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Impacts of climate change on extreme precipitation events in arid (Bandar Abbas) and semi-arid (Shahrekord) stations in Iran

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Abstract
The aim of this paper is to project extreme precipitation events in an arid and a semiarid station. In order to project climate change based on general circulation models (GCMs), we have applied LARS-WG[1] downscaling tool. This stochastic weather generator down-scaled the climate of two synoptic stations using HADCM3 model and A2 emission scenario for 2040. We extracted extreme precipitation events, as daily 90th and 10th percentile for rainy days (considered if daily precipitation was greater than 1 mm), for based and projected data. The research outcomes showed an increase both in 90th percentile by 13 mm and in 10th percentile by 0.2 mm in arid station, Bandar Abbas. In the semiarid station, Shahrekord, the 90th percentile precipitation increased by 6.1 mm and the 10th percentile precipitation decreased by 3.4 mm. In total, for both stations, 90th percentile precipitations showed a more stable trend than the 10th percentile.

Keywords
10th percentile, 90th percentile, HADCM3, LARS_WG, RMSE.

1. Introduction
Climate is a complex system with changes that primarily occur as a result of increases in greenhouse gas contents (IPCC-TGCIA, 2007: 1-18). Climate change has serious impacts on water resources, agriculture and climatic parameters at the regional scale. One of the most important outcomes of climate change is its effects on extreme events such as hurricanes, hill storms, drought, heat waves and untimely frosts (IPCC-TGCIA, 2007). General Circulation Models (GCMs) are one of the most reliable tools for the study of climate variability and climate change impacts. GCMs are capable of simulating ocean-atmospheric variables used for the scenario approved by IPCC (Lane, 1999). However the main problem with GCMs is its low spatial resolution and a number of simplifications in the climate processes. In order to improve the spatial resolution of GCMs, it is necessary to downscale their outputs before application to climate change impact studies (Willby, 1998).

There are two primary methods for downscaling climate models; dynamic and statistical. Dynamic downscaling methods include a network of high resolution climate models. One of the most significant consequences of global warming is the increase in the magnitude and frequency of extreme precipitation events attributed to increased atmospheric moisture levels, thunderstorm activity, and/or large-scale storm activity (Sen, 2004). The word “extreme” is unusually associated with physically severe conditions or events. However, extreme can also be

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1. Long Ashton Research Station-Weather Generator

defined in statistical terms as "the largest and smallest element of a set" (Benestad, 2005). Moreover, extremes are represented by the tails of a variable's distribution and considered to be very rare natural occurrences (IPCC, 2002). Extreme weather events are defined as rare and abnormal events (Bartolin et al., 2008: 1752) which are far from the center of distribution. Therefore, extreme precipitations are intelligible by percentiles. For example, Becker et al. (2008) analyzed daily precipitation data from 148 weather stations located in the Yangtze River Basin to detect cycles in the annual frequency of occurrence of precipitation events of 1- 5- and 10-day durations. These events were defined in terms of exceedances of some selected thresholds.

Alijani et al. (2007) showed that daily rain tended to be variable and intense across most of Iran and that a disproportionately large portion of the annual rainfall was attributed to a small number of high intensity to extreme rainfall events. Rahimzadeh et al. (2009) examined extreme temperature and precipitation as indicative climatic variables to determine recent climatic changes over Iran. They found a negative trend for about two-thirds of the country for the annual total wet day's precipitation. Positive trends in the Simple Daily precipitation Intensity Index were found for the northern half of the country. They observed a negative trend in very wet days that exceeded the 95^{th} percentile over the eastern and western regions and a positive trend over the central region of the country; although a clear negative trend was observed for extremely wet days that exceeded the 99^{th} percentile over the majority of the country.

In all reviewed papers, climate change is represented by the tails of a variable's distribution. However in this paper, we intend to project climate change effects on extreme precipitation events (90^{th} and 10^{th} percentile of daily precipitation) according to general circulation models (GCMs) and LARS-WG downscaling tool. This stochastic weather generator down scaled climatic data of two synoptic stations using HADCM3 model and A2 emission scenario for 2040.

2. Study Area

The present study was conducted for two synoptic stations, arid (Bandar Abbas; 27°N, 56°E) and semiarid (Sharekord; 32°N, 50°E), located in south and southwest of Iran (Fig. 1).

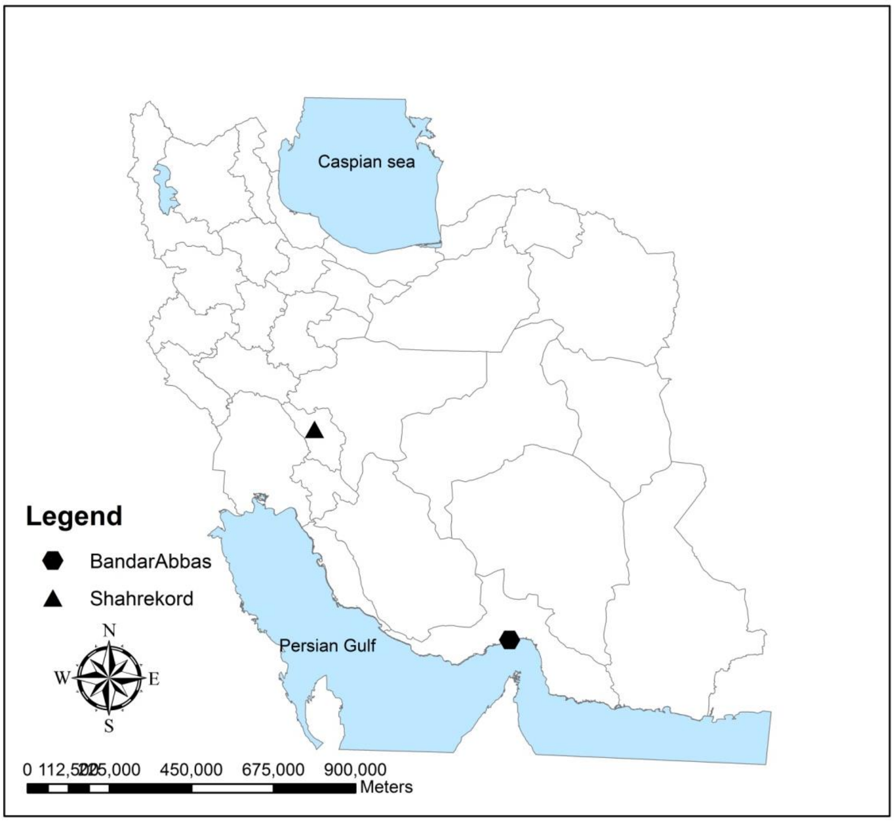

Fig. 1. Location of weather stations

According to the Köppen climate classification, Bandar Abbas is arid. In some years, it may experience less than 100 mm precipitation with an average annual temperature of 27°C. In contrast, Shahrekord is known as a semiarid station which sometimes experiences less than 200mm annual precipitation with an average annual temperature of 11.8°C.

2. 1. Data

Daily precipitation data was downloaded from the National Meteorological Organization website for Bandar Abbas and Shahrekord stations for 1971-2000.

Daily precipitation data is projected for both stations for 2040 by HADCM3 model, downscaled by LARS-WG. This scenario assumes a very heterogeneous world with continuously increasing global population and regionally oriented economic growth that is more fragmented and slower in other scenarios. Also, this scenario assumes delayed development of renewable energy and so assumes a high rate of greenhouse gas emission. In this study, scenario A2 is used in order to simulate the highest amount of climate change impacts on extreme precipitation events.

3. Materials and Methods

Figure 2 illustrates the methodology of this study. There are two important steps; first, downscaling GCM outputs for stations under A2 emission scenario, and secondly, assessing the impacts of climate change on extreme precipitation events (90^{th} and 10^{th} percentile of daily precipitation).

3. 1. Downscaling GCM data using LARS-WG

Despite significant increases in the resolution of General Circulation Models (GCMs), they cannot yet predict meteorological outputs for small scales such as a city (Salon et al. 2008). Different dynamic and statistical models have been developed to downscale GCM outputs. Racsko et al. (1991) and Semenov and Barrow (1997) provided a downscaling method of LARS-WG that uses the length of wet and dry day series, daily precipitation and daily solar radiation inputs. It does not directly use large-scale atmospheric variables; and local station climate variables are adjusted proportionally to present climate change (Sajjad Khan et al., 2006).

We based the climate change scenario used in this study on the output from the Hadley Centre Climate Model (HADCM3) included in the LARS-WG model. The HADCM3 was used to predict climate change for the IPCC 3rd and 4th Assessment Reports, and has been widely used in other studies for impact assessment.

In order to verify the results of the simulations, we used a number of statistical tests to compare the synthetic data produced by the weather generator to the observed data in the baseline period; this comparison tests how well the downscaling process performs in reporting the characteristics of the observed data. In order to assess LARS_WG performance through statistical indicators, four widely used statistical indicators are chosen: the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and the mean bias error (MBE).[1]

3. 2. Extreme precipitation events

In climatology, extreme analyses are based on statistical distribution tails of daily climatic element observations during an adequate time series. Therefore, for investigating climatic extremes, attention should be paid to low and high values. Accordingly, in this research, two extreme indices (90^{th} and 10^{th} percentile indices) are used during 1961-2006 and 2011-2040 for both stations. The annual calculated precipitation that was equal or less than the 10^{th} percentile and precipitation equal or greater than 90^{th} percentile was chosen as indices of extreme precipitation.

1. $RMSE = \sqrt{\sum_{i=1}^{n} \frac{(x_i - y_i)^2}{n}}$, $MBE = \frac{\sum_{i=1}^{n}(x_i - y_i)}{n}$, $MAE = \frac{\sum_{i=1}^{n}|x_i - y_i|}{n}$, $R^2 = \frac{[\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})]^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}$

In all equations, X_i is the actual idata and Y_i is the simulation data by the model. $\bar{X}$, $\bar{Y}$ are the mean of the total data for X_i and Y_i in the statistical population. N is the total of the estimated sample.

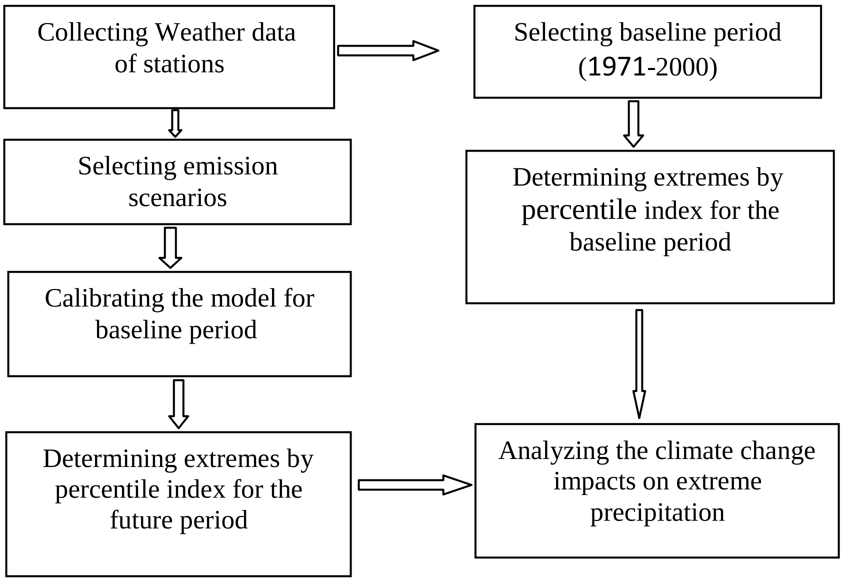

Fig. 2. Impacts of climate change on extreme precipitation events

Based on the 10^{th} and 90^{th} percentiles and in order to extract the impacts of climate change, three kinds of trend lines are calculated including; total precipitation that resulted from the $10^{th}$and 90^{th} percentiles; the ratio of precipitation from total annual precipitation; and the number of rainy days for each percentile of both stations.

Time series trend analyses were estimated using linear regression thus:

$Zt= a+bT+eT$ (1)

where Zt is the time series for a given percentile, T is time ($T= 1,2,3,4,..., n$), a and b are coefficient of regression equation, and e is the estimation error. b value shows changes of the variable in time (trend) (Cryer and Chan, 2008).

3. 3. Selected indices

There are a variety of definitions for extreme daily precipitation. In this research, 6 extreme precipitation indices are used. Table1 shows these indices in detail.

4. Results and Discussion

4. 1. Performance evaluation of LARES-WG model

Table 2 shows the results of LARS-WG evaluation based on R^2, RMSE, MAE and MBE. The accuracy of LARS-WG downscaling model is acceptable for both stations.

4. 1. 1. Annual extreme total precipitation characteristics under climate change condition

Trend analyses of annual extreme total precipitation between two time periods, baseline and future, for both stations under scenario A2 are reported in Figures 3-6. Table 3 shows the average of the extreme precipitation events.

Table 1. Selected indices for analysis of extreme precipitation for BandarAbbas and Sharekord stations

No.	Index abbreviation	Definition	Unit
1	(90thPTP)	90^{th}percentile of total precipitation: Annual total daily precipitation≥90^{th} percentile.	mm
2	(10thPTP)	10^{th}percentile of total precipitation: Annual total daily precipitation ≤10^{th} percentile.	mm
3	(RH 90thPP)	Ratio of 90^{th} percentile precipitation: Total amount of extreme annual 90^{th} percentile precipitation to total amount of annual precipitation.	%
4	(RH 10thPP)	Ratio of 10^{th}percentile precipitation: Total amount of extreme annual10^{th}percentile precipitation to total amount of annual precipitation.	%
5	(F 90thPPe)	Frequency of 90^{th}percentile precipitation events: Number of days per year with precipitation≥ 90^{th} percentile	Days
6	(F10thPPe)	Frequency of 10^{th}percentile precipitation events: Number of days per year with precipitation ≤ 10^{th} percentile	Days

Table 2. Evaluation of LARES-WG model based on R^2, RMSE, MAE and MBE

Statistical tests				Parameter	Station
RMSE	MBE	MAE	R^2		
2.93	-0.41	1.62	0.98	Precipitation	BandArbbas
3.92	0.46	3.03	0.98		Shahrekord

Average 90th PTPs are 90.1 and 103.8 mm for baseline and future events, respectively in arid station (Bandar Abbas). This shows that heavy precipitation events will increase in future. In contrast, in the semi-arid station (Sharekord) these values are 130.43 and 124.33 mm for baseline and future events, respectively.

A weak decreasing linear trend is distinguishable for the 90th PTP for future data in the arid station (Bandar Abbas) (Fig. 3). In contrast, baseline data is stable with only a slight annual change in rate. Annual 90th PTP for projected data is more varied compared to baseline.

The 90th PTP for baseline and projected data for semi-arid station (Sharekord) shows a similar decreasing trend (Fig. 4). The projected 90th PTP has more variability than the baseline values for semi-arid station (Sharekord) which was similar to the arid station (Bandar Abbas).

During 1977 to 1987, the fluctuation in the time series showed a dramatic change between different years which is statistically significant at the 0.05 probability level for 90th PTP. The dramatic change appeared to be the result of natural events because this station was autochthonous in these years (Asakareh, 2011). Of note, the 90th PTP trend for the 90th percentile is statistically significant (P=0.05).

Table 3. Average annual 10th and 90th percentile daily precipitation events for both stations (mm)

90th percentile		10th percentile		Station
Future	Baseline	Future	Baseline	
103.8	90.1	0.77	0.56	BandarAbbas
124.33	130.43	10.56	13.94	Shahrekord

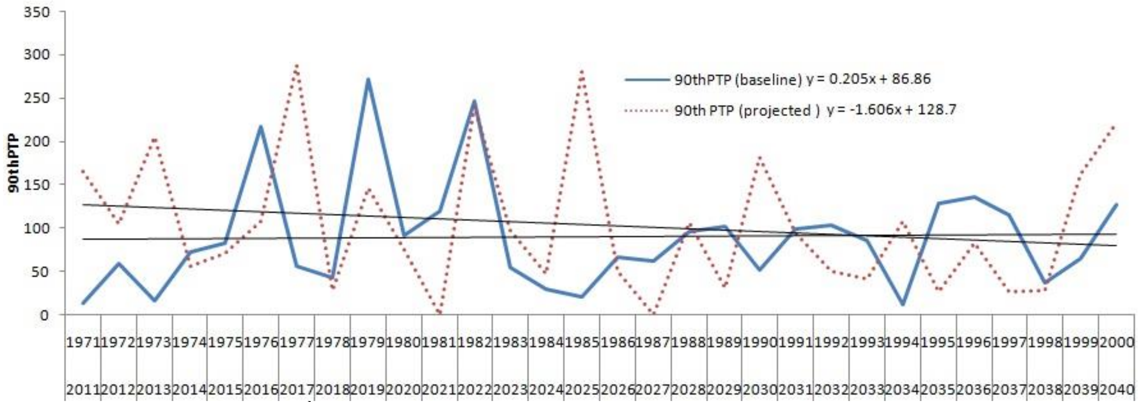

Fig. 3. Trend analysis of 90th PTP (mm) for baseline and projected data under A2 scenario in arid station, Bandar Abbas

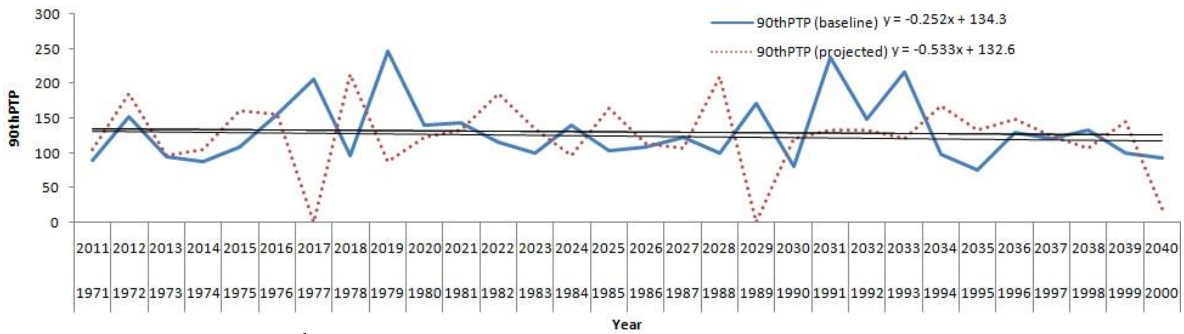

Fig. 4. Trend analysis of 90th PTP (mm) for baseline (a) and future (b) periods of A2 scenario in semi-arid station, Sharekord

The 10^{th} PTP is an indicator of low precipitation. There are different weak trend lines in the arid station for baseline and projected data (Fig. 5). Dramatic changes in 10^{th} PTP are shown during the 1995-1997 baseline periods and the 2022 and 2023 projected data time series.

The average 10^{th} PTP time series shows irregular conditions both in the baseline and projected data for semi-arid station (Shahrekord). In both stations the projected data shows a slight decreasing linear trend. There are different trends for baseline data, increasing for arid station (Bandar Abbas) and decreasing for semi-arid station (Shahrekord).

4. 1. 2. The ratio of extreme precipitation to total precipitation

Figures 7 to 10 show trend analyses of the ratio of extreme precipitation to total annual precipitations. The RH 90^{th} PP to the annual total precipitation trend decreased for projected data, however it increased for baseline in both stations (Figs. 7 and 8). The RH 90^{th} PP to the annual total precipitation is 42.1 and 40.9% of the average for baseline and projected data in the arid station (Bandar Abbas). In contrast, the SH 90^{th} PP in the annual total precipitation is 40 and 35.1% in baseline and projected data for the semi-arid station, Sharekord.

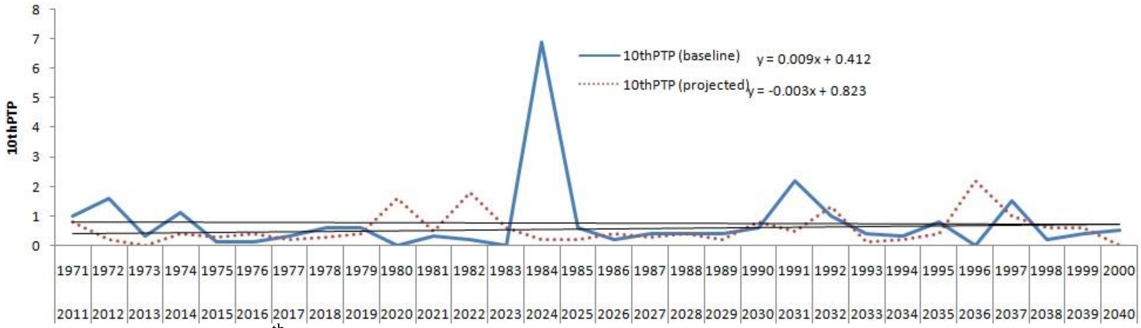

Fig. 5. Trend analysis of 10^{th} PTP (mm) for baseline and future periods under the A2 scenario for arid station, Bandar Abbas

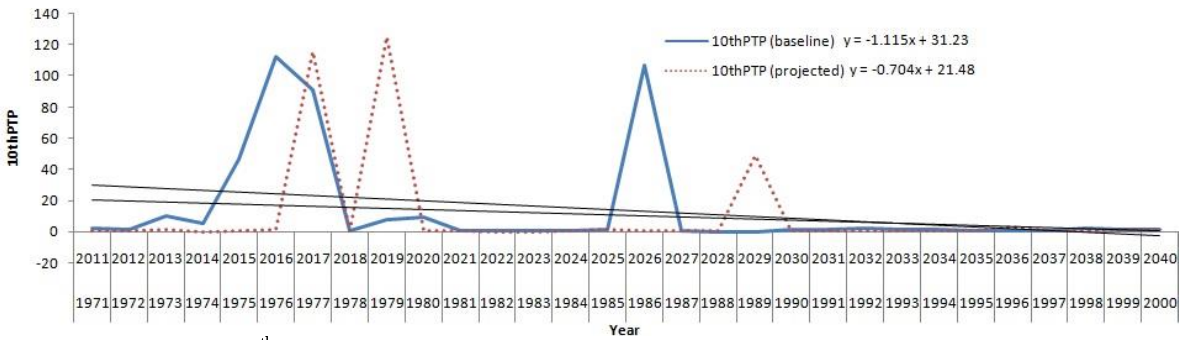

Fig.6 Trend analysis of 10^{th}PTP (mm) for baseline and future periods under the A2 scenario for the semi-arid station (Sharekord)

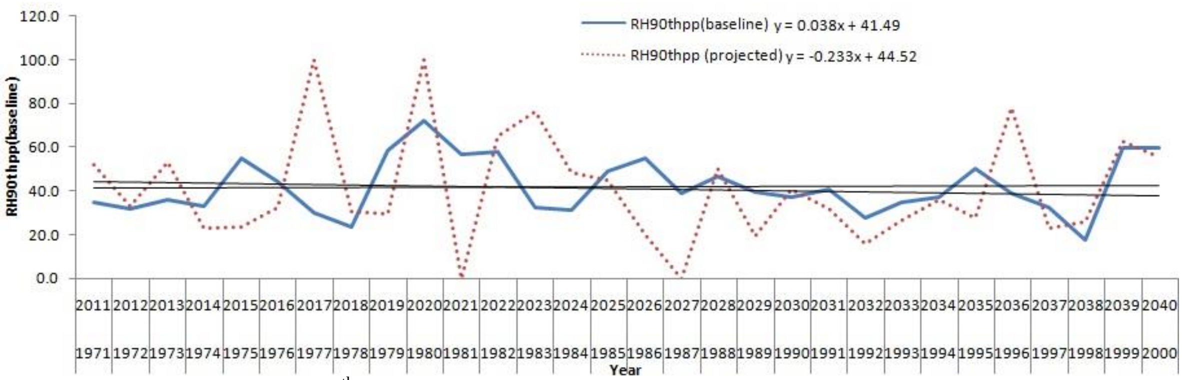

Fig. 7. Trend analysis of RH 90^{th} PP (%) to total annual precipitation of baseline and projected data under scenario A2 in arid station (BandarAbbas)

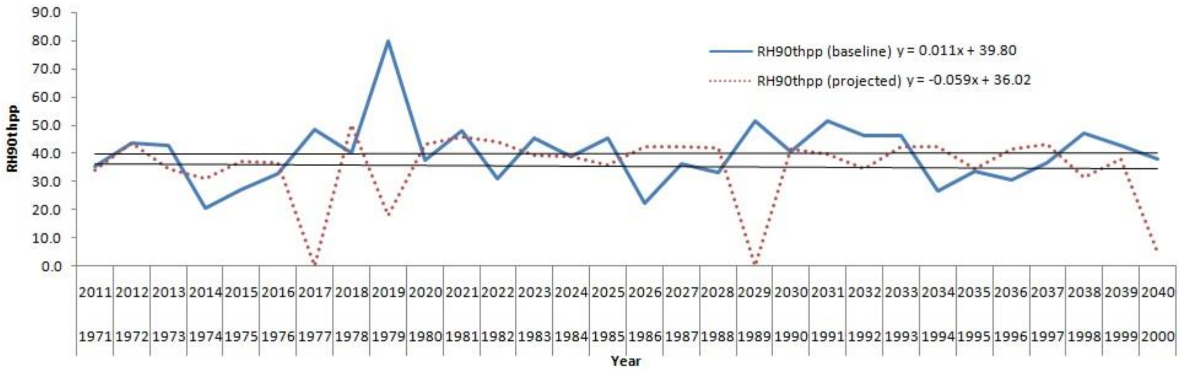

Fig. 8. Trend analysis of the RH 90th PP (%) to total annual precipitation of baseline and projected data under scenario A2 in semi-arid station, Sharekord

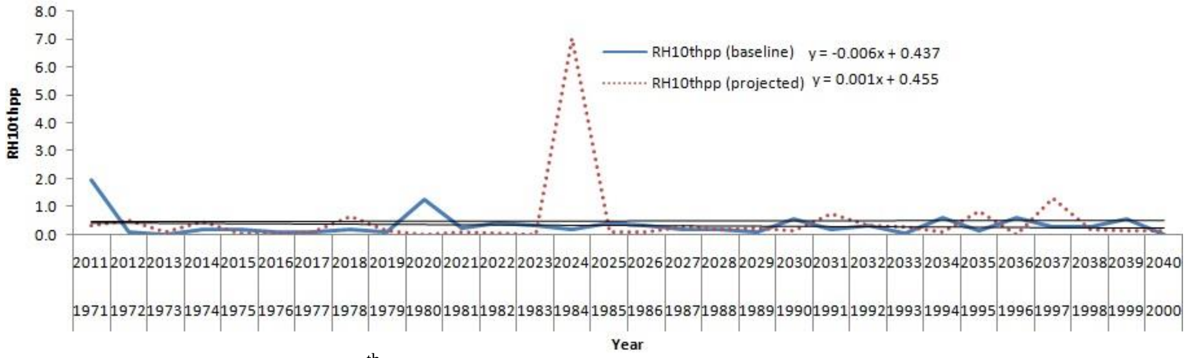

Fig. 9. Trend analysis of RH 10th PP to total annual precipitation in baseline (a) and projected data (b) under scenario A2 in the arid station (BandarAbbas)

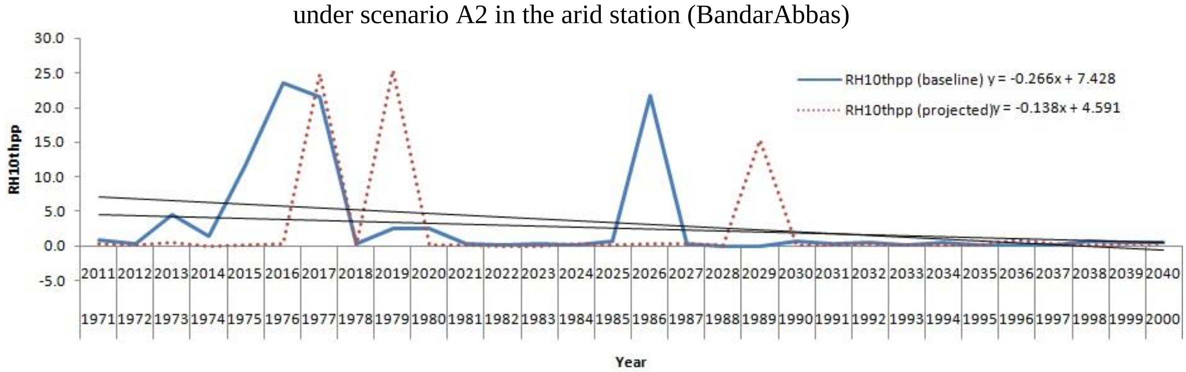

Fig. 10. Trend analysis of RH 10th PP (%) to total annual precipitation of baseline and projected data under scenario A2 in semi-arid station, Sharekord

RH 10th PP to the annual total precipitation trend decreased for baseline and increased for projected data in the arid station (Bandar Abbas), however it increased for both periods in semi-arid station (Sharekord). The ratio of this average annual total precipitation was calculated to be 0.3 and 0.5% in baseline and projected data, respectively, in the arid station (Bandar Abbas). Average SH 10th PP to total annual precipitation is 3.3 and 2.4% for baseline and projected data, respectively, in semi-arid station, Sharekord.

Therefore the ratio of heavy precipitation will decrease in projected data while ratio of average RH 10th PP increased in the arid station (Bandar Abbas). As seen in Figure 10, the RH 10th PP to the total annual precipitation is low for both studied periods in the semi-arid station, Sharekord, which is similar to arid station (Bandar Abbas). In total, RH 90th PP and RH 10th PP for total annual precipitation are predicted to decrease in future decades in the semi-arid station, Sharekord.

4. 1. 3. Changes in the frequency of extreme precipitation events

Figures 11 to 14 show trends in the number of days with extreme precipitation events. Since the number of days is a discrete variable, figures are presented in perpendicular-shaped.

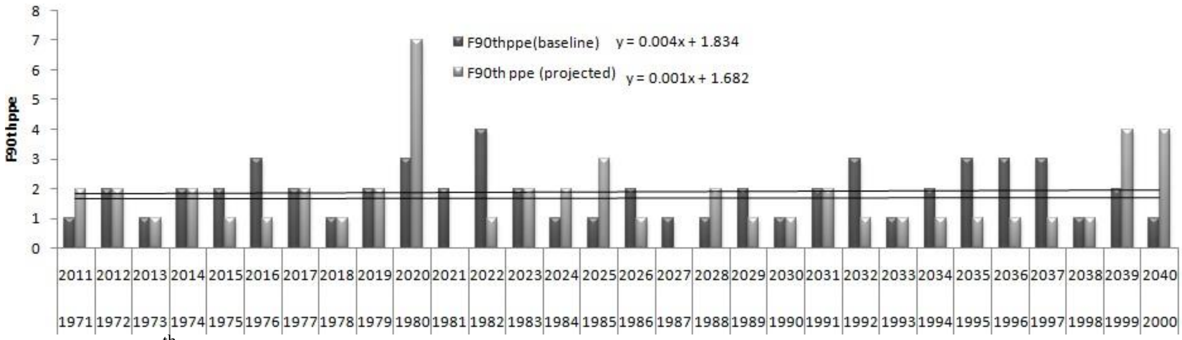

Fig. 11. F 90th PPe (day) trend in baseline and projected data under scenario A2 in arid station, Bandar Abbas

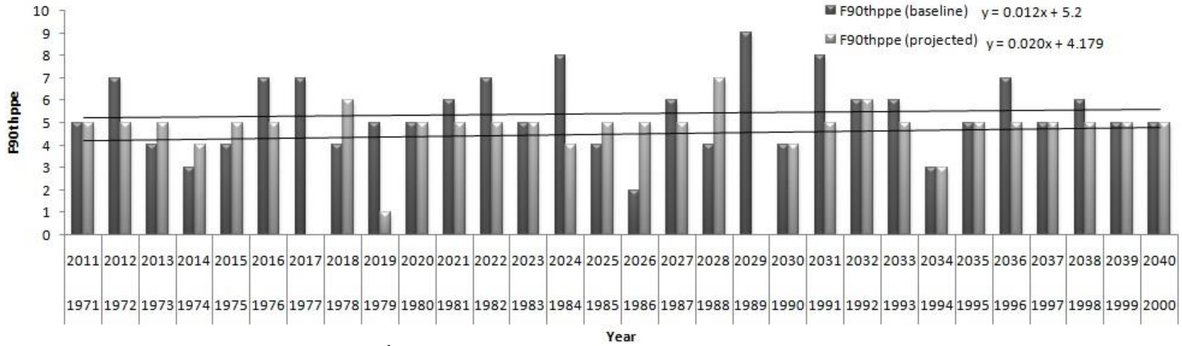

Fig. 12. Trend analysis of the F 90thPPe (day) for baseline and projected data under scenario A2 in semi-arid station, Sharekord

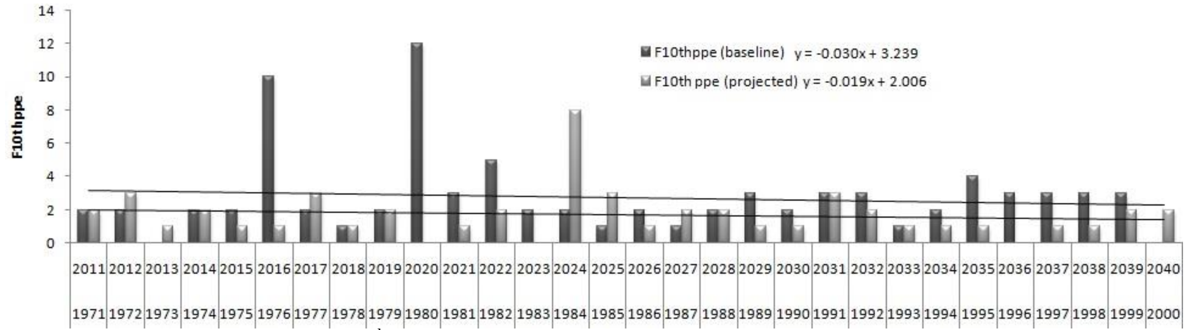

Fig. 13. Trend analysis of the F10th PPe (day) of the baselineand projected data under scenario A2 in arid station, BandarAbbas

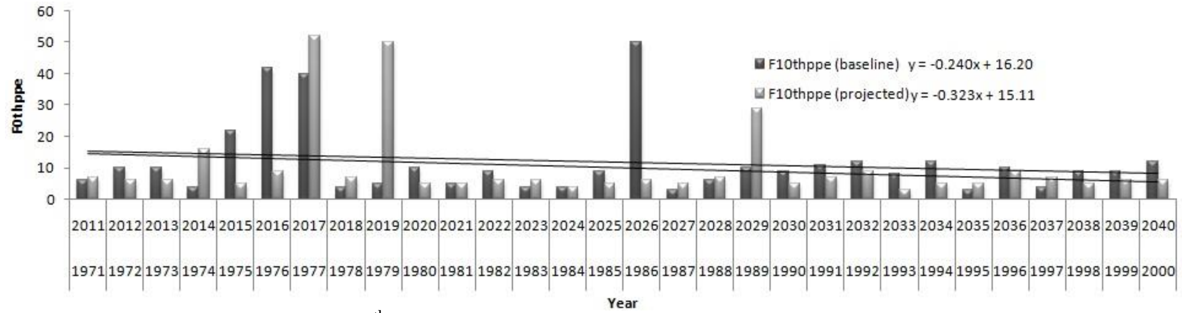

Fig. 14. Trend analysis of the F 10thPPe for the baseline and projected data under scenario A2 in semi-arid station, Sharekord

Figures 11 to 14 show changes in the annual number of days with 90th and 10th percentile precipitation between baseline (defined as the 1961–2000 period) and projected data (defined as the 2011–2040 period) for both stations. The results show that F 90th PPe is more stable than F 10th PPe for projected and baseline data in both stations. There are 8 days with F 90th PPe in the projected data in arid station and 7 days in the semi-arid station, in projected data.

The F 10th PPe gives a slightly downward trend at 0.03 and 0.02 mm year^{-1} for baseline and projected data, respectively in the arid station. Therefore, there is a decrease in F 10thPPe of approximately 3 days in 100 years for baseline and 2 days in 100 years for projected data for this station.

The F 90th PPe gives a slightly downward trend at 0.02 and 0.01 mm year^{-1} for projected data and baseline, respectively, for the semi-arid station (Sharekord).Therefore there is a decrease in F 90th PPe of approximately 1 day in 100 years for baseline and 2 days in 100 years in the projected data for the semi-arid station.

Based on Figure 10, the F 10th PPe shows a downward trend at 0.24 and 0.32 mm year^{-1} for baseline and projected data, respectively, in the semi-arid station. An abrupt change occurred at the end of the 1985 decade in the baseline and will occur in 2016 and 2018 in the future.

5. Conclusions

Trends of three indices including annual extreme total precipitation, annual frequency of extreme precipitation, and ratio of extreme precipitation to the extreme precipitation events have been analyzed in this study for baseline (1971-2000) and projected data (2011-2040).

In this analysis for arid station, Bandar Abbas, there is an increase in low value precipitation events and heavy precipitation events for projected data. This increase in projected data is more variable than baseline (based on R^2 value). The results show a general intensification of RH10th PP and a decrease in the ratio of heavy precipitation in arid station, Bandar Abbas. The above analyses indicate an increase in RH10th PP and a decrease in the ratio of heavy precipitation during the rainy years in the Bandar Abbas arid station. Therefore, the increase in annual precipitation resulted from the 10th percentile precipitation event. Totally, for the arid station (Bandar Abbas) the results show an increase in the number of rainy days and decrease in heavy precipitations of projected data.

Trend analysis of extreme precipitation events in Sharekord semi-arid station differs from the Bandar Abbas arid station. This shows increases in low value precipitation events and in heavy precipitation events for projected data. For semi-arid station, projected data shows an increase in heavy precipitation and decrease in low value precipitation. Therefore, the intensity of precipitation in semi-arid station will intensify.

Heavy precipitation can cause damages to both soil and water resources. These damages can cause problems such as desertification, decreases in agricultural productivity due to land degradation and soil erosion.

References

1. Asakereh, H., 2012. Frequency Distribution Change of Extreme precipitation in Zanjan City. Geography and Environmental Planning Journal, vol. 45, No.1, 13-18 pp.
2. Benestad, S., Rasmus. E., 2006. Can we expect more extreme precipitation on the monthly time scale? Journal of Climate, Vol. 19: 630 637.
3. Becker. S., Hartmann. H., Zhsng. Q., Wu. Y., Tiang. T., 2007. Cyclicityanalysis of Precipitation regimes in the Yangtze River Basin, China. Int. J. Climatol. 28: 579–588.
4. Bartolini, G., Morabito, M., Crisci, A., Grifoni, D., Torrigianitonmaso, P., Martina, M.G., and Orlandini, S., 2008. Recent trends in orlandini. Simon 2008, Recent trends in indices of extremes. International Journal of Climatology. 28:1751-1760.
5. Alijani. B., O'Brien, J., Yarnal, B., 2007. Spatial analysis of precipitation intensity and concentration in Iran, Theor. Appl. Climatol. 94: 107-124.
6. Cryer, J.D., Chan, K.S., 2008. Time Series Analysis, Springer Texts in Statistics.
7. IPCC. 2007. Climate Change- the scientific basis. IntergovernmentalPanel on Climate Change. Cambridge University Press: Cambridge.
8. IPCC- TGCIA- Carter, T.R., Alfsen, K.E.B., Dai, P., Desanker, S.R., Gaffin, F., Giorgi, M., Hulme, M., Lal, L.J., Mata, L.O., Mearns, J.F.B., Mitchenll, T., Morit, R., Moss, D., Murdiyarson, J.D., Pabon-Caicedo, J., Palutikof, M.L., Parry, C., Rosenzweig, B., Seguin, R. Scholes, J., Whetton, P.H. 2007. Generate Guidelines on the Use of Scenario Data for Climate Impact and Adaptation Assessment, Intergovermental Panel on Climate Change, Task Group on Scenarios for Climate Impact Assessment, Version2: 66 pp.
9. IPCC, 2002. IPCC Workshop on Changes in Extreme Weather and Climate Events. Beijing, China, IPCC, 107 pp.

10. Racsko, P., Szeidl, L., Semenov, M., 1991. A serial approach to local stochastic weather models. Ecological Modeling 57, 27–41.
11. Rahimzadeh, F., Asgari, A. Fattahi, 2009. Variability of extreme temperature and precipitation in Iran during recent decades. Int. J. Climatol. 29: 329-343.
12. Semenov, M.A., Barrow, E.M. 1997. Use of a stochastic weather generator in the development of climate change scenarios. Climate Change 35, 397–414.
13. Sajjad Khan, M., Coulibaly, P., Dibike, Y., 2006. Uncertainty analysis of statistical downscaling methods. Journal of Hydrology 319, 357–382.
14. Semenov M.A., Brooks R.J., Barrow E.M., Richardson C.W. 1998. Comparison of the WGEN and LARS-WG stochastic weather generators in diverse climates. Climate Research10, 95-107.
15. Salon, S., Cossarini, G., Libralato, S., Gao, X., Solidoro, S., Giorgi, F., 2008. Downscaling experiment for the Venice lagoon. I. Validation of the present-day precipitation climatology. Clim Res 38:31–41.
16. SenRoy, Sh., Balling, J.R., Robert, C. 2004. Trends in extreme daily precipitation indices in India. Int. J. Climatol.24: 457-466.
17. Lane, M.E., kirshen P.H., Vogel R.M. 1999. Indicators of impact of global climate change on U.S water resources. ASCE, journal of Water Resource Planning and Management.125(4): 194-204.
18. Wilby, R.L., Wigley T.M.L., Conway D., Jones P.D., Hewitson B.C., Main J., Wilks D.S. 1998. Statistical downscaling of General Circulation Model output: A comparison of methods. Water Resources Research, 34, 2995–3008.