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A new method for modelling precipitation variability in relation to climate change

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ABSTRACT

Climate change is one of the main consequences of anthropogenic activities. Since the 1950s, gradual changes and an increase in climate warming have been observed. Previous research has been indicating potential associations between climate warming and spatiotemporal changes in precipitation. Moreover, the regional patterns of precipitation have a key role in the continuous monitoring of climate characteristics and natural hazards such as floods and droughts. Therefore, precise and accurate measurements of precipitation concentration and spatiotemporal variability in their patterns are very crucial. In this study, a new method for measuring precipitation concentration is developed and applied to 54 meteorological stations in Pakistan. Furthermore, to assess the precipitation patterns, the proposed method provides solid evidence for considering the effect of temperatures under climate warming. Furthermore, using the spatial correlation between the proposed method and its competitor, a comparative analysis is made to evaluate the performance of the proposed method. Moreover, the spatial variability structure in various precipitation patterns is assessed and compared using spatial predictive maps. Outcomes associated with this research show significant deviations between the proposed method and the existing one. In this paper, regression analysis revealed that the additional input can potentially improve the precipitation estimates under the appropriate sampling estimator. This is the first study that has documented the impact of climate warming on measuring precipitation concentration. These findings can contribute to a better understanding of precipitation concentration in relation to climate warming.

Key words: auxiliary information, precipitation concentration, predictive maps, regional patterns, spatial correlation

HIGHLIGHTS

- Develop a new method (RCTIPC) for precipitation modelling.
- Comparison between PCI and RCTIPC for precipitation modelling.
- Analyzing regional precipitation variability with climate change impact.
- Spatial variability structure in various precipitation patterns is assessed and compared using spatial predictive maps.

1. INTRODUCTION

Among several environmental processes, spatiotemporal variability in precipitation has an important role in regional climatology (Coffel & Horton 2015; Khan *et al.* 2021; Wolski *et al.* 2021). In recent years, the perpetual increase in climate warming threatens to deteriorate the role of flood and drought mitigation, climatic, ecological, and regional environmental policies (Perkins-Kirkpatrick & Gibson 2017). Similar to the other socioeconomic and financial sectors, extreme temperature and high concentration in rainfall have direct severe negative effects on agricultural economics (Powell & Reinhard 2016). In particular, extreme events such as floods and droughts badly affect crop growth and yield production seasons. For instance, the US economy bears $220 million in losses in 2010 and 2012 due to high night-time temperatures and warm winter (Melillo 2014). In recent research, Azad *et al.* (2022) assessed the patterns of monsoon precipitation in 29 stations of Bangladesh. Islam *et al.* (2020) discovered the spatiotemporal trend in precipitation under various statistical models. Therefore, the accurate quantification of precipitation with its variability patterns aids in making long-term policy and climate monitoring modules.

Accordingly, the regional distribution of extreme temperature has significant importance for defining regional climatology and watersheds (Courty *et al.* 2018). Hence, the simultaneous study of these hydrological factors increases hydrological research's impact and reliability. In several previous research, time-series data of precipitation and rainfall are jointly configured to make inferences in climate research and forecasting (Coles & Tawn 1991; Guler *et al.* 2007; Mahdian *et al.* 2009; Diacono *et al.* 2013; Xu *et al.* 2014; Rahman & Islam 2019; Praveen *et al.* 2020). Recently, Saunders *et al.* (2017) have considered spatial distributions of rainfall using the max-stable spatial model in South-East Queensland, Australia. Baek *et al.* (2017) have made a joint analysis of the seasonal climatic variation using the correlation between precipitation and temperature. Other recent studies include Gehman *et al.* (2018), Dado & Takahashi (2017), Longman *et al.* (2018), Zscheischler *et al.* (2017), etc.

Besides the use of advanced statistical and geospatial tools, precise estimates and accuracy in reporting any random phenomenon are the key factors for reliable inferences and conclusions. In previous research, numerous studies are based on the precise estimation of climatic variables (Gabella & Notarpietro 2004; Germann & Joss 2004; Ahmad *et al.* 2017) and studying their temporal changes (Carrera-Hernández & Gaskin 2007). However, to improve and update the rainfall statistics, the role of auxiliary information on the recording and reporting stage of rainfall data is not considered in the literature.

For developing countries, it is essential to review the standard monitoring and data recording modules (Mirza 2003; Hussein *et al.* 2013). From these perspectives, precise quantification of precipitation and other climate factors using optimized gauge monitoring networks present a challenge (Chebbi *et al.* 2013). However, the existence of and setting of severally available optimized gauge networks reduces the scope of the optimization approaches. Contrarily, geospatial analysis and prediction using geostatistical tools are the alternative way to explore and infer. One drawback of these methods is the use of raw data. That is, no remedy is suggested or made for unreliable and unrepresentative data. This leads to an increase in uncertainty about the results of these models.

In order to increase the precision and accuracy of precipitation estimates, integrated auxiliary information-based sampling estimators are proposed (Cochran 2007; Mauro *et al.* 2017; West 2017). Several studies have developed various efficient estimators that utilize auxiliary information under different sampling strategies (Sahai & Ray 1980; Lohr & Prasad 2003; Hou *et al.* 2017). Furthermore, many researchers have used auxiliary variables in various statistical models (Zhu & Lin 2010; Apaydin *et al.* 2011; Paloscia *et al.* 2013).

In previous research, Oliver (1980) developed a coefficient of variation-based index called the Precipitation Concentration Index (PCI). The PCI characterizes and classifies the behavior of precipitation of its annual variability structure. Several studies have used the PCI and extended its methodologies in various regional studies in recent years. These include Huang *et al.* (2015, 2018), Li *et al.* (2017) and Bartolini *et al.* (2018). The PCI explores the yearly distribution of rainfall at a single station. In the original and later modified versions of the PCI, no external sources of variation were addressed in their estimation procedure. Moreover, rainfall data does not account for the prolonged behavior of precipitation (Montazerolghaem *et al.* 2016) and the size of the catchment. Furthermore, many other meteorological factors such as temperature, wind speed and runoff are also neglected.

Pakistan is considered one of the most three countries with the highest levels of water stress in the world (Farooqi *et al.* 2005). The average value of rainfall in Pakistan is 287.75 mm. The water shortage in Pakistan is reaching an alarming level that is posing a serious threat to the stability of the country. Accordingly, drought hazards due to the water shortage and the periodic drought events are the serious challenges (El Kharraz *et al.* 2012; Lal 2018). There are a number of people that lost their lives due to the drought events that occurred in the Tharpaker district (Rana & Naim 2014). Moreover, the water scarcity and drought phenomena effect of the agriculture and livestock sectors and caused a problem in hydropower energy generation. Consequently, the country bears severe economic crises and a shortfall in Gross Domestic Product (GDP). These crises are transpired due to a huge disparity between the demand and supply of energy. Although the development of a large number of the water reservoirs is being progressed. Nevertheless, the climate change and global warming have been formed several other challenges that related the existing water reservoirs in Pakistan.

The objective of this research is the precise and accurate measurement of precipitation concentration and spatiotemporal variability in their patterns. Using an auxiliary information-based sampling estimator, we postulated that the use of temperature as auxiliary information can be used to improve precipitation estimates. This is logical, as many authors have provided evidence of the use of auxiliary information. In our recent research, we have used a number of information-based auxiliary estimators to analyze drought in Pakistan (Ali *et al.* 2020a, 2021a, 2021b; Jiang *et al.* 2020). By acknowledging the positive role of auxiliary information in the estimation phase, this study is based on integrating extreme (minimum and maximum) temperature as an auxiliary variable to improve the estimation of precipitation. The specific questions which drive the research are: (1) How can we improve the raw rainfall data by modeling the relationship between temperature and rainfall in the context of global warming and (2) how to examine and assess the patterns of precipitation. In this article, a new technique of measuring precipitation-related statistics such as mean and its variability is provided. The proposed technique uses improved time-series data of precipitation estimates for defining precipitation patterns. Consequently, this research proposed a new formula for measuring precipitation variability: The Regional Contextual Temperature Index of Precipitation Concentration (RCTIPC). To illustrate all the steps involved in estimating RCTIPC, time-series data of monthly total precipitation, minimum temperature and maximum temperature of 54 meteorological stations of Pakistan have been considered. The proposed method's performance is compared with PCI using spatial correlation and spatial predictive maps of various precipitation patterns under the spatial Poisson Log Normal (PLN) model.

2. MATERIALS AND METHODS

2.1. Study area and data collection

Meteorological data of 54 stations located in the distinct regions of Pakistan as shown in Figure 1 have been used to apply the proposed criterion. In the current research, secondary time-series data of varying indicators, including precipitation and temperature (ranging from January 1971 to December 2017) are collected from the Karachi Data Processing Center (KDPC) (http://www.pmd.gov.pk/rmc/RMCK/Services_Climatology.html). Furthermore, before dispatching data, issues interrelated to the tabulation, removal of errors, adjusting outliers, quality control, and missing values are performed by RClimDex (Zhang & Yang 2004). Consequently, the data bank fulfils the requirement of Word Meteorological Organization (WMO). Table 1 provides the climatological and geographical information of precipitation in the selected meteorological stations.

2.2. The RCTIPC

This section configures the role of temperature as an auxiliary variable in the estimation process of precipitation. First, we describe the geostatistical settings of environmental variables and their estimation process. Second, we use Mukerjee *et al.*

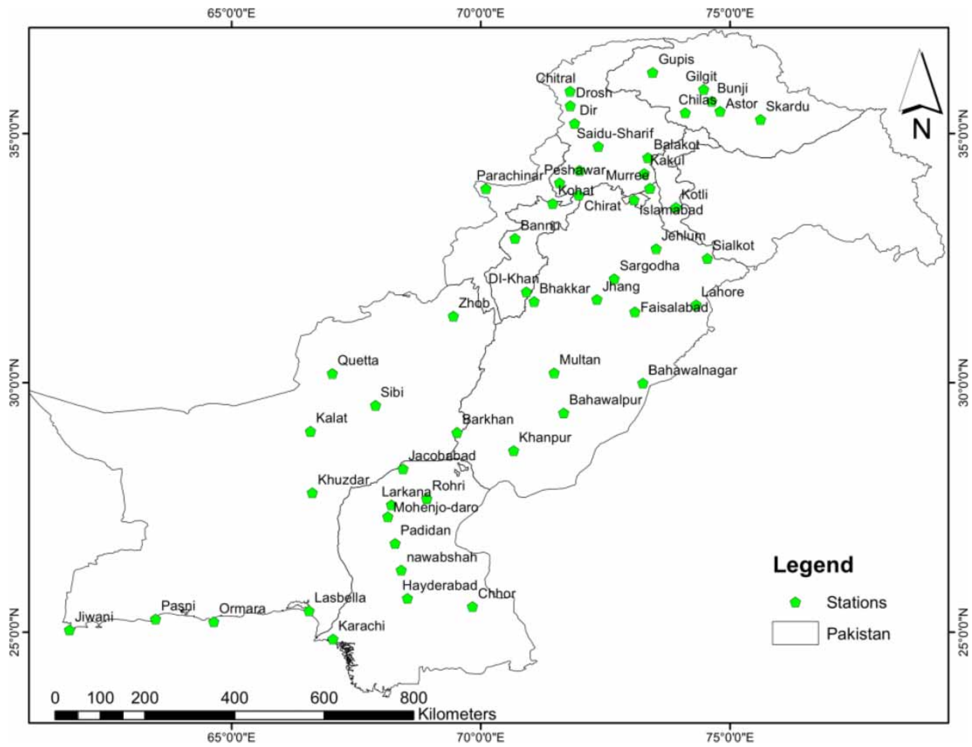

Figure 1 | Geographical locations of study area.

Table 1 | Climatological and geographical information of the selected meteorological stations

Meteorological stations	Latitude	Longitude	Elevation (m)	Mean precipitation (mm)	Mean minimum. temperature (mm)	Mean maximum temperature (mm)
Astore	35.57	74.63	2,168	39.21	4.099	15.754
Badin	24.65	68.85	9	18.31	20.284	33.291
Bahawal Pur	29.35	71.69	110	15.19	18.332	33
Bahawalnagar	30	73.24	163	19.8	18.76	32.605
Balakot	34.55	73.36	3,199	131.7	12.107	25.189
Barkhan	29.9	69.57	1,097	34.24	14.912	28.382
Bunji	35.66	74.6	1,372	13.33	11.321	23.856
Cherat	33.82	71.89	1,372	51.17	12.967	21.341
Chhor	25.51	69.78	5	19.09	18.058	35.046
Chilas	35.42	74.09	1,250	15.73	14.311	26.426
chitral	35.77	71.77	1,497.8	37.78	8.55	23.462
Dalbadin	28.89	64.4	843	6.72	13.897	32.032
DIK	31.86	70.9	171.2	26	16.908	31.563
Dir	35.2	71.87	1,375	115.47	7.917	23.03
Drosh	35.57	71.8	1,463.9	47.45	11.051	24.185
Faisalabad	31.45	73.14	185.6	32.43	17.088	31.06
Garhi Dupatta	33.52	73.92	813.5	123.15	12.341	26.104
Gilgit	35.28	71.84	1,460	11.65	7.646	24.053
Gupis	36.23	73.43	2,156	15.83	6.425	18.839
Hyderabad	25.4	68.36	28	12.9	21.047	34.279
Jacobabad	28.28	68.45	55	11.04	20.187	34.169
Jhelum	32.94	73.73	287.19	73.1	16.816	30.613
Jiwani	25.05	61.77	58	8.63	21.212	30.305
Kakul	34.19	73.26	1,308	110.97	10.684	23.074
Kalat	29.05	66.59	2,015	15.46	5.811	22.186
Karachi	24.9	67.17	22	15.38	21.006	32.159
Khanpur	28.63	70.66	88.41	10.5	17.373	33.362
Khuzdar	27.82	66.61	1,231	21.14	14.879	28.9
Kohat	33.59	71.44	489	47.39	16.965	29.62
Kotli	34.23	73.62	614	103.65	15.387	28.437
Lahore	31.5	74.36	216.15	55.66	18.57	30.682
Lasbella	25.87	66.71	87	14.66	18.564	35.725
Mianwali	32.58	71.54	210	45.74	16.905	31.633
Multan	30.16	71.52	121.95	17.81	18.377	32.532
Murree	33.91	73.39	2,291	145.16	8.672	17.419
Muzaffarabad	34.36	73.47	838	124.05	13.509	27.638
Nawabshah	26.24	68.39	37	11.95	18.17	35.606
Nokkundi	28.83	62.75	682	2.99	17.231	32.64
Padidan	26.77	68.29	46	9.72	18.227	34.881
Panjgur	26.73	64.15	968	8.24	15.051	30.181
Parachinar	33.9	70.09	1,725	81.53	7.796	21.034

(*Continued.*)

Table 1 | Continued

Meteorological stations	Latitude	Longitude	Elevation (m)	Mean precipitation (mm)	Mean minimum. temperature (mm)	Mean maximum temperature (mm)
Pasni	25.25	63.42	9	8.27	20.252	31.302
Peshawar	34.02	71.52	327	40.1	16.211	29.644
Quetta	30.18	66.98	1,719	21.45	8.038	24.978
Rawalpindi	33.61	73.1	508	102.72	14.689	28.796
Risalpur	34.08	71.99	308	55.5	14.671	29.778
Rohri	27.67	68.89	66	9.01	19.814	34.228
Sakardu	35.3	75.62	2,317	19.08	4.822	18.78
Sargodha	32.07	72.69	187	39.88	17.343	31.509
Sialkot	32.49	74.52	255.1	83.53	16.432	29.477
Sibbi	29.55	67.88	133	14.02	19.374	35.156
Zohub	31.35	69.47	1,405	23.38	12.033	26.58

(1987) estimator to configure extreme temperature as auxiliary information for estimating regional precipitation. Mukerjee *et al.* (1987) estimator is a generic method that utilizes multiple auxiliary information in the estimation process in which the marginal effect and temporal fluctuation of related variables are accounted.

Here, we recall the definition of geostatistical data. Let $x_1, i = 1, \ldots, n$ be the location points in a certain region. In geostatistics and geospatial analysis, such data are often collected at spatially sampled locations of continuous phenomenon of a discrete set of locations at particular regions $A \subset R^2$ (Diggle *et al.* 1998). To assemble these settings in rainfall recordings, let z be the total monthly precipitation measured at a certain location $s = (x, y)$. In the theory of survey sampling (Cochran 2007) this z can be considered as a sample information of the whole region for which we are going to generalize the findings. Therefore, the selection of this location point should be well spatially representative (Henry & Cassidy 1978; Joss *et al.* 1990; Thornton & Running 1999; Eslamian 2014).

Furthermore, let T_{min} and T_{max} and R be the values of the minimum temperature, maximum temperature, and total precipitation mapped over a specific region, which are recorded monthly. As the time-series meteorological data are based on a single observatory, the annual mean precipitation can be greatly dispersed from the original values. However, it is impossible to measure the precipitation record at all the points. In this context, efforts can be made to include auxiliary information to minimize the gap between observed and true values. Hence, if there are positive correlation between rainfall and auxiliary information, the mean of study variable can be obtained with a more accurate way. Hence, under the rationale of Mukerjee *et al.* (1987) estimator, we suggest the following equation for precipitation improvement.

$$\bar{u} = \bar{r} + b_1\,(T_{\mathrm{min}} + \bar{t}_{\mathrm{min}}) + b_2(T_{\mathrm{max}} + \bar{t}_{\mathrm{max}}) \quad (1)$$

where $\bar{r}$ is the improved annual mean of the precipitation, $\bar{t}_{\mathrm{min}}$ and $\bar{t}_{\mathrm{max}}$ are the regional mean maximum and minimum temperature, b_1 and b_2 are the slopes coefficient between precipitation and temperature, T_{max} and T_{min} are the overall mean maximum and minimum temperature. In this study, we assume that compared to precipitation, the spatial variations in extreme temperature are significantly low. Our experimental results show that minimum and maximum temperatures are strongly correlated with total monthly recorded rainfall. For generalization, we used time-series data of four meteorological stations having different climatology (see Table 2). Here we observed significant changes in simple precipitation estimates from those estimated from regression estimation settings.

To analyze the pattern of precipitation data, Oliver (1980) has developed a coefficient of variation-based PCI. The PCI characterizes and classifies the behavior of precipitation of their annual variability structure. The PCI formula utilizes monthly recorded data of precipitation of a specified gauge station. Equation (2) describes the estimation procedure of

Table 2 | Summary statistics of four stations for numerical illustration

Station name	Sialkot	Sargodha	Jhelum	Sakardu
Latitude	32.4945° N	32.0740° N	32.0740° N	32.0740° N
Longitude	74.5229° E	72.6861° E	73.7257° E	75.6166 ° E
Mean minimum temperature	16.438	17.392	16.822	4.807
Mean maximum temperature	29.4483	31.51	30.607	18.829
Correlation minimum temperature	0.445	0.429	0.467	0.166
Correlation maximum temperature	0.204	0.254	0.204	0.272
Slope with minimum temperature	7.4812	2.821	5.75	−0.512
Slope with maximum temperature	3.7532	1.93	2.813	−0.714
Overall mean of precipitation	84.0427	40.054	73.841	19.321
Regression mean using two auxiliary variables	57.853	22.557	48.372	8.426

PCI values.

$$PCI = 100 \times \frac{\sum_{i=1}^{12} P_i^2}{\left[\sum_{i=1}^{12} P_i\right]^2} \tag{2}$$

Here, Equation (2) can be written as

$$PCI = 100 \times \frac{\sum_{i=1}^{12} P_i^2}{[12 \times \overline{P}]^2} \tag{3}$$

where $\overline{P} = \sum_{i=1}^{12} P_i/12$, P_i represents the amount of monthly precipitation in the ith month and $\overline{P}$ is the average annual precipitation. The PCI less than 10 indicates a uniform pattern, and the PCI greater than 20 is classified as high concentration, whereas its inner range classifications are defined in Table 3.

To assess the effect of the auxiliary variable, we extended and analyzed the results of precipitation estimates to check the precipitation variability. Therefore, instead of using a simple average in the denominator of Equation (3), we suggest a regression estimation method for precipitation average. Using this proposal, dissemination of regional variation and classification will incorporate more regional representativeness, reduce sampling error, and account for the effect of extreme temperature. We hypothesize that a more efficient estimator gives more information. The efficiency measures extracted information in terms of variance of an unbiased estimator, which means smaller variance and greater efficiency. Without using the mathematical theory, here we use the traditional mean and the mean of regression estimator proposed by Mukerjee *et al.* (1987) on real datasets. In this research, the minimum temperature is used as the first auxiliary variable, and the maximum temperature is used as a second.

Table 3 | Classification of the PCI and RCTIPC

Values of PCI and RCTIPC (X)	Pattern
$X < 10$	Uniform pattern
$10 < X < 15$	Moderate concentration
$15 < X < 20$	Irregular concentration
$X > 20$	High concentration

Therefore, in line with Oliver (1980), we suggest a RCTIPC technique.

$$RCTIPC = 100 \times \frac{\sum_{i=1}^{12} P_i^2}{[12 \times \overline{U}]^2}$$

where $\overline{U}$ is the mean precipitation estimates while considering the regional effect of extreme temperature under regression estimation settings.

RCTIPC measures the annual precipitation variability within a single monitoring station. However, RCTIPC is based on regionally improved mean precipitation under global warming contest, unlike simple precipitation mean. Similar to PCI, the classification of various patterns can be configured by classifying the range of RCTIPC. Table 3 shows the range and corresponding patterns of annual precipitation distribution.

2.3. Numerical illustrations

This section aims to illustrate the efficiency of the proposed index through numerical examples and comparisons. The main objective is to show that the proposed index is more sensitive to climate warming than the existing one. Here, we consider the time-series data of rainfall and temperature of district Jhelum for the year 2017. Table 4 shows the summary statistics of the regression model. We observed that precipitation is strongly correlated with minimum and maximum temperatures. That is, the study variable has a correlation value ($r = 0.6635$) with minimum temperature and ($r = 0.4356$) with maximum temperature. And the least square multiple regression lines are significant (P-value $= 0.00497$ with 9 degrees of freedom) (see Table 4). In this example, the estimated quantitative values of rainfall (66.44167) and PCI (17.77721) observed irregular behavior in the year 2017. In contrast, the proposed estimator produced high concentration patterns with an improved rainfall estimate of 59.671 and RCTIPC values of 22.0404 (see Table 2). This indicates that the high variability in annual precipitation is observed after employing extreme temperature. In Table 5, the detailed summary of the Jhelum station is shown with regression and correlation coefficient of the study variable and auxiliary variables. We observed that the sum of a square and mean value of the study variable for each year from 1971 to 2017 have random behavior. And the effect of minimum temperature is positive with high slope and correlation values between rainfall and minimum temperature (see Table 2). On the other hand, the maximum temperature has less slope value than the minimum temperature for all year. Also, there is a low correlation between the study variable and maximum temperature. Finally, minimum temperature has more effect on rainfall than the maximum temperature. In the last two columns of Table 5, results of PCI and RCTIPC are given for all years 1971–2017. In general, significant differences in PCI and RCTIPC have been observed each year.

2.4. Spatial comparison under the PLN model

In recent research, a large number of applications related to the geostatistical count data are based on Gaussian random fields. The initial proposal of the PLN model mainly for the analysis of spatiality correlated count data (Aitchison & Ho 1989). By assuming the total number of various patterns of rainfall is spatially correlated variable, the use of the PLN model appears to the appropriate model for modeling the count of rainfall patterns. In this paper, the spatial PLN model was used for exploring the predictive distribution precipitation patterns observed from RCTIPC and PCI. This is due to the fact that the data of various categories is spatially counted. In previous research, Ali *et al.* (2020a, 2020b) used PLN to explore the various patterns of drought for Pakistan. A brief description on PLN is as follows:

Suppose the pairs (x_i; y_i) where x_i is the reference points and y_i is the observed value of the counts of patterns, where the spatial distribution of y_{in} is abnormal. Diggle *et al.* (1998) introduced a class of generalized linear spatial models (GLSM): PLN and binomial logit normal spatial models for non-Gaussian spatial data sets. These models are helpful for modeling

Table 4 | Example data of actual rainfall at 1-month timescale (Jhelum: for 1 year 2017)

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	41,564.18	20,782.09	10.12697	0.00496891
Residual	9	18,469.37	2,052.152		
Total	11	60,033.55			

Table 5 | Time-series data of the PCI and RCTIPC for district Jehlum

Years	$\sum y^2$	$\bar{y}$	$\bar{t}_{min}$	$\bar{t}_{max}$	b_1	b_2	$r_{(y,t_{min})}$	$r_{(y,t_{max})}$	PCI	RCTIPC
1971	105,023.7	64.67	16.41	31.58	4.88	2.85	0.6	0.29	17.44	18.17
1972	82,853.13	51.91	16.28	31.25	5.28	4.47	0.67	0.4	21.35	21.83
1973	62,614.74	52.03	16.35	30.94	3.85	2.48	0.58	0.36	16.06	15.72
1974	261,649.8	81.92	17.03	30.48	7.56	4.11	0.5	0.24	27.08	28.39
1975	61,342.83	45.98	16.31	30.95	3.53	1.55	0.52	0.22	20.15	19.42
1976	326,375.4	103.2	16.01	30.45	11.9	8.11	0.73	0.42	21.25	17.77
1977	344,041.2	86.93	15.98	29.97	8.59	2.22	0.43	0.1	31.62	26.77
1978	195,575.8	74.97	16.93	30.53	8.47	6.12	0.6	0.34	24.17	25.06
1979	323,594.5	97.46	16.75	30.33	8.64	3.38	0.52	0.19	23.66	23.4
1980	168,011.7	78.1	16.65	30.7	6.08	2.37	0.49	0.18	19.13	19.08
1981	145,289.2	79.63	17.04	30.95	6.28	3.68	0.62	0.35	15.91	17.34
1982	146,982.9	69.73	16.29	30.47	4.02	−0.18	0.36	−0.01	21	20.09
1983	212,170.1	89	16.28	29.17	3.07	0.29	0.23	0.02	18.6	17.92
1984	198,857.3	90.74	15.74	28.98	6.73	5.51	0.57	0.38	16.77	12.22
1985	164,211.5	70.45	16.27	30.48	6.63	3.37	0.59	0.26	22.98	20.95
1986	90,763.92	51.5	16.78	31.38	3.75	1.35	0.39	0.13	23.76	25.06
1987	131,211.7	77.67	16.1	29.59	5.01	2.92	0.52	0.28	15.11	13.01
1988	88,884.94	54.42	16.5	30.95	4.29	3.07	0.48	0.29	20.84	20.94
1989	295,555.6	82.83	17.27	31.36	7.57	2.21	0.42	0.11	29.91	34.74
1990	98,175.92	55.7	16.19	30.68	4.73	2.26	0.5	0.23	21.98	20.3
1991	214,421.1	99.37	17.23	30.38	2.88	−0.35	0.24	−0.03	15.08	15.59
1992	162,396.3	82.19	16.41	29.88	6.17	3.83	0.55	0.32	16.69	14.96
1993	205,957.7	94.53	16.59	29.45	3.61	0.34	0.29	0.02	16	15.75
1994	121,461	63.48	16.52	31.18	4.99	2.25	0.49	0.2	20.93	21.17
1995	307,584	83.29	17.08	30.53	9.31	3.78	0.51	0.19	30.79	33.35
1996	481,962.9	96.49	16.62	30.01	9.28	3.6	0.41	0.15	35.95	33.85
1997	165,023.4	82.43	16.68	30.11	5	2.86	0.47	0.21	16.87	16.25
1998	416,530	111.3	16.69	28.8	10.76	8.81	0.56	0.38	23.35	17.78
1999	185,227.4	80.12	17.11	30.59	6.19	3.83	0.51	0.28	20.04	21.29
2000	74,819.59	52.36	17.77	31.44	3.73	0.65	0.47	0.08	18.95	22.73
2001	152,943.9	70.03	17.4	31.22	6.3	3.71	0.57	0.3	21.66	26.4
2002	109,862.5	62.23	16.91	31.61	6.93	6.51	0.77	0.56	19.7	25.75
2003	50,743.94	44.38	17.76	31.81	3.42	2.46	0.57	0.36	17.89	24.59
2004	159,427.6	80.13	17.46	30.16	4.97	2.15	0.45	0.19	17.25	18.51
2005	162,976.7	71.58	17.82	31.4	5.29	2.7	0.41	0.19	22.09	28.02
2006	82,656.94	55.18	17.08	30.25	2.63	0.35	0.34	0.04	18.85	19.47
2007	393,410.5	102.7	18.35	30.94	9.09	4.12	0.45	0.18	25.88	36.59
2008	117,859.8	69.39	17.1	30.53	3.6	1.36	0.39	0.13	17	17.66
2009	102,923	68.85	17.23	30.23	4.34	3.57	0.54	0.36	15.08	15.46
2010	53,203.38	45.18	17.27	31.44	3.48	2.37	0.54	0.33	18.1	21.68
2011	125,387.8	65.94	17.28	31.48	5.8	3.84	0.59	0.32	20.02	24.79
2012	106,754.6	62.36	16.96	30.78	5.32	3.36	0.6	0.32	19.06	20.28

(*Continued*.)

Table 5 | Continued

Years	$\sum y^2$	$\bar{y}$	$\bar{t}_{min}$	$\bar{t}_{max}$	b_1	b_2	$r_{(y,t_{min})}$	$r_{(y,t_{max})}$	PCI	RCTIPC
2013	126,872.1	59.78	16.55	31.17	4.66	2.55	0.46	0.22	24.65	25.23
2014	169,726.4	76.48	17.03	30.72	6.23	4.05	0.54	0.31	20.15	21.47
2015	137,672.2	78.6	16.47	29.63	5.65	3.1	0.63	0.28	15.48	13.88
2016	138,549.4	86.75	16.95	30.19	5	3.63	0.57	0.38	12.79	12.68
2017	113,007.5	66.44	17.2	31.43	6.21	4.56	0.66	0.44	17.78	22.04

spatial count data sets when the spatially varying attribute of interest is functionally related to a realization of a non-Gaussian random field (Zhang 2002). Several studies used GLSM to model spatial count data in various disciplines (Cameron & Trivedi 2013). Royle & Wikle (2005) adopted the spectre parameterization of the spatial varied mean of a PLN model in order to obtain a maps of avian count data. Wakefield (2006) applied a general linear model with spatial autocorrelation for mapping the illness of esophageal cancer incidence data. They suggested that GLSM approach for modeling and mapping spatial counts of disease incidence is efficient and robust for inference. Furthermore, using the PLN spatial model is a naturally good candidate for modeling spatial count data (Jing & De Oliveira 2015). However, it is impossible to estimate the parameters and posterior sampling due to the high dimensional integral of likelihood. One solution is to employ numerical algorithms such as Markov chain Monte Carlo (MCMC) with the help of advanced methods such as Langevin–Hastings algorithms, data-based transformations, and group updating may incorporate in their estimation. In the current study, geo-count (Jing & De Oliveira 2015) and geoRglm (Christensen & Ribeiro 2002) R packages are employed to implement the

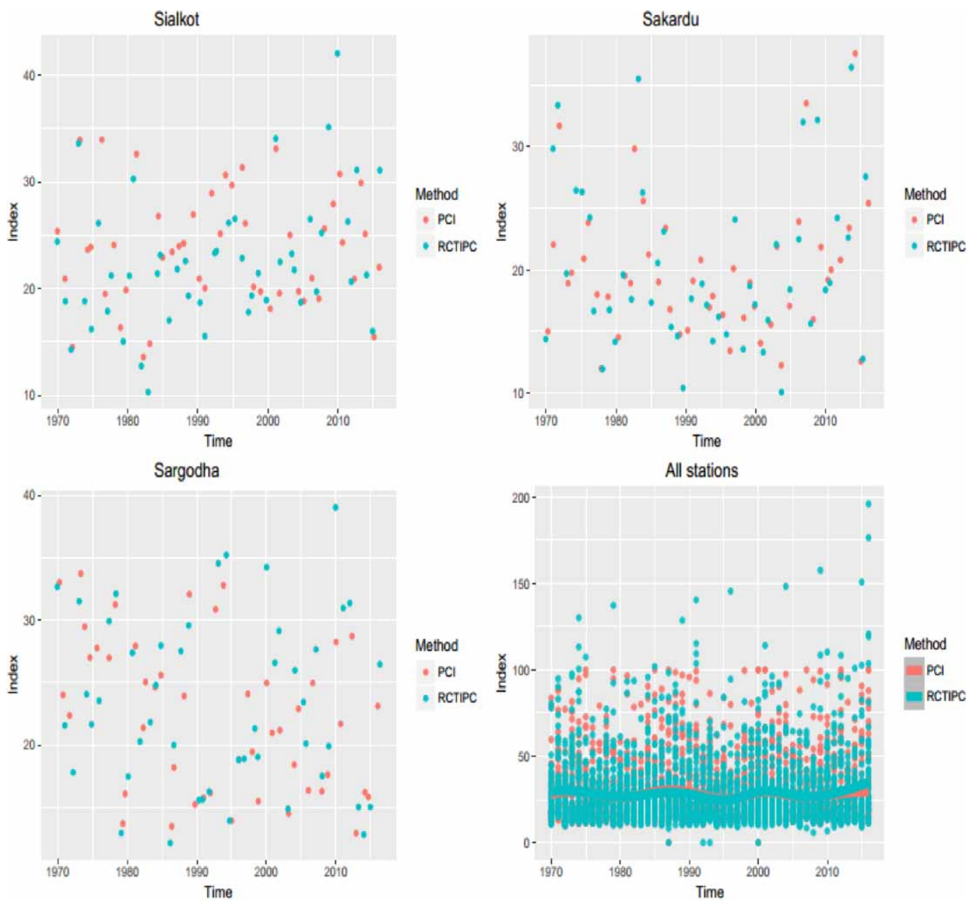

Figure 2 | Temporal plots showing quantitative deviance between observed PCI and RCTIPC.

Table 6 | Frequencies of precipitation concentration patterns from 1971 to 2017

	RCTIPC				PCI			
Stations	**Uniform**	**Moderate**	**Irregular**	**High Concentration**	**Uniform**	**Moderate**	**Irregular**	**High Concentration**
Islamabad	0	3	15	29	0	3	15	29
Barkhan	3	4	16	24	0	7	17	23
Dir	1	36	10	0	1	38	8	0
Multan	0	0	8	39	0	0	6	41
Khuzdar	0	1	22	24	0	3	16	28
Chitral	0	8	25	14	0	8	23	16
Bahwalnagar	0	2	5	40	0	0	6	41
Mianwali	0	8	22	17	0	7	21	19
Balakot	0	30	13	4	0	32	13	2
Karachi	0	1	1	45	0	1	1	45
Sargodha	0	5	13	29	0	5	14	28
Gharhidopatta	1	36	7	3	1	39	6	1
Gupis	0	8	17	22	0	5	18	24
Muzafrabad	2	26	12	7	1	28	16	2
Nawabshah	0	0	1	46	0	0	0	47
Kohaat	0	22	12	13	0	21	15	11
Astor	0	20	18	9	0	18	20	9
Risalpur	0	15	18	14	0	13	18	16
Bunji	0	8	16	23	0	7	17	23
Chilaas	0	6	16	25	0	6	16	25
Lahore apo	0	1	11	35	0	1	11	35
Kakul	1	35	9	2	0	34	13	0
Hyderabad	0	0	1	46	0	0	0	47
Khanpur	0	1	1	45	0	0	2	45
Kotli	1	15	21	10	0	11	30	6
Sakardu	0	11	18	18	0	7	21	19
Kalat	1	0	7	39	1	0	5	41
Jacobabad	0	1	1	45	0	0	1	46
Jehlum	0	5	15	27	0	1	22	24
Karachiap	1	1	1	44	1	1	0	45
Lahore pbo	0	1	11	35	0	0	14	33
Rafique paf	0	0	0	47	0	0	0	47
Murree	0	29	12	6	0	33	13	1
Padidan	0	0	0	47	0	0	0	47
Panjgur	0	0	4	43	0	0	3	44
Parachinar	6	32	5	4	0	42	3	2
Pasni	1	0	3	43	1	0	0	46
Peshawar	0	15	21	11	0	13	21	13
Quetta	0	6	8	33	0	1	4	42
Badian	0	0	0	47	0	0	0	47
Gilgat	0	9	18	20	0	5	18	24

(*Continued.*)

Table 6 | Continued

Stations	RCTIPC Uniform	RCTIPC Moderate	RCTIPC Irregular	RCTIPC High Concentration	PCI Uniform	PCI Moderate	PCI Irregular	PCI High Concentration
Chhor	0	0	0	47	0	0	1	46
Zohab	0	8	20	19	0	7	20	20
Sialkot	0	3	15	29	0	3	10	34
Sibbi	1	4	5	37	1	3	5	38
Bahawalpur	0	2	6	39	0	1	8	38
Rohri	0	0	2	45	0	0	0	47
Cherat	0	12	23	12	1	15	21	10
DI-khan	0	12	14	21	0	8	14	25
Drosh	1	22	16	8	0	21	21	5
Faisalabad	1	4	5	37	1	4	5	37
Nokunddi	2	0	0	45	0	0	1	46
Jiwani	0	0	1	46	0	0	0	47
Dalbadian	0	0	5	42	0	0	2	45

model using MCMC algorithms. Moreover, the segregated maps of all patterns are prepared to compare the distributional behavior of RCTIPC and PCI.

3. RESULTS AND DISCUSSIONS

The numerical illustration in Section 2.3 shows that auxiliary information is inevitable for improving precipitation data. In the light of this example, we performed the same analysis for all the stations. It has been observed that the proposed method provides quite different estimates from simple mean precipitation. Figure 2 shows the temporal difference between the estimated value of PCI and RCTIPC at Sargodha, Sialkot, and Skardu. Furthermore, the difference between the quantitative values of RCTIPC with PCI in all the stations can be seen from the bottom right graph of Figure 2. These preliminary results show significant variation between estimates under both of these methods. To assess and evaluate the effect of extreme temperature at regional level, the computations and inferences have been extended for all the 54 meteorological stations of Pakistan. Under PCI and RCTIPC, Table 6 gives the results on each frequency count of uniform and irregular patterns from 1971 to 2017. These outcomes show significant deviations in the counts of annual variability patterns determined by the PCI and RCTIPC. However, both methods have similar behavior in some homogenous climatic situations. In general, the comparison of the two results reveals that the extreme temperature has reshaped the estimated values of precipitation.

3.1. Spatial association and comparison

This section performs spatial comparative analysis using Tjostheim's coefficient index (Tjøstheim 1978) and modified *t*-test (Dutilleul *et al.* 1993). Tjostheim's coefficient and modified *t*-test are widely used to measure the association between two stochastic processes observed over space. We have used spatiotemporal regional spatial count data (see Table 6) of *irregular*,

Table 7 | Spatial correlation between the PCI and RCTIPC

Pattern	Spatial correlation	*F*-statistics	*P*-value
Uniform	0.2586	3.5485	0.0655
Moderate	0.982	248.57	0.0000
Irregular	0.9508	67.075	0.0000
High concentration	0.99	197.447	0.0014

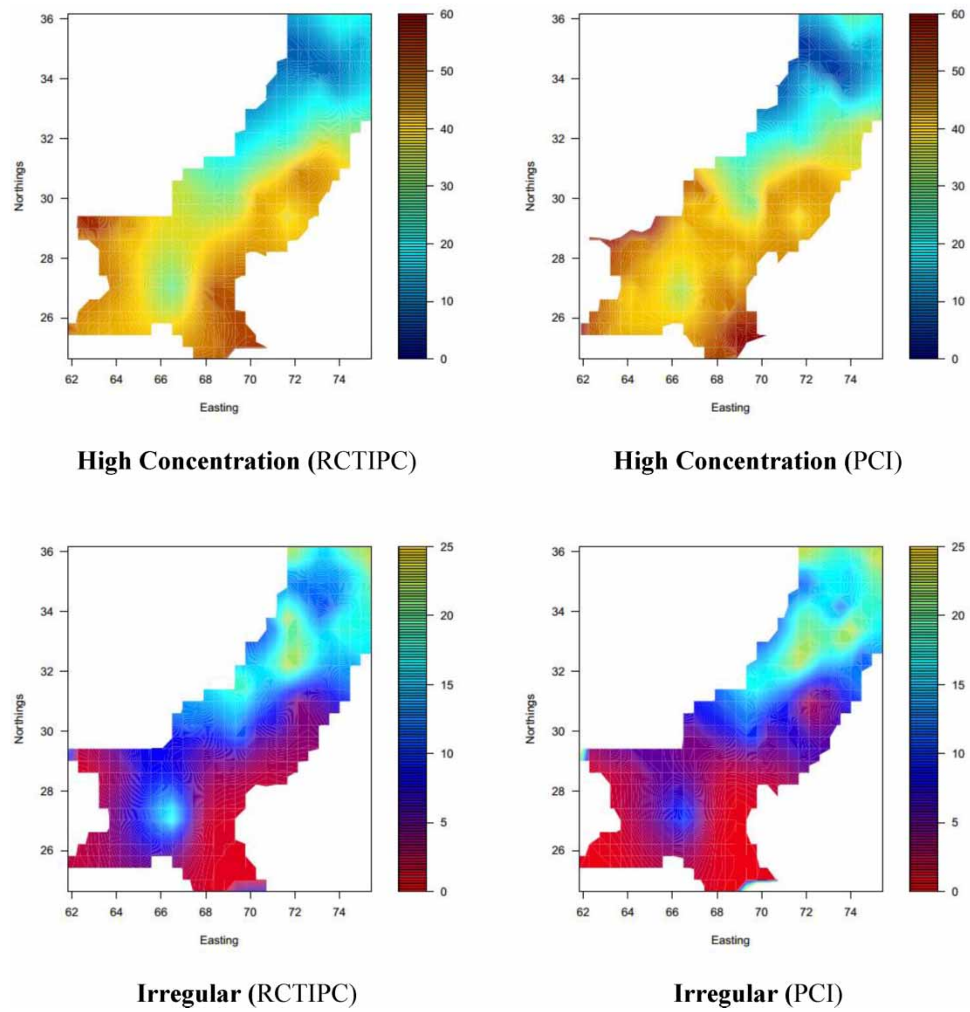

Figure 3 | Spatial predictive distribution of observed count of high and irregular concentration patterns (1971–2017).

uniform, and *moderate* patterns observed under RCTIPC and PCI methods in all the selected stations. In computation, this research employed *SpatialPack* (Osorio *et al.* 2016) R package for assessing the spatial association.

Table 7 gives numerical estimates of spatial association among the counts of patterns of precipitation variability assessed from PCI and RCTIPC. In *uniform* patterns of frequency counts, there is a low spatial correlation ($P < 0.05$) between PCI and RCTIPC. Irrespective to the *uniform* pattern, there is a significant high correlation between PCI and RCTIPC. However, RCTIPC is highly correlated with PCI in other patterns. This shows that, the extreme temperature has significant impact on varying precipitation estimates under spatial configuration.

3.2. Predictive distributions of various patterns

It is essential to make the spatial comparison to check and infer the discrepancies between the historical count of various precipitation patterns under PCI and RCIPCT. Therefore, this section separately provides comparative spatial inference using predictive distributions of historical counts of various precipitation patterns. To do this, *go-count* (Jing & De Oliveira 2015) and *geoRglm* (Christensen & Ribeiro 2002) R packages are employed to analyze spatiotemporal count data of uniform and irregular patterns using a spatial PLN model. Figure 3 shows the spatial predictive distributions of high concentration and irregular patterns under PCI and RCTIPC. From the map, we can see a minor change in the patterns under both methods.

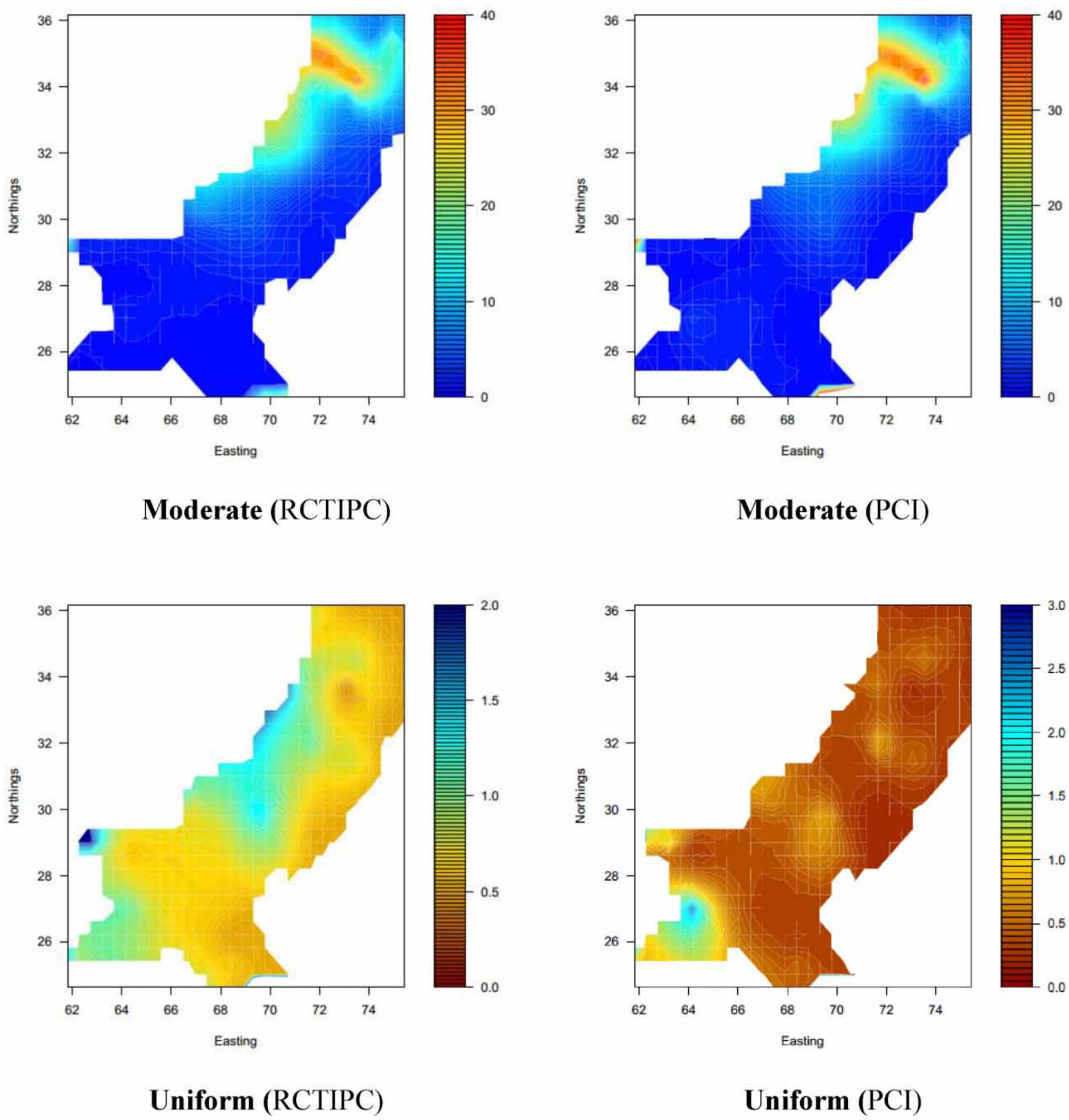

Figure 4 | Spatial predictive distribution of observed count of moderate and uniform concentration patterns (1971–2017).

In contrast to the high concentration and irregular patterns, many discrepancies have been observed in uniform patterns. As shown in Figure 4, the spatial distributions of uniform patterns significantly deviate from each other. This also signifies the weak associative property between PCI and RCTIPC at a spatial scale (Table 7). However, the spatial behavior of moderate concentration is quite similar in both methods. Overall, these inconsistencies and similarities are caused by including the role of extreme temperature in the estimation of precipitation data. Therefore, instead of using only Mukerjee *et al.* (1987) estimator under simple random sampling settings, advanced estimators and data improving techniques can be configured to incorporate multiple auxiliary information under spatial and cluster settings (Kanwai *et al.* 2016; Grafström *et al.* 2017). However, the findings of this research show that extreme temperature being a strong candidate for auxiliary variable is useful to improve annual precipitation estimates for better regional representation.

4. CONCLUSIONS

The objectives of this study were to examine the relation of precipitation with temperature and develop a better method for measuring precipitation concentration. For this purpose, the current research proposes a new approach that incorporates temperature as a piece of auxiliary information for analyzing regional precipitation variability. Under the climate warming scenario, regression analysis revealed that the additional input can potentially improve the precipitation estimates under the appropriate sampling estimator. This is the first study that has documented the impact of climate warming on measuring precipitation concentration. Overall, this study strengthens the analysis of precipitation concentration under climate warming. Empirical findings from this research provide some guidance for government and experts. A more reliable statistical procedure is needed to increase the meteorological products by employing advanced probabilistic and machine learning techniques which would encourage the researchers to propagate more reliable climatological information.

A few limitations of the study are the subjective selection of the auxiliary information-based sampling estimator and the contemplative inference of the interpolation techniques. Therefore, future research may be based on the optimum selection of the sampling estimator or techniques such as bootstrapping and the most appropriate interpolation methods.

DATA AND CODE AVAILABILITY

All the data were analyzed using R software. The data and code used to support the findings of this study are available from the corresponding author upon request.

ETHICAL APPROVAL

The manuscript is prepared in accordance with the ethical standards of the responsible committee on human experimentation and with the latest (2008) version of Helsinki Declaration of 1975.

FUNDING

The authors have not received any funding from any project.

COMPETING INTERESTS

The authors declare that they have no competing interests.

AUTHOR CONTRIBUTIONS

All authors have equal contribution.

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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