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ORIGINAL ARTICLE

Comparing the Performance of Dynamical and Statistical Downscaling on Historical Run Precipitation Data over a Semi-Arid Region

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Abstract
Precise evaluations of climate model precipitation outputs are valuable for making decisions regarding agriculture, water resource, and ecosystem management. Many downscaling techniques have been developed in the past few years for projection of weather variables. We need to apply dynamical and statistical downscaling (DD and SD) to bridge the gap between the coarse resolution general circulation model (GCM) outputs and the need for high-resolution climate information over a semi-arid region. We compare the requirements of DD (RegCM4) and SD (Delta) approaches, evaluate the historical run of NNRP1 data in comparison with station data, and analyze the changes in wet days and precipitation values through both methods during 1990–2010. In this study, we did not want to use prediction data under different scenarios of climate change, and we have just applied observed data to assess the amount of precise of NNRP1 data, over the observed period. SD method requires less time and computing power than DD. The DD approach performs better over the evaluation period according to efficiency criteria. In general, the Pearson correlation in DD with observation data in evaluation period was higher than ($r > 0.72$ and $R^2 > 0.52$) SD ($r > 0.65$ and $R^2 > 0.41$) over three study stations. Similarly, MAE and NSE show better results from DD relative to SD. SD underestimates the number annual mean wet-days for all three stations examined. DD overestimates a number of annual mean wet-days, but with less deviation from the observed mean.

Keywords Delta method · RegCM4 · NNRP1 · Bias correction · Resolution · Wet-day

1 Introduction

The Fifth Assessment Report of the Intergovernmental Panel on Climate Change describes the state of the science of climate change (IPCC AR5 2013). General circulation model (GCM) outputs often have global coverage, they do not provide high spatial resolution outputs on proper scales for management decision-making (Meehl et al. 2007; Ullah et al. 2018). For transforming these coarse outputs to a finer resolution, there are two broad fundamental approaches, namely Statistical Downscaling (SD) and Dynamical Downscaling (DD) (Abbasnia et al. 2016). Both approaches provide researchers with access to fine-scale resolution projections of drought, flood, and climate change impacts on hydrology, water resources, air pollution, and crop yields.

SD uses equations to associate the variables simulated well by GCMs (predictors) and surface climate variables based on observed records (predictands). This method does not model atmospheric dynamics (Ayar et al. 2016). The three most commonly used approaches for statistical downscaling are (1) transfer functions (Imbert and Benestad 2005), (2) weather typing (Huth et al. 2008), and (3) stochastic weather generator (Buishand et al. 2003). Several variations on a fourth approach Bias Correction (BC), have been developed to downscale climate variables from climate models (Li et al. 2010; Chen et al. 2011; Maraun 2016).

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Dynamic downscaling, nesting a fine scale climate model in a coarse scale model to simulate higher spatial resolution by solving equations of motion and thermodynamics, lateral boundary conditions, parameterization, and physical processes (Giorgi et al. 2001). DD and SD approaches have their own advantages and disadvantages, but there is no consensus that one approach is superior in terms of reproducing the observed variability of local climates (Mearns et al. 1999; Gutowski et al. 2000). DD approaches have heavy computational costs, long runtime, and require convection schemes and input data (Benestad 2010; Kim et al. 2016a, b). SD approaches are simple, require less computational demand, time, cost, and are easily implemented, which explains their relative popularity of SD approaches (Souvignet and Heinrich 2011; Manzanas et al. 2017a, b; Nikulin et al. 2017).

Over the last two decades, dynamical and statistical downscaling approaches have been compared in New Zealand (Kidson and Thompson 1998), Europe (Murphy 1999; Manzanas et al. 2017a, b), eastern Nebraska (Mearns et al. 1999), Colorado (Wilby et al. 2000), Japan (Oshima et al. 2002), Romania (Busuioc et al. 2006), UK (Haylock et al. 2006), North America (Wang and Zhang 2008), southeastern United States (Lim et al., 2007), Philippines (Robertson et al. 2011), northeastern United States (Tryhorn and DeGaetano 2011), Spain (Casanueva et al. 2016), China (Su et al. 2017), and Eastern Africa (Nikulin et al. 2017). Several researchers point to the SD and DD differences in projected precipitation changes. Jang et al. (2013) assessed the difference in 100-year average precipitation changes over northern California region outputs from SD (BCSD (Bias-Correction and Spatial Downscaling)) vs DD (MM5 (the Fifth-Generation NCAR/ Penn State Mesoscale Model)). The BCSD method of Wood et al. (2004) is an empirical statistical technique in which the monthly precipitation and temperature output from a GCM are downscaled. The MM5 model is a regional mesoscale model used for creating weather forecasts and climate projections. The most prominent features of the MM5 are multiple-nesting capability, availability of four-dimensional data assimilation (FDDA), and a large spectrum of physics options (Boo et al. 2004). The precipitation change from MM5 simulations and BCSD estimations show the opposite spatial patterns in many places over the study region. The BCSD method has limitations in projecting future precipitation values. Mehrotra et al. (2013) saw SD as providing better simulations of point rainfall, spell lengths, and amounts, but DD was well suited where regionally averaged rainfall is of primary concern.

Schmidli et al. (2007) compared daily precipitation statistics obtained by using six SD and three DD approaches over the European Alps. Their result revealed that all SD approaches underestimate the magnitude of the interannual variations, but the DD approaches produce about the right amount of interannual variability. Vrac et al. (2012) analyzed the performance of SD and DD and compared the potential benefit of applying a SD model to different DD approaches. The evaluated the uncertainty in downscaling of wind, temperature, and rainfall cumulative distribution functions for eight stations in the French Mediterranean basin over 1991–2000. They showed that SD approach produces accurate results. Gutmann et al. (2012) investigated the amount of winter precipitation over complex terrain by SD and DD approaches. The results showed that there are regions of significant difference between the two methods. Ayar et al. (2016) compared six SD and five RCM models are used in terms of precipitation outputs. The stochastic and resampling-based SD approaches better modeled marginal properties of rain occurrence and intensity, while RCMs and resampling-based SD approaches well reproduced spatial and temporal variability.

The large year-to-year variation in precipitation amounts is key for water resources planning, hydrological and agricultural modeling, and environmental assessments, especially in arid and semi-arid regions. In this work, we (1) compare the requirements of DD (RegCM4) and SD (Delta) approaches, (2) compare local predictions against observations, and (3) evaluate the downscaled predictions results (obtained either with SD or with DD) against observations, across yearly and seasonal timescales.

2 Data and Methods

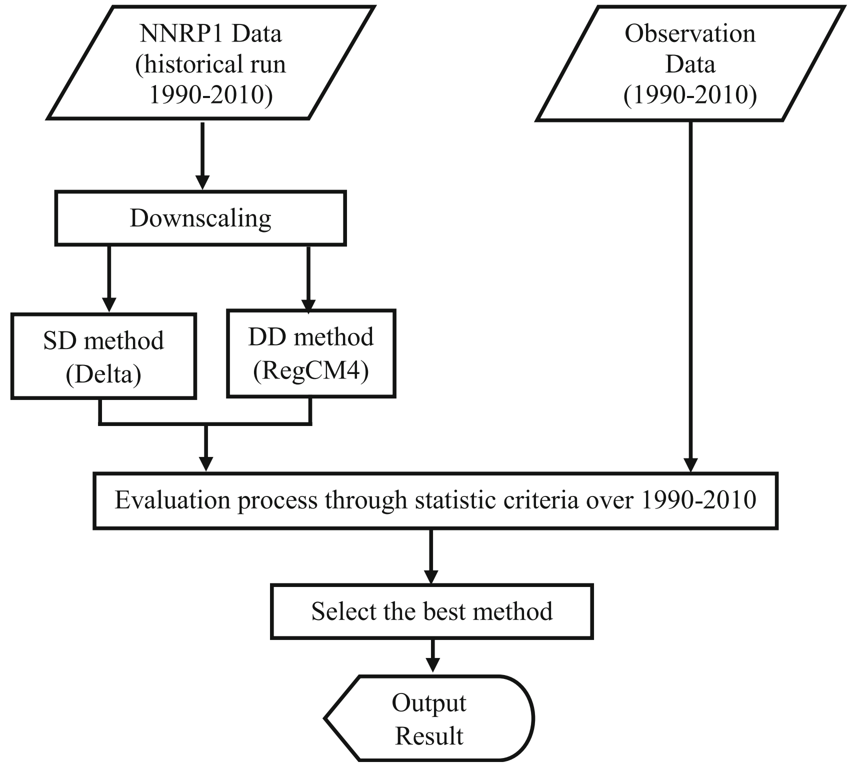
2.1 Downscaling Methods

In this study, we used both approaches for downscaling, namely SD and DD. In the SD approach, the Delta method was applied, and for DD, the RegCM4.1 model was run. These methods were run on the data of the NNRP1 (NCEP/NCAR Reanalysis Product version 1) model. The following sections (2.1.1 and 2.1.2) provide more details of the mentioned models and approaches. In addition, all the steps of this research were presented in Fig. 1.

2.1.1 Statistical Downscaling

Statistical downscaling is based on the relationship between the local climate surface variables and large-scale (typically circulation) atmospheric variables. We utilize the Delta method of SD approaches, as it is the most widely used with RCM outputs (Maraun et al. 2010; Themeßl et al. 2012; Kang et al. 2016; Kim et al. 2016a, b; Manzanas et al. 2017a, b), easy to run, and it is a relatively simple method (Dessu and Melesse 2013). Wetterhall et al. (2012) called this method as a direct method. Maraun et al. (2010) revealed that Delta approach is not a bias correction of a climate model, but only employs the model's response to climate change to modify observations, as it is a useful benchmark for bias correction. Whereas in a large

Fig. 1 The flowchart of different steps in this study



number of climate change impact assessment studies have used a bias correction downscaling method which often referred as the delta change method (Eckhardt and Ulbrich 2003; Teutschbein and Seibert 2012; Sunyer et al. 2012; Sachindra et al. 2014). The delta-approach, add only the climate change signal from GCMs to observations (Hay et al. 2000). Delta method has the advantage of simplicity and modest data requirements. In this study, downscaled precipitation is calculated as follows (Eq. 1):

$$P_{SD}^{Delta} = P_{Mod,daily} \times \left(\frac{\overline{P}_{Obs}}{\overline{P}_{Mod}} \right)_{monthly} \quad (1)$$

where P_{SD}^{Delta} is downscaled data of precipitation, $\overline{P}_{Obs}$ is the mean observed precipitation, and $\overline{P}_{Mod}$ denotes the NNRP1 mean precipitation data over the control period (GCM historical run). If we want to use future data then we should apply future period in the equation. In this study, we have developed a tool (AgriMetSoft SD-GCM 2017) for running the Delta technique. The SD-GCM (Statistical Downscaling of General Circulation Models) software is a useful tool for downscaling CMIP5 models under RCP Scenarios. In this tool, the observation data and output data would be in Excel format files and the order of data in the columns are not important, therefore user can easily load the input observation data. This tool has an option for the verification metrics, including Nash-Sutcliffe Efficiency (NSE), Spearman Correlation, RMSE (Root Mean Squared Error), d (index of agreement), and MAE (Mean Absolute Error). For further details, refer to the help file of the SD-GCM tool.

2.1.2 Dynamical Downscaling

We used the Regional Climate Model (RCM) version 4.1, RegCM4 (Giorgi et al. 2012), developed at the Abdus Salam International Centre for Theoretical Physics (ICTP). It is an improved version of RegCM3 (Pal et al. 2007), which is also an evolution of its previous version RegCM2 (Giorgi et al. 1993a, b). The dynamical core of

Table 1 The RegCM4 configuration used in this study

Contents	Description
Resolution	20 km
Vertical layer (top)	18 sigma (50 hPa)
Map projection	Lambert conformal
Horizontal grid	137×147 ($i_y \times j_x$)
Cumulus convection (Convection scheme)	Grell (Grell et al. 1994)
Model icbc data source	NNRP1
Model SST data source	OI_WK
Simulation period	1/ 1 /1988 to 12/ 31 /2010 (24 months spin up)

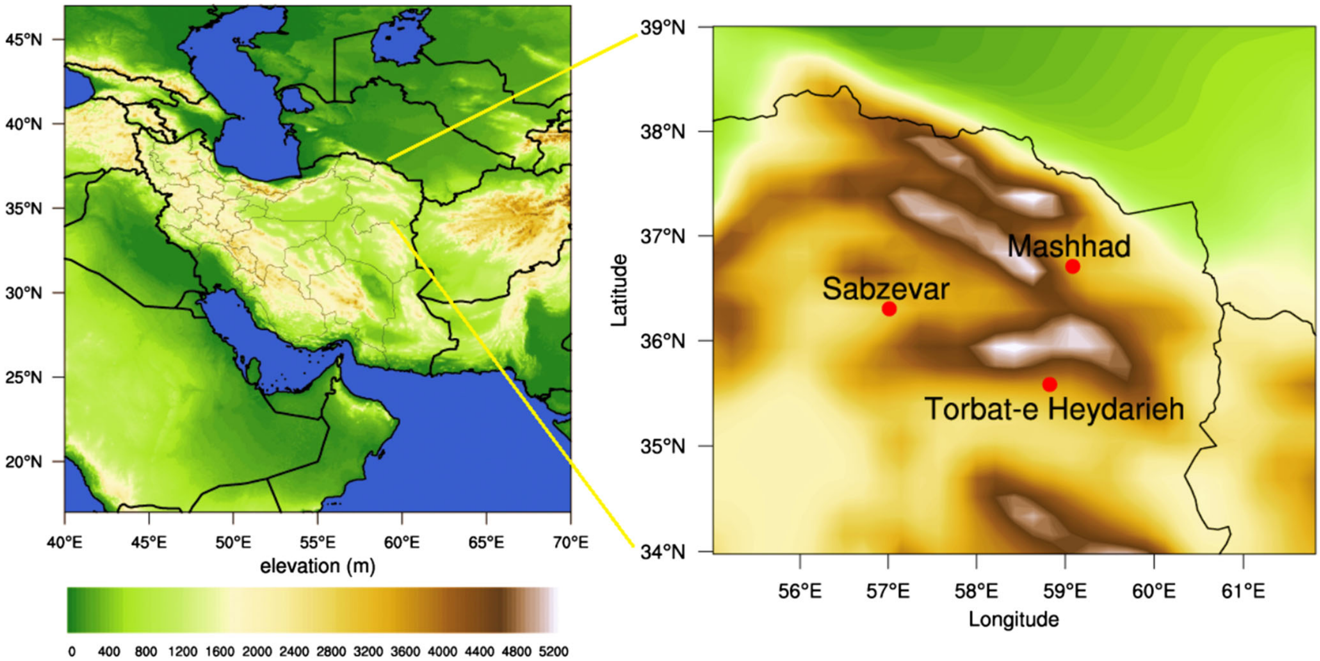


Fig. 2 The study area location with three stations

the RegCM is essentially equivalent to the hydrostatic version of the NCAR/Pennsylvania State University mesoscale model MM5 (Grell et al. 1994). Lateral boundary conditions were obtained from the NCEP/NCAR Reanalysis 1 (NNRP1) dataset at 2.5° × 2.5° latitude-longitude horizontal resolution over the observed period of 1990–2010. NNRP1 data was produced by the National Centers for Environmental prediction (NCEP) in collaboration with the National Centre for Atmospheric Research (NCAR) and it covers the period from 1948 to present day. The data assimilation system uses a 3D-variational analysis scheme, with 28 sigma levels in the vertical and a triangular truncation of 62 waves that corresponds to a horizontal resolution of approximately 200 km. For more details refer to Kalnay et al. (1996).

Sea-surface temperature (SST) was taken from the National Oceanic and Atmospheric Administration (NOAA) Optimum Interpolation SST (OISST) dataset with a weekly temporal resolution and 1° × 1° spatial resolution (Reynolds et al. 2002). Global terrain 30 arc-seconds resolution global land cover characteristics (GLCC; Loveland et al. (2000)) were used. For land use, we used GTOPO topography data. Details of the model configuration are presented in Table 1.

2.2 Verification Metrics Used and Used Graphs

We used three performance and evaluation metrics: MAE (MacLean 2005), Pearson's correlation coefficient (R), and NSE (Nash and Sutcliffe 1970). MAE was used to determine the average magnitude of the error. The R coefficient was used to measure the degree of agreement between observation data and simulation data. The NSE ranges from minus infinity to 1, with a value of 1 indicating perfect agreement between measured and model-estimated values. A value of 0 indicates that the measured mean is as good a predictor as the model, whereas negative values indicate that the measured mean is a better predictor than the model. These equations are defined as following, with O observed, $\overline{O}$ mean observed, S simulated values, and N is the number of observations:

$$MAE = \frac{\sum_{i=1}^{N} |S_i - O_i|}{N}, \qquad (2)$$

Table 2 Physiographic details of study locations, weather data during the observation period (1990–2010)

Location	LA (°N)	LN (°E)	Elev. (m)	Ave. Tmax	Ave. Tmin	Total Precipitation(mm)	Climate (De Martonne)
Mashhad	36°16′	59°38′	999.2	22	8.3	256	semi-arid
Sabzevar	36°12′	57°43′	972	24.8	11.8	198	arid
Torbat	35°16′	59°13′	1450.8	20.5	7.5	273	semi-arid

LA latitude, *LN* longitude, *Elev.* elevation, *Tmax* maximum temperature (°C), *Tmin* minimum temperature (°C).

Table 3 The system requirements and used runtime

Method	Contents	Description
DD	RAM(GB)	32
	Hard(GB)	150
	Number of cores	16
	Runtime	35 days
SD	Ram(GB)	3
	Hard(GB)	3
	Number of cores	2
	Runtime	10 min

$$R = \frac{\left(\sum_{i=1}^{N} S \times O\right) - \left(\frac{\sum_{i=1}^{N} S \times \sum_{i=1}^{N} O}{N}\right)}{\sqrt{\left(\sum_{i=1}^{N} S^2 - \frac{\left(\sum_{i=1}^{N} S\right)^2}{N}\right)} \times \sqrt{\left(\sum_{i=1}^{N} O^2 - \frac{\left(\sum_{i=1}^{N} O\right)^2}{N}\right)}} \quad (3)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} \left(O_i - \overline{O}\right)^2} \quad (4)$$

Box-Whisker plots presenting observation data versus the downscaling methods over (1990–2010) were drawn. In this graph, the horizontal line in the middle of the box represents the median, the upper edge of the box represents the 75th percentile (upper quartile, UQ), while the lower edge is the 25th percentile (lower quartile, LQ). The boxes extend between the 25th to the 75th percentiles refers to the Interquartile Range (IQR), and the whiskers show the 5th and 95th percentiles, points are values outside this range.

In addition, the Cumulative Distribution Function plot (CDF) was also depicted. In this graph, the horizontal axis is the allowable domain for the given probability function. Since the vertical axis is a probability, it must fall between zero and one. We applied CDF for comparing the changes in precipitation of observation, statistical, and dynamical total precipitation during 1990–2010.

Table 4 The results of statistical criteria between observed precipitation data and SD, and DD methods during 1990–2010 (monthly)

		NSE	MAE	R*
DD	Mashhad	0.09	13.35	0.72
	Sabzevar	−0.26	12.96	0.74
	Torbat	0.5	12.22	0.73
SD	Mashhad	−0.59	15.86	0.65
	Sabzevar	0.18	10.47	0.70
	Torbat	−0.16	16.1	0.69

*: R at 95% confidence level and p value<0.05

2.3 Study Area

This study area (Fig. 2) was comprised of three different semi-arid locations: Mashhad, Sabzevar, and Torbat-e Heydarieh (Torbat), all located in Khorasan-e Razavi province, northeastern Iran. The study area province is located between 33° 52′ S and 37° 42′ N latitude and 56°19′ W and 61°16′ E longitude, with an area of 118,851 km^2. Daily precipitation (mm) data were collected from the meteorological station at each location over 1990–2010 (Table 2). Homogenization and quality control of weather data were performed by the national meteorological organization of Iran (www.weather.ir) before the release of such data to users. The precipitation data in Table 2 refers to yearly mean total precipitation amounts during 1990–2010. Also, the number of wet days (#) were calculated from precipitation data via MATLAB programming language (R2017b, Version 9.1) for each day that the total precipitation was >0 .1mm (Buishand et al. 2003).

3 Results and Discussion

3.1 Comparison of System Requirements

As seen in Table 3 and similar to other studies (Murphy 1999, 2000; Maurer and Hidalgo 2008), the DD method required more RAM (32GB) and hard drive space (150GB, due to precise settings such as boundary conditions and convection scheme) than the SD Delta method (RAM 3GB and hard 3GB). RAM is an acronym for Random Access Memory. The runtime for data loading and extracting in NC format file, applying the desired model for downscaling, and finally receive the downscaled weather data was also less intensive for SD (shown in Table 3).

3.2 SD and DD Methods Evaluation

DD method outputs performed better than SD method outputs overall for Mashhad and Torbat for all three efficiency metrics (Table 4 and Fig. 3). SD had better results at Sabzevar when performance was judged on NSE and MAE criteria. Figure 3 shows the relationships between monthly precipitation over each station (Mashhad, Sabzevar, and Torbat) and the corresponding values from the SD and DD precipitation. These results reveal that there is an acceptable agreement between the station-observed precipitation data and SD and DD precipitation data, with $R^2 > 0.52$ for DD method and $R^2 > 0.41$

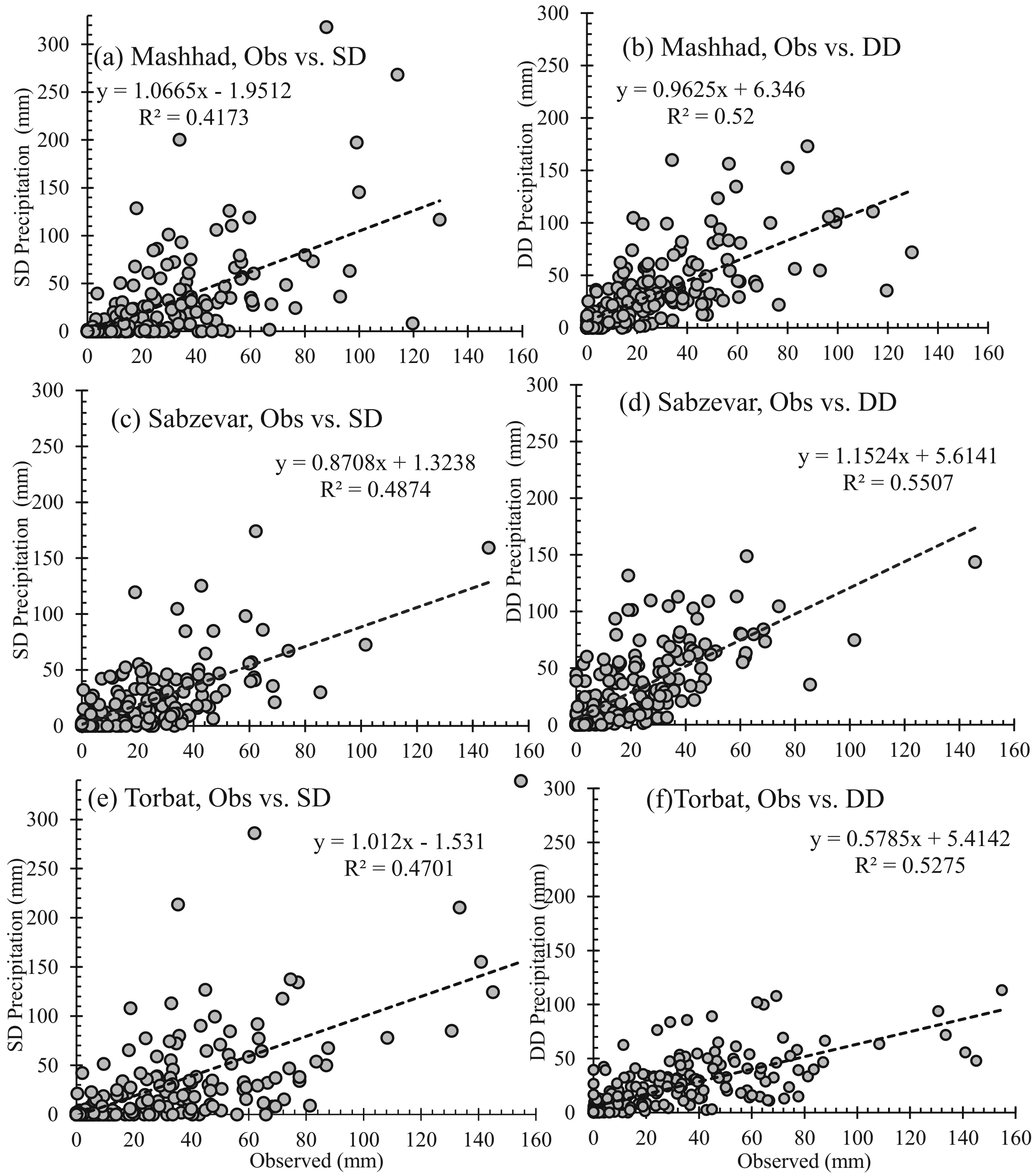


Fig. 3 Relationships of the monthly precipitation observed data vs. the SD and DD precipitation over the three stations

for SD method (at 95% confidence level and p value<0.05). Overall, the SD method shows weaker correlations than the DD for precipitation, but the difference in the results of correlation in the two approaches is negligible. The highest R^2 among three stations is achieved at the Sabzevar station for both SD and DD approaches.

Table 5 The annual mean of wet days, and total annual of precipitation during 1990–2010, with observation, statistical, and dynamical data output, over three locations

	The annual mean of wet-days (#)			Total annual of precipitation (mm)		
	Observation	SD	DD	Observation	SD	DD
Mashhad	45	19	69	243	235	310
Sabzevar	36	28	53	187	179	283
Torbat	42	19	52	266	251	268

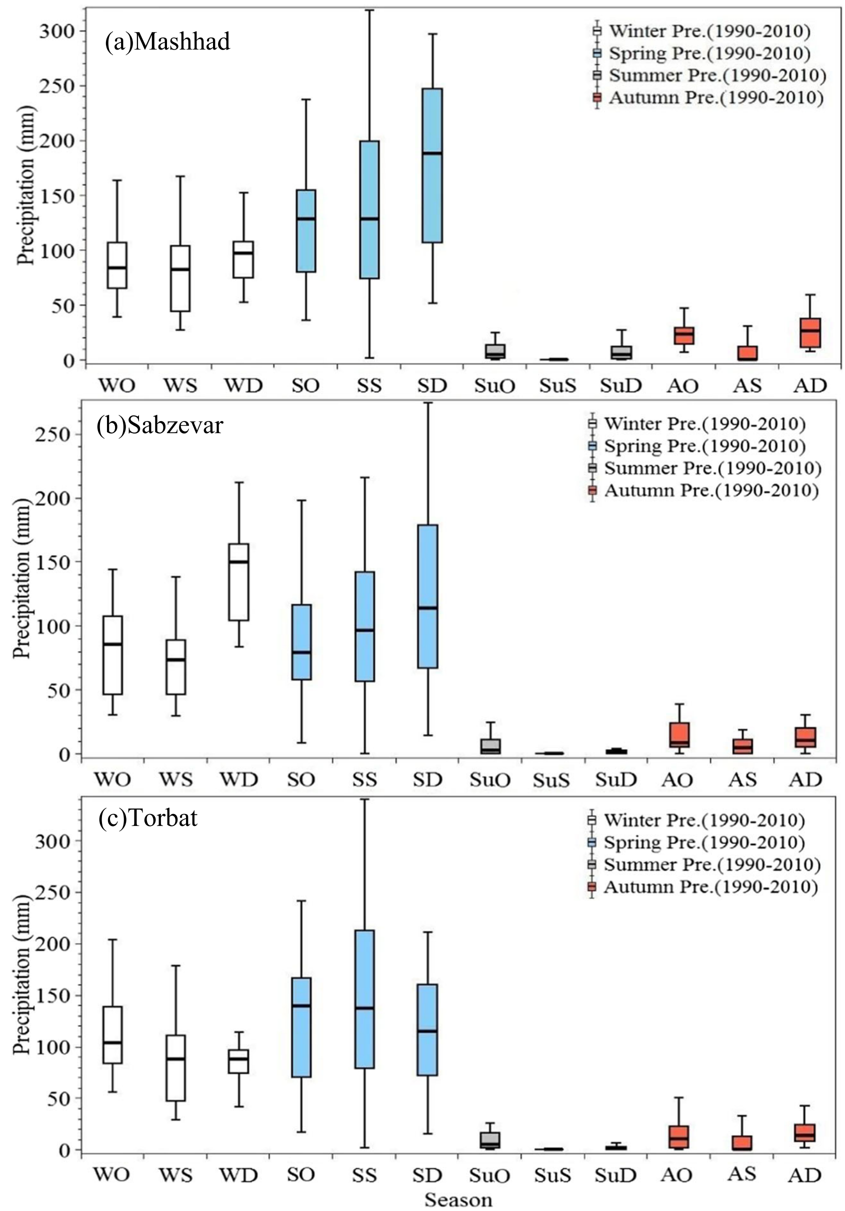


Fig. 4 Box plots for seasonal total precipitation (Pre.) values during 1990–2010 over three stations, that the first character of the word refers to W(Winter), S(Spring), SU(Summer), A(Autumn), and the second one refers to S(Statistical), D(Dynamical), and O(Observation)

3.3 Precipitation and Wet-Days

Total annual precipitation (mm) and annual mean of the number of wet days (#) observation and simulated downscaled data over 1990–2010 are presented in Table 5. SD underestimates annual mean wet days for all stations, while the DD overestimates these values. Sabzevar is drier than the other stations in this study. Similar to wet days, SD underestimates total annual precipitation and DD overestimates these values Table 5. Tryhorn and DeGaetano (2011) found a similar overestimation of mean precipitation bias by the DD approach. DD precipitation bias is larger than SD for all stations. Frost et al. (2011) similarly found that SD approaches underestimated the number of wet-days. Wang et al. (2016) also found that the BC-based methods like our SD Delta method underestimated the wet-day frequency and the precipitation intensity. Our results confirm the findings of Maraun (2013) and Chen et al. (2011).

For Mashhad station in winter, SD more closely matched observed (1990–2010) median precipitation and DD showed a bias toward overestimation (Fig. 4a). As you see in Fig. 4a (Mashhad), Delta method showed a wider range (from minimum to maximum) of the predicted precipitation values than RegCM4, also the maximum values of precipitation by Delta are greater than the RegCM4's output, over winter and spring, whereas the highest IQR happened by RegCM4 over spring, summer, and autumn. Both downscaling approaches overestimate precipitation in spring over Mashhad and Sabzevar. For

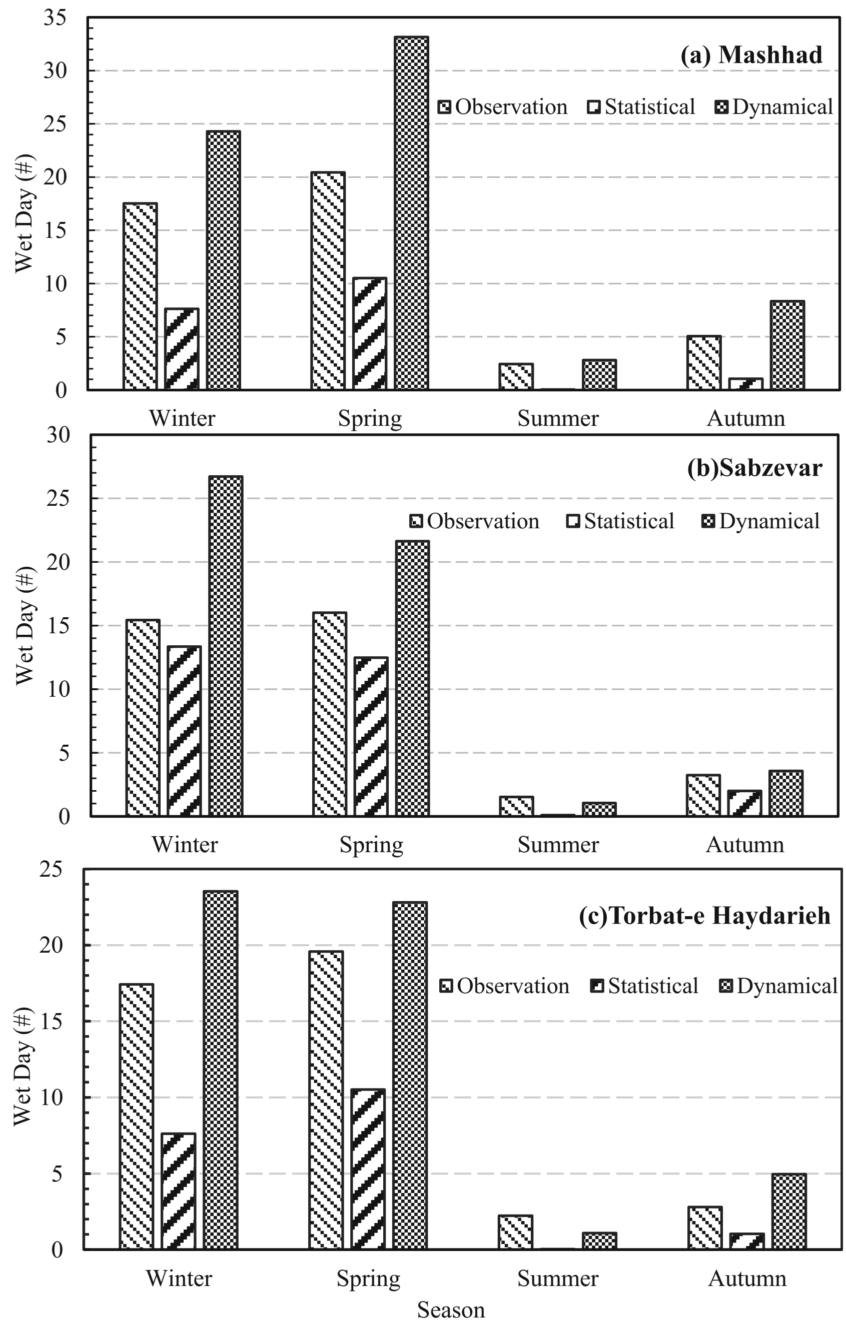


Fig. 5 The average seasonal wet-days during 1990–2010 of observation, statistical, and dynamical data output, in the three locations

autumn, observation variability and median precipitation are better represented by DD and slightly underestimated by SD. In comparison with the median of observation and Delta method, RegCM4 had the largest variation of the median, and the highest median values predicted by the RegCM4 has occurred in winter (WD) and spring (SD).

At Sabzevar (Fig. 4b) SD performed fairly well with regard to the variability and median of precipitation in winter. DD overestimated variability and median precipitation in winter and spring, and strongly overestimates the percentile above 75th. The upper quartile of the seasonal precipitation distribution increases during winter and spring, in compare to observation data. At Torbat (Fig. 4c), both the SD and DD approaches underestimated the values of precipitation, but adequately capture median winter value. SD obtained the highest IQR in spring, and DD did relatively well for IQR in spring and autumn. Overall, in three stations, SD approach overestimated the precipitation's values over spring; also, DD has the same behavior in spring, except for Torbat station. From the analysis for all stations, SD presented lower values of precipitation than DD, at summer and autumn.

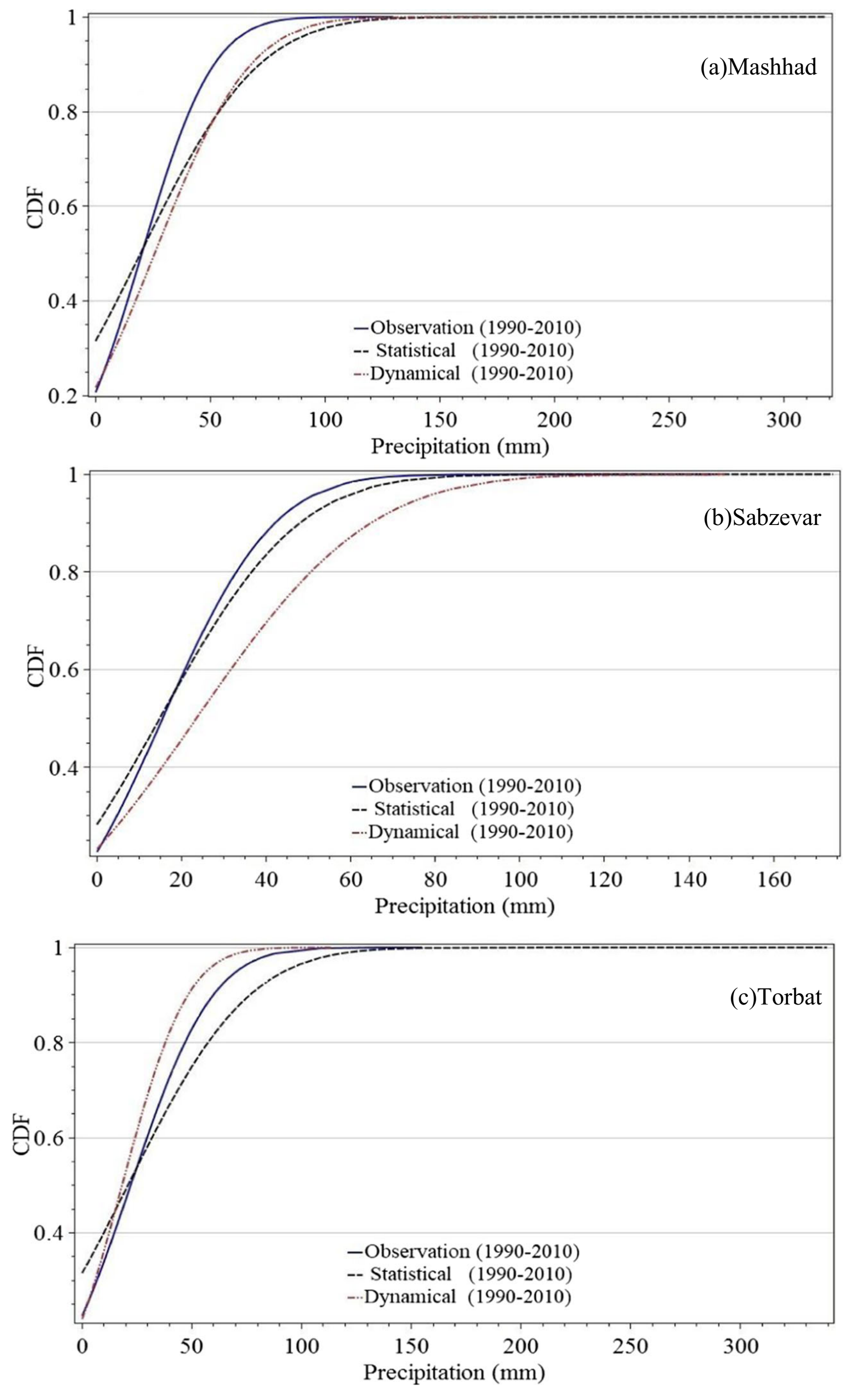


Fig. 6 Cumulative distribution functions (CDF) of observed, statistical, and dynamical total precipitation in three locations

At Mashhad station, the SD approach tends to underestimate the number of wet days in winter, spring, and summer. DD tends to overestimate wet days for these seasons (Fig. 5a). As illustrated in Fig. 5b, Sabzevar station shows trends similar to Mashhad: SD predictions are much closer to the observation station data and DD overestimates values for all seasons except summer. This may be because Sabzevar station is an arid area in contrast to the semi-arid climate of the other two sites. Torbat (Fig. 5c) shows similar results as Mashhad station; the SD approach underestimates wet days, and DD tends to overestimate for all seasons except summer. Mashhad and Torbat have similar climate and both of them are semi-arid. To summarize, for the four seasons of three data outputs (station, SD, and DD) in three locations, the number of wet days in a historical run versus observation data, are almost well captured by DD at autumn. Generally, the SD method tends to underestimate this value, while DD overestimates it, during winter, spring, and summer.

Figure 6 shows CDFs for observed versus SD and DD precipitation at three locations. For the observed precipitation at Mashhad (Fig. 6a), the probability of more than 40 mm of total precipitation is 20% ((1–0.80)*100 = 20%), but the values from SD and DD using historical data are 30% and 32%, respectively. At Mashhad, DD and SD show similar outputs of precipitation values greater than 50 mm of 20% probability. At Sabzevar DD significantly overestimates the probability of precipitation over 20 mm; SD only slightly overestimates this (Fig. 6b). The probability of total precipitation of more than 50 mm is 20% from DD, but this value is 10% from SD and 10% from observed data. DD outputs suggest a 60% probability of total precipitation less than or equal to 30 mm, but this value is 75% for SD and 80% for historical data. The historical probability for more than 25 mm of total precipitation at Torbat is 45% from the SD approach and 40% for DD. All three cases (observed, SD, and DD) agree on the probability of 120 mm or more of total precipitation (Fig. 6c). Overall, the DD approach more closely matches observed than SD at Torbat.

Average daily precipitation from 1990 to the end of 2010 from the dynamic simulation of the RegCM4 model in northeastern Iran is shown in Fig. 7. Precipitation simulations of the dynamic model in Sabzevar were 0.5–0.6, Torbat 0.7–0.8, and Mashhad, 0.8–0.9 mm / day, while observed values at these three stations have been reported 0.52, 0.73, and 0.67 mm / day, respectively. The simulated precipitation values in Torbat and

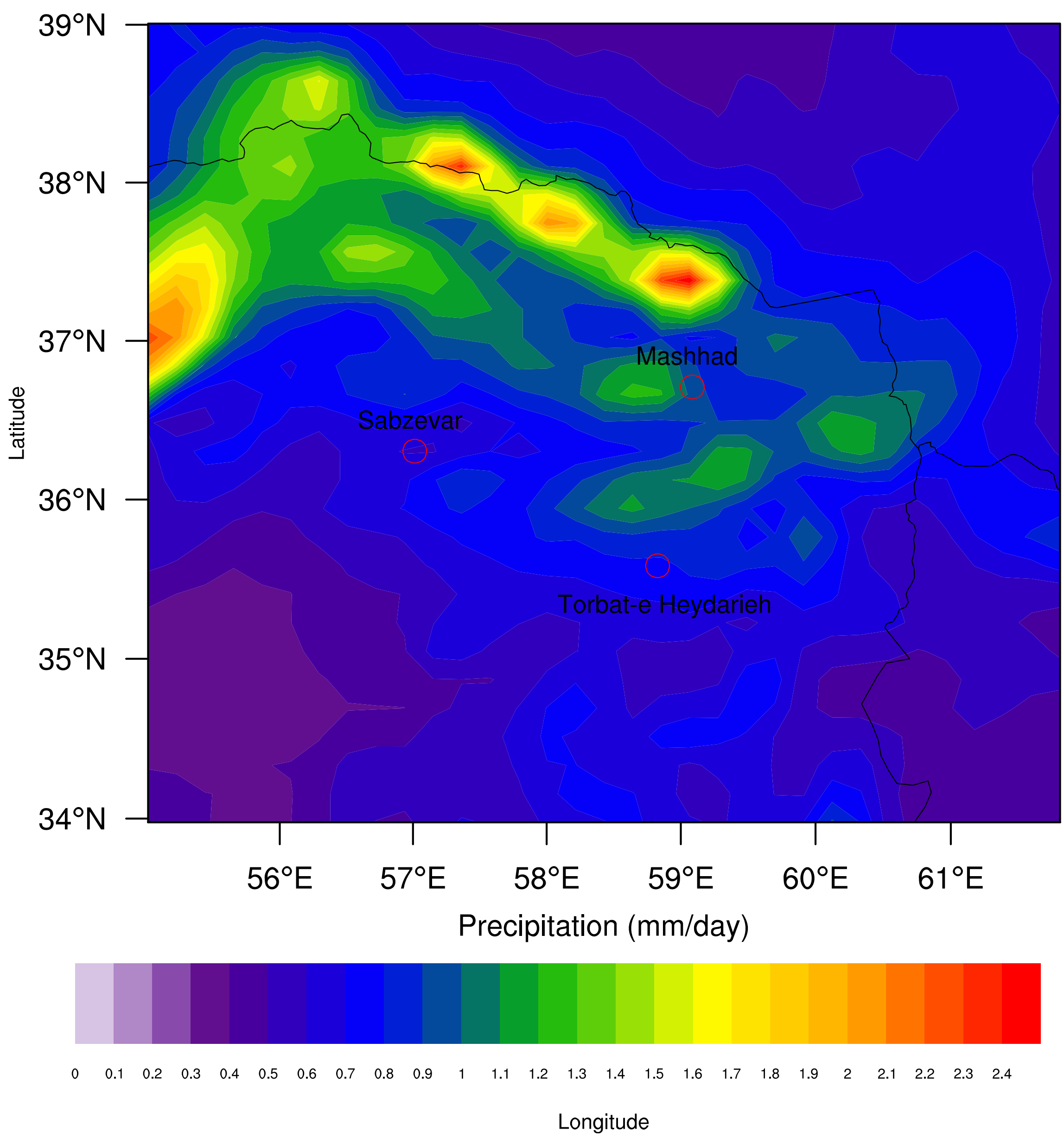


Fig. 7 The result of average daily precipitation through DD method during 1990–2010

Sabzevar are fully matched with observational values, but at Mashhad station, the dynamic model has a near 2 mm overestimate.

Both SD and DD approaches reproduced precipitation and wet days of the case study, but both represented biases with respect to observations as well. The statistical criteria show that the DD approach yielded better results than SD. This finding agrees with the results of Mearns et al. (1999), Gutowski et al. (2000), and Yarnal et al. (2001).

4 Conclusion

This analysis has focused on the performance of SD and DD approaches over NNRP1 precipitation historical data (1990–2010). We assessed their accuracy vs. observation data on precipitation amount and number of wet days, on annual and seasonal scales. DD is more complex and needs high frequency (6 hourly) GCM outputs and is associated with a heavy computational cost of RCMs. SD is computationally efficient, require less computational demand, time, cost, and are easily implemented. For this semi-arid area, the SD approach underestimates annual mean precipitation and number of wet days in all stations, whereas the DD overestimates these values. In all stations, the Pearson correlation coefficients for DD were greater than 0.72; for SD coefficients were more than 0.65 (p value<0.001). MAE results of DD for Mashhad and Torbat were 13.35 and 12.22, respectively; for SD they were 15.86 and 16.1. For Sabzevar station, MAE of DD was 12.96, whereas for SD it was 10.47. The Pearson correlation, NSE, and MAE values all point to the DD approach as more efficient. This finding agrees with other downscaling studies of precipitation and highlights the advantages of considering different downscaling methods (Hayhoe et al., 2006; Haylock et al. 2006; Maurer and Hidalgo 2008; Wang et al. 2016).

One of the limitations of this study was that it has been applied over a not very big region over the northeast of Iran. Better results may be obtained in different climates, with a further number of stations. Finally, according to the results of this research, we emphasize that the choice of most appropriate downscaling method depends on the user's requirements (time and expense), time scale (seasonally, monthly or daily scale), and the climate of regions of interest.

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