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Twenty-first century climate extremes' projections and their spatio-temporal trend analysis over Pakistan

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ABSTRACT

Study region: The study area comprising Pakistan is distributed in five homogeneous climatic zones.

Study focus: An integrated five step approach has been used for zonal climate extreme analysis. Seven out of thirteen most appropriate Global Climate Models (GCMs) were selected using Posterior Inclusion Probability in the Bayesian model averaging approach. The output of selected GCMs is then downscaled using statistical downscaling. Climate extremes are projected for the baseline and future time periods. Spatio-temporal trend and statistical significance analysis were performed for climate extremes.

New hydrological insights for the region: Most of the climate extremes have heterogeneous trends for the precipitation under RCP4.5 and RCP8.5. The increasing trends in climate extreme are noted in the northern region, monsoon region, and south-west parts of Pakistan. Significantly increasing trend is observed in TMAXmean and TMINmean across the country. TN10P (Cool nights) and TX10P (Cool days) have decreasing trends in the future for most of the GCMs across the country for RCP4.5 and RCP8.5. In contrast, TN90P (warm nights) and TX90P (warm days) have increasing trends for all GCMs in future under both scenarios. For RCP8.5, temperature extremes have significantly increased except TN10P and TX10P indicating significantly decreasing trends. There is notable increase in the number of summer days in future under both scenarios.

1. Introduction

Due to anthropogenic activities, the intensities and frequencies of extreme events would likely to increase during the 21st century (IPCC, 2007b; IPCC, 2013; Troyat al, 2015; Lader et al., 2017; Wu, 2020; IPCC, 2021). It can be seen from observational data that the frequencies, intensities and durations of extremes events have changed with time (World Meteorological Organization, 2013; Sheikh et al., 2015; McPhillips et al., 2018; Almazroui, 2020; IPCC, 2018; Kharin et al., 2018). Extreme heatwave, intense rainfall in Monsoon and droughts are the major examples happened in the past decades (Sheikh et al., 2015, Ikram et al., 2016, Choudhary, 2017; Hegerl et al., 2011; Field et al., 2012). In 2010, Pakistan faced deadliest flood (Haq et al., 2012) caused 2000 causalities and total economic impact was approximately PKR 855 Billion (Asian Development Bank, 2010). Lau and Kin (2012) investigated a connection between

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the flood of 2010 in Pakistan and the Russian heat wave. Pakistan has widely been experienced by the impacts of climate change in the recent past and this boosted vulnerability of the country to the threat of changing climate has extensively accredited (Ali et al., 2015; 2019a; 2019b; Saeed and Athar, 2018; Khan et al., 2015, 2017; Chaudhry, 2017; Ghulam et al., 2017; Malik et al., 2012; Sheikh et al., 2009; Farooqi et al., 2005). During 1961–2010 in Pakistan, 0.5 °C and 0.8 °C increase on average in mean and maximum temperature, have been observed (Ali et al., 2019a; Khan et al., 2022). The future's projected increase in temperature is higher than the global on average, particularly, the northern parts located at higher elevations are more probably to experience preeminent surface air temperature (Ali et al., 2015, Khan et al., 2015, Kiani et al., 2021).

Climate change and particularly climate extremes have significant impacts not only on food security, socioeconomic factors, demographic trends and water availability but also have a strong link with national security (Vogel, 2019). The Quadrennial Defense Review and National Security Strategy of the United States of America (USA) both identify that climate change is likely to trigger outcomes that will threaten the U.S. security (McElroy and Baker, 2014). Unfortunately, Pakistan facing the same situation as it experienced many extremes events in the last decades. The increase in extreme events observed in the last decades is expected to continue in the future as the natural variability and accelerated warming combine to produce changing weather conditions around the globe. Consequently, this will impact critical infrastructure, food security, water security, energy security and brings into focus the need to consider the accelerating nature of climate stress, in concert with the more traditional political, economic, and social indicators. Therefore, the knowledge on future climate change in particular climate extremes is pertinent to appraise its expected impacts and to formulate effective policies seeking timely adaptation and mitigation strategies.

The observed increase in droughts, floods and heat waves, which have sternly impacted the society and environment over the recent past decades, has brought attention to the study of climate extremes (Hegerl et al., 2011; Field et al., 2012; AghaKouchak et al., 2012). There are various studies about climate extreme analysis globally as well as regionally. About Pakistan, there are a few studies including Sheikh et al. (2009) who performed climate extreme analysis using observed daily data (temperature for the duration of 1971–2000, precipitation for the duration of 1961–2000) for the South Asian countries, Pakistan, India, Sri Lanka, Bangladesh and Nepal. Islam et al. (2009) investigated climate extremes using the outputs of a single Regional Climate Model, PRECIS (PRECIS=Providing Regional Climate for Impact Studies). In their study, they considered baseline duration (1961–1990) and last future of the 21st Century (2071–2100) and concluded that the cold spell has significantly decreased, and the warm spell has increasing trends in the future. Sajjad and Ghaffar (2018) performed a study about climate extremes by using the outputs of three GCMs with RCP4.5 and RCP8.5, however, they considered Pakistan as a single homogeneous climate zone. They concluded that climate extremes are changing, for example, summer days, mean minimum and mean maximum temperatures are increasing in the future. Ali et al. (2019) performed a study about climate extreme analysis using the outputs of various GCMs. However, they considered each province/state as a homogeneous climate region which effect the analyses.

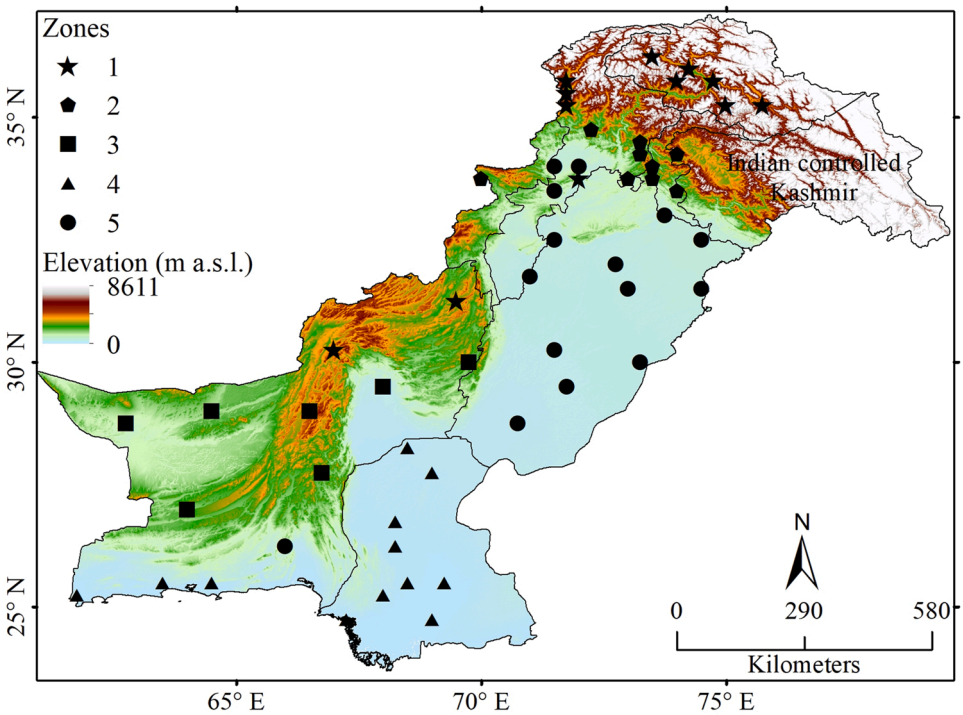

Fig. 1. Five homogenous climate regions of Pakistan. The Kashmir is added in this Figure following one of our collaborative institutes (ICIMOD) guidelines. The Indian controlled Kashmir is not included in our analysis due to unavailability of observed data and is not shown in any tables/figures of the paper.

The climate of Pakistan has significant spatial variation from coastal area in the south and one of the largest non-polar glaciers in the north. These altitudinal variations also affect the rainfall, temperature change and climate extremes. About two-third of the area is arid in the country out of which half of that is extremely arid where annual rainfall is less than the average (Adnan, 2009). Construction of homogenous climatic regions (given in Fig. 1) could provide the basis for better understanding about climate extremes (Ullah et al., 2020). Therefore, it is important to conduct climate extremes analysis based on homogeneous climatic zones which may give better and representative results.

The Atmosphere-Ocean General Circulation Model (AOGCM) are the sophisticated tools developed to simulate climate variability on a wide range, i.e., from synoptic time scales to multi-century climate change. However, the outputs of these models have coarser resolution and therefore, are unable to reflect some of the regional and local climate variability. Consequently, we need some tools that can be used to make available the climate information on higher resolution. Downscaling is a process to transform the climatic information to finer resolution from coarser resolution. There are two approaches for downscaling: dynamical downscaling (DD) and statistical downscaling (SD). DD use regional climate model (RCM) by utilizing additional information in terms of topography and sea surface temperature besides the outputs of GCMs. On the other hand, SD required observed station data and the output of GCMs. Empirical relations can be developed between observed station data and GCMs' outputs for downscaling purposes. Both approaches have their pros and cons, however, one difference is that DD requires high computational power (e.g., parallel computing system or supercomputer) and huge storage capacity for their outputs. On the other hand, SD does not require such type of high computational power and storage capacity as compared to DD. For further details about statistical downscaling, we refer to Wilby et al. (1998); Wilby and Dawson (2013); Liu et al. (2016); Pourmokhtarian et al. (2016); Lun et al. (2020); Hewitson et al. (2014); Gutiérrez et al. (2013); Ali et al. (2019).

There are various climate and weather extremes which occur due to the different intensities, durations and frequencies of climate variables. Examples of these climate extremes include typhoons or cyclones, heavy precipitation, heat waves etc. These phenomena further exacerbate other events like flooding and health's problems related to climate which causes casualties and other losses. Expert Team on Climate Change Detection Monitoring and Indices (ETCCDMI) developed climate indices which can be used for measuring different climate extremes. A list of the core Climate Indices of ETCCDMI with brief definitions and their units can be found at (http://etccdi.pacificclimate.org/) and also provided in the supplementary information (S8).

The major aims of this study include: 1) Climate extremes' projection in the homogeneous climatic zones for selected GCMs; 2) spatio-temporal trend analysis of the projected climate extremes and 3) significance analysis of the projected climate extremes. The findings of this study may help policy makers in decision making in various areas like water management, agriculture, water availability, urban planning, food security etc. Further, the findings of this study may help to address some of the Sustainable Development Goals (SDGs) of the United Nations Development Programme (UNDP) related to climate change actions, water management, hunger and environment. The remaining paper is structured as: Section 2 presents data and study area, Section 3 is reserved for methodology, Section 4 has results, Sections 5 and 6 are about discussion and conclusions and recommendations, respectively.

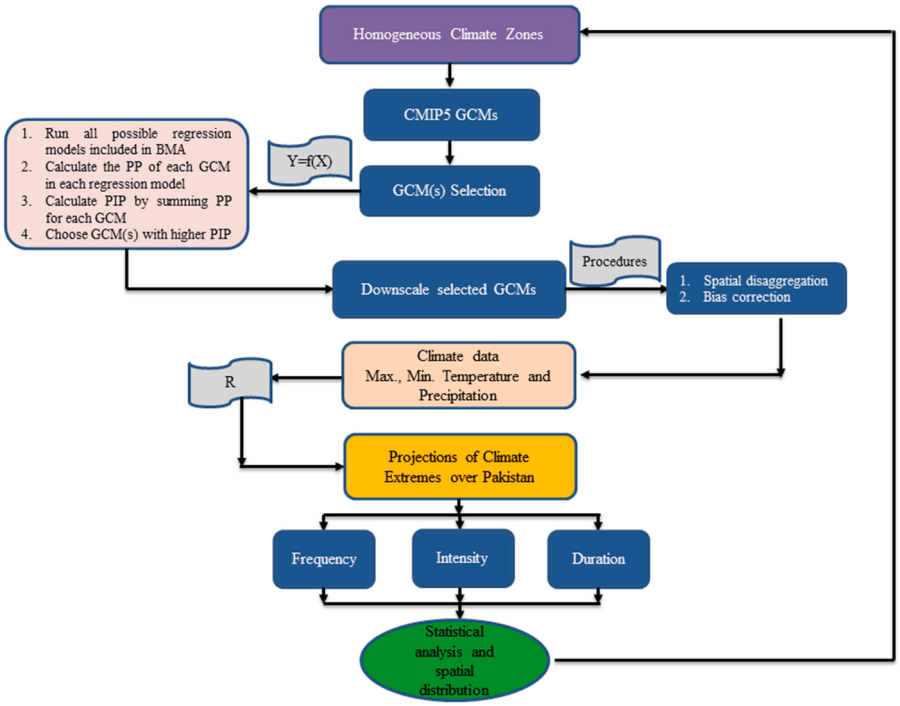

Fig. 2. Schematic presentation of methodology comprises of various phases to reach objectives of this study.

2. Data and study area

Two types of data sets (observed climate data and high resolution statistically downscaled GCMs' outputs data) have been used in this study on daily basis. The observed data for the duration of 1976–2005 was acquired from Pakistan Meteorological Department (MPD) while the outputs of GCMs are downloaded from World Climate Research Programme (https://esgf-node.llnl.gov/search/cmip5) and then statistically downscaled for 34 meteorological stations across Pakistan. The duration of simulated data is from 1976 to 2100, where the duration of 1976–2005 is considers as baseline or reference period and the remaining duration is divided into three future durations, i.e., future one (F1 =2011–2040), future two (F2 =2041–2070) and future three (F3 =2071–2100). The target area for this study is Pakistan which has 23.4°– 38° N, 61°– 78° E latitude and longitude, respectively. Pakistan has four neighbor countries, India in the eastern side, China in the north-east side, Afghanistan in the western side, Iran in west-south side. It has ocean is in the south and ~ 26,000 sq. km glacier cover area about one-fourth of the glaciers in High Mountain Asia (Muhammad et al., 2019a, 2019b). Pakistan has a total area of 881,913 square kilometers and remains 33rd largest country of the world. It remains 6th largest country with respect to population and contains approximately 220 million inhabitants according to the latest census of the country (Pakistan Economic Survey, 2020–21; WPRev: Worldometer, 2021; Worldometer, 2021).

3. Methodology

An integrated approach comprises mainly of five major steps have been developed and implemented to accomplish this study. These steps are: GCM selection; downscaling the outputs of selected GCMs; evaluation downscaling skills; projection of climate extremes and finally their spatio-temporal trends analysis. In the first step, a set of GCMs is selected for all considered climate variables for each climate zone by incorporating Bayesian Model Averaging (BMA) (Khan et al., 2021) from the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al., 2012). In the second step, the outputs of selected GCMs are statistically downscaled to project the climate extremes in each climate zone. Finally, the projected climate extremes are analyzed by incorporating statistical techniques, for example, probability density function, spatio-temporal trend analysis and their statistical significance. The detail description about each part is discussed in the subsequent subsections and presented schematically in Fig. 2.

3.1. GCM(s) selection

Initially, 13 GCMs were selected based on available literature where different approaches have been used for GCMs' evaluation. For example, we selected a set of GCMs based on the literature review of Ashfaq et al. (2017) and skills score, warm, dry, wet and cold criteria of Lutz et al. (2016). As the aim of this study to analyze climate extremes in each climate zone, therefore, it is important to evaluate GCMs in each climate region given in Fig. 1. To refine further the choice of GCMs, model evaluation procedures is carried out by using BMA which is a regression-based approach where the dependent variable represents observed data and covariates represent GCMs' outputs. In BMA, all possible combinations of the regression model (or customized number of regression models) can be estimated where each covariate (outputs of GCM) has a weight called posterior probability and it depends on how closely it realized the observed data. Consequently, the GCMs having higher weights which perform better in terms of projected observed data closely. The model's selection criterion is posterior inclusion probability of the GCM which is the sum of posterior probabilities of each covariate (GCM) in all regression models included in BMA. For further details about the methodology of model selection, we refer to Khan et al. (2021). A brief detail about 13 GCMs is given in supplementary information (S9).

3.2. Downscaling GCMs' outputs

In statistical downscaling stationarity is an important assumption as without stationarity the same relationship may not exist in future (Dixon et al., 2016; Lanzante et al., 2018). However, spatial disaggregation quantile delta mapping (SDQDM) is a nonparametric method and therefore, there is no parameters which need to be calibrated (Gudmundsson et al., 2012). A prerequisite condition for a statistical downscaling method, e.g., SDQDM, that a reliable long-term historical dataset is available over a study domain to build a relationship between GCM outputs and the observed data. In other words, observed statistical characteristics at each station are reflected in the SDQDM processes using the observed dataset within a study domain. For instance, a 50th percentile value of GCM's output is simply interpolated by IDW (inverse distance weighting) to stations and then the interpolated values correspond to the same percentile values of observation at each station are bias corrected by QDM. In this way, all GCM outputs are bias-corrected at all stations and preserve GCM-driven climate signals (Cannon et al., 2015; Cannon, 2018). The resolution of the downscaled data is determine by the resolution of reference or observed data. For further details about downscaling/bias correction, we refer to Cannon et al. (2015), Cannon (2018), Brekke et al. (2013) and Wood et al. (2004).

Before the implementation of bias correction, it is assumed that $Y_o(t)$, $Y_{m,h}(t)$ and $Y_{m,f}(t)$ denote observed, model's simulated historical and future data, respectively. In the subscript o, m, h, f and t represent observed, model, historical, future and time, respectively. Similarly, F_o, $F_{m,h}$, $F_{m,f}$ represent cumulative distribution function of observed data, model's simulated data for historical time and future time period, respectively. We start with time-dependent cumulative distribution function of model projected series.

$$F_{m,f}\left(y_{m,f}(t)\right) = P\left(Y_{m,f}(t) \leq y_{m,f}(t)\right), F_{m,f}(t) \in [0,1] \tag{1}$$

Find the relative change using the ratio of inverse CDF of model predicted data applied to the CDF of model predicted data and the

inverse CDF of historical observed data applied to model predicted data. Mathematically this can be represented by Eq. (2).

$$\Delta_m(y(t)) = \frac{F_{m,f}{}^{-1}\left(F_{m,f}(y_{m,f}(t))\right)}{F_{m,h}{}^{-1}\left(F_{m,f}(y_{m,f}(t))\right)} = \frac{y_{m,f}(t)}{F_{m,h}{}^{-1}\left(F_{m,f}(y_{m,f}(t))\right)} \tag{2}$$

The quantile of model's predicted data can now be bias corrected by applying the inverse CDF estimated from observed data set over the historical duration.

$$\widehat{Y}_{m,h}(t) = F_o{}^{-1}\left(F_{m,f}(y(t))\right) \tag{3}$$

The $F_o{}^{-1}$ is the inverse of cumulative distribution function estimated from observed data during the calibration period and $\widehat{Y}_{m,h}(t)$ is the bias corrected model's simulated data for the historical duration. The bias corrected future projections can be obtained by applying the relative changes to the historical bias corrected data given in Eq. (3) and expressed in Eqs. (4) and (5) for temperature and precipitation, respectively.

$$\widehat{Y}_{m,f}(t) = \widehat{Y}_{m,h}(t).\Delta_m(y(t)) \tag{4}$$

$$\widehat{Y}_{m,f}(t) = \widehat{Y}_{m,h}(t) + \Delta_m(y(t)) \tag{5}$$

3.3. Evaluating skills of downscaling method

It is important to assess the skills of downscaling methos before proceeding for making futures' projections. There are various criteria that can be used for this purpose, however, the Mean Error (ME), Mean Square Error (MSE), Percent bias (PBIAS) and Root Mean Square Error (RMSE) are used in this study.

3.4. Climate extremes analysis

Extreme events are easy to recognize but due to different reasons, it is difficult to define it (McPhillips, 2018; Broska et al., 2021). The reasons including no uniform definition of extreme events, the word extremeness is relative and strongly depends on the context. To calculate the climate extremes indices, the observed and downscaled model-simulated data was prepared for each climate zone for the reference and future durations. The R's package ClimDEX is used to compute 27 core climate indices based on daily minimum, maximum temperature and precipitation (Karl et al., 1999; Peterson, 2005; ETCCDI). The parameters of climate extremes which are considered important for impact assessment include are intensity, frequency and persistence. Statistical analysis of the projected climate extremes is then performed using probability density function (PDF) which shows full distribution of climate extremes for different durations. A comparison between baseline and future durations is made by using PDFs of climate extremes which provide information about shift/changes in the mean as well as in variability of climate extremes. It is important to understand the spatial distribution of climate extremes, therefore, the projected climate extremes are spatially interpolated over the whole domain. The interpolation is performed for the changes in comparison to reference period (percent changes for some climate extreme) in climate extremes for selected GCMs in the future durations for both scenarios to 1 * 1 km grid size.

Thirdly, it is extremely important to know about the trend and statistical significance of the climate extremes in the future. This will help policy makers to make policy accordingly and on priority basis. The statistical significance of each climate extreme was tested at 5 % level of significance and noted that if the P-value for a particular climate extreme is less than or equal to significance level, then we say that it is significantly changing. If the P-value for a particular climate extreme index is greater than the significance level, then we say that it is insignificantly changing (decreasing/increasing).

3.5. Uncertainty assessment

Uncertainty assessment in climate projections particularly in climate extremes is important (Li et al., 2022; Ali et al., 2019). This can help stakeholders and policymakers in taking mitigation, adaptation measures in relevant sectors. For the assessment of uncertainty in climate extremes, the observed climate extremes are compared with the projected climate extremes for various GCM for the reference period. This can show the deviation of projected climate extremes from observed climate extremes as well as between different GCMs' projected extremes. For the assessment of uncertainty assessment in climate extremes, PDFs and box-whisker plots are used. To assess whether the observed and model simulated climate extremes follow the same probability distribution, the Kolmogorov-Smirnov (S-K) Test has been implemented. The null hypothesis in S-K Test is that the two data sets follow the same probability distribution. If p-value of the test is less than or equal to 0.05, this mean that the observed and simulated climate extremes don not follow the same probability distribution at 5 % level of significance. In addition, the trajectory of projected climate data along with observed data can also provide information about the uncertainty in the projected data for both RCPs.

4. Results

Results of this study are divided into three parts. Firstly, evaluation of downscaling skills, secondly, the results of climate extremes analysis including probability density functions of projected climate extremes, spatial-temporal trend analysis and statistical

significance of climate extremes are presented. In the end, uncertainties in climate extremes are given.

4.1. Downscaling skills' evaluation

The downscaling method is evaluated graphically and numerically by using climate extremes for the reference period. Fig. 3 shows the comparison between climate extremes estimated from GCM output and downscaled data with observed climate extremes. The downscaled R95p follows the pattern of observed R95p in terms of average values and variability in comparison to the GCM output. For SU25, the distribution of observed data is closely followed by the downscaled one as compared to the GCM output. For R99p and TXx, the performance of downscaling method shows that these climate extremes are closely approximated by the downscaled data as comparison to the GCM output. The number of CWD is significantly overestimated by GCM in terms of variability and maximum number of CWD. On the other hand, TNx is significantly underestimated by GCM output compared to the downscaled average, minimum, and maximum values. The results show that all these climate extremes are approximated closely by the downscaled data in comparison to the GCM output.

Table 1 show evaluation of downscaling method using daily climate data. The results are based on four criteria, ME, MSE, PBIAS and RMSE for GCM outputs and downscaled climate data with observed data. The results of these statistics show that the downscaled data is closer to the observed data as compared to the GCM original outputs in all climatic regions of the country except a few values. Therefore, the downscaled climate data is used for further analysis.

4.2. Extremes' analysis

Fig. 4 shows the result of SU25 (the number of days when temperature is 25 °C or higher) for both climate change scenarios. SU25 has an increasing pattern in all climate zones for RCP4.5. There is positive increment in the mean number of summer days in future across the country, however, a maximum increase is noted during F1 in contrast to F2 and F3 in zone 1. In zone 2, there is clear increasing trend in the number of summer days during all future durations. In zone 3–5, the maximum increase in the number of summer days is noted during F2. The number of summer days varies zonal-wise with lowest of approximately 185 days per year in zone 1. The maximum annual increase is observed during F1 in zone 1, F2 in zones 3–5 and F3 in zone 2.

The results of summer days under the RCP8.5 indicate a clearly visible increasing shift in the future. It is significantly increasing, however, a maximum increase is noted during F1 in zone 4. In zone 1, the average number of summer days are approximately 160, 170, 200 and 225 during baseline, F1, F2, and F3, respectively. The increase in summer days will help in growing crops in zone 1, however, it will severely affect crops' production, human health, population's migration, water availability and food security in the remaining zones. Therefore, optimal utilization and smart management of available water may help to cope the worser situation about water scarcity in the future. In addition, the increasing number of summer days will increase the rate of snow and glacier melt and consequently more water will be available in summer with increased probability of hazards (Muhammad et al., 2021; Tian et al., 2017), however, the mass of glaciers may be reduced (Muhammad et al., 2016).

The spatio-temporal distribution of changes in TX90p (warm days) for CanESM2 during future is shown in Fig. 5. The TX90p represent total percentage of days when daily maximum temperature is greater than 90th percentile. Under RCP4.5, the TX90p has mixed and heterogenous trends. The warm days are mostly decreasing except the south-west part of the country during all three future durations. Maximum decrease in TX90p is observed in east-central, central and central-western parts of the country while maximum

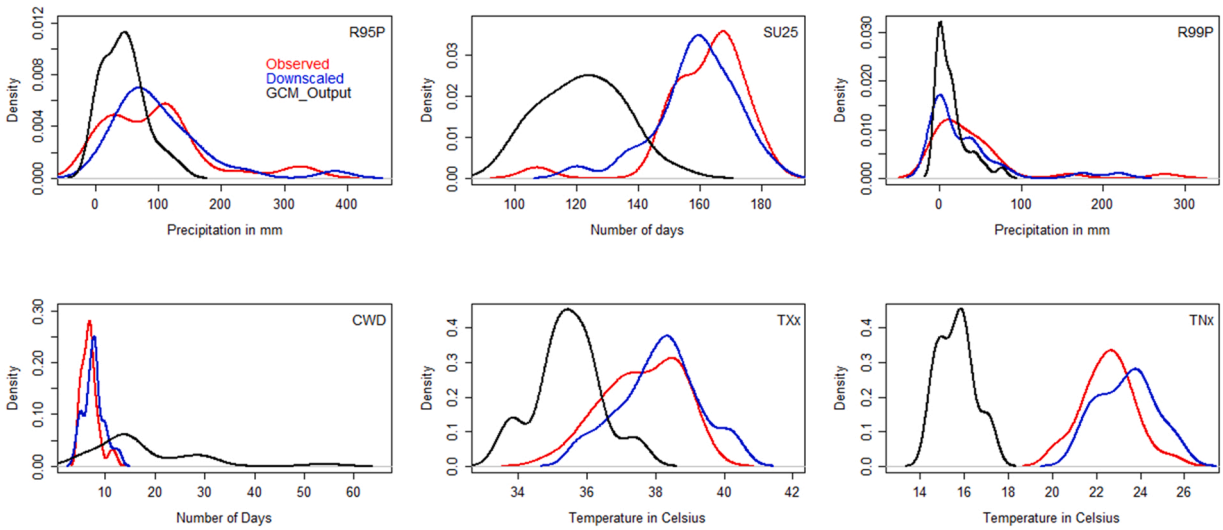

Fig. 3. Evaluation of downscaling skills by using climate extremes. The evaluation is performed for the reference period using PDFs for GCM outputs and downscaled data with observed data.

Table 1
A comparison between observed, GCM output and downscaled climate data (maximum, minimum temperature and precipitation) for each climate zone in Pakistan. Four error statistics including ME, MSE, PBIAS and RMSE are considered for the evaluation of downscaling skills of the utilized method.

Zone	Variable	GCM output and Observed data				Downscaled and Observed data			
		ME	MSE	PBIAS	RMSE	ME	MSE	PBIAS	RMSE
Zone 1	Max TMP	-11.526	151.569	-126.6	12.311	**-0.831**	**10.234**	**-9.1**	**3.199**
	Min TMP	-0.182	**25.397**	-13.9	**5.040**	**-0.077**	39.399	**-5.9**	6.277
	Precioitation	-8.231	88.039	-36.8	9.382	**-0.556**	**18.202**	**-2.5**	**4.266**
Zone 2	Max TMP	6.818	79.461	31	8.194	**-0.062**	**20.878**	**-0.2**	**4.569**
	Min TMP	**9.425**	103.424	186.5	10.170	-13.544	**11.771**	**0.1**	**3.431**
	Precioitation	2.476	**157.756**	271	**12.560**	**0.152**	260.064	**4.7**	16.127
Zon 3	Max TMP	-3.640	101.498	-12	10.074	**0.542**	**81.709**	**1.8**	**9.039**
	Min TMP	-8.768	90.191	-47.2	9.500	**-0.036**	**10.641**	**0.2**	**3.258**
	Precioitation	**0.205**	**192.064**	**26.7**	**13.859**	0.980	251.940	127.3	15.873
Zone 4	Max TMP	-0.951	28.244	-3.0	5.314	**-0.124**	**23.807**	**-0.4**	**4.879**
	Min TMP	-3.730	35.780	-25.9	5.982	**-0.033**	**23.122**	**-0.2**	**4.808**
	Precioitation	0.046	**4.929**	**18.7**	3.220	**-0.029**	9.019	**-11.9**	3.003
Zone 5	Max TMP	-3.482	29.930	-10.2	5.471	**0.013**	**13.650**	**0**	**3.694**
	Min TMP	-7.079	60.533	-35	7.780	**0.011**	**10.306**	**0**	**3.210**
	Precioitation	0.370	**16.649**	111.7	**4.080**	**-0.083**	27.490	**-25**	5.243

Note: The bold figures show better performance for a particular data (GCM output or downscled).

increase is noted in the south-western part of the country during F2 and F1, respectively, under the RCP4.5. The maximum increase and decrease in RCP4.5 are approximately 2 days each. Under RCP8.5, the pattern is similar as for RCP4.5, with higher increment. Also, the maximum increase under RCP8.5 is noted during F2. During F1, there is a decrease in TX90p across the country except south-western part of the country where it is increasing. Maximum increase in TX90p is observed during F2 while minimum decrease is noted during F1. F3 has moderate increase in TX90p under the RCP8.5, however, during this time period, there is an increase in the northern part of the country which is rich with water resources.

Fig. 6 present the probability density functions of total precipitation for canESM2 with both climate change scenarios. The total precipitation is increasing in Zones 1–3 and decreasing during F3 in zones 4–5. A part of Zones 1 is frozen water resources with mostly glacier and snow covered and zone 2 has monsoon effect with heavy precipitation. The accumulated precipitation reaches to 1500 mm and 3400 mm in zone 1 and zone 2, respectively. In zone 3, the relative changes are comparatively insignificant due to less precipitation accumulation. The pattern is different in the results of RCP8.5 with different values.

Fig. 7 shows the future's spatio-temporal distribution of percent changes in R99p over Pakistan for canESM2 under RCP4.5 and RCP8.5. The R99p represent annual total precipitation when daily precipitation is greater than 99th percentile. Maximum increase is noted in the south-east part and in the coastal areas during future durations. We found a maximum decrease of 38 % and increase of 238.40 %. Under the RCP8.5, the results of R99p show an increase during F1, mixed results (increase/decrease) during F2, and maximum increase during F3. Maximum decrease and increase are observed during F2 and F3, respectively under the RCP8.5. In addition, maximum increase is observed during F2 and F3 under the RCP4.5 and RCP8.5. Maximum decrease in R99p is observed in the northern and south-western parts of the country while maximum percent increase is noted in the south-east part of the country in the entire duration under both scenarios. The possible consequences of increasing R99p would be flash flooding, damages infrastructures, crops loses and casualties in the future. However, proper planning about storage of water, plantation and hazard's resilience infrastructure can reduce such type of damages.

Fig. 8 shows the changes in CWD (consecutive wet days) for both climate change scenarios for CanESM2. The results indicate a mixed trend with increasing CWD in the future in zone 1. In zone 2, there is decreasing trend during most of the years, while an increase in few years in the future. Zone 3 has mixed trend in CWD throughout the future. In zone 4, the first half of each future duration has a mixed trend, however, a decrease in CWD in the second half in all future durations is noted. In zone 5, the first half of each time periods indicate a decrease in contrast to an increase in the second half for most of the years. The maximum increase (14 days) and decrease (13 days) is noted in zone 2. The results of changes in CWD under RCP8.5 follow similar pattern, however, maximum increase (14 days) and decrease (17 days) are noted in zone 2.

Fig. 9 represents the magnitudes and statistical significance (at 5 % level of significance) of zonal temperature extremes under RCP4.5 and RCP8.5. Fig. 9 indicates a clearly visible trend in some climate extremes, for example, TN10P (cold nights) and TX10P (cold days). These two climate extremes varies in different zones and models. Cold nights are significantly increasing only for FGOALs2 in zone 2. In zone 4 and 5, the cold nights and cold days are significantly decreasing. In contrast, TN90P (warm nights) and TX90P (warm days) are significantly increasing in most of the GCMs/zones with few exceptions of insignificant decrease and increase indicating future climate warming under RCP4.5. Summer days are increasing throughout the future durations under RCP4.5 except short-term decrease in zone 1 and 2. The increasing summer days will have significant impact on agriculture, water and other important sectors. Ice days are either decreasing or not changing except zone 2 and 3. Similarly, frost days are mostly decreasing.

Most of the temperature extremes are changing significantly under the RCP8.5 are shown in Fig. 9. Cold night (TN10p) and cold days (TX10p) are significantly decreasing throughout future. In contrast, the warm night (TN90p) and warm days (TX90p) are significantly increasing throughout except for CCSM4 in zone 5 with significantly decreasing trend during F1 and F2. Summer days are

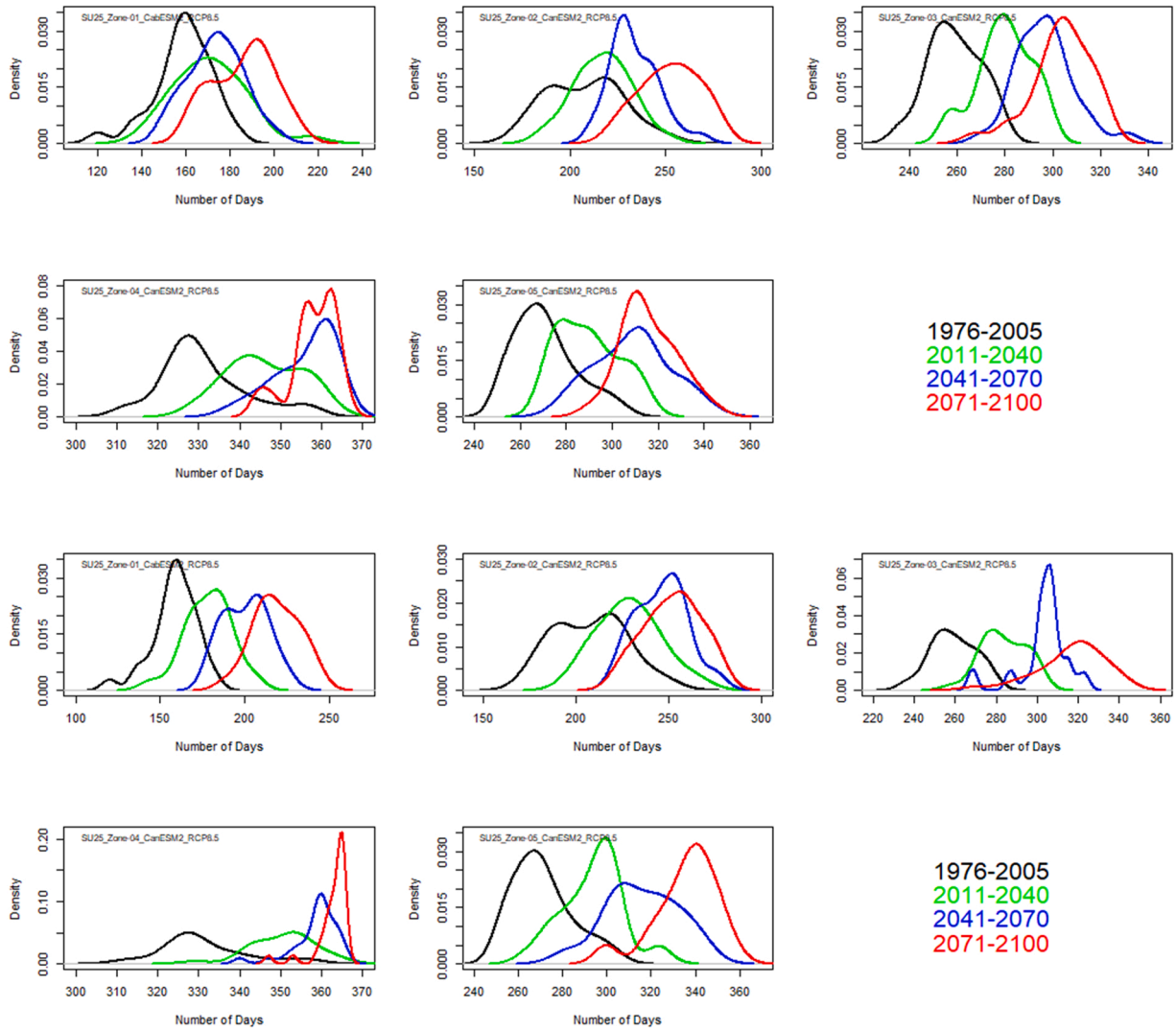

Fig. 4. Probability density functions of SU25 (summer days) for the baseline and future durations (F1, F2 and F3) for RCP4.5 (upper 2 panels) and RCP8.5 (lower 2 panels) with CanESM2 for all climate zones. Number of summer days and their density are presented on x-axis and y-axis, respectively.

significantly increasing in most of the future durations. Frost days (FD0) are decreasing throughout the future except F3 in zone 3 under GFDL-ESM-2 M model. The results of tropical nights (TR20) show significant increase in future except a decrease during F1 in zone 5 for CCSM4.

The results of precipitation extremes under both scenarios are shown in Fig. 10 which indicate an irregular spatio-temporal trend. Notably, precipitation from extremely wet days (R99p) is increasing during F2 and F3 except a decrease in zone 3 with most of the decrease during F1 under the RCP4.5. In addition, the number of heavy precipitation and very heavy precipitation days are increasing across zone 1 and 2 in contrast to the decreasing trends in the remaining zones with few exceptions.

The results of precipitation extremes under RCP8.5 show that most of the extremes have mixed trend with few significant changes. Like in RCP4.5, most of the significant changes are observed in the high-altitude areas represented as zone 1 and 2. In zone 1, R95p is decreasing initially in F1 followed by a significant increase during F2 and insignificant increase during F3 for CMCC-CMS model. Similarly, R99p is decreasing during F1 but significantly increasing during F2 and F3 for CMCC-CMS model. A similar trend is noted in PRCPTOT with a decrease during F1 and increase during F2 and F3. Consecutive dry days (CDD) are insignificant except a significant increase by MIROC-ESM-CHEM model in zone 4 and CanESM2 in zone 5. In zone 1 and 2, the CDD are increasing in F2 and F3 except CanESM2 indicating decreasing trend during F3. During F1, CDD has mixed trend in zone 1 and 2. Likewise, the CWD also have mixed trend and mostly decreasing during F1 and increasing during F2 and F3 in zones 1 and 2. In zones 4 and 5, CWD has mostly increasing trend with few exceptions. For some more results, we refer to supplementary material.

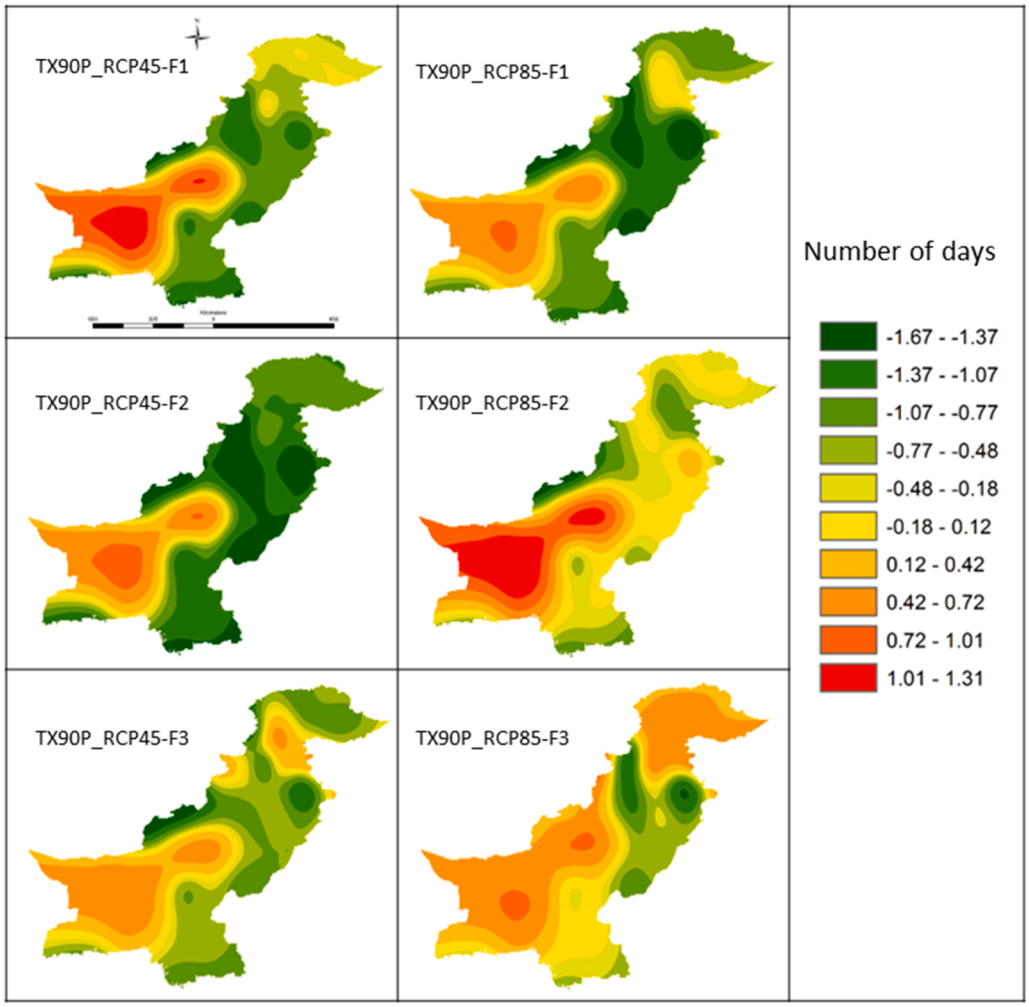

Fig. 5. Spatio-temporal distribution of changes in TX90p (warm days) over Pakistan for future duration (F1, F2, and F3) in comparison to the baseline duration for CanESM2 model under the RCP4.5 and RCP8.5. The left side panel is for RCP4.5 while the right-side panel is for RCP8.5.

4.3. Uncertainties in the projected climate extremes

Figs. 11–12 show a comparison of observed climate extremes with projected climate extremes for the reference period using PDFs and box whisker plots, respectively. The R99p is approximated in a better way by CMCC-CMS in comparison to other GCMs. Some of the GCMs have bimodal distribution. The SU25 is projected reasonably by CanESM3 and CMCC-CSM as compared to the other GCMs. In terms of extreme values, the highest number of summer days are180 and 183 for observed and CanESM2 projected data, respectively. The average summer days are 162 and 159 for observed and CanESM2 projected data, respectively. For inmcm4, the average number of summer days is 129 with a significance difference in minimum and maximum number of summer days in comparison to observed data. The other extremes like R99p, TX90p and TN90p are closely approximated by various GCMs, however, the observed maximum R99p is underestimated by all GCMs. The number CDD is overestimated by all GCMs, however, the CMSS-CSM has approximately better in terms of average values. From Fig. 11 for most of the climate extremes, the observed extremes and model predicted extremes follow the same probability distribution using K-S test. However, for CDD the distribution of model simulated CDD is different for that of observed CDD for the mentioned GCMs.

The uncertainty is higher in the projected CDD in comparison to other climate extremes as shown in Fig. 12. It is anticipated that the uncertainty in the projected extremes will increases in the future. The trajectory (supplementary information, S1) of projected climate data closely approximates the observed maximum, minimum temperature and precipitation, however, in the future, there may be higher uncertainties in comparison the reference period. The uncertainties level may vary in both RCPs in the future. As some of the climate extremes are interpolated from stations to the full domain of the study which can introduce uncertainties especially where the meteorological stations are at larger distance and have significant elevation variation. Therefore, it is important for relevant policy makers to keep in mind the uncertainties in projected climate extremes while developing future plans.

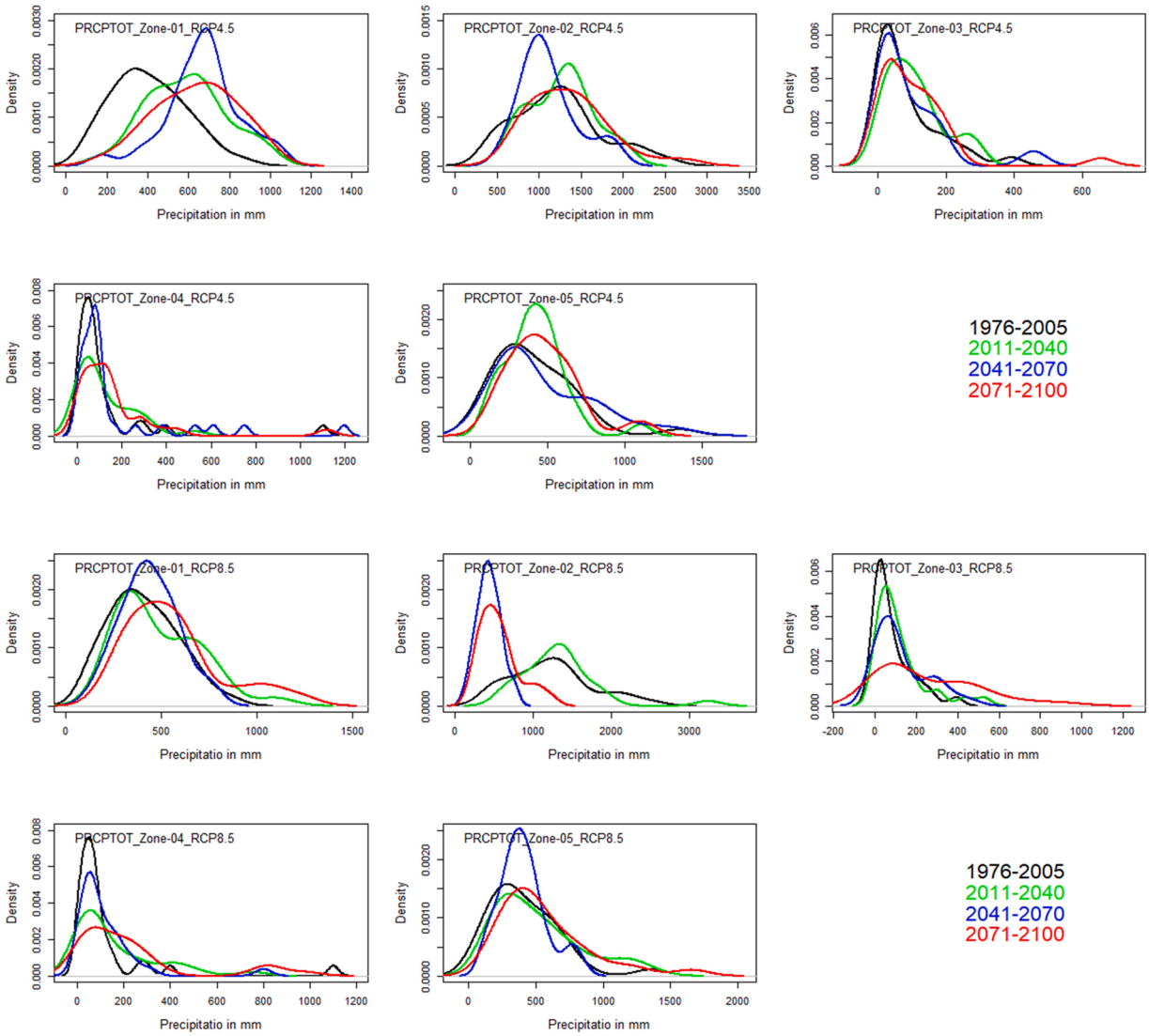

Fig. 6. Probability density functions of PRCPTOT (Precipitation Total) for RCP4.5 (upper 2 panels) and for RCP8.5 (lower 2 panels) with CanESM2 for all climate zones. On x-axis the precipitation in mm and on y-axis their density is given, respectively.

5. Discussion

If we look at the worst impacts of weather and climate extremes in the South Asian region, the findings are alarming. Recently, WMO (2021) stated that climate and weather extremes killed thousands of people, displaced millions of people, causing a heavy toll on ecosystems and infrastructure and consequently cost hundreds of billions of dollars. In the light of the above consequences, it is important to have enough information about the duration, frequency and persistence of these extremes during the recent and future duration as well.

Toward this end, there are a few studies regarding climate extreme analysis and projections over Pakistan. For instance, Sheikh et al. (2009) analyzed climate extremes using daily data for temperature (for the duration of 1971–2000) and precipitation (for the duration of 1961–2000) for the South Asian countries. They concluded that the warm and cold extremes are more and less common, respectively. Further, their study suggested mixed trend for the indices related to heaviest rainfall (R95p and R99p) throughout South Asia. A conducted study by Islam et al. (2009) to project temperature and precipitation extremes using daily outputs of a regional climate model (PRECIS: Providing Regional Climate for Impact Studies) with 50 by 50 km horizontal resolution over Pakistan. They considered the 1960–1990 and 2071–2100 as reference and future durations, respectively. In their study, they concluded that the annual cold spell suggests significant decreasing trend, however, annual warm spell show slight upward trend in Pakistan. In another study over Pakistan, Sajjad and Ghaffar (2018) analyzed climate extremes using ensemble mean (daily outputs) of three GCMs with two emission scenarios (RCP4.5 and RCP8.5). Their findings suggested that summer days has increasing trend over north-eastern part

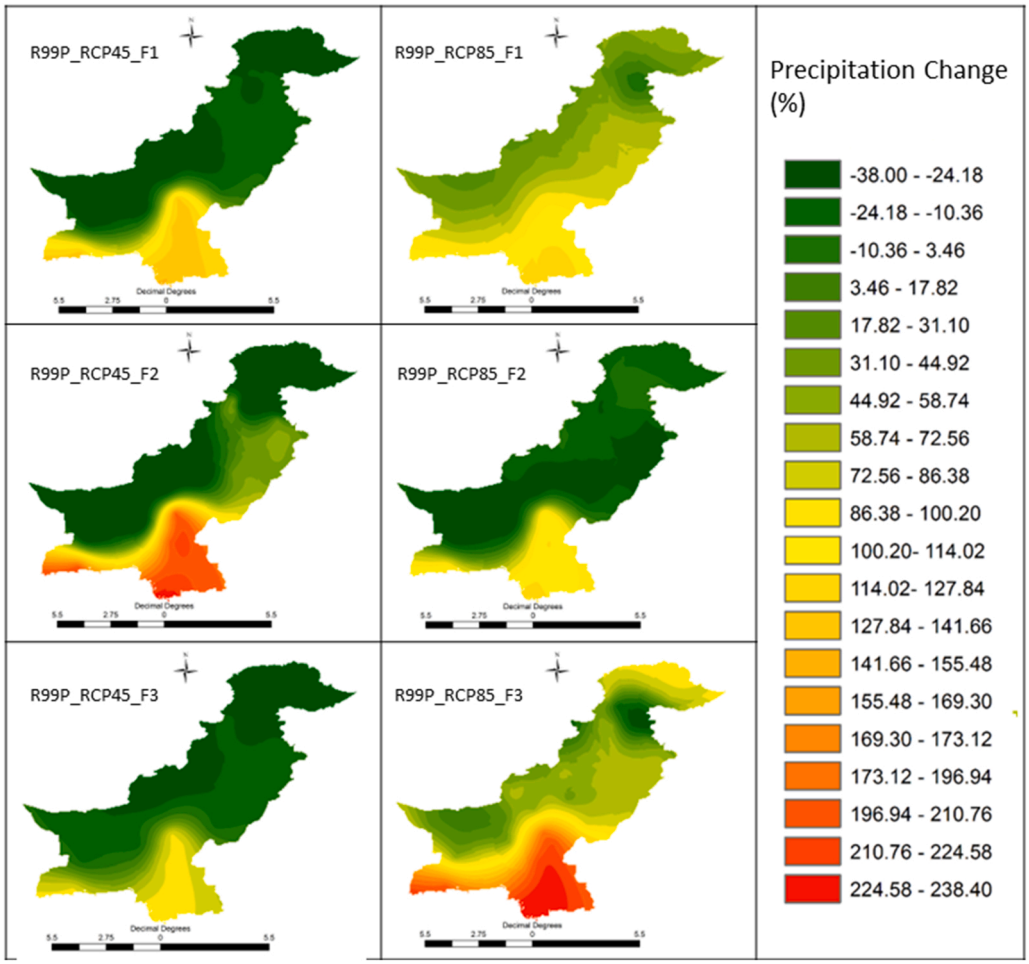

Fig. 7. Spatio-temporal distribution of percent changes in R99p over Pakistan in future periods (F1, F2, and F3) in comparison to the baseline duration for CanESM2 model under the RCP4.5 and RCP8.5. The left side is for RCP4.5 while the right-side panel is for RCP8.5.

of the country. Their findings further suggested that the frequency of heavy precipitation has significantly increasing trend over the north-western part of the country. Ali et al. (2019) projected climate extremes for the reference duration (1976–2005) and future durations (2006–2035, 2036–2065, 2066–2095) over six sub-region of Pakistan using daily data. Their results suggested that the consecutive wet days and consecutive dry days are increasing and decreasing in the future across the country generally and in the south-eastern part particularly. However, the sub-regions they considered in their study have no scientific background.

As the heavy precipitation increasing across the country and extremely heavy precipitation increasing significantly in the south-eastern part, therefore, there may be flooding and can damage human lives, infrastructure and crops. On the other hand, summer days and consecutive dry days are increasing across the country, while the consecutive wet days are decreasing. This may cause droughts in some parts of the country in the future and can further increase the demand of water for agriculture and other purposes. The decrease in cold nights and days and increase in warm nights and days indicate a warming climate in the future. The northern part of the country is rich with water resources (Himalaya-Hindukush-Karakoram = HKH), which may have severe consequences of this warming climate. The potential consequences include, glacial lake outburst flood (GLOF), floods due to higher snow and glacier melt, glacier surges and collapses (Muhammad and Tian, 2020) as this region is very sensitive to climate change. According to Archer (2003), with the increase of 1 °C increase in temperature can cause a 16–17 % increase in river flow in the Upper Indus Basin. The abrupt changes (increase/decrease) in river flow in the northern part of the country can disturb the supply-demand balance of water of the country and can be a disaster for hydropower, agriculture and infrastructure (Khadka et al., 2014). Shen et al. (2003) noted that short-term increase in temperature can cause GLOF. In addition, in the warming climate the snow and glaciers will melt at higher rate (Gul et al., 2017) and can not only disturb the current systembut also the glacier will lose their mass sooner (Sigdel et al., 2020). This needs special attention from government and relevant stakeholders to focus on mitigation and adaptation strategies for minimizing the impacts of climate change on snow and glaciers.

The other important region of Pakistan is the central-eastern part mainly comprised of Punjab province which is considers as food-basket for the country. The increase in heavy and extremely heavy precipitation can destroy cops and toll heavy cost to the

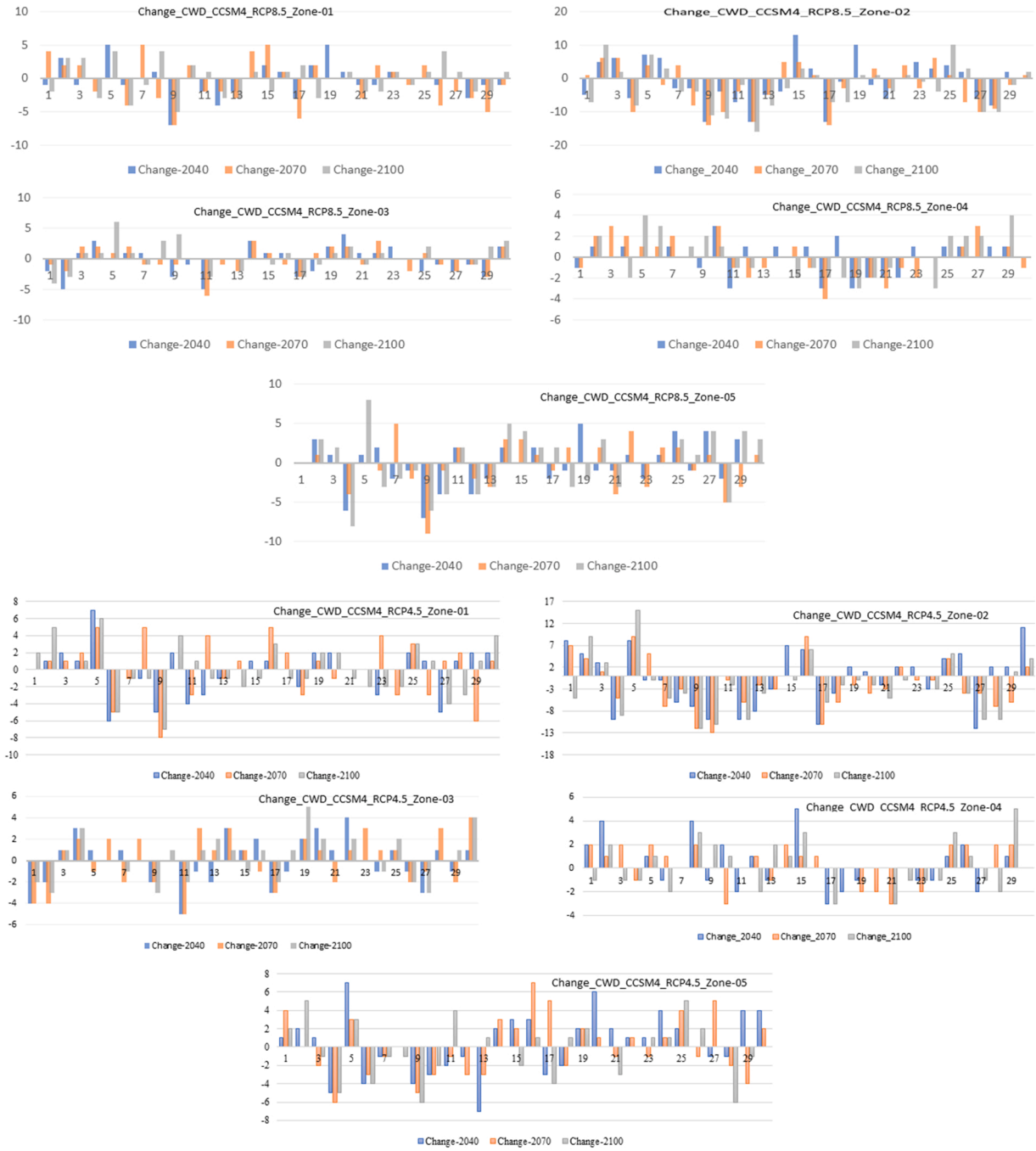

Fig. 8. Changes in the CWD during future durations in comparison to baseline period for RCP4.5 (upper 3 panels) and for CP8.5 (lower 3 panels). On x-axis, years are given (1−30) and on y-axis, the number of days changed are given.

infrastructure due to flooding situation in the future. As the warm days and nights are increasing while the cold days and cold nights are decreasing, therefore, the crops may need more water in future as compared to the requirement of today. In addition, the consecutive wet days and consecutive dry days are decreasing and increasing, respectively, which can further exacerbate the demand of water in the future. Beside all these problems, taking appropriate mitigation and adaptation measures and better management of available water resources can reduce the worse consequences of weather and climate extremes considerably in the future. This can further help to meet the UNDP' SDGs related to hunger, climate action and environment. FAO already stated in 2016 that the hunger level is constantly rising since 2014 and it may be difficult to meet zero hunger by 2030.

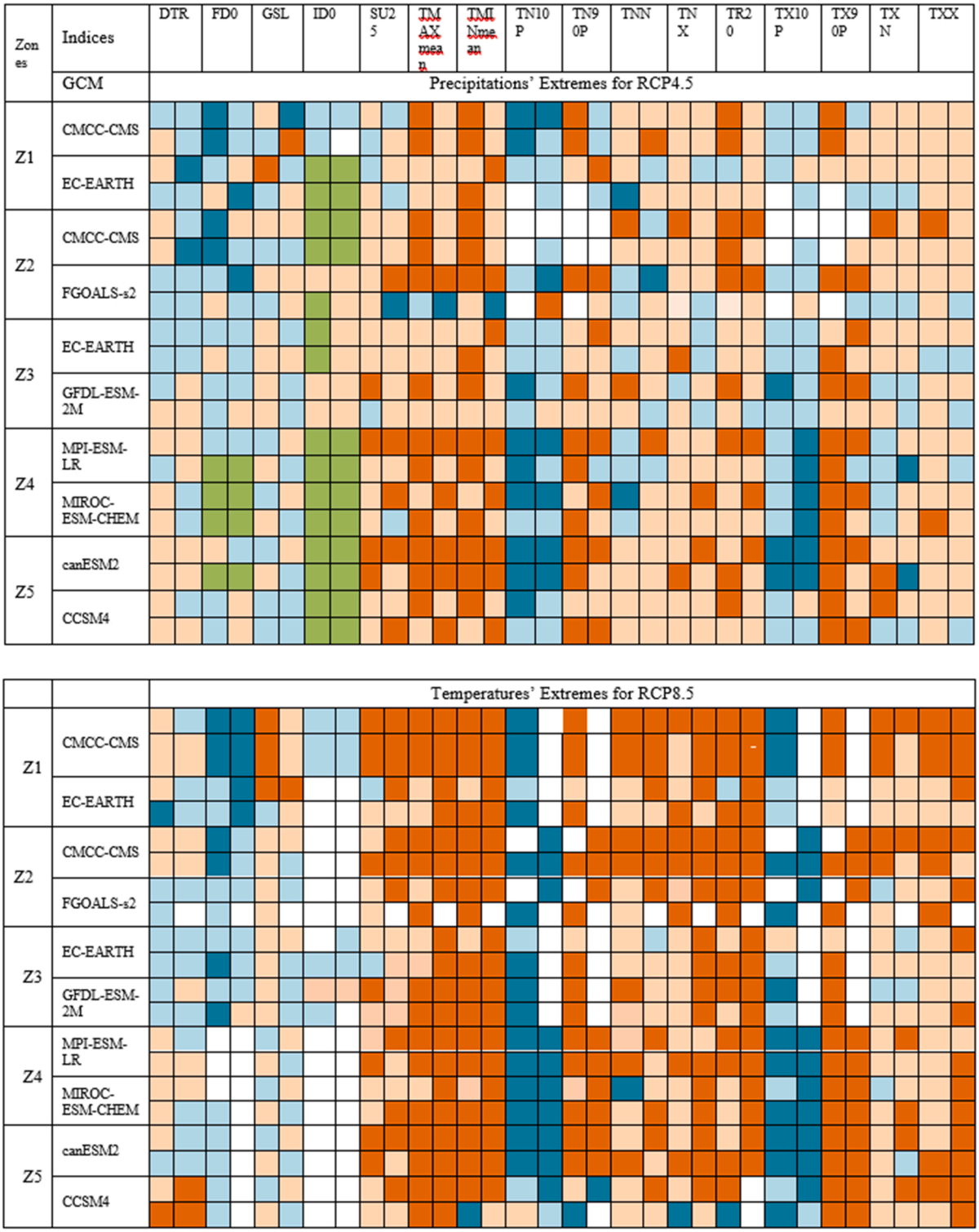

Fig. 9. Temperatures' extremes, their statistical significance and change (increasing/decreasing) for selected GCMs in each climate zone for both scenarios. There are four squares for each climate extreme index against the baseline, F1, F2 and F3 as defined at the end of Fig. 10. The definition given at the end of Fig. 10 is applicable to both Figs. 9–10.

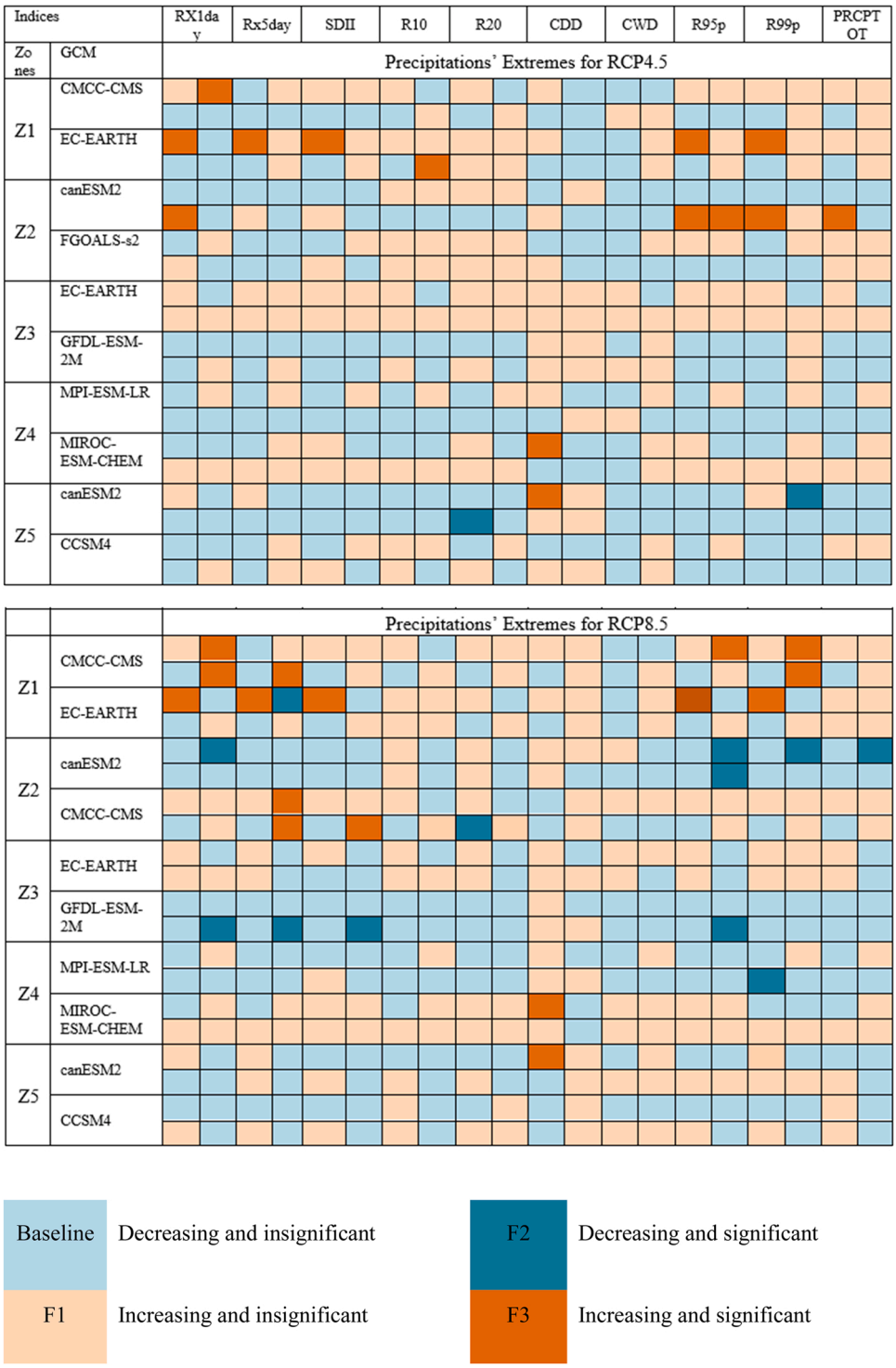

Fig. 10. Precipitations' extremes, their statistical significance and changes (increasing/decreasing) for selected GCMs for each climate zone under the RCP4.5 and RCP8.5. There are four squares for each climate extreme index for four time period, i.e., baseline, F1, F2 and F3 defined in the following note: *Note: There are four squares for each climate extreme index for four time durations,* i.e.*, baseline, F1, F2 and F3 defined below. The colors represent different status for different extreme events. Light aqua, dark aqua, light orange and dark orange show insignificant decrease, significant decrease, insignificant increase and significant increase, respectively. The same interpretation applicable to each climate extreme index for each GCM in each climate zone in* Figs. 9–10.

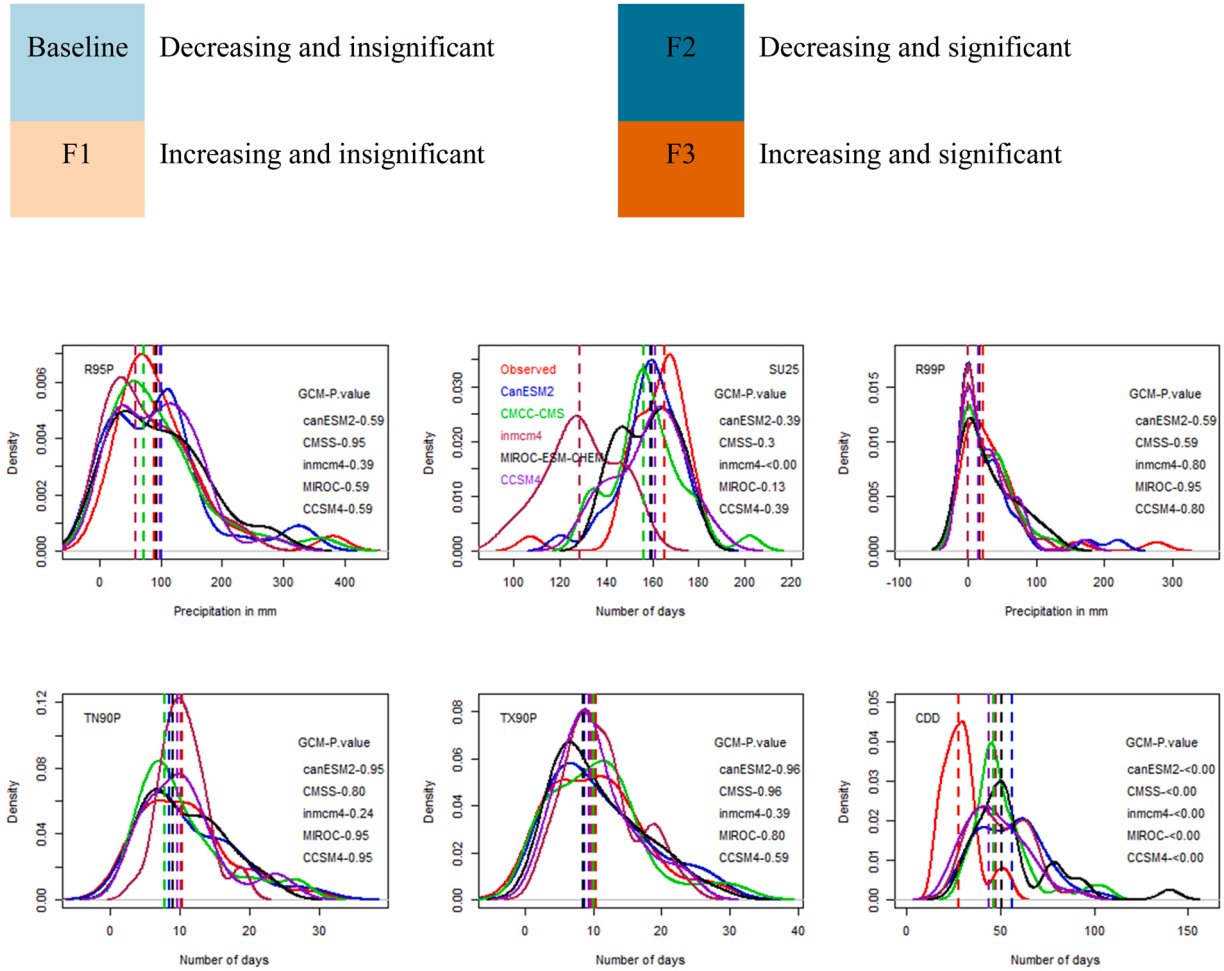

Fig. 11. Uncertainty in projected climate extremes using various GCMs for selected climate extremes during the reference period (1976–2005) using PDFs. The p-value of the K-S Test is given for each model in comparison to the observed data. The vertical lines show the median values of each data set.

6. Conclusions and recommendations

There is a clear shift (increasing) in total precipitation for CanESM2 model under the RCP4.5 in future except in zone 5 with an increase during F1 and F2 and a decrease during F3. Warm nights are mostly increasing in future with significant increase under RCP8.5. The number of warm days (TX90p) are increasing during F1 and F2 and decreasing during F3 for CMCC-CMS model. It has significantly increasing trend under both scenarios except few decreasing or insignificantly increasing trends. In contrast, TN10P and TX10P have decreasing trends under both scenarios in the future except a few exceptions of increasing trends. The trends in TX90P, TN90P, TN10P and TX10P indicate that there will warmer climate with more number extremes related to high temperature in the future.

Summer days are homogenously increasing for CanESM2 and CMCC-CMS models under both RCP4.5 and RCP8.5. The changes are apparent both in the number of mean days and in the variability of summer days. The number of summer days shows an increase with a minimum of 2 days and a maximum of 55 days in a year. The maximum increase is noted in the central-west part of the country during F3 under RCP8.5. The number of very wet days (R95p) are increasing in future except F3 for some climate zones. The spatial distribution of climate extremes of the extreme wet days (R99p) indicates a higher increase (in percent) in zone 4 during F2 and F3 under RCP4.5 and RCP8.5. In contrast, the overall extreme wet days in zones 1–3 are decreasing. There is a mixed trend in the number of warm nights in CanESM2 model. Maximum change is 2 days in zone 2 during F3 under the RCP4.5 and RCP8.5. The changes in the number of warm days have mixed trends throughout the country. The maximum increase is observed in zone 4 while maximum decrease in zone 1, 2 and 5.

The trend of climate extreme and their significance vary between climate zones of the country. The findings may help the government and policy makers in mitigation and adaptation strategies regarding climate change impacts in Pakistan. In addition, the results suggest to find connection between climate extremes in the high altitude areas contributing snow and glacier melt. This can

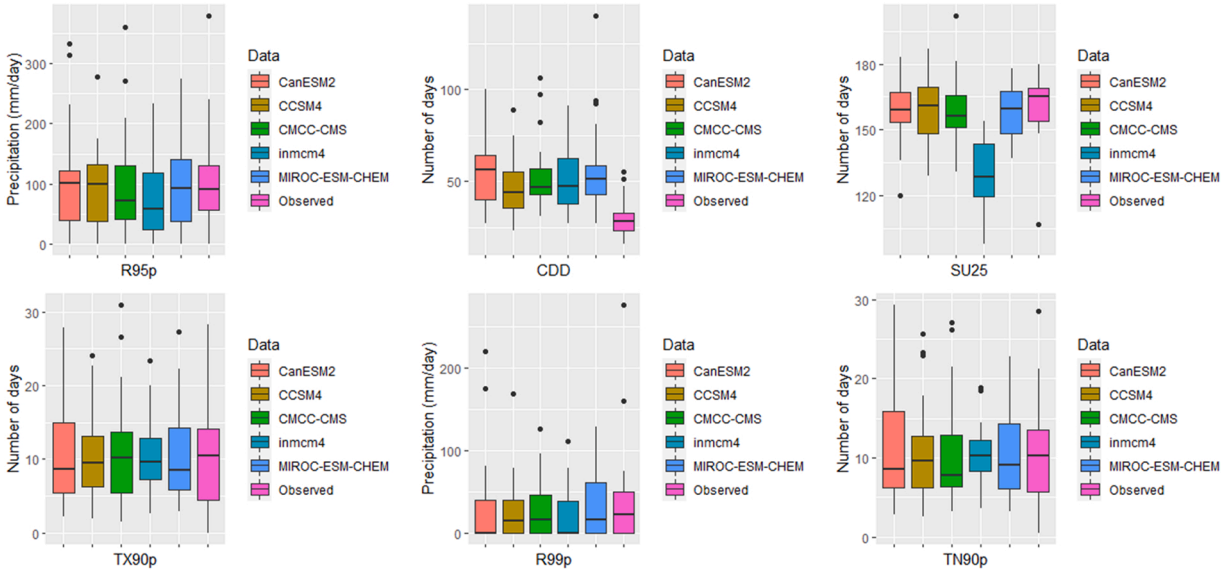

Fig. 12. A comparison between observed and downscaled climate extremes for different GCMs for the reference period (1976–2005) using box-whisker plots. This figure provide uncertainty among different GCM in comparison to observed data.

further help to analyze the future's contribution of snow and glacier melt due to climate extremes. Similarly, it may be interesting to investigate the potential impact of climate extreme on spatio-temporal distribution of rainfall in zone 2 (monsoon dominated region) which receives more than 80 % rainfall during monsoon (mid of June-mid of September) season. More importantly, it is suggested to investigate the potential impact of projected climate extremes on food security in zone 5. The remaining zone are mostly drought prone, therefore drought situation in zones 3–4 is the key future's research area. Further, we will need crops and foods which are resilient to projected climate in the future.

CRediT authorship contribution statement

Dr. Firdos started the idea of this paper, collected and analyzed data and wrote this paper. Dr. Shaukat helped in writing and ideas of the work. Mr. Hamd Ullah help in preparing the results. Dr. Sher contributed to writing and data analysis of this paper.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ejrh.2022.101295.

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