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ORIGINAL ARTICLE

Analysis of the changes in historical and future extreme precipitation under climate change in Adama city, Ethiopia

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Abstract

Under the conditions of climate change, extreme events occur more frequently with higher energy for devastation. Planning for effective management of climate-related risks demands clear information at the local scale. This study aims to characterize the extreme events in the daily precipitation records and to assess the changes under future climate conditions in flood vulnerable city of Adama. For this, the extreme rainfall events during 1965 and 2016 were analyzed on the basis of 10 selected extreme precipitation indices. Using a statistical downscaling model (SDSM), future daily precipitation in the city for the period 2021–2080 was downscaled from the outputs of two Global Circulation Models (CanESM2 and HadCM3) under five climate change scenarios. Taking the climate conditions during 1971 and 2000 as a base, changes in precipitation extreme events in future periods (2021–2050 and 2051–2080) were investigated using the delta approach. The study reveals that the extreme precipitation events in Adama city were increasing over the period of 1965–2016. The results also indicate a successful application of the SDSM for downscaling local-scale future daily precipitation from the outputs of large-scale atmospheric information for the study area. Moreover, under future climate change scenarios, the extreme precipitation would increase up to 2080, despite the changes will be highest during 2050 and 2080, indicates the study area could experience frequent and more severe floods during the coming 60 years due to the changes in global climate. This study would support planning for effective management of flood risks due to the impacts of climate change on extreme precipitation in Adama city.

Keywords Climate change · Sustainability · Statistical downscaling · Flood risk · Climate extreme

Introduction

The augmentation of climatic change due to global warming has become a major concern of climate scientists (Mekonen and Berlie 2019; Geremew et al. 2020). Climate change alters the frequency and intensity of extremes with high variability across the spatial scales. According to the report of the Intergovernmental Panel on Climate Change (IPCC), in many regions of the world, intensity and frequency of extreme precipitation events will increase until the end of this century (IPCC 2014). In Ethiopia, climate extremes have been considered as a major trigger for climate-related natural disasters (e.g., flood) (Mekasha et al. 2014; Dawit et al. 2019).

Information about extreme precipitation has a significant role in the management of flood risk effectively. Reliably identified the trend of extreme precipitation and its potential alteration in the future due to the changes in global climate allows to assess and model the influences of climate change on hydrological characteristics of a particular area (Supharatid et al. 2016; Mohammed et al. 2020). Consequently, it helps to identify potential risks at an early stage and supports planning for mitigation and adaptation. In most regions of the world, however, it is not yet possible to make concrete assessments of how climate change has affected extremes as compared to mean climate, and how it will modify extremes in the future (Basistha et al. 2009; Shang et al. 2011).

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In the context of Ethiopia, the trend of extreme precipitation in time-series records has been assessed for different areas of the country, such as Debre Markos town (Shang et al. 2011), north-east highlands of Ethiopia (Mohammed et al. 2018); upper Awash basin (Shawul and Chakma 2020); Northeastern Highlands of Ethiopia (Mekonen and Berlie 2019) and Northwest Ethiopia (Geremew et al. 2020). These studies emphasize that the trend of long-term precipitation extreme is less uniform when it comes to a smaller scale (local scale), indicating a small-scale analysis is necessary to adequately address the climate-related risks.

Climate information for the future period is projected by several global circulation models (GCMs) and readily available for the end of the twenty-first century, yet at a coarser resolution, 70 km or more (Gharbia et al. 2016; Deb et al. 2018; Navarro-Racines et al. 2020). Hence, it does not fit the desires of impact studies that usually demand climate information at finer-scale (tens or hundreds of square kilometers) (Pervez and Henebry 2014). As more emphasis is placed on evaluating potential circumstances for future climate change at the local scale, several researchers have downscaled long-term future climate conditions projected by GCMs using statistical downscaling methods (Abbasnia and Toros 2016; Shiferaw et al. 2018; Salvacion et al. 2018; Moses and Gondwe 2019). The statistical downscaling method assumes the present-day empirical relationship between the local observed climate variable (e.g., Precipitation) and its estimates by GCMs remains unchanged under the future climatic conditions. This method provides station-based climate information with a low computational cost (Wilby and Dawson 2013; Gharbia et al. 2016).

To this point, some attempts have been made to downscale the outputs of GCMs to provide the long-term future climate conditions in Ethiopia for hydrological applications (Dile et al. 2013; Samuale et al. 2014; Rukundo and Doğan 2016; Mohammed et al. 2020). However, the downscaling of GCMs estimates for cities is limited, although there is an example to the contrary (Feyissa et al. 2018). Given the importance of information about local climate conditions for the planning of sustainable management of risks posed by the changes in global climate, future changes in precipitation extreme under changing climate in flood vulnerable area, Adama city, deserves further analysis.

Hence, the aim of this study is to analyze the trend of extreme precipitation in Adama city and its future variability under climate change. More specifically, the study is conducted (1) to analyze the trend of extreme precipitation in Adama city over the period of 1965–2016; (2) to statistically downscale future daily precipitation from the estimates of GCMs for the years 2021–2080; and (3) to investigate the future changes in precipitation extreme in the city.

Materials and Methods

Study Area

Adama city is one of the fast-growing urban areas in Ethiopia with a population growth rate of about 9% between 2004 and 2016 (Bulti and Asefa 2019). The city is located at 8° 33′ north latitude and 39° 16′ east longitude. It is suited on the flat terrain of the Rift Valley and surrounded by mountains and ridged topography. Urban flood has been a regular feature of Adama City during rainy seasons with substantial damages (Bulti et al. 2017). Figure 1 shows the study area along with the nearby metrological stations. In this study, Adama observation station is selected as a representative station due to its location and available length of time-series precipitation data. The station is located at 8.55-degree latitude and 39.28-degree longitude with an altitude of 1622 m.

Data used

Data used in this study were collected from different sources. The daily rainfall data recorded at Adama weather observation station were obtained from the National Meteorological Agency (NMA). Due to extended missing observation (i.e., more than 1 year), only 52 years (1965–2016) time-series precipitation data were selected and acted on. First, the proportion of missing observation in the selected time-series data was checked and found to be 7.47%. It is within the maximum flexible threshold values adopted by other studies (Ngongondo et al. 2011; Mohammed et al. 2018). Next, the missing data were filled using the Kalman Smoothing function in R-based ImputeTS package. This function provides acceptable results and it is recommended for long time-series data (Steffen 2019).

In addition, three large-scale datasets (described below) were used: NCEP reanalysis dataset for the calibration and validation, and CanESM2 and HadCM3 datasets for the baseline and climate scenario generation. They are chosen because they are freely available online and predictors are organized in such a way that they can directly be used in the statistical downscaling model (SDSM) presented in Sect. 2.3.2. In addition, they have been widely applied in similar studies (Dile et al., 2013; Mekonnen and Disse 2018; Deb et al. 2018; Mohammed et al. 2020).

- *CanESM2* (second generation Canadian Earth System Model) is coupled atmosphere–ocean global climate model developed by the Canadian Centre for Climate Modelling and Analysis (CCCma). CanESM2 pro-

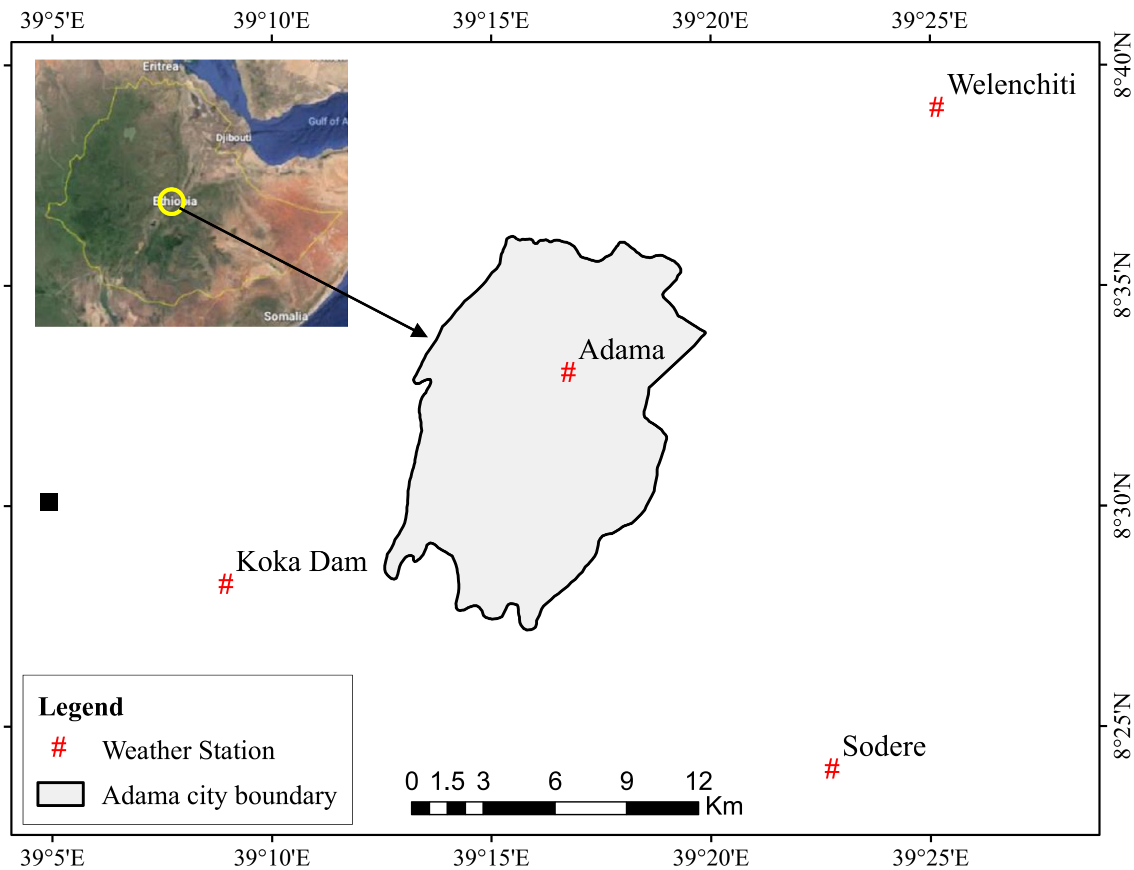

Fig. 1 Location map of the study area

vided long-term climate simulation based on the three greenhouse gases (GHG) emission scenarios (Representative Concentration Pathways, RCPs), including a stringent mitigation scenario (RCP2.6); medium stabilization scenario (RCP4.5) and high emission scenario (RCP8.5). The CanESM2 model has a resolution of 2.79^0 latitude and 2.81^0 longitude. More descriptions can be found in IPCC (2014).

- *HadCM3* (third-generation Hadley center Climate Model) is a coupled atmosphere–ocean general circulation model developed at the Hadley Centre in the United Kingdom. The model generated climate variable using two emission scenarios in the future atmosphere: medium–high (A2) and medium–low (B2). This GCM has a resolution of 2.5° latitude by 3.75° longitude. More description can be found in Semenov and Stratonovitch (2010).
- *NCEP* (National Centre for Environmental Prediction) reanalysis dataset contains large-scale atmospheric variables representing the present-day condition, and it was used for calibration and validation of the downscaling model in this study. The NCEP dataset was normalized over the complete 1961–1990 period data and interpolated to the equal grid as CanESM2 and HadCM3 from its horizontal resolution of 2.5° latitude and 2.5° longitude (Mekonnen and Disse 2018).

The archives of large-scale datasets were downloaded from the Environment Canada website (https://ccdsdscc.ec.gc.ca/?page=pred-canesm2) for the grid box containing the study area (CanESM2_BOX_015X_36Y and HadCM3_BOX_11X_31Y). The archive of CanESM2 include historical large-scale simulation data (CanESM2_historical_1961_2005) and predicted data corresponding to three emission scenarios (RCP2.6, RCP4.5 and RCP8.5) for the years 2006–2100. HadCM3 archive also includes data for both scenarios (H3A2a and H3B2a) spanning from 1961 to 2099 (the "a" in A2a and B2a refers the ensemble member in the HadCM3 A2 and B2 experiments). In addition, archives of both datasets contain reanalysis data (NCEP-NCAR_1961_2005 for CanESM2 and NCEP_1961-2001 for HadCM3). The datasets include 26 predictor variables under each of the emission scenarios of respective GCMs and reanalysis data. However, the NCEP-derived predictor's data and the predictors supplied for the GCMs were slightly vary (Table 1).

Table 1 Gridded predictors of CanESM2 and HadCM3 datasets

Variable	Description	Variable	Description
temp	Mean temperature at 2 m	s850[b]	Specific humidity at 850 hPa height
mslp	Mean sea level pressure	r850 [a]	relative humidity at 850 hPa height
p500	500 hPa geopotential height	*_f	Geostrophic air flow velocity
p850	850 hPa geopotential height	*_z	Vorticity
shum	Near-surface specific humidity	*_u	Zonal velocity component
rhum [a]	Near-surface relative humidity	*_v	Meridional velocity component
prec[b]	Total precipitation	*zh	Divergence
s500[b]	Specific humidity at 500 hPa height	*thas	Wind direction
r500[a]	Relative humidity at 500 hPa height		

[a]Found only for HadCM3

[b]Found only for CanESM2

*Refers to different atmospheric levels: the surface (p_), 850 hPa height (p8) and 500 hPa height (p5)

Methods

Analysis of extreme precipitation

Extreme precipitation indices Extreme precipitation in Adama city was analyzed using standard indices for the extreme precipitation defined by Expert Team on Climate Change Detection and Indices (ETCCDI). These indices are easy to calculate and understand, and they provide scientifically robust measures of the variability of rainfall extremes (Zhang et al. 2011). Moreover, they have been widely used in several similar studies in different regions of the world for recent years (e.g., Lima et al 2015; Gujree et al. 2017; Shawul and Chakma 2020; Berhane et al. 2020; Geremew et al. 2020). The definitions of the indices used in this study are presented in Table 2. The linear trends of the indices were computed from daily precipitation data using the R-based RClimDex software package, and the statistical significance of the trends was assessed at $\alpha = 0.1 \text{amd} \alpha = 0.05$.

Correlation analysis The linear relationship between extreme precipitation indices was also assessed using Pearson correlation analysis. In essence, it was conducted to compare the precipitation indices for mean conditions (SDII and PRECTOT) and other extreme indices. Such analysis may also help to identify the data with irregular behavior as a result of a few individuals, highly faulty daily values in time-series data, which affect overall data statistics (Santo et al. 2013); hence, it helped as an additional tool for examining the data closely. In this case, the correlation coefficient (r) was calculated to determine the extent to which the indices are linearly related. Based on the recommendation of Evans (1996), the strength of observed correlation was described: very weak ($|r| < 0.19$), weak ($|r| < 0.39$), moderate ($|r| < 0.59$), strong ($|r| < 0.79$), very strong ($|r| < 1$). The statistical significance of the correlations was determined using the two-tailed test of the Student's distribution and evaluated at the $\alpha = 0.05$ level.

Downscaling future precipitation

Statistical downscaling model (SDSM) The choice of the proper downscaling method relies on the needed temporal and spatial resolutions of the climate variability, as well as the resource and time constraints. In this study, the statisti-

Table 2 Definitions of indices for analysis of extreme precipitation in Adama city

ID	Indicator name	Indicator definitions	Units
PRECTOT	Annual total wet-day precipitation	Total wet-day precipitation ≥ 1 mm	mm
SDII	Simple daily intensity index	Mean precipitation amount on wet-day (≥ 1 mm)	mm/day
Rx1day	Max 1-day precipitation amount	Maximum 1-day precipitation	mm
Rx5day	Max 5-day precipitation amount	Maximum 5 consecutive days precipitation	mm
R10	Number of heavy precipitation days	Annual count when precipitation ≥ 10 mm	days
R20	Number of very heavy precipitation days	Annual count when precipitation ≥ 20 mm	days
CDD	Consecutive dry days	Maximum number of consecutive days when precipitation < 1 mm	days
CWD	Consecutive wet days	Maximum number of consecutive days when precipitation ≥ 1 mm	days
R95p	Very wet days	Annual total precipitation from days > 95th percentile	mm
R99p	Extremely wet days	Annual total precipitation from days > 99th percentile	mm

cal downscaling model (SDSM) was selected to downscale local daily precipitation from the outputs of selected GCMs. The structure of the model for climate scenario generation is depicted in Fig. 2. The downscaling experiment was realized using SDSM4.2 software. It is a freely available Windows-based decision support tool for generating single-site daily climate variables under the current and future regional climate forcing (Wilby and Dawson 2007). It provides a robust scenario building technique for a specific location for which there are archived GCMs outputs and adequate observed daily local variable for calibrating the model (Gebrechorkos et al. 2019). In general, downscaling experiment using SDSM in this study involves the selection of candidate predictors; model calibration and validation; and synthesizing future precipitation.

Selection of predictors Statistical downscaling methods require appropriate large-scale atmospheric variables that enable identification of robust empirical associations between gridded predictor variables and site-scale predictands. However, choosing a predictor is one of the most challenging tasks, as the explanatory power of each variable varies in both spatial and temporal scales, indicating the selection process can be exposed to some level of subjectivity. To reduce this, a quantitative approach presented in other similar studies (Huang et al. 2011; Mahmood and Babel 2014), was used to examine the predictive variables.

Initially, the correlations between the daily rainfall (predictand) and each of the 26 NCEP atmospheric variables

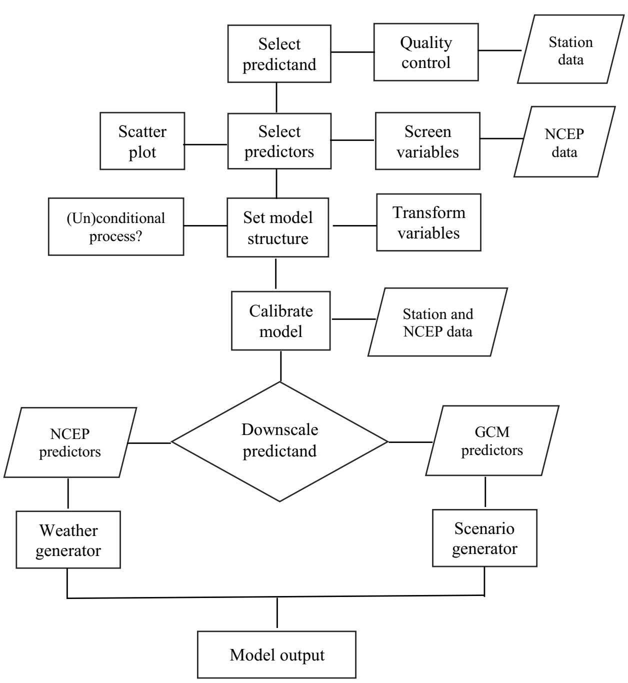

Fig. 2 SDSM Version 4.2 climate scenario generation, adapted from Wilby and Dawson (2007)

were identified. Then, 11 variables with relatively large values of absolute correlation were selected, from which the variable with the highest correlation coefficient is assigned as a superior predictor (SP). Then, the absolute correlation between predictor variables (r), the partial correlation coefficient (Pr) and the P values were determined in the presence of *SP*. Then, the percentage reduction (PR) for each variable was calculated using Eq. 1. The second candidate predictor was determined using a combination of the correlation coefficient (r), p value and the percent reduction (PR). In this case, a predictor with, $r < 0.7$, $p < 0.05$, and minimum PR. By repeating this procedure, further additional predictors were selected. Due to variation in the supplied predictors for the two GCMs, two sets of predictors were selected one for each GCM for calibration of the models. In most cases, 3–5 predictors are considered sufficient to detect the variation of a predictand during SDSM calibration (Chu et al. 2010; Feyissa et al. 2018). Because in the regression equation, an increase in the number of predictors can increase the probability of multiple co-linearity (Mahmood and Babel 2014):

$$\mathrm{PR} = \frac{(\mathrm{Pr} - r)}{r} \times 100. \tag{1}$$

Model calibration and validation Using the respective sets of selected NCEP predictors, two precipitation models (for each of the GCMs) were developed under conditional processes on the monthly timescale with a fourth root transformation of the predictand. The models were calibrated for daily rainfall data observed over the period of 1965–1990, and used for historical rainfall generation (i.e., downscaling of NCEP reanalysis data). The models were validated over the years 1990–2005 (CanESM2) and 1990–2001 (HadCM3). The variation of the length of the validation periods is due to the availability of NCEP data corresponding to the GCMs. The performance of the models was evaluated using graphical and statistical methods. First, the models were validated by plotting the observed against simulated monthly mean precipitation. Second, two statistical parameters: the coefficient of determination (R^2) and the ratio of the standard deviation of the simulated data to the observed data (RSD) were used. RSD indicates the level of dispersion, and its optimum value is 1, suggests that both datasets (simulated and observed) have the same kind of (Mahmood and Babel 2014; Moses and Gondwe 2019). Both parameters are computed using daily and monthly average precipitation data of observed and downscaled reanalysis data (NCEP_CanESM2 and NCEP_HadCM3).

Climate scenario generation The calibrated model was used for the generation of ensembles of the daily precipitation corresponding to the future period. Using predictors of the respective GCMs, future daily rainfall was generated under five climate change scenarios (H3A2a and H3B2a of HadCM3 and RCP 2.6, RCP4.5 and RCP8.5 of CanESM2).

Analysis of future changes in precipitation extreme

Future changes in extreme rainfall under climate change scenarios were assessed on the basis of four indices that were included in SDSM4.2. They are the annual percentage of wet-days (wet-days%), the ratio of the sum of the values over the 95th percentile of the sum of all values (POT95), longest wet-spell (CWD) and annual total precipitation (PRECTOT). The event limit was set to 1 mm/day to count the rain day with less than 1 mm as dry day.

The future changes in the indices were computed using the delta approach. It is a widely used method in similar studies (Choi et al. 2009; Salvacion et al. 2018; Feyissa et al. 2018). The standard delta approach for precipitation is the relative difference between GCM-simulated precipitation of the future and baseline periods, and takes the form of Eq. 2. The analysis of the changes over the future period was carried out by dividing into two-time horizons: 2020s (2021–2050) and 2050s (2051–2080). The present-day estimate (1971–2000) was considered as a base for standardizing the time-series resulting from climate change. Such an approach helps to reduce the systematic bias in the mean and variance of GCMs predictors (Wilby and Dawson 2007):

$$\Delta_{\mathrm{Pi}} = \frac{V_{\mathrm{Pi}} - V_{\mathrm{base}}}{V_{\mathrm{base}}} \times 100. \tag{2}$$

where: V_{base} is the mean of all ensembles of each index for the base period (1971–2000). V_{Pi} is the mean of all ensembles of the corresponding index for the future periods (2020s, 2050s).

Results

Trend of extreme precipitation from 1965 to 2016

Trends of extreme precipitation indices

The computed annual statistics and trends of the selected extreme precipitation indices in Adama city over the period of 1965–2016 are summarized in Table 3. The graphical illustration of the trend of corresponding indices is also depicted in Fig. 3. Overall, the results show that there were statistically significant trends in the majority of the indices in the study period. The computed values of six indices (60% of the analyzed indices) showed a rising trend, while the rest of the indices showed a declining trend over the span of 52 years. The p-value statistics shows that the observed trends of seven indices were significant. In contrast, no sufficient evidence was found to support the upward trend of R95p and downward trends of Rx1day and R99p.

Table 3 Statistical parameters and trends of extreme precipitation indices in Adama city from 1965 to 2016

Indices	Annual statistical parameters			Trend test	
	Minimum	Maximum	Mean	Trend (per 10 years)	*p* value
PRECTOT (mm)	578.4	1357.6	868.7	30.69	0.061**
SDII (mm)	4.7	15.8	10.7	0.37	0.075**
Rx1day (mm)	30.7	104.8	61.4	− 0.89	0.587
Rx5day (mm)	61	190.1	111	5.24	0.053**
R95p (mm)	0	558.2	206	13.4	0.194
R99p (mm)	0	221.3	51.1	− 1.91	0.723
R10 (no of days)	10	46	28.4	1.33	0.056**
R20 (no of days)	2	29	13.3	1.11	0.026*
CDD (no of days)	25	148	74.7	− 5.72	0.061**
CWD (no of days)	3	70	10.3	− 2.45	0.014*

* Significant at $\alpha = 0.05$; ** significant at $\alpha = 0.1$

On average, the study area received 868.7 mm annual total precipitation over the study period. The values were increasing at a rate of 30.69 mm/decade. Likewise, the amount of mean precipitation on a wet-day (SDII) varied from 4.7 to 15.8 mm. The values were increasing by 0.37 mm every 10 years over the study period. The observed rising trends of both indices were statistically significant ($\alpha = 0.05$).

With regard to the two absolute extreme indices (Rx1day and Rx5day), the results show that there was remarkable variation in the amount of the indices: Rx1day (30.7–104.8 mm) and Rx5day (61–190.1 mm). The highest 1-day precipitation was decreasing at the rate of 0.89 mm/decade, yet the trend is not statistically significant. On the other hand, the maximum precipitation of consecutive 5-days was showing significant ($\alpha = 0.1$) increasing trend (5.24 mm/decade) during the study period.

The results also show the values of the non-fixed (percentile) threshold indices, which represents a fraction of the total annual rainfall on wet-days attributed to the 95th and 99th percent rainfall events. Very wet-days (R95p) showed a tendency to increase, whereas extremely wet-days (R99p) decreased over the study period. However, the observed trends in both cases are not statistically significant. The annual mean values of both percentile indices were 206 mm (R95p) and 51.1 mm (R99p). The values of the indices were

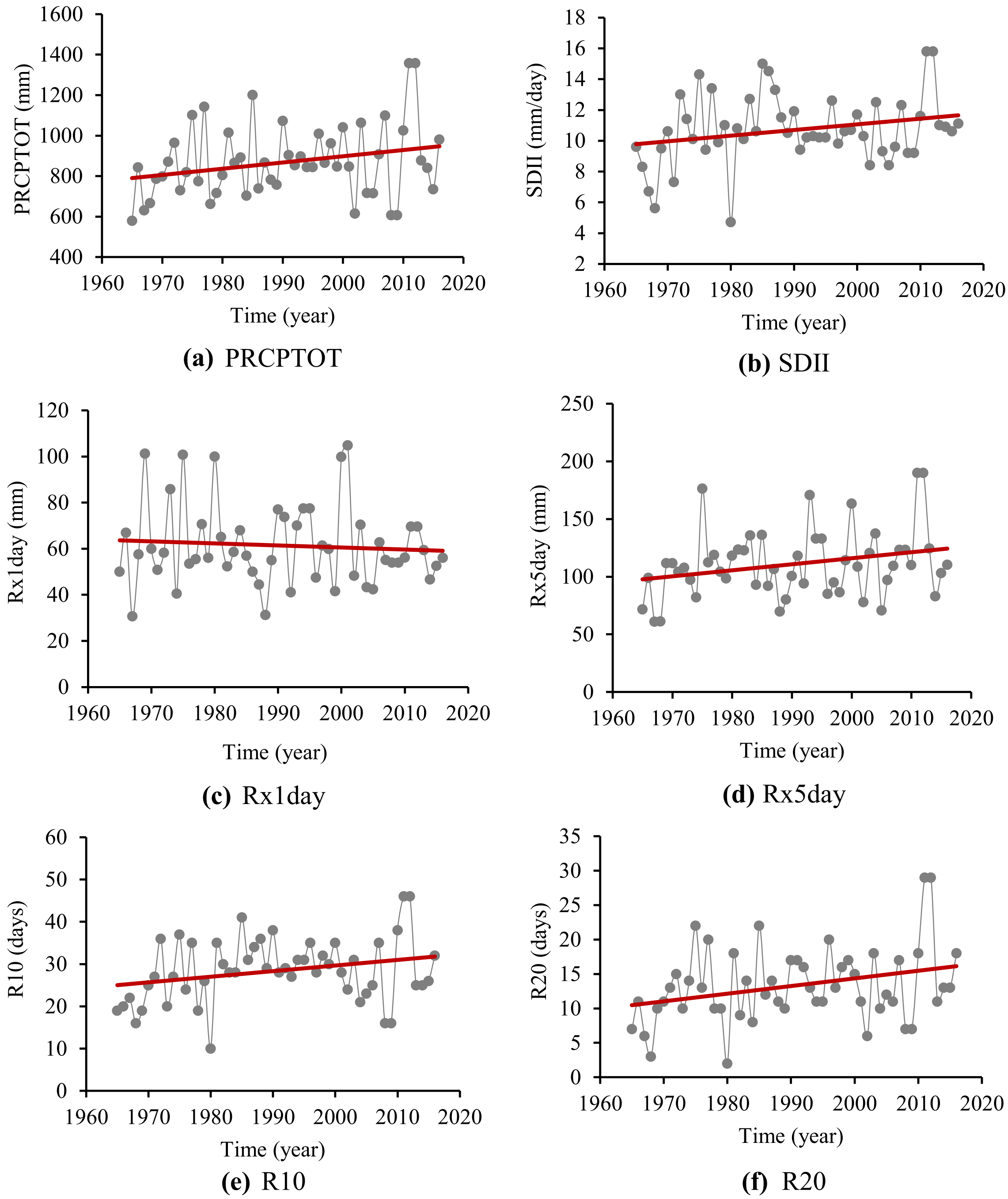

Fig. 3 Trends of standard extreme precipitation indices in Adama city between 1965 and 2016

increasing (R95p) and decreasing (R99p) over time, respectively, yet the trends were not statistically significant.

Furthermore, it can be seen that the annual count of days with precipitation greater than fixed thresholds (heavy rainfall days and very heavy precipitation days) was increasing over the study period, ranging 10–46 days (R10) and 2–29 days (R20). The values were increasing at the rate of 1.33 days/decade for R10 and 1.11 days/decade for R20 at $\alpha = 0.1$ and 0.05 significant levels, respectively. Likewise, the two spell indices (maximum length of consecutive days with a rainfall below and above 1 mm) showed a tendency to decline over time. The values were decreasing at the rate of 5.72 days/decade (CDD) and 2.45 days/decade (CWD). The observed decreasing trends in both cases are also found to be statistically significant at $\alpha = 0.1$ and 0.05, respectively.

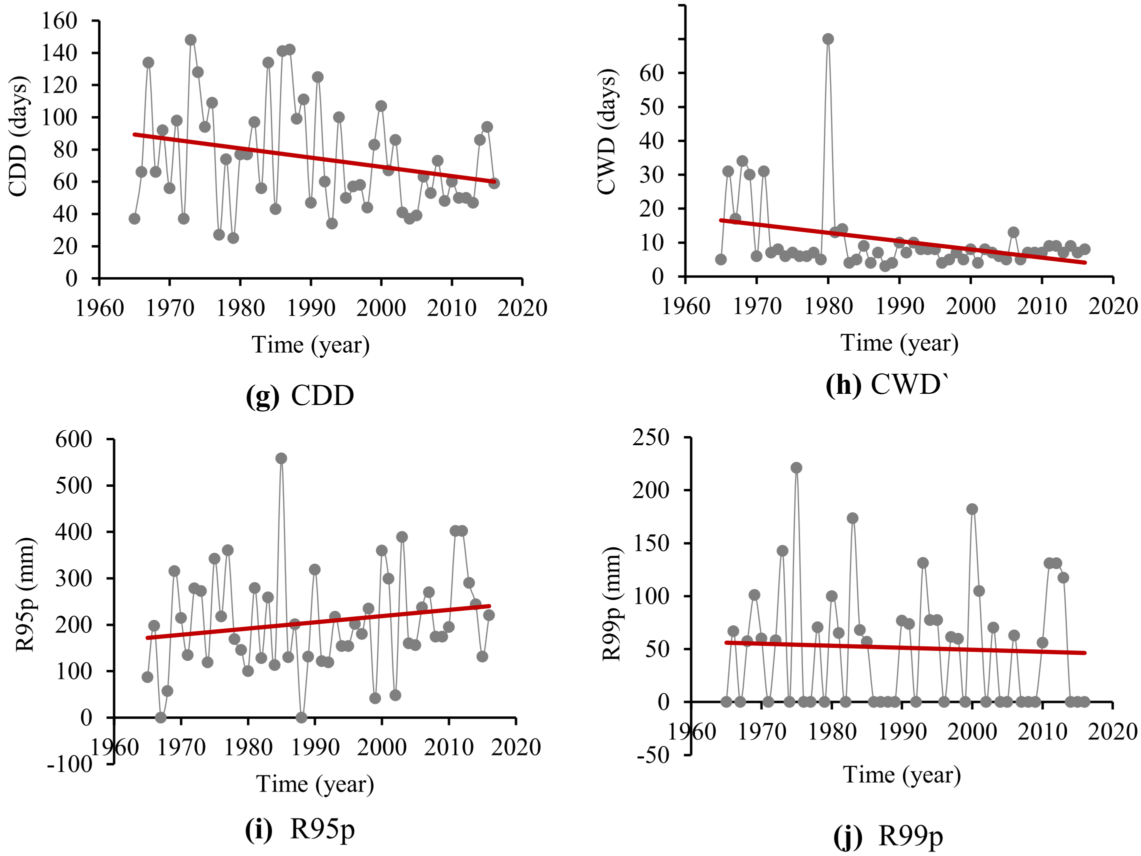

Fig. 3 (continued)

Correlation between extreme precipitation indices

The computed values of the correlation coefficient indicating the level of the linear relationship between the changes in the analyzed indices are shown in Table 4. Overall, the results show that most of thhhe extreme rainfall indices are correlated, although the strength of the correlation varies from moderate to very strong. However, the correlation of the CDD index with other indices is found to be weak ($|r| < 0.39$). In addition, CDD is negatively correlated with the analyzed indices. Moreover, a statistically significant positive correlation is found between the pattern of PRECTOT and other indices except Rx1day and CWD. Likewise, the observed positive correlations of SDII with the four indices (Rx5day, R10, R20 and R95p) and the

Table 4 Summary correlation analysis between the selected extreme precipitation indices in Adama city from 1965 to 2016

	PRECTOT	SDII	Rx1day	Rx5day	R10	R20	CDD	CWD	R95p	R99p
PRECTOT	1									
SDII	69.8*	1								
Rx1day	26.4	5.3	1							
Rx5day	62.4*	50.2*	48.8*	1						
R10	83.4*	82.1*	− 0.6	43.3*	1					
R20	89.7*	79.8*	6.2	56.3*	85.9*	1				
CDD	− 29.9*	− 11.8	1.4	− 22.4	− 11.6	− 23.3	1			
CWD	− 8.5	− 57.5*	31.7*	− 5	− 44.5*	− 36.0*	5.8	1		
R95p	75.8*	66.1*	46.5*	61.4*	51.9*	66.4*	− 34.8*	− 14	1	
R99p	41.8*	26.7	78.4*	63.1*	19.8	26.5	− 4	12.6	52.4*	1

*Correlation is significant at the 0.05 level

Table 5 Candidate predictors for calibration of SDSM

Short name	Long name	CanESM2	HadCM3
s500	Specific humidity at 500 hPa height	√	
r500	Relative humidity at 500 hPa height		√
p5_u	Zonal velocity component at 500 hpa	√	
p5_v	Meridional velocity component at 500 hPa height		√
shum	Near-surface specific humidity	√	√
p8_z	Vorticity at 850 hPa	√	
p8zh	Divergence at 850 hPa height		√
prcp	Total precipitation	√	

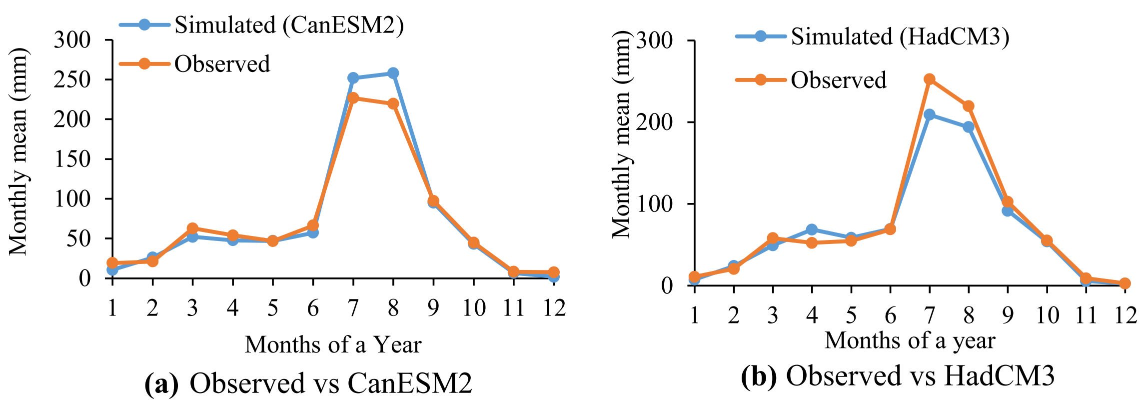

Fig. 4 Observed versus simulated monthly mean precipitation for the period of **a** 1991–2005, **b** 1991–2001

negative correlation with CWD are also significant at the selected level of the analysis.

Future precipitation

Selected predictors for SDSM

With the procedures described in Sect. 2.3.2, the candidate predictors shown in Table 5 were selected for calibration of SDSM for a downscaling experiment in this study. In the process of screening predictors, specific humidity at 500 hPa height (s500) and divergence at 850 hPa height (p8zh) were identified as super predictors for CanESM2 and HadCM3, respectively. Using these, additional four predictors from CanESM2 and three predictors from HadCM3 were selected.

Performance of SDSM

The performance of the downscaling model calibrated using the respective sets of selected predictors was evaluated on the basis of graphical and statistical parameters. Figure 4 illustrates the graphs of the monthly mean observed and the downscaled reanalysis data for each month of validation periods. It can be seen from the graphs that there is a

Table 6 Performance assessment of SDSM during validation periods: 1991–2005 for NCEP_CanESM2 and 1991–2001 for NCEP_HadCM3

	NCEP_CanESM2		NCEP_HadCM3	
	Daily	Monthly	Daily	Monthly
R^2	0.088	0.992	0.100	0.986
RSD	0.49	1.17	0.51	0.84

good agreement between the generated and observed values of precipitation, except a slightly overestimate for July and August in the case of CanESM2 and underestimate for HadCM3.

The computed values of the coefficient of determination and the ratio of the standard deviations of simulated to observed time-series data are summarized in Table 6. The values of RSD show that the variations in monthly data are about the same in both GCMs. However, it can be seen that the values of the parameters computed from the daily time-series are relatively lower than the results of monthly time-series data, indicating the monthly variations are better captured by the SDSM. This is due to the fact that the amount of daily precipitation at a specific site is poorly determined by the regional climate forcing. Hence, the results of the statistical parameters obtained in this study are quite respectable. In general, the overall evaluation of the SDSM performance suggests that the agreement between simulated and observed data is satisfactory, indicating a potential application of the calibrated model for downscaling future daily precipitation from the outputs of the two GCMs for the study area.

Future annual precipitation scenarios

The future daily precipitation was downscaled from the outputs of the selected GCMs under five climate change scenarios. Figure 5 shows the plots of annual future precipitation (aggregated from daily values) in Adama city from 2021 to 2080. The statistical parameters summarized in Table 7 provides the descriptive information about future annual rainfall scenarios in Adama city from 2021–2080. Overall, the results show that the city will receive remarkable annual precipitation over the coming 60 years. The range of future annual precipitation is greater under the scenarios of CanESM2 than that of HadCM3 in which the highest annual mean rainfall is projected. In addition, it can be seen from Fig. 5 that under all climate change scenarios, the maximum annual rainfall is expected in the far-future period (2050s).

Regarding the two ends of each statistic, the information summarized in Table 7 shows that the city expects the maximum annual precipitation between 1065.8 mm (H3A2a) and 2251.6 mm (RCP8.5) over the coming 60 years, whereas the minimum rainfall ranging from 445.7 mm (RCP2.6) to 717.7 mm (H3A2a) is predicted within the same period. In addition, maximum and minimum values of mean annual rainfall varies between 907.1 mm (H3A2a) and 670.8 mm (RCP4.5). Further, with reference to the values of standard deviations, it can be viewed that the relative dispersion in the annual precipitation is about the same for the two scenarios of HadCM3. However, in the case of the scenarios of CanESM2, dispersion in annual rainfall under RCP8.5 is higher than the other two scenarios (RCP2.6 and RCP4.5) which showed about similar dispersions.

Table 7 Statistics of future annual precipitation in Adama city over the years 2021–2080 under the five climate change scenarios

	Annual precipitation			
	Maximum	Minimum	Mean	Std. dev.
CanESM2				
RCP2.6	1358.9	445.7	716.6	180.8
RCP4.5	1580.2	501.5	670.8	161.1
RCP8.5	2251.6	512.0	762.7	253.6
HadCM3				
H3A2a	1123.3	717.7	907.1	84.9
H3B2a	1065.8	693.2	879.7	84.1

Future changes in extreme precipitation

With future daily precipitation data, the likely changes of precipitation extreme in the near-future (2020s) and far-future (2050s) periods under five scenarios were assessed with respect to the conditions during 1971–2000. Table 8 shows the computed future changes of extreme precipitation indices: wet-day%, POT95, CWD and PRECTOT. Overall, the future changes of the selected indices are found to be increasing under the majority of climate change scenarios over the analysis period, despite the magnitude significantly vary between GCMs, scenarios and time-windows.

Each of the three scenarios of CanESM2 projected to consistently increasing changes over the years 2021–2080 with different ranges across the indices: wet-days% (11.2–23.1%), POT95 (4.7–23.9%), CWD (9.1–32.5%), PRECTOT

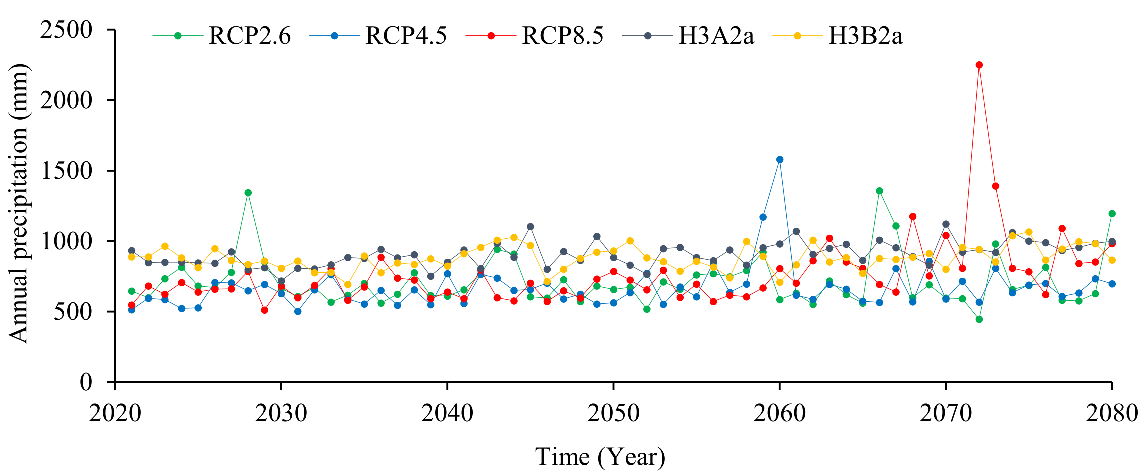

Fig. 5 Annual rainfall in Adama city based on the projection of CanESM2 and HadCM3 for the period of 2021–2080

Table 8 Percentage change of extreme precipitation indices in the future (2021–2080) with reference to a base period (1971–2000)

Model/scenarios	Time-zone	Wet-days%	POT95	CWD	PRECTOT
CanESM2					
RCP2.6	2020s	12.9	14.6	9.1	28.2
	2050s	13.8	17.9	15.2	31.1
RCP4.5	2020s	11.2	4.7	14.7	13.1
	2050s	14.2	16.1	32.5	29.6
RCP8.5	2020s	13.8	8.6	16.2	20.8
	2050s	23.1	23.9	28.9	55.1
HadCM3					
H3A2a	2020s	− 2.2	0.0	9.8	2.5
	2050s	1.5	0.3	25.6	10.5
H3B2a	2020s	− 0.5	− 0.2	20.6	2.5
	2050s	− 1.3	− 0.5	42.4	5.4

(13.1–55.1%). In addition, the difference between the projection of RCP2.6 and RCP4.5 will decrease in most of the analyzed indices in the far-future (2050s).

With regard to HadCM3, the consistency of increasing changes was observed throughout the study period, except in the case of wet-days% and POT95 corresponding to H3B2a. In addition, the ranges of the changes projected by H3A2a and H3B2a scenarios for the analyzed indices are relatively small, except for CWD. H3B2a projected wet-days% and POT95 decrease throughout the study period, despite the changes are small.

With the exception of CWD, CanESM2 offers maximum values of the indices in both analysis periods. In addition, the projected change by both models are more significant in the far-future, but for H3B2a results for wet-days% and POT95. In the 2020s, RCP2.6 showed a maximum of two indices (PRECTOT, POT95), while in the 2050s, excluding CWD, the maximum in the selected indices changes were made via RCP8.5.

In all analyzed scenarios, the increase in CWD and PRECTOT indices is predicted. The maximum and minimum changes in CWD are 42.4% (H3B2a) and 9.1% (RCP2.6), respectively. With respect to the results of each model, the maximum value for CWD in CanESM2 is equal to 32.5% corresponding to RCP4.5 in the 2050s. The maximum change in total annual precipitation is also predicted to be 55.1% (RCP8.5) in 2050s, while the minimum value is predicted by the two scenarios of HadCM3 and equal to 2.5%.

Discussion

In general, the results reveal that most of the extreme rainfall indices, including Rx5day, SDII, R10, R20, R95p and PRECTOT showed a statistically significant upward trend over the years 1965–2016. Some of the findings are slightly different from the results reported by Shawul and Chakma (2020) for the rainfall time-series (1980–2012) in the upper Awash basin in which Adama station belongs. The authors reported a negative trend for SDII and R20, and no statistically significant trend for R10 over the study period for Adama station. The disparity between the findings of the present study and that of Shawul and Chakma (2020) could be because of the different periods analyzed. It has been argued that the length of climate records is an important factor that affects the probability of identifying trends in any given time-series data. In the present study, rather long period has been analyzed, which may include different trends within different sub-periods. The results of this study suggest that the extreme precipitation in Adama city was increasing over the past 52 years, which could explain the notable impacts of climate change. Furthermore, consistent with Lima et al. (2015), a statistically significant correlation is found between PRECTOT and SDII and other indices. This indicates the trends of annual total and average daily precipitation of wet-days were changing with the changes in the trends of most of the extreme precipitation indices.

The performance of the downscaling model used in this study was also found to be good in predicting the daily precipitation during the validation period. The results are comparable to that of studies conducted to inspect the impacts of climate change on future precipitation extremes in Addis Ababa city (Feyissa et al. 2018) and Amhara Regional State (Ayalew et al. 2012). The results indicate a successful application of the SDSM for downscaling local-scale daily precipitation from the estimates of large-scale atmospheric information for the study area.

Future changes in extreme precipitation in Adama city are also another important finding of this study. Under all scenarios of the GCMs, almost all of the analyzed extreme precipitation statistics will increase up to 2080, despite the changes will be higher in the far-future (2050–2080) than near-future (2021–2050). The changes in wet-day%, POT95 and PRECTOT could reach 23.1%, 23.9%, and 55.1%, respectively and predicted by the worst scenario of CanESM2. The changes in the longest wet-spell will also increase by 42.4% that projected by the worst scenario of HadCM3. The results suggest that the study area is expected to receive more severe extreme precipitation events over 2021–2080 as compared to the condition during 1971–2000. In accordance with this result, Feyissa et al. (2018) reported the extreme precipitation in Addis Ababa city will increase over the twenty-first century, while the present study is pertaining to Adama city which has been little explored. With a high rate of urbanization in Adama city that has expanded built-up area at the cost of agricultural land in the upper watershed area of the city administration (Bulti and Abebe 2020), the future increase of extreme precipitation events can produce high runoff, thereby increases the chance of more severe floods to occur.

Given the importance of improved understanding of the trend of extreme precipitation in planning for sustainable flood risk management, the findings of this study can serve as a springboard for decision-makers for early identification of potential impacts due to predicted changes. For mitigation planning, it is ideal to consider the changes under the worst scenario; however, it could not be always possible due to the existing limited resources. In this regard, the results presented here can support the analysis of alternative responses to the impacts of climate change under different scenarios. Moreover, the results could also be used in various modeling studies (e.g., Flood modeling) to assess the impacts of future climate conditions.

Conclusions

The intent of this study was to provide information about the characteristics of extreme precipitation events in the observed daily precipitation records in flood vulnerable city of Adama and its changes under future climate conditions. For this, the extreme rainfall in Adama city during 1965–2016 was analyzed based on the trends of 10 selected precipitation extreme indices computed from daily time-series records. Using SDSM, the projections of GCMs (CanESM2 and HadCM3) under 5 climate change scenarios were downscaled to provide daily precipitation in the study area for the period 2021–2080. Taking the climate conditions during 1971–2000 as a base period, future changes in extreme precipitation were investigated using delta approach.

The study reveals that the extreme precipitation events in Adama city were increasing over the period of 1965–2016. The results also indicate a successful application of the SDSM for downscaling local-scale future daily precipitation from the outputs of large-scale atmospheric information for the study area. Moreover, under future climate change scenarios, the extreme precipitation would increase up to 2080, despite the changes will be higher during 2050–2080. The findings infer that as compared to the past period, Adama city could experience frequent and more severe floods during the coming 60 years due to the changes in global climate.

The length and quality of time-series records used and the variety of precipitation extreme indices examined here allowed to describe the structure and changes of extreme precipitation over the past 52 years in Adama city. Moreover, the important large-scale datasets (i.e., quality of predictors and climate change scenarios), the downscaling model and the statistics/indices used in this study enabled to examine the changes in extreme precipitation under future climate conditions in the city. The findings of this study would support planning for effective management of flood risks due to the impacts of climate change on extreme precipitation in Adama city.

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