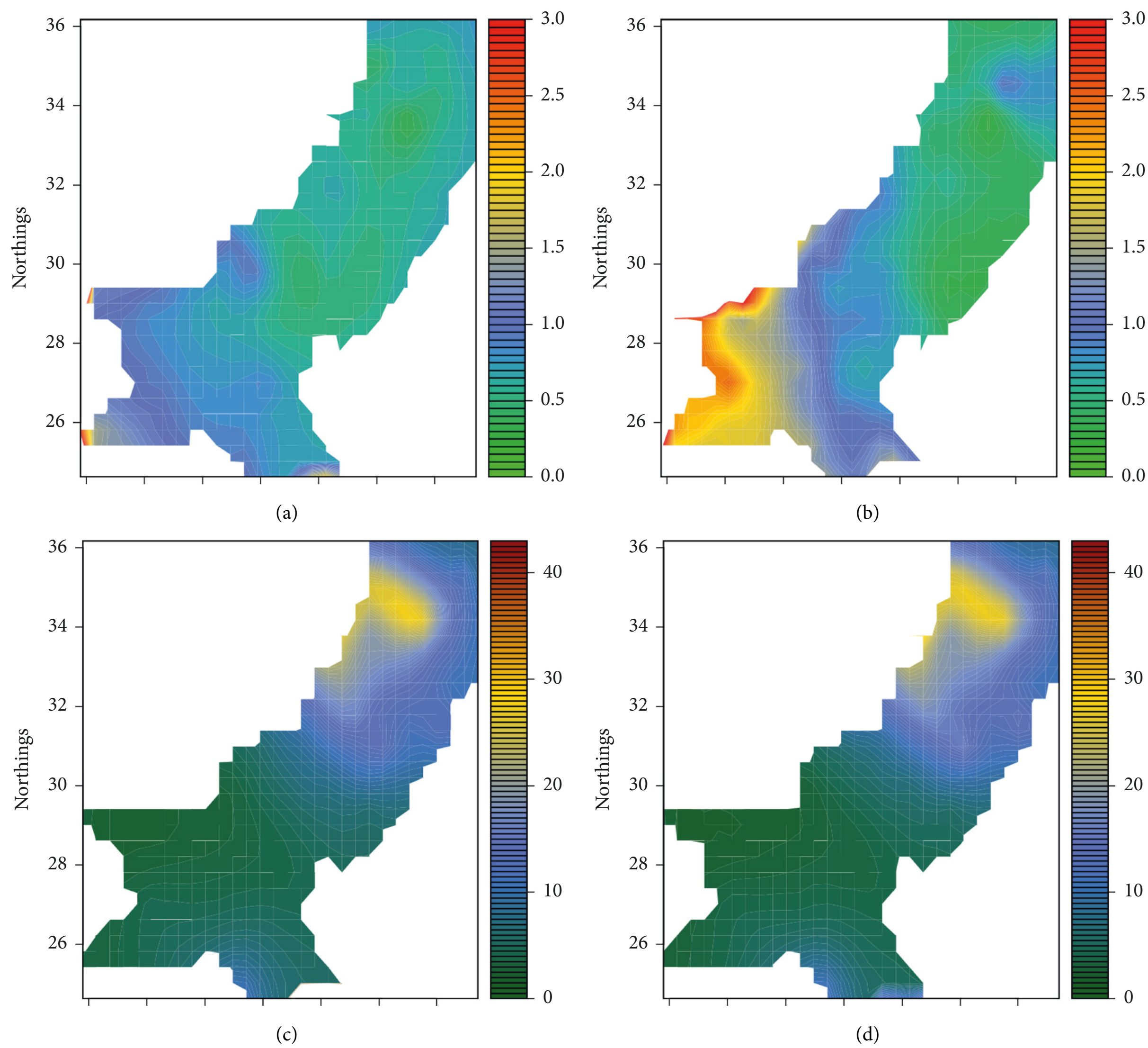

Figure 5: Predictive distribution of uniform and moderate patterns: (a) PCI uniform, (b) RCPCI uniform, (c) PCI moderate, and (d) RCPCI moderate.

log-normal spatial model is frequent for modeling spatial count data. In the current analysis, several spatiotemporal counts of varying classes (i.e., uniform, moderate, irregular, and strongly irregular) are used in the spatial Poisson log-normal model to determine the spatial distribution of each pattern of rainfall. In the current study, Geo-count [23] and geoRglm [24] R packages are employed for practical implementation of the model using MCMC algorithms. Figures 5 and 6 depict the predictive distribution of uniform, moderate, irregular, and strongly irregular counts of precipitation patterns in time series data of PCI and RCPCI. The predictive distribution of uniform and irregular counts of precipitation patterns is significantly different in both indices, however for moderate and strongly irregular counts of

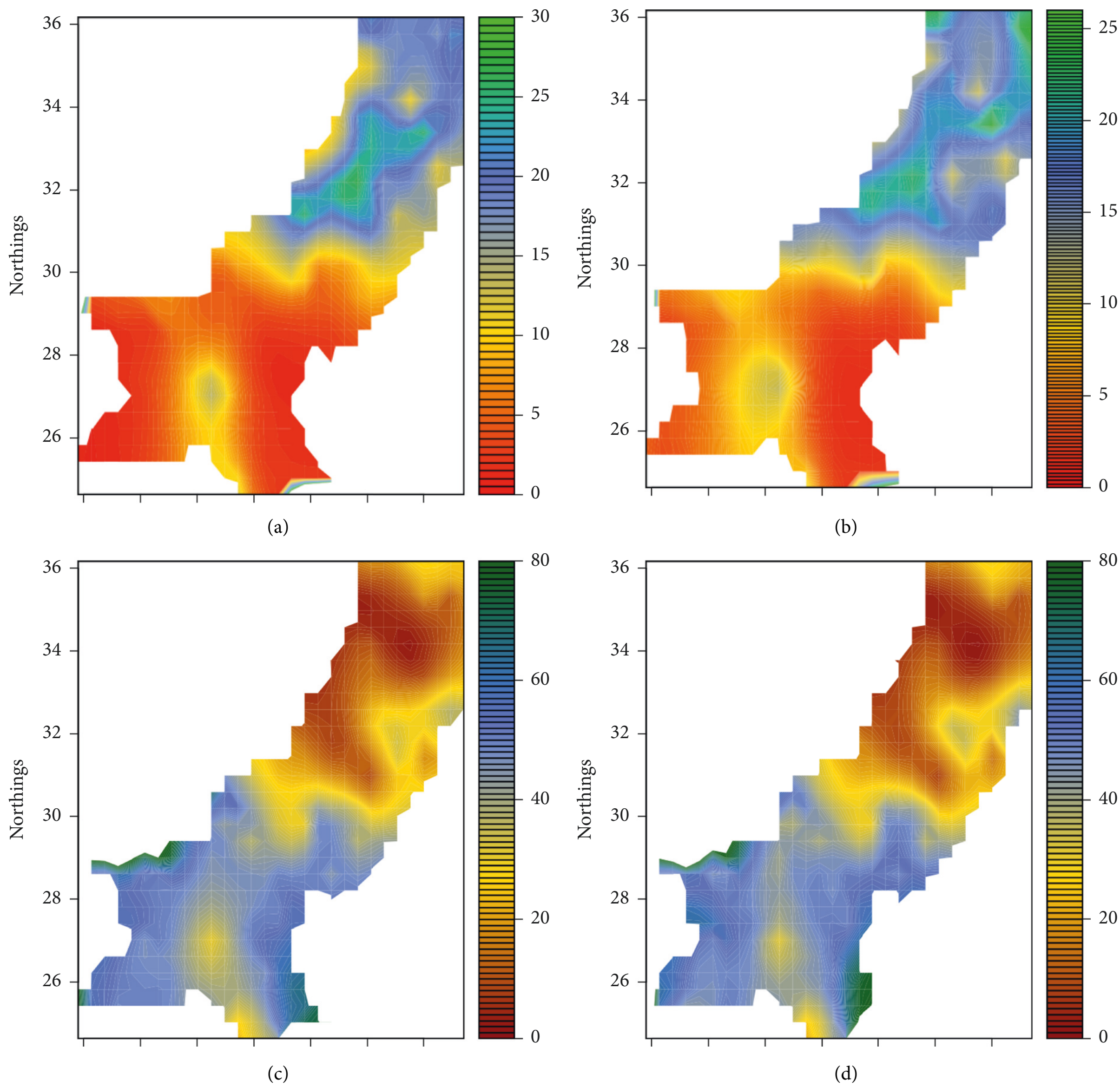

Figure 6: Predictive distribution of irregular and high concentration of precipitation patterns: (a) PCI irregular, (b) RCPCI irregular, (c) PCI high concentration of precipitation, and (d) RCPCI high concentration of precipitation.

precipitation patterns, both indices behave similarly. Overall, these inconsistencies and similarities are caused by incorporating the role of maximum temperature in the estimation of precipitation. In this research, the extreme temperature is a strong candidate of auxiliary variable. Therefore, it is suggested to improve annual precipitation estimates for better regional representatives.

5. Conclusion

Accurate precipitation monitoring policies are important for water resources assessments, agricultural planning, and flood frequency analysis. Several research provide various methodologies for assessing and monitoring of precipitation. However, these research have not considered of the temperature to assess and monitor the variability in precipitation. This issue underpins to develop new methodology for assessing and monitoring precipitation more accurately. Therefore, the current study proposes a new method called RCPCI, which incorporates extreme temperature as auxiliary information for analyzing regional precipitation variability. Comparative results associated with this study showed that the spatial correlation between RCPCI and PCI of different precipitation patterns is strongly high. The results for the spatial predictive distribution of frequencies of precipitation patterns under the Poisson log-normal spatial model show the significant deviation in uniform and irregular patterns, and similar behavior is observed in moderate and high concentration patterns. These all discrepancies show that RCPCI recommended a precipitation index that incorporates extreme temperature as auxiliary information.

Data Availability

The data will be provided if required.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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