Model. Earth Syst. Environ. (2017) 3:1647–1662
DOI 10.1007/s40808-017-0370-4

ORIGINAL ARTICLE

Evaluating the variability and trends in extreme climate events in the Kashmir Valley using PRECIS RCM simulations

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Received: 16 August 2017 / Accepted: 18 August 2017 / Published online: 28 August 2017

Abstract Climate is the major force that shapes the Earth. Under climate change conditions, the extreme events shall occur more frequently with greater force for devastation. In this study, Predicting Regional climate for impact studies-Regional climate model (PRECIS RCM) was used to analyze the trends in temperature and precipitation using climate indices for the Kashmir valley, western Himalaya. We analyzed 27 climate extremity indices using PRECIS RCM simulations for a baseline (1961–1990) and future scenario (1990–2098) using RCLIMDEX model. Trend analysis was carried out using Mann–Kendall test method and Theil-Sen estimator. PRECIS RCM covers Kashmir valley in 14 grids of 50 km × 50 km horizontal resolution each. The climatic grids for baseline data (1961–1990) indicated no noteworthy patterns in hot and cold extreme indices. However, climate grids for future simulations (1990–2098) showed an increasing trend in all hot extreme events but no significant trend in cold extremes. The futuristic frequency and intensity in the extreme temperature events showed significant increase compared to extreme precipitation events. The overall results indicated that grids pertaining to valley plains shall have more extreme events in maximum temperatures while as the grids towards the mountain fronts shall have more extreme events in precipitation and minimum temperatures in the future. The results establish a strong link between changing climate and climatic extremes in the region. The study is finally aimed to use PRECIS RCM simulations for impact assessment studies in the region.

Keywords Climatic extremities · PRECIS · Climatic variability · RCM · RCLIMDEX

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Introduction

Climatic extremities occur within the natural variability of the climate system (IPCC 2013). Due to anthropogenic climate change, the occurrence of such extremities have increased and shall continue to increase in the coming decades (Smith 2011; Field 2012; IPCC 2015). Changes in extreme weather and climate patterns are amongst the most serious challenges to mankind in the times to come (Brown et al. 2007; CCSP 2008; Richardson et al. 2009; Coumou and Robinson 2013; IPCC 2014).

Extreme event's definition, depends on the local reference distribution (Beniston et al. 2007a). In other words, events that would be classified as 'extreme' in one location might not be considered unusual in another. The intergovernmental panel on climate change (IPCC) defined extreme events of meteorological conditions, as events that are rare within their statistical reference distribution at a particular place. Definitions of "rare" vary, but an extreme weather event would normally be as rare as or rarer than the 10th or 90th percentile (IPCC 2013).Very often, the degree of risk associated with a given event is also dependent on the local expectation or degree of preparedness (Miceli et al. 2008; Eiser et al. 2012).

Characterizing the extreme events, involves percentile-based, threshold-based or duration-based indices, or by analyzing the statistical behavior of the tail of a weather element's probability distribution (Sillmann 2009; Fernández-Montes and Rodrigo 2012). Such indices are used by international committees to assess extremes in temperature and precipitation and to make a global and multi-model comparison possible (Folland et al. 1999; Karl and Easterling 1999; Nicholls and Murray 1999; Meehl et al. 2007; Sunyer et al. 2013; Jones et al. 2013; Dong et al. 2015). Observational datasets are generally perceived as ideal for the analysis of extreme events. However, observed data records in the most cases, are too short and do not cover uniformly and suffer from inhomogeneity, for example, due to changes in observational practices. These limitations make it diffcult to use observational datasets for a global or even regional study of extreme events (Parmesan and Yohe 2003; IPCC 2013).

Several studies to date have concentrated on the analysis of indices for climate extremes based on observational data from weather stations (Frich et al. 2002; Klein Tank and Koennen 2003) while others focused primarily on the changes of extremes in future climate projections (Meehl et al. 2000; Meehl and Tebaldi 2004; Tebaldi et al. 2006). Over the last two decades, the analysis of such extreme events has become increasingly important due to the recognition of their significant impacts on society and natural systems. The scientific study of the nature of extreme climate events becomes imperative to gain an understanding of their possible occurrence and dimensions in present and future climate (Easterling et al. 2000a, b; White et al. 2001; IPCC 2013).

As extreme weather events occur more frequently and become more intense, the socioeconomic costs of such events are likely to increase as well (Easterling et al. 2000a, b; Beniston 2007b). As a result, the demand for information services on weather and climate extremes is growing (Klein Tank et al. 2009). Understanding the effects of the climate change and taking initiative on impact assessment, mitigation and adaptation regarding climate change, statistical analysis can enable us to develop reliable prediction methods (Berrang-Ford et al. 2011; Green et al. 2011; IPCC 2014).

The present study are the initial results of the comprehensive impact assessment studies undergoing at the Jammu and Kashmir state climate change centre, Kashmir. The trend analysis and the evaluation of the climate extremes for baseline and the future using PRECIS RCM simulations done in the present work was initialized in order to use PRECIS RCM for the impact assessment studies in the region. Kashmir valley in particular is extremely sensitive to global climatic variability (Muslim et al. 2015). Kashmir being a micro-climate in itself, the indicators of changing weather patterns are loud and clear in this region (Romshoo et al. 2017). This is possibly one of the reasons behind the increase in the occurrence of several weather extremes in the region such as unusually heavy precipitation that resulted in the floods (e.g. 2014 floods) and cloudbursts (e.g. 2010 Leh cloudburst) or temperature extremes (Ashrit 2010; Juyal 2010; Bhatt et al. 2011, 2016; Thayyen et al. 2013; Tabish and Nabil 2015; Meraj et al. 2015a, b, 2016; Kumar and Acharya 2016). The amount of downpour witnessed during extreme precipitation events is generally huge and in almost all the cases, beyond the carrying capacity of the land system. For example, Fig. 1 shows how water moved through different watersheds of the Kashmir valley in September, 2014 when continuous rainfall from 1st to 7th September 2014, resulted in the devastating floods (Romshoo 2015). The present study analyses the occurrence of such extreme events in the future using RCM simulations. PRECIS RCM data has been used extensively for climate change assessment studies on agriculture, terrestrial vegetation, water resource and atmosphere dynamics (Xiong et al. 2007; Akthar et al. 2008; Muslim et al. 2015; Sethi et al. 2015; Javan et al. 2015).

Study area

Kashmir valley is a longitudinal depression in the great northwestern complex of the Himalayan ranges. It constitutes an important relief feature of tremendous geographic significance. Carved out tectonically, the valley has a strong genetic relationship with the Himalayan complex, which exercises an all-pervading influence on its geographic entity. Territorially, it forms the interior part of the Jammu and Kashmir. The latitudinal extent of the state is 32.17°N–37.6°N, whereas the longitudinal extent is 73.26°E–80.30°E (Fig. 2).

The state of Jammu and Kashmir is situated in subtropical latitudes, but owing to orographic features and snow clad peaks, the climate over greater parts of the state resembles to that of mountains and continental parts of the temperate latitudes. Climate of Kashmir falls under Sub-Mediterranean type with four seasons based on mean temperature and precipitation (Bagnolus and Meher-Homji 1959). However, micro level variations in general weather and climatic conditions of the state do exist. Due to the large variations in altitude from 300 m in the south to 8500 m in the north, the climate of the state of Jammu and Kashmir varies from tropical to arctic. However, authors maintain that the climate of Kashmir is highly variable and do not conform to any definite type, and presents a fresh classification of the seasons of Kashmir based on Hadlow's world scale for mean monthly temperature (Kaul and Qadri 1979).

The general climate of the state can be understood easily by describing the weather conditions of different seasons of Jammu division, Kashmir Valley and Ladakh division separately. In general, the valley has fairly long period of winter

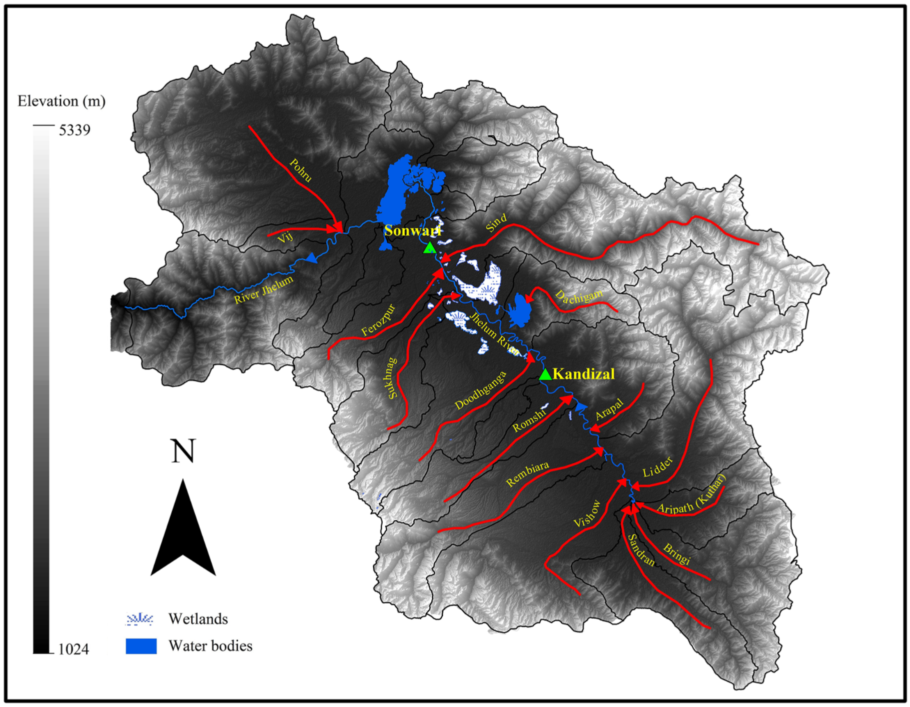

Fig. 1 Map showing the movement of water through different watersheds of the Kashmir valley during 2014 floods. The *arrows* are hypothetical and denote the direction and concentration of water at different points during the deluge

and spring. On the basis of temperature and precipitation, a year in valley is divisible into the following four seasons:

1. Winter Season (November–February),
2. Spring Season (March–Mid-May),
3. Summer Season (Mid May–Mid-September),
4. Autumn season (Mid-September–October).

The local weather classification however, recognizes the following six seasons with duration of 2 months each:

1. Sonth (Spring): Mid-March–Mid-May
2. Grishm (summer): Mid May–Mid-July
3. Wahrat (Rainy): Mid July–Mid-September
4. Harud (Autumn): Mid-September–Mid-November
5. Seshur (Season of severe cold): Mid-January–Mid-March

This classification is based is based on empirical experiences of the people about temperature and precipitation conditions in different parts of the year, which is scientific and gives a more reliable picture of the weather conditions of the valley of Kashmir (Lone et al. 2015).

Methodology

In order to evaluate the variability and trends in the extreme climate patterns across the Kashmir region, PRECIS RCM data was extracted over the South Asian domain using RCLIMDEX model. Trend analysis was performed using Mann–Kendall trend test. The flow chart of overall methodology is shown in Fig. 3.

PRECIS RCM

Predicting Regional climate for impact studies-Regional climate model (PRECIS RCM), developed by the Hadley Centre, UK has been used worldwide to assess and understand the possible impacts of the changing climate on different earth system processes. For south Asian domain, PRECIS RCM is run at IITM, Pune at 50 km × 50 km horizontal resolution in order to develop the high-resolution climate change scenarios for the region. Some of the basic aspects of this RCM are discussed briefly in this section (Noguer et al. 2002; Kumar et al. 2006; Raneesh and Thampi 2013).

PRECIS simulations have been made using the lateral boundary data from a high resolution atmospheric GCM (150 km) called Hadley Centre Atmospheric Model (HadAM3H) using 'time slice' experiments. Climate change scenarios have been generated for the baseline (1961–1990) and for 2080s (2071–2100) corresponding to IPCC-SRES A2 and B2 emission scenarios. Here, three simulations from a 17-member PPE (Perturbed Physics Ensemble) were produced using HadCM3 (Hadley Centre Climate Model). They had been used as LBCs (Lateral Boundary Conditions) for the 138 year simulations of the regional climate model, PRECIS. Unlike the previous simulations, which correspond only to one distant future time slice, these continuous simulations provide an opportunity to assess the impact of

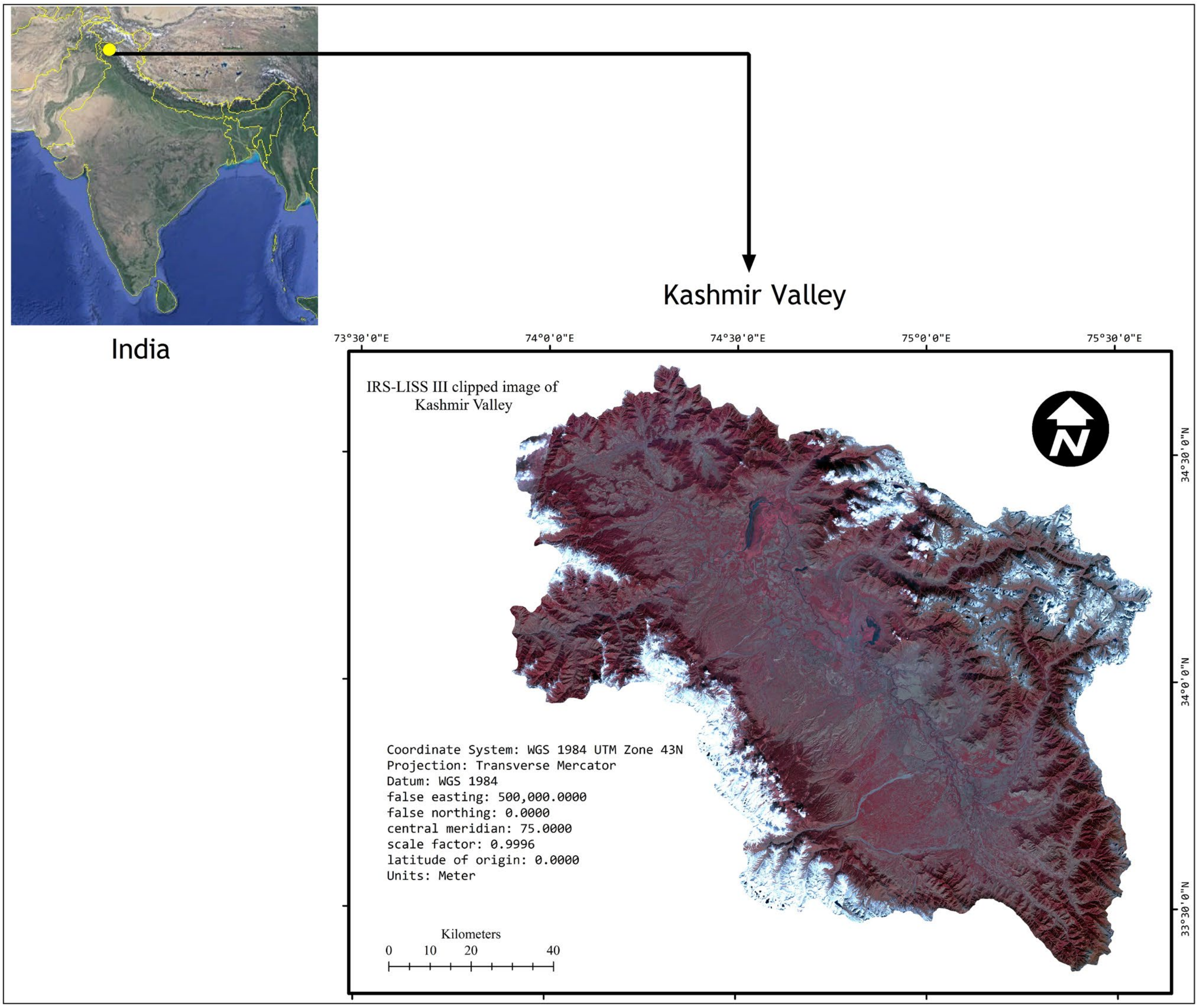

Fig. 2 Location of the Kashmir valley with respect to India. The *upper left inset* in the figure shows the union of India. The location of the Kashmir valley with respect to India is shown in the *bottom right inset* using IRS LISS III image of the region. The map coordinates are in the UTM 43 (North) World Geodetic System (WGS-1984) reference system

climate change on the Indian monsoon for three time slices representing the near, medium and long term with implications for policy on these timescales (Thampi and Raneesh 2015; Patwardhan et al. 2016).

The perturbed physics approach was also used in response to the call for better quantification of uncertainties in climate projections (Collins et al. 2011; IPCC 2013). The basic approach involved taking a single model structure and making perturbations to the values of parameters in the model, based on the discussions with scientists involved in the development of different parameterization schemes (Jakeman et al. 2006; Chen and Patton 2012). In some cases, different variants of physical schemes may also be switched in and out. Any number of experiments that are routinely performed with a single model could be produced in an 'ensemble mode', which subject to constraints on computer time (Collins et al. 2011). A significant amount of perturbed physics experimentation has been done with HadCM3 and variants (Kumar et al. 2011; Collins et al. 2011).

Quantifying Uncertainty in Model Predictions (QUMP) simulations comprise 17 versions of the fully coupled version of HadCM3; one with standard parameter setting and 16 versions in which 29 of the atmosphere component parameters are simultaneously perturbed (Collins et al. 2006; Toniazzo et al. 2008). Based on a preliminary evaluation of these 17 global runs for their ability to simulate the gross features of the Indian monsoon, the LBCs of three QUMP simulations, viz. Q0, Q1 and Q14 were made available by Hadley Centre, UK (Rajbhandari et al. 2015). Hence, these three QUMP runs were carried out at IITM, Pune from 1961

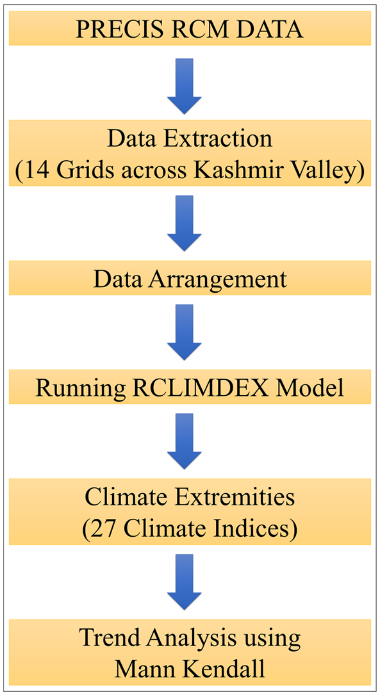

Fig. 3 Conceptual chart of the methodology

to 2098 and were utilized to generate an ensemble of future climate change scenarios for the Indian region. These simulations are available at 50 km × 50 km horizontal resolution and analyzed for the Kashmir region in the present study.

RCLIMDEX model

ClimDex is a Microsoft Excel based program that provides an easy-to-use software package for the calculation of indices of climate extremes for monitoring and detecting climate change (Zhang and Yang 2004). It is developed by Byron Gleason at the National Climate Data Centre (NCDC) of NOAA (National Oceanic and Atmospheric Administration), and has been used in CCl/CLIVAR workshops on climate indices since 2001. The original objective was to port ClimDex into an environment that does not depend on a particular operating system, hence R is used as platform to run the model, since R is a free and yet very robust and powerful software for statistical analysis and graphics. It runs under both Windows and UNIX environments (Peterson et al. 2001).

In 2003, it was discovered that the method used for computing percentile-based temperature indices in ClimDex and other programs resulted in homogeneity in the indices series. A fix to the problem requires a bootstrap procedure that makes it almost impossible to implement in an Excel environment (Zhang and Yang 2004). This has made it more urgent to develop this R based package. RClimDex (1.0) is designed to provide a user friendly interface to compute indices of climate extremes. It computes all 27 core indices recommended by the CCl/CLIVAR expert team for Climate Change Detection Monitoring and Indices (ETCCDMI) as well as some other temperature and precipitation indices with user defined thresholds. The 27 core indices include almost all the indices calculated by ClimDex (Version 1.3). This version of RClimDex has been developed under R 1.84 (Kabore et al. 2017; Adnan et al. 2017).

The main objective of constructing climate extreme indices is to use them for climate change monitoring and detection studies that requires the indices to be homogenized. As in ClimDex, we require that the data is quality controlled before the indices can be computed. RClimDex is capable of computing all 27 core indices listed below (Tables 1, 2). The “Set Parameter Values” window allows the user to enter the first and last years of the base period for the threshold calculation, the station latitude (Southern Hemisphere is negative) to determine in which hemisphere the station is located, a user defined daily precipitation threshold, P (in mm), to compute the number of days when daily precipitation amounts exceed this threshold (the Rnn indicator), and four user defined temperature thresholds.

The “User defined Upper Limit of Day High” allows the calculation of the number of days when daily maximum temperature has exceeded this threshold. The “User defined Lower Limit of Day High” allows the calculation of the number of days when daily maximum temperature is below this value. The “User defined Lower Limit of Day Low” allows the calculation of the number of days when daily minimum temperature is below this limit. These indices are called SUmm, FDmm, TRmm, IDmm where “mm” corresponds to user defined value (Abbas 2013).

Mann–Kendall trend test

Mann–Kendall trend test is one of the robust statistical trend tests for hydro-meteorological variables (Yue et al. 2002a, b; Karpouzos et al. 2010; Tao et al. 2011, Salami 2014). Various authors have used Mann–Kendall test for trend analysis in the metereological data. Kumar et al. (2016) carried out long term trend analyses of past climatic variables using nonparametric tests for the Giridih district in Jharkhand (India). Singh et al. (2016) used to check the trend in extreme indices over Northwest Himalaya. Vasileiou et al. (2013) checked potential spatial and temporal changes of extreme temperature in Eastern Greek Islands. The advantage of this method is that it doesnot need any assumptions for the normality of the datasets.

In detail, the Mann–Kendall test is used in testing the null hypothesis H0 of no trend against the alternative hypothesis

Table 1 List of expert team on climate change detection, monitoring and indices (ETCCDMI) extreme temperature indices

ID	Indicator Name	Definitions	Units
CSDI	Cold spell duration indicators	Annual count of days with at least six consecutive days when TN <10th percentile	Days
DTR	Diurnal temperature range	Monthly mean difference between TX and TN	0 °C
FD0	Frost days	Annual count when TN(daily minimum) <0 °C	Days
ID0	Ice days	Annual count when TX(daily maximum) <0 °C	Days
GSL	Growing season Length	Annual count between first span of at least of 6 days with TG >5 °C after winter and first span after summer of 6 days with TG <5 °C	Days
SU25	Summer days	Annual count when TX(daily maximum) >25 °C	Days
TR20	Tropical nights	Annual count when TN(daily minimum) >20 °C	Days
TXx	Max TMax	Monthly maximum value of daily maximum temp	
TNx	Max TMin	Monthly maximum value of daily minimum temp	
TXn	Min TMax	Monthly minimum value of daily maximum temp	
TNn	Min TMin	Monthly minimum value of daily minimum temp	
TN10p	Cool nights	Percentage of days when TN <10th percentile	Days
TX10p	Cool days	Percentage of days when TX <10th percentile	Days
TN90p	Warm nights	Percentage of days when TN <90th percentile	Days
TX90p	Warm days	Percentage of days when TX <90th percentile	Days
WSDI	Warm spell duration indicators	Annual count of days with at least four consecutive days when TX >90th percentile	Days

TX daily maximum temperature, TN daily minimum temperature, TG daily mean temperature

Table 2 List of ETCCDMI extreme precipitation indices

ID	Indicator name	Definitions	Units
CDD	Consecutive dry days	Maximum number of consecutive days with RR <1 mm	Days
CWD	Consecutive wet days	Maximum number of consecutive days with RR ≥1 mm	Days
PRCPTOT	Annual total wet-day precipitation	Annual total PCP in wet days (RR ≥1 mm)	mm
RX1day	Max 1-day precipitation amount	Monthly maximum 1-day precipitation	mm
Rx5day	Max 5-day precipitation amount	Monthly maximum consecutive 5-day precipitation	mm
R10	Number of heavy precipitation days	Annual count of days when PCP ≥10 mm	Days
R20	Number of very heavy precipitation days	Annual count of days when PCP ≥20 mm	Days
Rnn	Number of days above nn mm	Annual count of days when PCP ≥nn mm, nn is user defined threshold	mm
R95p	Very wet days	Annual total PCP when RR >95th percentile	mm
R99p	Extremely wet days	Annual total PCP when RR >99th percentile	Days
SDII	Simple daily intensity index	Annual total precipitation divided by the number of wet days (defined as PRCP ≥1.0 mm) in the year	mm/day

PCP precipitation, *RR* rainfall rate

H1 where there is an increasing or decreasing monotonic trend. The test calculates the S statistic:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathrm{sign}(x_j - x_i)$$

where x_i and x_j are sequential data values and n the length of the time series and

$$\mathrm{sign}\,(x_j - x_i) = \begin{cases} 1 & \text{if } x_j - x_i > 0 \\ 0 & \text{if } x_j - x_i = 0 \\ -1 & \text{if } x_j - x_i < 0 \end{cases}$$

If $n > 10$, then the z statistics is given as below,

$$z = \begin{cases} \frac{S-1}{\sqrt{\mathrm{var}(S)}} & S > 0 \\ 0 & S = 0 \\ \frac{S+1}{\sqrt{\mathrm{var}(S)}} & S < 0 \end{cases}$$

where

$$\mathrm{var}(S) = \frac{1}{18}\left[n(n+1)(2n+1) - \sum_{i=1}^{m} e_i(e_i - 1)(2e_i + 5)\right]$$

The null hypothesis is rejected $|Z| > Z\,(1 - \alpha/2)$ at α level of significance. The analysis is carried out for 0.10 significant level.

The magnitude (slope) of the identified trends is estimated by using the robust and sensitive to outliers Theil-Sen estimator (Ohlson and Kim 2015). The Theil-Sen estimator is a method for robust linear regression, which calculates the slope of all data pairs according to:

$$Q = \frac{x_j - x_i}{j - i},$$

For all $j > i$ and $i = 1, 2, 3, \ldots, n - 1$; $j = 1, 2, 3, \ldots, n$. Where x_i and x_j are the measurements at time i and j respectively. The Theil-Sen estimate is the median slope of all slopes (Q) determined by all pairs of sample points. The median of these estimates of slope is the nonparametric slope estimate (Lanzante 1996). Compute as follows:

Rank the N values of slope Q from smallest to largest:

$$Q(1) \leqslant Q(2) \leqslant \cdots \leqslant Q(N)$$

Compute the non-parametric estimate of the slope as

$$\beta = \frac{Q(N + 1)}{2}, \quad \text{if N is odd.}$$

and

$$\beta = \frac{1}{2}\left[Q\left(\frac{N}{2}\right) + Q\left(\frac{N + 1}{2}\right)\right], \quad \text{if N is even.}$$

Result and discussions

Data homogeneity

In order to understand the variability in the climate data, the RCM data was extracted for 14 grids that cover the Kashmir region for MinTemp, MaxTemp and precipitation. Analysis of data revealed homogenity for the grids 6–7, 10–11 and 13–14 (Fig. 4). Out of these pairs, only one was used for analysis to reduce the redundancy. Homogenity was observed within the data from observation stations towards east and south of Kashmir valley compared to observation stations towards north. The divergent trends in stations of south and north Kashmir (Qazigund and Kupwara) has been reported by Muslim (2013). In general, there is variablity in precipitation and temperature in Himalayan region and varies greatly between inner and outer parts (Singh et al. 1997; Winiger et al. 2005; Bookhagen and Burbank 2006). It has been observed a lot of variation between sites of Kashmir that were in proximity or located even at similar latitudes/longitudes. The Baramulla and Sonamarg stations even though located at almost the same latitude, yet differ in precipitation by 800 mm (Muslim 2013). Similarity in climatic trends in data from south-east stations across valley was also reported by Ali (1988).

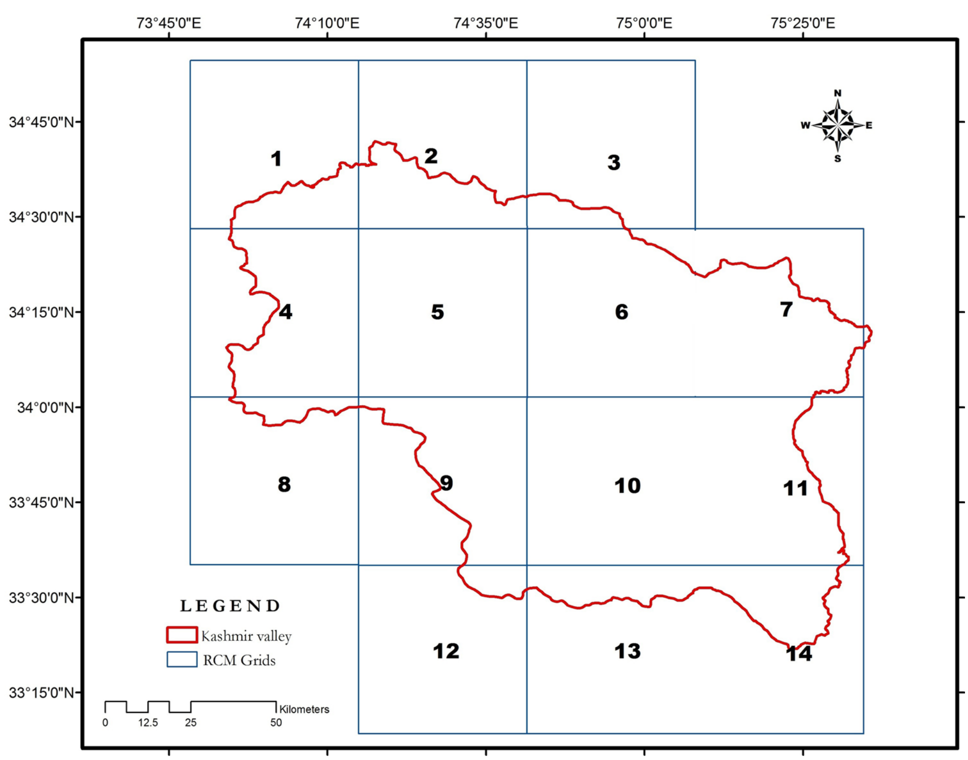

Fig. 4 PRECIS RCM grids of 50 km × 50 km horizontal resolution over the Kashmir valley and the homogeneous grids 6–7, 10–11 and 13–14 evaluated after analysis

Annual trends in extreme indices of temperature for 1961–1990 (baseline)

The results showing trends in annual extreme indices of temperature for the baseline (1961–1990) have been presented in Table 3. Large variations in trends of annual indices of temperature were observed spatially across the climatic grids. Statistically insignificant trends were noticed for cold spell duration indicator (CSDI), diurnal temperature range (DTR), frost days (FD0) and cool nights (TN10p) for all climate grids. However, cold spell duration indicator (CSDI) was significant for grid 1 whereas cool night indicator (TN10p) was significant for grids 1, 4, 5 and 6. Positive slope with rising trend for cold spell duration indicator (CSDI) in grid 3 was also observed. Min Tmax (TXn), Min Tmin (TNn) and Warm nights (TN90p) have insignificant but positive trends for the baseline data.Whereas, Index Warm night (TN90p) is significant for grids 1, 4, 5, 6, 9 and 12.

Furthermore, indices like Summer days (SU25), Tropical nights (TR20), Max Tmax (TXx), Max Tmin (TNx), Cool days (TX10p), Warm days (TX90p) and Warm spell duration indicator (WSDI) does not have any notable magnitude. However, no particular trends could be perceived in Tropical nights (TR20) for any climate grids over the baseline period.

The study of overall pattern of climatic grids on baseline data for temperature indices indicated no noteworthy patterns in hot and cold extreme indices.The analysis of the data for six IMD (Indian Meteorological Department) stations across Kashmir revealed slightly increasing trends in minimum and maximum temperatures, though not so significant with $R2 < 0.5$. The trend analysis of maximum temperature across stations showed an $R2 < 0.311$ and for minimum temperature the value is below 0.44. Also, the increases in minimum and maximum temperatures across six stations were far from consistent (Muslim 2013). This strong increasing trends in the minimum temperature as compared to maximum, are contributing more towards the decrease in the diurnal temperature range (DTR) over the region (Jaswal and Rao 2010). However, for rest of India, rate of increase of minimum temperatures is slightly more than that of maximum temperature (IMD 2009).

Annual trends in extreme indices of precipitation for 1961–1990 (baseline scenario)

The results showing trends in annual extreme indices of precipitation for the period of 1961–1990 are presented in Table 4. Most of the precipitation indices for the baseline data are insignificant with positive slope. However, Rx5day (Max 5-day precipitation amount) is statistically significant with positive slope in all grids except in grids 2 and 4. R99p (Extremely wet days) is also observed with the rising slope in grids 1, 3, 5, 6, 8 and 10 with significance at 0.1 level. For grid 2, significant result is observed for CWD (Consecutive Wet day) index. Max 1-day precipitation amount (RX1-day) shows statistically significant positive results for grid 3, grid 5, grid 6, grid 8 and grid 10, respectively. Grid 6 is significant for index, Number of days above 25 mm (Rnn). Very wet day (R95p) index is positively significant in grid 3, grid 5 and grid 6. Simple daily intensity index (SDII) is statistically significant with rising trend and slope in grid 5, grid 6, grid 8 and grid 10.

The precipitation over the region has shown slight decrease across four stations (Srinagar, Pahalgam, Kokernag, Gulmarg), although, trend was not so significant ($R2 < 0.17$) except for stations of (Qazigund and Kupwara) showing an increasing trend ($R2 > 0.60$) (Muslim 2013). Romshoo et al. (2011) also observed decline in the precipitation across the valley, characterized with weak trend $R2 = 0.15$. Kumar and Jain (2010) also recorded same results while analysing the rainfall across five stations of Kashmir valley from 1902 to 1982. In the country as a whole, the all India annual rainfall for the period 1901–2009, does not confine to any significant trend (IMD 2009).

Annual trends in extreme indices of temperature for 1991–2098 (future scenario)

The results of annual trends in extreme indices in simulated temperature data of climatic grids for future (1991–2098) climate are presented in Table 5. Almost all temperature indices are observed with statistically significant trends for the future scenarios. Statistically significant negative trends are found in indices, Cold spell duration indicators (CSDI), Frost days (FD0), Cool nights (TN10p) and Cool days (TX10p) over the study area, except grid 12 that has negative trend but statistically insignificant, clearly signifying overall warming under the simulated future temperature as shown in Fig. 5a–f.

The mean annual temperature is projected to increase from 0.9 ± 0.6 12 to 2.6 ± 0.7 °C in the 2030s. The net increase in temperature ranges from 1.7 to 2.2 °C with respect to 1970s. Futuristic temperatures, thus show rise in all seasons (INCCA 2010). Indices, Ice days (ID0), Growing season Length (GSL), summer days (SU25), Tropical nights (TR20), Max Tmax (TXx), Max Tmin (TNx), Min Tmax (TXn), Min Tmin (TNn), Warm nights (TN90p), Warm days (TX90p) and Warm spell duration indicator (WSDI) are observed with statistically significant positively results and rising slope in all grids except in grid 12, which is showing positively insignificant trend.

The daily extremes in surface air temperature, that is, daily maximum and daily minimum may intensify in the 2030s. The spatial pattern of the change in the lowest daily minimum and highest maximum temperature suggests a warming of 1 to 4 °C towards the 2030s (INCCA 2010).

Table 3 Annual Trends in Extreme Indices in observed temperature data of climatic grids for baseline (1961–1990) scenario

Indicator Name	Grid 1		Grid 2		Grid 3		Grid 4		Grid 5		Grid 6		Grid 8		Grid 9		Grid 10		Grid 12		Grid 13	
	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2
CSDI	−1.07	(−)*	−0.37	(−)	0.09	(+)	−0.31	(−)	−0.43	(−)	−0.50	(−)	−0.44	(−)	−0.26	(−)	−0.44	(−)	−0.28	(−)	−0.44	(−)
DTR	−2.33	(−)	−2.19	(−)	−3.72	(−)	−2.36	(−)	−3.07	(−)	−2.22	(−)	−1.89	(−)	0.01	NA	−1.89	(−)	−1.69	(−)	−1.28	(−)
FD0	−0.18	(−)	−0.09	(−)	−0.08	(−)	−0.22	(−)	−0.29	(−)	−0.19	(−)	−0.16	(−)	−0.25	(−)	−0.16	(−)	−0.25	(−)	−0.16	(−)
SU25	−0.02	(−)	−0.14	(−)	−0.50	(−)	0.06	(+)	−0.17	(−)	0.09	(+)	0.08	(+)	0.03	(+)	0.08	(+)	−0.07	(−)	0.03	(+)
TR20	NA	NA	NA	NA	NA	NA	−1.50	(−)	−11.00	(−)	NA	NA	−2.00	(−)	NA	NA	−2.00	(−)	NA	NA	−2.00	(−)
TXx	0.77	(+)	−1.25	(−)	−1.40	(−)	−0.29	(−)	1.86	(+)	0.59	(+)	0.89	(+)	0.87	(+)	0.89	(+)	2.05	(+)	1.79	(+)
TNx	1.14	(+)	0.83	(+)	−0.60	(−)	0.77	(+)	−3.42	(−)	1.34	(+)	−0.63	(−)	1.58	(+)	−0.63	(−)	1.58	(+)	−0.63	(−)
TXn	0.80	(+)	1.50	(+)	1.67	(+)	1.43	(+)	1.43	(+)	1.33	(+)	1.48	(+)	1.58	(+)	1.48	(+)	2.43	(+)	2.00	(+)
TNn	1.00	(+)	1.04	(+)	0.86	(+)	0.33	(+)	0.82	(+)	1.05	(+)	0.56	(+)	0.48	(+)	0.56	(+)	0.48	(+)	0.56	(+)
TN10P	−0.65	(−)	−0.42	(−)	−0.82	(−)	−0.71	(−)*	−1.02	(−)*	−1.03	(−)*	−0.60	(−)	−0.50	(−)	−0.60	(−)	−0.52	(−)	−0.60	(−)
TX10P	−0.44	(−)	0.29	(+)	0.25	(+)	−0.14	(−)	−0.49	(−)	−0.27	(−)	−0.13	(−)	−0.55	(−)	−0.13	(−)	0.46	(+)	−0.22	(−)
TN90P	1.02	(+)*	0.57	(+)	0.85	(+)	1.67	(+)*	1.16	(+)*	1.53	(+)*	0.74	(+)	0.80	(+)*	0.74	(+)	0.95	(+)*	0.80	(+)
TX90P	0.19	(+)	−0.22	(−)	0.13	(+)	0.41	(+)	0.37	(+)	0.35	(+)	0.47	(+)	0.49	(+)	0.47	(+)	0.43	(+)	0.35	(+)
WSDI	0.05	(+)	−0.05	(−)	0.07	(+)	0.12	(+)	0.18	(+)	0.13	(+)	0.11	(+)	0.13	(+)	0.11	(+)	0.14	(+)	0.02	(+)

Asterisk denotes that the trends of the respective indices are statistically significant

Table 4 Annual Trends in Extreme Indices in observed precipitation data of climatic grids for baseline (1961–1990) scenario

Indicator name	Grid 1		Grid 2		Grid 3		Grid 4		Grid 5		Grid 6		Grid 8		Grid 9		Grid 10		Grid 12		Grid 13	
	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2
CDD	0.33	(+)	0.05	(+)	−0.09	(−)	0.26	(+)	0.09	(+)	0.39	(+)	0.14	(+)	0.03	(+)	0.14	(+)	0.22	(+)	0.19	(+)
CWD	0.11	(+)	1.00	(+)*	0.15	(+)	0.14	(+)	−0.23	(−)	−0.10	(−)	−0.25	(−)	−0.16	(−)	−0.25	(−)	0.03	(+)	0.07	(+)
PRCPTOT	0.00	(+)	0.03	(+)	0.01	(+)	0.01	(+)	0.02	(+)	0.01	(+)	0.01	(+)	0.01	(+)	0.01	(+)	0.00	(+)	0.01	(+)
RX1day	0.08	(+)	0.23	(+)	0.21	(+)*	0.08	(+)	0.32	(+)*	0.18	(+)*	0.17	(+)*	0.06	(+)	0.17	(+)*	0.06	(+)	0.07	(+)
RX5day	0.04	(+)*	0.20	(+)	0.07	(+)*	0.03	(+)	0.17	(+)*	0.08	(+)*	0.11	(+)*	0.03	(+)*	0.11	(+)*	0.04	(+)*	0.04	(+)*
R10mm	0.03	(+)	0.30	(+)	0.10	(+)	0.13	(+)	0.43	(+)	−0.09	(−)	0.30	(+)	0.19	(+)	0.30	(+)	0.21	(+)	−0.07	(−)
R20mm	0.27	(+)	0.25	(+)	0.20	(+)	0.29	(+)	1.00	(+)	0.25	(+)	0.55	(+)	0.22	(+)	0.55	(+)	0.33	(+)	0.31	(+)
R25mm	0.24	(+)	−1.29	(−)	0.33	(+)	0.21	(+)	1.17	(+)	0.50	(+)*	0.60	(+)	0.29	(+)	0.60	(+)	0.32	(+)	0.25	(+)
R95p	0.01	(+)	0.04	(+)	0.01	(+)*	0.01	(+)	0.05	(+)*	0.01	(+)*	0.01	(+)	0.01	(+)	0.01	(+)	0.00	(+)	0.01	(+)
R99p	0.02	(+)*	−0.04	(−)	0.04	(+)*	0.02	(+)	0.13	(+)*	0.03	(+)*	0.05	(+)*	0.02	(+)	0.05	(+)*	0.01	(+)	0.02	(+)
SDII	0.79	(+)	1.48	(+)	1.25	(+)	1.00	(+)	4.44	(+)*	1.82	(+)*	2.31	(+)*	1.14	(+)	2.31	(+)*	0.80	(+)	1.11	(+)

Asterisk denotes that the trends of the respective indices are statistically significant

Moreover, Diurnal temperature range (DTR) is detecting positive slope with statistically significant values for grid 1, grid 2, grid 5, grid 6, grid 8, grid 9, grid 10 and grid 13. Insignificant positive results are seen in grid 3, grid 4 and grid 12 as shown in Table 5.

The minimum and maximum temperatures are steadily rising but rise is more in case of maximum temperatures. DTR is increasing over Kashmir region due to higher increasing trends in the maximum temperature, whereas strong increasing trends in the minimum temperature are contributing more towards the decrease in DTR over the Jammu region (Jaswal and Rao 2010).

Annual trends in extreme indices of precipitation for 1991–2098 (future scenario)

The results derived from annual trend analysis of extreme precipitation indices under IPCC-SRES A1B2 emission scenarios from PRECIS RCM are presented in Table 6. Comparatively large variability in patterns of extreme precipitation indices for all the grids across the study area was observed under future climatic simulations. Most of the precipitation indices are insignificant for future consecutive dry days (CDD), number of very heavy precipitation days (R20), number of days above 25 mm (Rnn), very wet days (R95p) and simple daily intensity index (SDII) for almost all grids across the study area (Fig. 5 a–f).

The projected precipitation is likely to decrease by about 16.67% in year 2090. Further, overall number of wetting days may decrease on an average by 6 days from years 2011 to 2090 (Muslim 2013). Consecutive Wet day (CWD) is significant for grid 1, grid 2, grid 3 and grid 6, Max 1-day precipitation amount (RX1 day) has upward significant trend for grid 6 and grid 9, Max 5-day precipitation amount (Rx5 day) has upward significant trend for grid 3, grid 6 and grid 9, Number of heavy precipitation days (R10) has downward significant trend for grid 8 and grid 10 and Extremely wet days (R99p) has the significant value for grid 3 and grid 6.

The number of rainy days in the Himalayan region may thus increase by 5–10 days on an average in the 2030s. However in case of Jammu and Kashmir they will increase by more than 15 days in the eastern parts. However, intensity of rainfall is likely to increase by 1–2 mm/day (INCCA 2010).

Conclusions

The results showed a marked change both in extreme precipitation and temperature patterns, particularly becoming conspicuous under future climatic scenario in the Kashmir region. The climatic extremities associated with baseline though positive are not statistically significant. However extremities associated with simulated future temperature

Table 5 Annual trends in extreme indices in simulated temperature data of climatic grids for future (1991–2098) scenario

Indicator Name	Grid 1		Grid 2		Grid 3		Grid 4		Grid 5		Grid 6		Grid 8		Grid 9		Grid 10		Grid 12		Grid 13	
	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2
CSDI	−2.56	(−)*	−4.50	(−)*	−3.96	(−)*	−4.39	(−)*	−5.00	(−)*	−4.82	(−)*	−5.50	(−)*	−4.83	(−)*	−5.50	(−)*	−4.83	(−)	−5.50	(−)*
DTR	13.75	(+)*	11.90	(+)*	4.66	(+)	6.98	(+)	10.89	(+)*	11.76	(+)*	14.48	(+)*	18.03	(+)*	14.48	(+)*	−8.25	(+)	9.09	(+)*
FD0	−1.09	(−)*	−1.15	(−)*	−1.26	(−)*	−1.35	(−)*	−1.28	(−)*	−1.11	(−)*	−1.36	(−)*	−1.27	(−)*	−1.36	(−)*	−1.27	(−)	−1.36	(−)*
SU25	0.85	(+)*	0.89	(+)*	1.05	(+)*	0.75	(+)*	1.12	(+)*	1.14	(+)*	1.00	(+)*	0.80	(+)*	1.00	(+)*	0.70	(+)	0.72	(+)*
TR20	NA	NA	NA	NA	NA	NA	1.25	(+)*	1.52	(+)*	20.45	(+)*	0.95	(+)*	1.54	(+)*	0.95	(+)*	1.54	(+)	0.95	(+)*
TXx	9.57	(+)*	9.34	(+)*	8.38	(+)*	10.46	(+)*	10.58	(+)*	7.38	(+)*	11.20	(+)*	9.70	(+)*	11.20	(+)*	11.43	(+)	11.54	(+)*
TNx	13.68	(+)*	12.08	(+)*	10.80	(+)*	16.67	(+)*	16.67	(+)*	17.65	(+)*	14.74	(+)*	18.46	(+)*	14.74	(+)*	18.46	(+)	14.74	(+)*
TXn	9.64	(+)*	10.00	(+)*	8.91	(+)*	9.37	(+)*	10.00	(+)*	10.00	(+)*	11.72	(+)*	11.67	(+)*	11.72	(+)*	7.95	(+)	11.27	(+)*
TNn	7.27	(+)*	7.10	(+)*	7.24	(+)*	6.21	(+)*	6.67	(+)*	7.05	(+)*	9.38	(+)*	6.36	(+)*	9.38	(+)*	6.33	(+)	9.38	(+)*
TN10P	−11.20	(−)*	−12.50	(−)*	−12.99	(−)*	−11.85	(−)*	−11.07	(−)*	−11.54	(−)*	−11.76	(−)*	−13.00	(−)*	−11.76	(−)*	−13.09	(−)	−11.78	(−)*
TX10P	−9.65	(−)*	−8.76	(−)*	−9.59	(−)*	−9.64	(−)*	−7.16	(−)*	−8.57	(−)*	−6.84	(−)*	−8.54	(−)*	−6.84	(−)*	−9.12	(−)	−8.46	(−)*
TN90P	1.87	(+)*	1.88	(+)*	1.80	(+)*	1.63	(+)*	1.75	(+)*	1.77	(+)*	1.66	(+)*	1.55	(+)*	1.66	(+)*	1.57	(+)	1.66	(+)*
TX90P	1.29	(+)*	1.32	(+)*	1.41	(+)*	1.37	(+)*	1.37	(+)*	1.45	(+)*	1.38	(+)*	1.33	(+)*	1.38	(+)*	1.56	(+)	1.45	(+)*
WSDI	0.36	(+)*	0.37	(+)*	0.40	(+)*	0.39	(+)*	0.40	(+)*	0.41	(+)*	0.41	(+)*	0.39	(+)*	0.41	(+)*	0.46	(+)	0.45	(+)*

Asterisk denotes that the trends of the respective indices are statistically significant

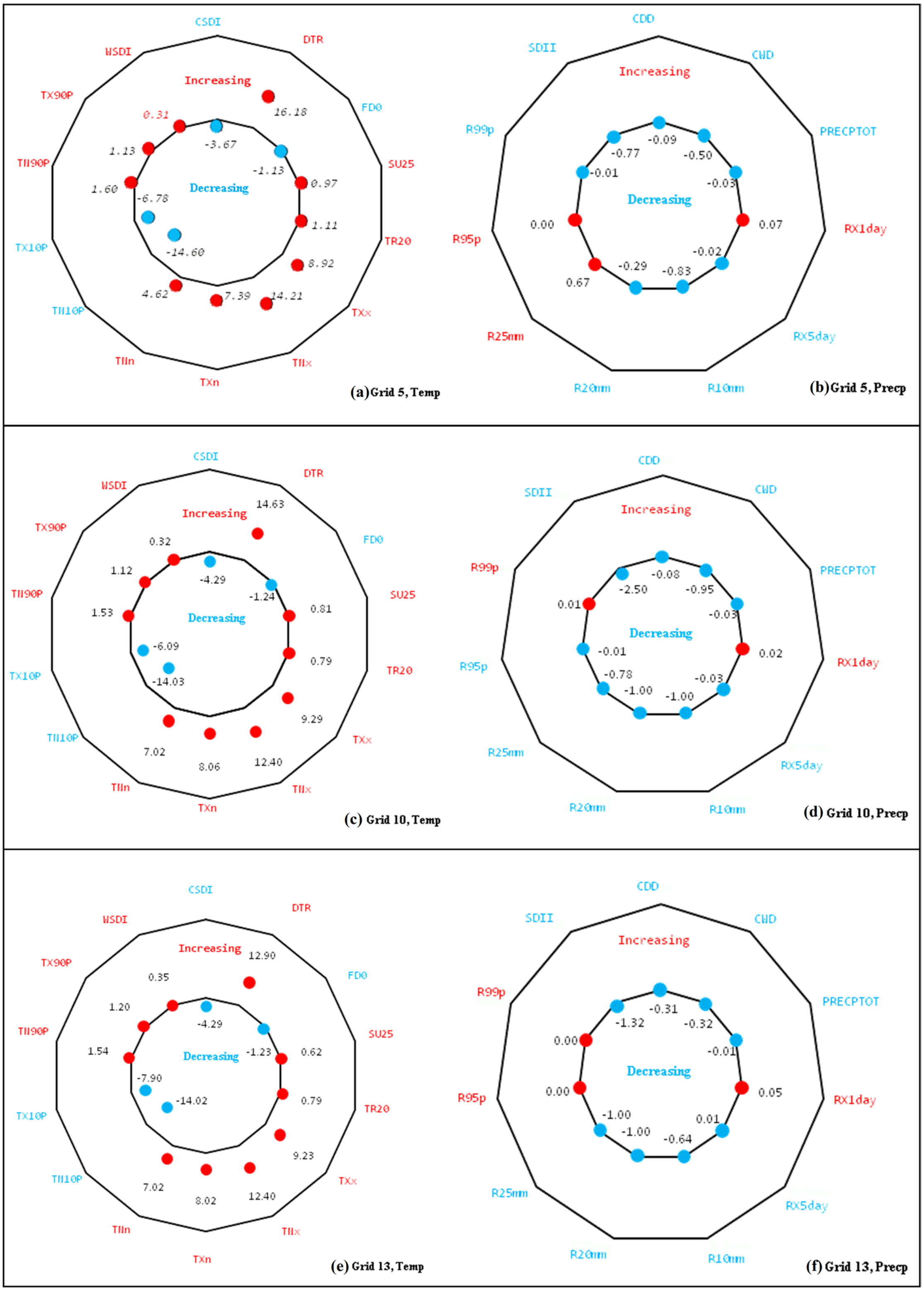

Fig. 5 a–f Radar plots represent the Theil-Sens slope for different climate extremities pertaining to precipitation and temperature data. The negative slope is represented by blue colored dots and positive slope is represented by red colored dots

Table 6 Annual Trends in Extreme Indices in simulated precipitation data of climatic grids for future (1991–2098) scenario

Indicator Name	Grid 1		Grid 2		Grid 3		Grid 4		Grid 5		Grid 6		Grid 8		Grid 9		Grid 10		Grid 12		Grid 13	
	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2	Q	Z2
CDD	−0.38	(−)	0.04	(+)	−0.27	(−)	0.07	(+)	−0.12	(−)	−0.13	(−)	0.14	(+)	0.04	(+)	0.14	(+)	0.06	(+)	0.08	(+)
CWD	0.71	(+)*	−1.72	(−)*	0.75	(+)*	0.27	(+)	0.22	(+)	0.67	(+)*	−0.29	(−)	−0.25	(−)	−0.29	(−)	0.29	(−)	0.20	(+)
PRCPTOT	0.00	(−)	−0.05	(−)	0.01	(+)	0.00	(+)	−0.01	(−)	0.00	(+)	−0.02	(−)	0.00	(−)	−0.02	(−)	0.00	(−)	0.00	(−)
RX1day	0.08	(+)	−0.10	(−)	0.16	(+)	−0.06	(−)	0.04	(+)	0.19	(+)*	0.05	(+)	0.12	(+)*	0.05	(+)	0.02	(+)	0.06	(+)
RX5day	0.06	(+)	−0.15	(−)	0.09	(+)*	−0.02	(−)	0.10	(+)	0.07	(+)*	0.03	(+)	0.06	(+)*	0.03	(+)	0.02	(+)	0.04	(+)
R10mm	−0.48	(−)	−0.92	(−)	−0.13	(−)	0.38	(+)	−0.42	(−)	−0.23	(−)	−0.78	(−)*	−0.37	(−)	−0.78	(−)*	−0.25	(−)	−0.19	(−)
R20mm	−0.50	(−)	−1.00	(−)	0.29	(+)	0.33	(+)	0.50	(+)	−0.29	(−)	−0.50	(−)	−0.54	(−)	−0.50	(−)	−0.67	(−)	−0.52	(−)
R25mm	−0.24	(−)	−2.00	(−)	0.36	(+)	−0.23	(−)	1.22	(+)	−0.18	(−)	−0.86	(−)	−0.50	(−)	−0.86	(−)	−0.75	(−)	−0.50	(−)
R95p	0.00	(+)	−0.03	(−)	0.02	(+)	0.00	(+)	0.02	(+)	0.01	(+)	−0.01	(−)	0.01	(+)	−0.01	(−)	0.00	(−)	0.01	(+)
R99p	0.02	(+)	−0.02	(−)	0.05	(+)*	−0.01	(−)	0.02	(+)	0.03	(+)*	0.00	(+)	0.01	(+)	0.00	(+)	−0.01	(+)	0.00	(+)
SDII	−0.86	(−)	−1.60	(−)	0.56	(+)	0.69	(+)	1.35	(+)	−0.67	(−)	−1.58	(−)	0.83	(+)	−1.58	(−)	0.14	(−)	0.48	(+)

Asterisk denotes that the trends of the respective indices are statistically significant

indices are observed with statistically significant trends while as simulated precipitation showed positive trends though not significant.The analysis of the data revealed that climatic grids in valley plains confirmed to climatic extremities mainly with respect to variation in maximum temperatures while as grids towards the periphery confirmed to climatic extremity with respect to precipitation and minimum temperature events. The current study also established that climatic extremities over the region are growing owing to changing climate in the region. Nevertheless, the prediction of climatic extremities is helpful in developing a broader understanding of future climate but their reliability depends on reliability of data used for the prediction. The overall results suggested that simulation of climatic extremities over the region through RCLIMDEX model is helpful in developing a broader understanding about the climate and extremities associated with past and futuristic climatic data over the region. Present finding also showed that nonparametric tests of Mann Kendall, have good capability for nonlinear trend detection in the time series climatology data series.

Acknowledgements This research work has been accomplished under the research grants provided by, (1) Department of Science and Technology, Government of India (DST-GOI) for the project titled "National Himalayan Mission for Sustainable Himalayan Ecosystem; Climate Change Centre, Jammu and Kashmir" and (2) Ministry of Environment and Forests (MOEF) sponsored scheme titled, "Environment Information System (ENVIS), Jammu and Kashmir centre". The authors express their gratitude to the funding agencies for the financial assistance. The PRECIS simulations from IITM, Pune were facilitated under a Joint Indo-UK collaborative programme on climate change impacts in India. We acknowledge the support received from NATCOM (MoEF, Government of India) and the Department for Environment, Food and Rural Affairs, Government of United Kingdom. We are grateful to the Hadley Centre for Climate Prediction and Research, UK Meteorological Office, for making available the PRECIS data for the simulations used in this study. we are thankful to Director, IITM, for facilitating data for the study. Finally, we would like to acknowledge the kind support provided by Prof. Md. Nazrul Islam, Executive Editor-in-chief of the journal for expediting the review process of our publication.

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