Stochastic Environmental Research and Risk Assessment
https://doi.org/10.1007/s00477-021-02064-3

ORIGINAL PAPER

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Spatio-temporal analysis of heating and cooling degree-days over Iran

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Accepted: 10 July 2021

Abstract
In this research, temporal trends and change points in heating degree-days (HDD), cooling degree-days (CDD), and their simultaneous combination (HDD + CDD) were analysed for a 60-year period (1960–2019) in Iran. The results show that less than 20% of the study stations had significant trends (either upward or downward) in HDD time series, while more than 80% of the stations had significant increasing trends in CDD and HDD + CDD time series. Abrupt changes in HDD time series mostly occurred in the early 1980s, but those in CDD time series were mostly observed in the 1990s. The cooling energy demand in Iran has dramatically increased as CDD values have raised up from 690 °C-days to 1010 °C-days in the last 60 years. HDD, however, almost remained constant in the same period. The results suggest that if global warming continues with the current pace, cooling energy demand in the residential sector will considerably increase in the future, calling for a change in residential energy consumption policies.

Highlights

- Monotonic trends in HDD, CDD and HDD + CDD time series were analysed in Iran.
- The series were also analysed for possible change points using the non-parametric method.
- Energy demand for cooling houses increased, while that for heating houses remained constant.
- Up to three upward abrupt change points were observed in the annual CDD series.

Keywords Change point detection · Geostatistical interpolation technique · Degree-day method · Spatial analysis · Trend analysis

1 Introduction

Energy demand has increased In the last few decades as a result of rising standards of living and population growth. Projected world population growth up to 50% in the next forty years may further energy demand by 80% (British Petroleum (2019). About 40% of the world's energy consumption is allocated to the residential sector (United Nations 2016). As a building's energy consumption for cooling and heating is directly related to the outdoor temperature (Atalla et al. 2018), it may also be affected by global warming arising from increasing emissions of greenhouse gases (IPCC 2014). The complex influence of anthropogenic factors on building energy performance, which can be much larger in developing countries such as Iran due to poor infrastructure and mismanagement, requires a reform of energy budgets. Adjusting living environment's temperature status with a reasonable consumption of energy along with effective environmental management can reduce expenses and maximize benefits from resources for the sake of society (Christenson et al. 2006). Accordingly, heating and cooling energy supply has

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nowadays become a critical problem in many countries due to anthropogenic influences. In this context, a time series analysis of climate indices related to energy demand measurement can improve understanding of anthropogenic influences in the energy sector, contributing to the developing adaptation and mitigation strategies.

In the recent years, a growing body of literature has studied the time series analysis of changes in climate indices affecting buildings' energy demands (Kadioğlu et al. 2001; OrtizBeviá et al. 2012; De Rosa et al. 2015; Shen and Liu 2016; Shi et al. 2018; D'Amico et al. 2019; Morakinyo et al. 2019; Islam et al. 2020; Ukey and Rai 2021). The main method used in the previous studies is degree-day method. Degree-day method is considered one of the simplest yet efficient methods for calculating the energy consumption of a building and evaluating climate change impacts (You et al. 2014). This simple method is also utilized in other scientific fields such as agriculture, architecture, entomology, etc. The degree-day method has been used for calculating energy consumption specifically for building's heating and cooling since 1932 (Dufton 1934) and it is generally considered a trusted method for this purpose (Atalla et al. 2018).

Two main aspects of the degree-day method are heating (HDD) and cooling (CDD) degree-day, as changes in HDD and CDD affect energy management for building and pose a substantial threat to livelihood patterns. HDD and CDD can be studied using different temperature thresholds. The temperature threshold is defined as the comfortable temperature for human so that there is no heating or cooling demand. The thresholds may differ depending on economic status, energy supply and human physiological needs (Table 1). In this study, as recommended by Iran Meteorological Organization (IRIMO), temperature threshold was determined 18 $^{\circ}$C for heating and 21 $^{\circ}$C for cooling.

Iran is a major energy supplier: the second oil and gas supplier and exporter in the world (before the USA sanctions against Iran in 2019). Yet, having more than 80 million population along with its old infrastructure made Iran also one of the major energy consumers. Energy consumption in the country is 4.4 times above the global average, making it one of the top ten greenhouse gas emitting countries (Gorjian et al. 2019). Achieving a sustainable development without considering energy sector is impossible. One of the most important potential factors of energy consumption increases in any region is temperature changes. Measuring cooling and heating degree-days can present a clear and reliable image of building, city and region's thermal demands. It can also play an important role in reforming energy consumption patterns.

In this study, the spatial and temporal patterns of HDD, CDD and their combination (HDD + CDD) are investigated, contributing to decision-making and planning process for energy management. Although many studies have performed on analysing warming and cooling heating and cooling energy demand for buildings using degree-day method (Table 1), there are still some knowdege gaps that are addressed in this study:

1. To the best of the authors knowledge, abrupt changes in HDD, CDD, and their combination (HDD + CDD) time series have not been studied. Previous studies (Kadioğlu et al. 2001; OrtizBeviá et al. 2012; Spinoni et al. 2015; Shi et al. 2018) have investigated the long-term changes in HDD and CDD time series, but not abrupt changes. It is examined for the first time in the present study. This study not only detects the time of the breakpoint, but also analyses pre- and post-breakpoint series trends. In addition, the potential of more than one breakpoints in a climate time series is considered in the present study which was not studied before.
2. Regionally, this is the first study carried out at different stations of Iran to detect trends in HDD, CDD, and HDD + CDD time series.
3. This study, presents a useful approach for HDD and CDD interpolation with a very high degree of logical compatibility by identifying the patterns of degree-days.
4. The return period of the studied indices is estimated for the first time, providing useful information to develop plans and policies for reducing risk and loss caused by extreme climate events in both short and long-term planning.

2 Materials and methods

2.1 Study area and data

The study area is the whole area of Iran with the total area of 1.648 million km^2. Iran has a complex topography with diverse climates including hot deserts in the centre, high altitude mountainous regions in the north and west, flat fertile plains in the southwest (and many other locations), and lowland humid areas in the north. Figure 1a demonstrates the location of the studied stations as well as Iran's digital elevation model (DEM) map. Figure 1b represents the spatial distribution of the country's average air temperature. The annual temperature difference in some areas reaches 25 $^{\circ}$C.

Daily weather data were downloaded from Iran Meteorological Organization, IRIMO. Many synoptic stations in Iran are newly established and do not have a long-term record. We first selected a set of the stations having observations since 1960 among more than 300 synoptic

Table 1 Overview of previous studies on the heating and cooling energy demand for buildings using degree-day

Research work	Study area	Study period	Threshold (°C)	
			HDD	CDD
Jiang et al. (2009)	Xinjiang Province, China	1959–2004	18	24
Eskeland and Mideksa (2010)	Europe	1995–2005	18	22
Petralli et al. (2011)	Florence, Italy	2004–2008	17	22
Zanobetti et al. (2012)	USA	1971–2000	18.3	18.3
Al-Hadhrami (2013)	Saudi Arabia	1970–2006	18.3	18.3
Spinoni et al. (2015)	Europe	1951–2011	15.5	22
Wang et al. (2015)	Woodbine, Iowa, USA	2008–2010	18.3	18.3
Mazdiyasni et al. (2017)	India	1960–2009	–	22
Villarini et al. (2017)	North America	1985–2015	18	18
Limones-Rodríguez et al. (2018)	Andalusia	1985–1999	14	21
Berger and Worlitschek (2018)	Switzerland	1981–2016	12	–
Morakinyo et al. (2019)	Hong Kong	1970–2015	–	26
Alola et al. (2019)	USA	1960–2015	18.3	18.3
Arnell et al. (2019)	Global	1981–2010	18	18
Islam et al. (2020)	Bangladesh	1980–2017	18	24

stations. Then, four stations (Chabahar, Dezful, Nozheh and Tabas) with more than 10% missing data were excluded. Finally, we identified 31 synoptic stations that had a long-term recorded data for the period 1960–2019.

2.1.1 Data quality control

To assess the quality of the used data, some traditional tests were used. Observations indicated that in the majority of studies (Shen et al. 2011; Do and Cetin 2018; Chham et al. 2019), Grubbs test (Grubbs and Beck 1972) was used to detect outliers in the time series. Grubbs test is robust against deviation from independence (De Bin et al. 2017), is considered the more powerful outlier detection test when there are more than one outlier (De Muth 2019). This test was hence selected for this purpose. In this procedure, when one or more data points at one station were detected as outliers, the data of the same year from one or more neighbouring stations were investigated. In the case, the data points of neighbouring stations did not match the outlier, the outlier was removed from the time series; otherwise, it was considered as a valid data point. The quality of air temperature time series in Iran was very good comparing other climatic variables. Outliers and missing data in all the studied stations amounted to less than 1%. Thus, alternative approaches to reconstructed missing values were unnecessary.

2.2 HDD + CDD index

Time series of HDD were prepared using the mean air temperature threshold equal to 18 °C. Indeed, the HDD in a year is the cumulative absolute values of differences between mean daily air temperature from 18 °C in the days when the mean air temperature is below 18 °C. Here, the mean air temperature (T_{mean}) was calculated by averaging the minimum air temperature (T_{min}) and maximum air temperature (T_{max}) recorded for the same day.

$$\mathrm{T_{mean}} = \frac{\mathrm{T_{max}} + \mathrm{T_{min}}}{2} \tag{1}$$

$$HDD_{daily} = \begin{cases} -T_{mean} + 18 & T_{mean} < 18 \\ 0 & T_{mean} \geq 18 \end{cases} \tag{2}$$

$$HDD_{monthly} = \sum_{i=1}^{N} HDD_{daily} \tag{3}$$

$$HDD_{yearly} = \sum_{i=1}^{12} HDD_{monthly} \tag{4}$$

where N is the number of days in a month that need heating.

Similarly, CDD was defined as follows:

$$CDD_{daily} = \begin{cases} -21 + T_{mean} & T_{mean} \geq 21 \\ 0 & T_{mean} < 21 \end{cases} \tag{5}$$

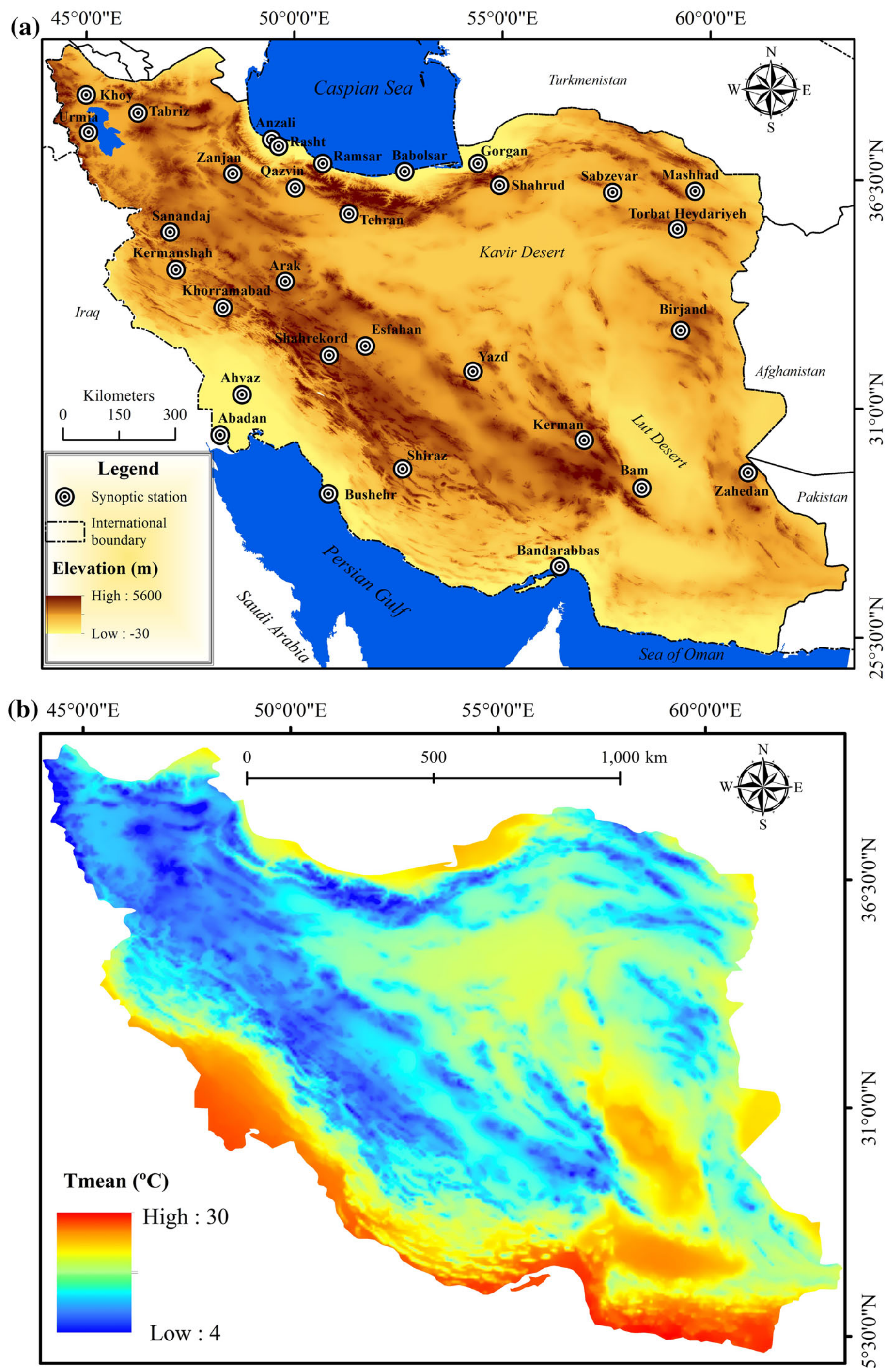


Fig. 1 **a** Locations of the studied stations and Iran's Digital Elevation Model (DEM) and **b** spatial distribution of mean air temperature

$$CDD_{monthly} = \sum_{i=1}^{N} CDD_{daily} \tag{6}$$

$$CDD_{yearly} = \sum_{i=1}^{12} CDD_{monthly} \tag{7}$$

In addition to the individual analysis of cooling and heating demands, their joint spatio-temporal distribution over Iran is also investigated through heating and cooling degree-day sums (HDD + CDD). The HDD + CDD index corresponds to the total amount of heating and cooling demand and overall outdoor thermal comfort. This index is used as an easy-to-understand indication of differences in heating and cooling demand in residential sector (Sivak 2008, 2009; Petri and Caldeira 2015). Following many studies carried out around the world to use the degree-day method to quantify the buildings' energy demands (Verbai et al. 2014; Kohler et al. 2016; Berardi and Jafarpur 2020;

Nurlybekova et al. 2021), the authors do not consider other influencing factors such as building insulation, internal heating system and interior design.

2.3 Monotonic trend analysis

The trend analysis and change point detection of climate parameters provide precious information for a physical understanding of climate change and its impact on the living environment. One of the most important challenges caused by global warming and climate change is an energy consumption shift. In analysing time series to detect temporal trends, both parametric and non-parametric statistical tests are applicable depending on the underlying probability distribution. The non-parametric tests are generally preferable over the parametric ones as they do not require data of interest to be normally distributed, are insensitive to outliers (Tabari 2019; Cengiz et al. 2020). Moreover, filling the gaps in time series is not needed when applying non-parametric methods. Among the non-parametric methods, the Mann–Kendall trend test (Mann 1945; Kendall 1975) and the Sen's slope estimator (Sen 1968) have been widely employed for anlaysing long-term changes in hydroclimatic series (Degefie et al. 2014; Atta-ur-Rahman and Dawood 2017; Asfaw et al. 2018; Dinpashoh et al. 2019; Ye and Messori 2020). The non-parametric Pettitt change point test (Pettitt 1979) has also been frequently used for detecting abrupt changes in these time series in climate (Li et al. 2016; Liu et al. 2016; Engström and Waylen 2017; Rizzo et al. 2020). In order to carry out the monotonic trend analysis for annual time series of the three indices of HDD, CDD and HDD + CDD, the following approaches were used.

1. To investigate HDD, CDD and HDD + CDD time series trend for the last 60 years, the non-parametric Mann–Kendall trend test was used (Mann 1945; Kendall 1975). For the series with significant autocorrelation coefficients, the modified M–K method by Hamed and Rao (1998) was utilized. This is due to the fact that the existence of positive (negative) serial correlation will increase (decrease) the possibility of rejecting the null hypothesis of no trend while it is actually true (Tabari and Hosseinzadeh Talaee 2011). M–K test was calculated at 0.05, 0.01 and 0.001 significance levels. Trend line's slope was also obtained via the non-parametric Sen's slope estimator (Sen 1968), which is resistant to the effect of extreme values in time series and thus gives a robust estimate of trend magnitude (Tabari et al. 2015).

2. In order to detect the breakpoint in time series, Pettitt (1979) test was employed. For cases with significant abrupt changes at a 0.05 significance level, change percentage was determined for post-breakpoint against pre-breakpoint. Also for stations that had experienced abrupt changes at a 0.01 significance level, the trend line slope for pre- and post-breakpoint series was obtained using a simple linear regression.

3. Since the Pettitt test is only capable of detecting a single breakpoint during a time series, therefore, some modifications were used here to develop this approach for multiple change points as follows: For those series that had one significant breakpoint (at a 0.01 significance level), the time series was divided into two sub-series in the detected point. Then, the Pettitt test was applied again for both sub-series. This is repeated if there was a significant change point in any sub-series. XLSTAT software was utilized to perform the statistical tests in this study (i.e. M–K, Sen, Pettitt and Grubbs). Detailed mathematical relationships for the statistical tests used are provided in the 'Appendix A'.

2.4 Spatial analysis

First of all, correlation among some available meteorological parameters (e.g. T_{min}, T_{max}, T_{mean}, frost days and rainfall) was calculated using the Pearson method to find two variables with a strong correlation with the studied parameters in order to improve the accuracy of the interpolation results. Next, ESRI ArcMap software was utilized in order to extract spatial distribution maps of the studied indices. For creating spatial distribution maps of the studied indices, Inverse Distance Weighting (IDW), Kriging and CoKriging geostatistical techniques were employed for the interpolation of the three studied indices over Iran. In CoKriging, three covariables can be utilized to improve the accuracy. In this study, the country's DEM as well as two other variables that had a strong correlation with the studied parameters were used as covariables. To evaluate the model's ability to predict new data, cross-validation was applied which is a resampling procedure for perfomence evaluation especially on a limited data sample. It is based on multiple permutations of the sample into training and testing subsets in order to overcome biases and overfitting problems (Rodríguez-Pérez et al. 2018; Zakeri et al. 2020). By applying cross-validation, performance evaluation criteria including Normalized Root Mean Square Error (NRMSE), Mean Absolute Percentage Error (MAPE) and Mean Bias Error (MBE) were obtained ('Appendix B'). Finally, the best model which can reasonably represent the region's topographical pattern was selected for preparing the final map for spatial analysis of the studied indices.

2.5 Return period

Three tests are commonly used to examine goodness of fit of statistical distributions: Kolmogorov–Smirnov (K-S), Chi-Square (χ^2), and Anderson–Darling (A-D). The non-parametric K-S test is independent of the sample size and does not depend on cumulative distribution function being tested. The K-S test is more powerful than the A-D and χ^2 tests and thus its results are less biased (Henderson 2006; Frey 2009; Rajan et al. 2014; Khomytska et al. 2019). K-S test has therefore got popularity for evaluating the performance of marginal distribution functions in fitting different meteorological variables (Soukissian and Karathanasi 2017; Sun et al. 2019; Martin-Vide and Moreno-Garcia 2020). Sixty-five statistical distributions were tested for the goodness of fit using the (K-S) test and the best distribution was used to estimate the return levels. Using EsyFit software, a frequency analysis was performed to estimate the magnitudes of the variable under consideration with respect to the following return periods: 2, 10, 25, 50, and 100 years.

3 Results

3.1 Spatial analysis

Table 2 shows the performance measurement of IDW, Kriging and CoKriging obtained by the cross-validation technique. The results revealed that Kriging and IDW methods were not sufficiently accurate for the purpose of this study, as detailed below. Since only 31 synoptic stations were qualified for the long-term analysis and this number of stations may not be sufficient for a country with 1.648 million km^2 area and with a complex topography. That is why in regions with complex topography (i.e. a region including vast mountain ranges, valleys, plains and deserts.) IDW and Kriging methods do not yield results consistent with the region's topographic and climatic conditions. It should also be pointed out that air temperature and indices based on that (e.g. HDD and CDD studied in this research) depend largely on the topography of the studied region. They have indeed an inverse relation with elevation, being lower in highly elevated mountainous regions than plains, deserts and its neighbouring coastal flatlands. The findings indicate that IDW and Kriging methods do not provide accurate results since the methods are incapable of distinguishing between air temperatures of high and low elevations. IDW and Kriging have been used in many studies because of its simple usability and without considering its error and related compatibility with actual conditions of that area which may lead to unreliable results. Although using covariables in CoKriging method increase its accuracy compared to Kriging and IDW methods, the model still may not be able to distinguish the difference of degree-days between elevated areas and lowlands. Using the DEM of Iran as one of the covariables significantly enhances logical compatibility of model by identifying the topographical pattern of degree-days especially when the number and distribution of the stations are not sufficient (Fig. 2). The DEM of the region was therefore used to improve the accuracy of the spatial analysis of the temperature-based indices. The results show that in the Kriging method, there were no significant differences between ordinary, simple, universal and disjunctive models, while in CoKriging method, some differences were observed. The results indicated that for the spatial distribution of the studied indices, the disjunctive CoKriging model offered relatively better results compared to the other models. That's to say, the error for the CoKriging method was 3 times smaller than that obtained from IDW and Kriging methods. This model was then used for the spatial distribution analysis of the studied indices.

Figure 3 shows the spatial distribution of annual HDD, CDD and HDD + CDD in Iran and Table 3 gives the average monthly HDD and CDD. The results show that there is no need for heating from June to September. As expected, the greatest demand for heating is during winter

Table 2 Performance measurs for IDW, Kriging and CoKriging interpolation methods

Variable	Error metric	IDW	Kriging	CoKriging (without DEM)	CoKriging (with DEM)
HDD	NRMSE (%)	19.6	17.5	6.3	4.7
	MAPE (%)	109.3	93.1	27.0	21.0
	MBE (°C-day)	36.3	18.0	− 7.3	3.1
CDD	NRMSE (%)	20.2	19.0	10.3	6.6
	MAPE (%)	53.8	52.4	28.4	23.8
	MBE (°C-day)	− 52.8	− 51.8	− 19.9	10.5
HDD + CDD	NRMSE (%)	23.7	22.8	18.9	17.3
	MAPE (%)	11.2	10.7	8.7	8.0
	MBE (°C-day)	− 22.5	− 18.8	− 4.5	3.6

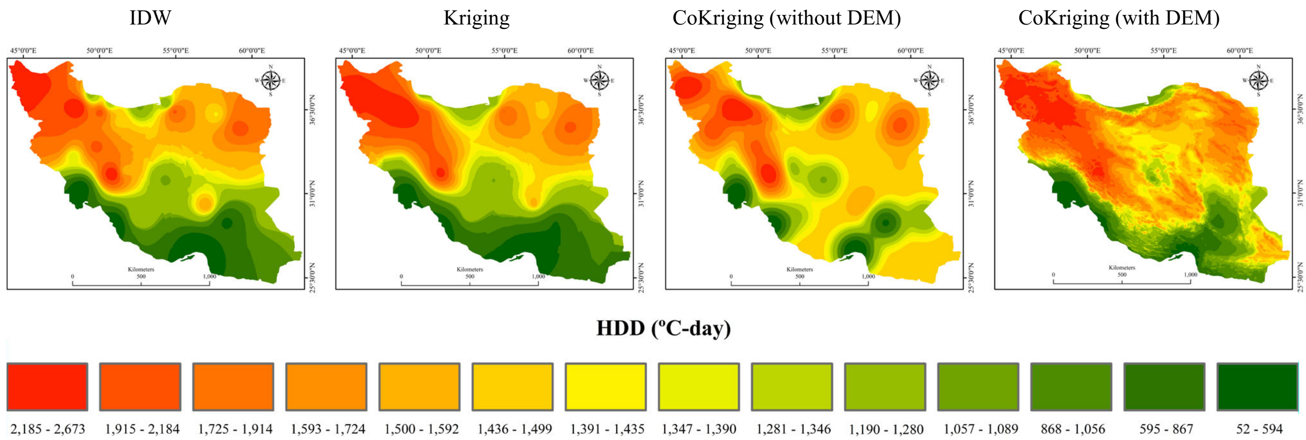


Fig. 2 HDD interpolation maps using different geostatistical techniques

months (from December to February) and the greatest demand for cooling is in the summer. In general, the demand for heating in Iran is more than cooling. As can be seen in Fig. 3, stations that are located in the southern tropical regions of the country had a higher energy demand for cooling than the other stations. In these locations, the highest CDD change range was also observed (Fig. 4a). On the other hand, the largest HDD change range were observed in the cold and mountainous regions, which are mainly located in the west of the country. According to Fig. 4b, the greatest range of HDD + CDD changes are seen in areas with cold or warm climates, such as the northwest and southwest of the country. In contrast, the change range is less in areas with relatively mild climates, such as coastal regions and some central areas of Iran.

3.2 Trend analysis

Table 4 represents the magnitudes of trends estimated by Sen's slope for monthly and annually HDD and CDD in the selected stations. Table 5 gives the number and percentage of the stations with positive and negative trends as well as the number and percentage of stations with upward and downward abrupt changes. According to these tables, 19% of the stations showed significant annual trends in HDD time series at the 0.05 significance level. Three stations located in the west and northwest of the country experienced a significant positive trend in HDD time series, while three other stations located in tropical regions had a significant negative trend. About 80% of the stations had slightly positive or negative annual trends that were not significant, implying that the station's trend is approximately zero. It seems that positive HDD slopes mostly exist in mountainous regions that are specifically located in the northwestern part of the country, while the negative HDD trend was commonly observed in tropical regions. The analysis of monthly trends showed that in the cold months of the year, especially November to January, the HDD trend was positive, while in the warm months of the year (April to June, September and October) the trend was negative in most stations. Cvitan and Sokol Jurković (2016) found a positive HDD trend for December in Croatia.

According to the results of Table 5, 87% of the sites showed significant ($\alpha < 0.05$) trends for CDD time series at the 0.05 significance level, which decreases to 74% for the higher significance level of 0.001. Among these stations, except Shahrekord station which had a significant negative trend, all the other stations experienced significant positive trends. The steepest CDD trend line belonged to the southwest of the country which is about 19.7 °C-days per year.

Table 4 also shows the output of the trend analysis for HDD + CDD time series in the selected stations in Iran. It can be suggested that all stations (except Zanjan) experienced a positive trend and 81% of them were significant at the 0.05 significance level. However, inspection of results revealed that such an increase is a result of increasing trends in CDD series. Increasing trends in HDD + CDD time series were intense in some of the stations. For example, trends in HDD + CDD time series in 42% of the selected stations were significant at a 0.001 significance level. The steepest trend line slope of 18.1 °C-days was also calculated for the southwest of the country (Abadan and Ahvaz stations).

3.3 Breakpoints

Figure 5 shows the results of the Pettitt test conducted for the three time series at the selected stations in Iran. The percentage change between the mean values of post-breakpoint and pre-breakpoint series along with the direction of abrupt changes are shown in the Fig. 5. Figure 6 shows the frequency of abrupt change years in 5-year

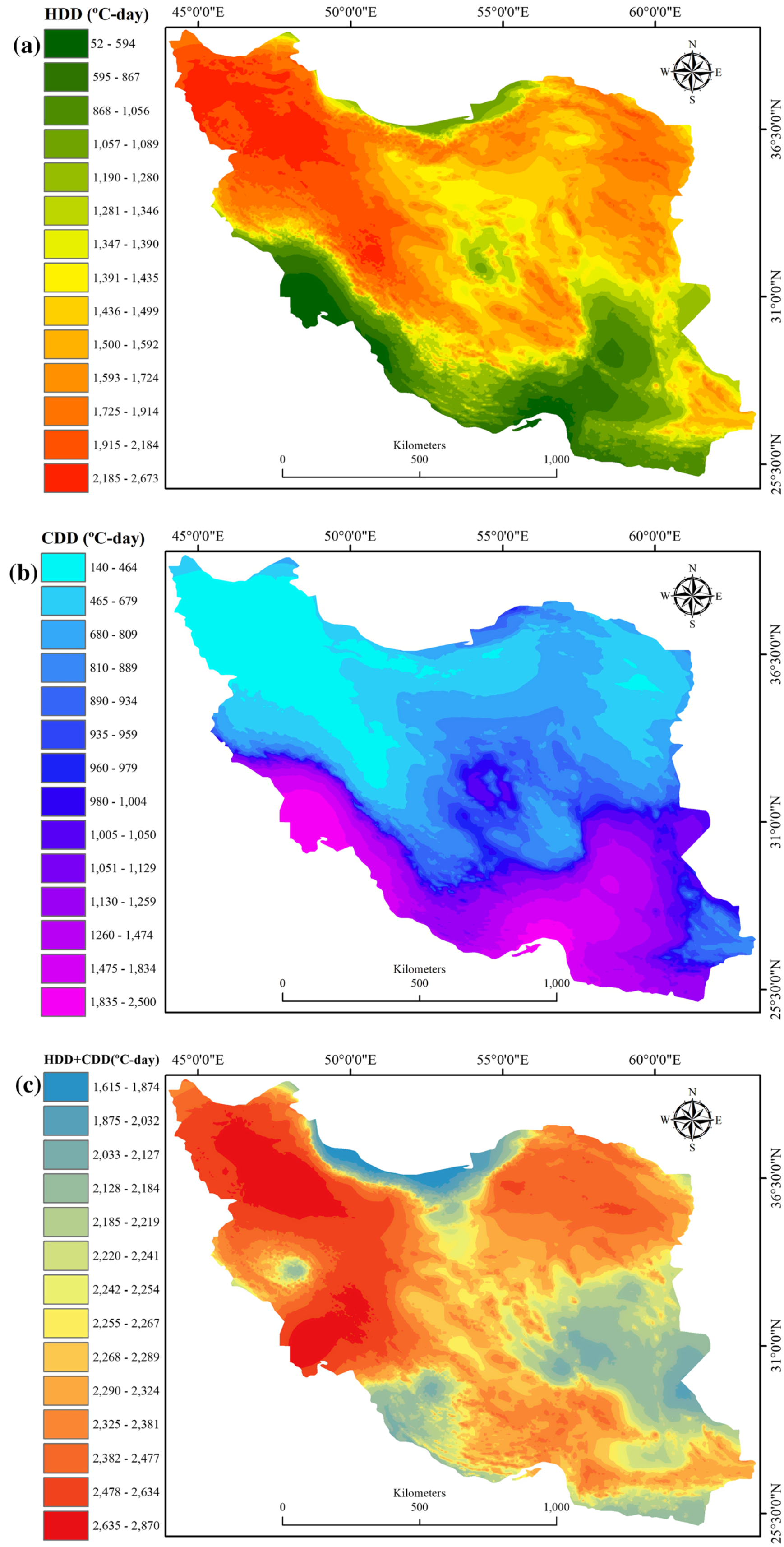


Fig. 3 Spatial distribution of the studied indices **a** HDD, **b** CDD and **c** HDD + CDD. The values are at an annual time scale and averaged over the 60-year period from 1960 to 2019

Table 3 Average of monthly HDD and CDD at the studied stations. The values averaged over the 60-year period from 1960 to 2019

Station name	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Abadan	131	74	17	0	0	0	0	0	0	0	16	96	0	1	22	127	312	412	461	445	338	193	28	0
Ahvaz	143	81	20	1	0	0	0	0	0	0	18	109	0	0	16	123	315	421	496	475	354	196	24	0
Anzali	255	249	223	117	17	0	0	0	0	22	108	202	0	0	0	1	12	85	150	140	58	6	0	0
Arak	456	367	275	129	32	0	0	0	2	80	257	381	0	0	0	0	9	95	191	160	44	1	0	0
Babolsar	237	223	196	86	9	0	0	0	0	16	100	196	0	0	0	1	21	101	167	166	86	12	0	0
Bam	194	117	40	4	0	0	0	0	0	2	47	152	0	2	24	104	241	347	386	332	234	109	11	1
Bandarabbas	28	11	1	0	0	0	0	0	0	0	0	11	2	9	54	161	298	362	389	375	312	238	89	10
Birjand	374	289	186	55	6	0	0	0	5	58	201	331	0	0	0	9	65	163	202	142	54	6	0	0
Bushehr	94	60	16	0	0	0	0	0	0	0	5	52	0	2	18	103	249	305	365	366	289	180	40	2
Esfahan	381	291	196	66	7	0	0	0	1	43	211	353	0	0	0	2	45	173	249	200	81	4	0	0
Gorgan	290	250	202	79	8	0	0	0	0	21	118	239	0	0	1	6	48	144	213	211	118	21	1	0
Kerman	371	279	192	63	6	0	0	0	7	68	220	347	0	0	0	2	41	136	176	108	35	1	0	0
Kermanshah	398	335	272	142	39	1	0	0	1	60	226	347	0	0	0	0	6	78	202	184	50	2	0	0
Khorramabad	322	262	200	85	12	0	0	0	0	24	165	284	0	0	0	0	27	140	250	237	99	10	0	0
Khoy	472	390	301	155	54	5	0	0	13	125	289	405	0	0	0	0	3	40	119	104	20	0	0	0
Mashhad	420	332	234	92	18	0	0	0	12	102	241	365	0	0	0	4	32	120	184	131	36	3	0	0
Urmia	493	422	336	193	77	8	0	0	16	138	307	445	0	0	0	0	1	21	84	69	8	0	0	0
Qazvin	454	366	278	134	33	1	0	0	3	76	245	393	0	0	0	0	10	87	173	150	48	2	0	0
Ramsar	282	256	231	127	24	1	0	0	0	20	116	220	0	0	0	1	6	63	134	136	61	6	0	0
Rasht	283	255	217	106	15	1	0	0	1	33	136	235	0	0	0	1	16	82	138	137	54	6	1	0
Sabzevar	374	278	179	49	5	0	0	0	1	36	175	327	0	0	1	18	97	226	292	237	121	17	0	0
Sanandaj	449	382	297	161	49	1	0	0	2	86	257	388	0	0	0	0	3	68	194	174	34	0	0	0
Shahrekord	500	396	339	196	75	4	0	0	20	146	301	439	0	0	0	0	0	19	86	56	4	0	0	0
Shahrud	455	363	262	101	19	0	0	0	4	77	249	402	0	0	0	3	31	115	188	154	56	3	0	0
Shiraz	320	240	166	53	3	0	0	0	0	15	154	279	0	0	0	3	64	180	255	224	105	8	0	0
Tabriz	475	388	326	174	51	3	0	0	5	99	282	420	0	0	0	0	4	64	165	158	44	0	0	0
Tehran	388	294	192	58	6	0	0	0	0	26	175	335	0	0	1	8	72	208	297	266	140	20	0	0
Torbat H.	463	372	270	106	19	0	0	0	9	99	260	406	0	0	0	2	29	114	173	123	33	1	0	0
Yazd	294	215	116	20	1	0	0	0	0	14	138	265	0	0	2	26	131	269	328	274	152	25	0	0
Zahedan	308	210	106	21	1	0	0	0	2	35	153	273	0	0	3	35	120	199	233	174	67	13	0	0
Zanjan	551	458	373	213	90	11	1	1	20	147	328	480	0	0	0	0	1	22	87	76	11	0	0	0

HDD (°C-day)					
CDD (°C-day)					
	>350	250-350	100-250	20-100	<20

periods. According to the results, all upward abrupt changes in HDD occurred before 1985, with 80% in 1981. All downward abrupt changes in HDD happened in the 90 s. 32% of the stations had no abrupt changes in their annual HDD time series.

Concerning CDD, the findings denoted that (except Shahrekord) all the other studied stations experienced upward abrupt changes in CDD values. About 70% of the experienced abrupt changes happened in the 90 s. The percentage of the CDD increase in post-breakpoint compared to pre-breakpoint is higher for the northern half of the country than for the southern half (Fig. 5b). From figures presented by Anjomshoaa and Salmanzadeh (2017) realized that from 1996 to 1998, Kerman city experienced a downward abrupt change during the heating season and an upward abrupt change during the cooling season, corroborating the results. They have also reported that the heating season begins later and finishes sooner in the recent years due to the impacts of global warming. Similarly, the cooling season begins later and finishes sooner than before.

According to Fig. 5c all the stations except two stations in the northwest of the country experienced an upward

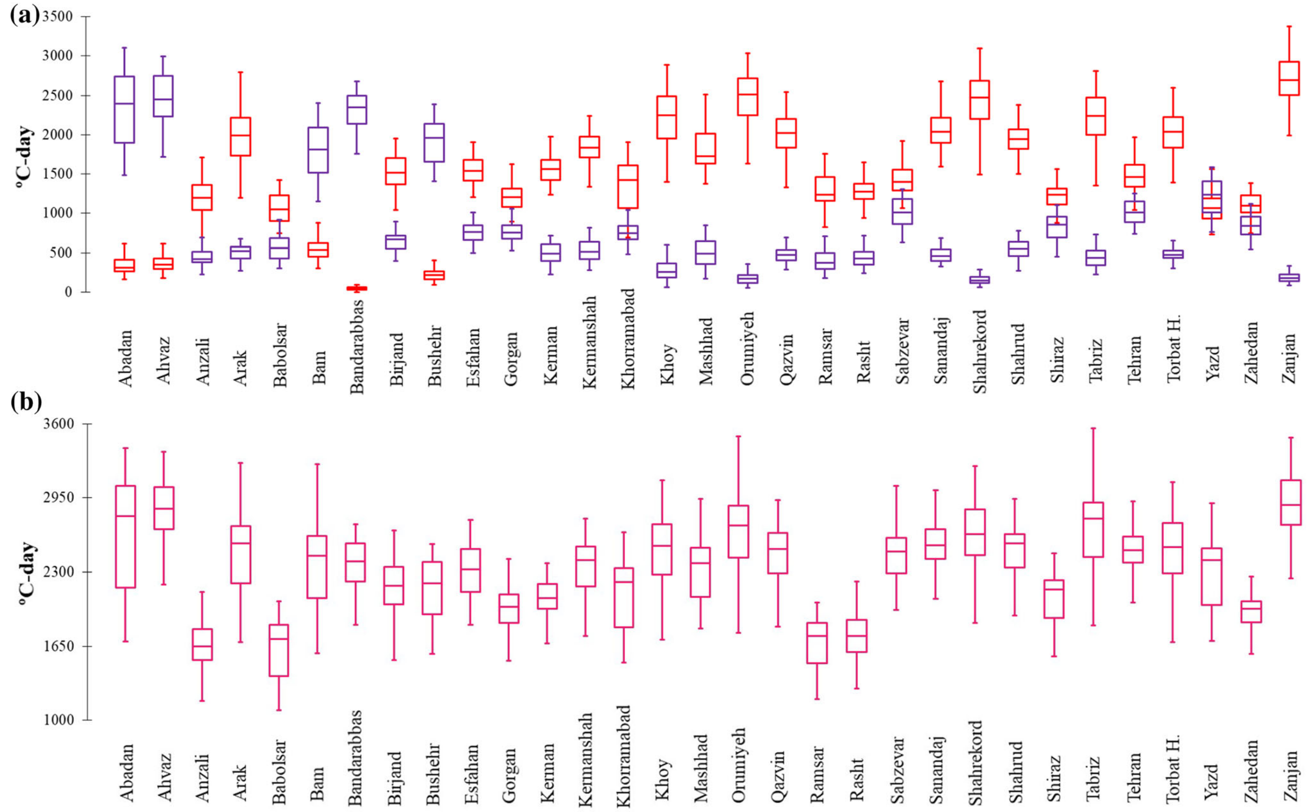


Fig. 4 Box plots for **a** HDD and CDD, and **b** HDD + CDD at the weather stations shown in Fig. 1a. In Figure (**a**), red and purple box plots indicate HDD and CDD, respectively

abrupt change in HDD + CDD time series, which in the 80 s. Specifically, 81% of the stations experienced their upward abrupt changes in 1981. It is noteworthy that at 25 stations, the abrupt change was so high that made their Pettitt test significant at the 0.001 significance level.

3.3.1 Time series trends before and after the abrupt change

Pre- and post-breakpoint series trends are also investigated via a linear regression. For the sake of brevity, the authors only considered abrupt changes that were significant at the 0.01 level and the figures are presented in Appendix. Four patterns are distinguishable in the trends of HDD, CDD and, HDD + CDD time series. The first pattern is a positive trend in both pre- and post-breakpoint sub-series. The second one is a negative trend in both pre- and post-breakpoint sub-series. The third pattern is a positive trend in pre-breakpoint sub-series and a negative trend in post-breakpoint sub-series. In fact, the the breakpoint truned the direction of the trends from positive to negative. The fourth pattern is the opposite form of the third one. These four patterns for the three studied indices at some selected stations are presented in Fig. 7. A close investigation of the results revealed that among 16 stations that had a breakpoint in their HDD series at a 0.01 significance level, 13 stations had a negative trend after the breakpoint. Actually by air warming, the heating demand was decreased after breakpoints at these stations, but the reason behind why these stations experienced an upward abrupt change before 1985 is still unidentified for us. At one station (Shahrekord), pre- and post-breakpoint series trend is close to zero. Closely investigating the findings of this research, it was found that at more than 90% of the selected stations, HDD trend was decreasing after 1980. In fact, at the majority of the stations experiencing an abrupt change in their HDD series, the abrupt change occurred in 1981 and the HDD trend was decreasing after the abrupt change. Also, most of the stations that didn't have an abrupt change experienced a positive HDD trend after 1980. De Rosa et al. (2015) also showed a negative HDD trend during the 1978–2013 period in Italy. In addition, You et al. (2014) reported that China's annual HDD trend for the 1979–2005 period was decreasing.

The results also showed that pre- and post-breakpoint CDD series trends were positive for the majority of the stations. Tavakol et al. (2020) also claimed that in Mississippi, USA, heat waves and hot days experienced an upward abrupt change in 1997; the trend before abrupt change was negative while the abrupt change caused a

Table 4 Magnitude of Sen's slope estimator. Significance levels are shown using M–K test with the background colour

Station name	HDD (□-day) Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Abadan	0.3	-0.2	-0.2	-	-	-	-	-	-	-	0.0	0.0
Ahvaz	-0.4	-0.4	-0.3	0.0	-	-	-	-	-	-	-0.1	-0.5
Anzali	0.1	0.0	-0.9	0.0	-0.2	-	-	-	0.0	-0.1	0.3	-0.1
Arak	1.3	0.9	0.6	0.2	-0.1	-	-	-	0.0	0.1	1.7	1.6
Babolsar	1.3	1.1	-0.1	0.0	-0.1	-	-	-	-	-0.1	0.5	1.0
Bam	-0.1	0.0	-0.3	0.0	-	-	-	-	-	0.0	0.0	0.0
Bandarabbas	0.2	0.1	0.0	-	-	-	-	-	-	-	-	0.0
Birjand	2.2	1.4	0.5	-0.1	0.0	-	-	-	0.0	0.2	1.0	1.7
Bushehr	-0.3	-0.3	-0.2	-	-	-	-	-	-	-	0.0	-0.4
Esfahan	1.6	0.7	-0.1	-0.5	-0.1	-	-	-	0.0	-0.4	1.0	0.8
Gorgan	0.7	0.3	-0.6	0.0	-0.1	-	-	-	-	-0.1	0.5	1.0
Kerman	0.5	0.5	-0.5	-0.7	-0.1	-	-	-	-0.1	-0.8	0.0	-0.3
Kermanshah	1.7	0.5	-0.3	-0.8	-0.6	-	-	-	0.0	-0.8	0.4	0.0
Khorramabad	2.7	1.9	1.7	0.5	0.0	-	-	-	-	0.2	1.8	2.4
Khoy	1.9	0.8	0.4	-0.3	-0.5	-0.1	-	-	-0.1	-0.6	0.7	2.0
Mashhad	0.0	0.9	-0.3	-0.6	-0.3	-	-	-	-0.3	-0.9	-0.1	0.0
Urmia	2.6	1.0	1.3	0.3	0.1	0.0	-	-	0.1	0.6	1.6	2.4
Qazvin	1.3	0.8	0.5	-0.1	-0.1	-	-	-	0.0	0.0	1.7	1.6
Ramsar	0.2	0.7	-0.1	0.1	-0.2	-	-	-	-	-0.1	0.2	0.6
Rasht	0.0	0.6	-0.3	-0.2	-0.2	-	-	-	0.0	-0.3	0.3	0.1
Sabzevar	0.2	0.8	-0.5	-0.6	0.0	-	-	-	0.0	-0.3	0.3	-0.1
Sanandaj	0.3	-0.7	-0.4	-1.0	-0.4	0.0	-	-	0.0	-0.4	0.6	-0.3
Shahrekord	2.0	2.2	1.8	0.9	0.9	0.1	-	-	0.4	1.1	2.0	2.2
Shahrud	1.3	0.7	-0.5	-0.9	-0.3	-	-	-	0.0	-0.6	0.7	1.3
Shiraz	0.7	0.4	-0.4	-0.8	0.0	-	-	-	-	-0.3	0.1	0.3
Tabriz	2.6	1.8	0.2	-0.4	-0.3	0.0	-	-	0.0	-0.3	1.3	2.6
Tehran	-0.7	0.0	-1.0	-0.9	-0.1	-	-	-	-	-0.2	0.0	-0.2
Torbat H.	1.8	1.4	0.6	-0.2	-0.1	-	-	-	0.0	0.2	1.2	1.1
Yazd	1.5	0.3	-0.4	-0.3	-	-	-	-	-	-0.2	0.2	0.8
Zahedan	-0.3	-0.1	-0.4	-0.3	-	-	-	-	-	-0.6	-0.3	-0.2
Zanjan	-0.3	-0.2	-1.0	-0.9	-0.2	-0.1	-	-	-0.2	-0.5	0.7	-0.1

Station name	CDD (□-day) Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annually HDD	CDD	HDD+ CDD
Abadan	-	0.0	0.4	2.1	2.7	2.9	3.5	4.0	3.0	2.5	0.3	0.0	0	21	21
Ahvaz	-	0.0	0.3	1.8	2.4	2.9	2.6	3.3	2.2	2.2	0.3	0.0	-2	18	15
Anzali	-	-	-	0.0	0.1	0.9	1.1	1.6	0.9	0.1	-	-	-2	5	4
Arak	-	-	-	-	0.1	0.8	1.4	1.0	0.4	0.0	-	-	6	4	10
Babolsar	-	-	-	0.0	0.5	1.5	1.4	2.2	1.6	0.3	-	-	3	8	11
Bam	-	0.0	0.4	2.0	2.6	2.6	2.7	2.5	2.6	1.6	0.2	0.0	-1	18	16
Bandarabbas	0.0	0.0	0.2	1.1	1.0	1.0	1.4	1.4	1.4	1.2	0.5	0.1	0	11	11
Birjand	-	-	-	0.1	0.1	0.5	0.6	0.0	0.0	0.0	-	-	6	1	8
Bushehr	0.0	0.0	0.3	1.1	1.6	1.4	1.8	2.1	2.1	2.1	0.5	0.0	-1	13	11
Esfahan	-	-	-	0.0	0.6	1.2	1.4	0.9	0.9	0.1	-	-	3	5	8
Gorgan	-	-	0.0	-0.1	0.1	1.0	1.1	1.3	0.8	0.1	0.0	-	1	5	5
Kerman	-	-	-	0.0	0.6	1.2	1.3	0.8	0.6	0.0	-	-	-2	5	2
Kermanshah	-	-	-	-	0.1	1.6	1.6	1.8	1.0	0.1	-	-	0	6	6
Khorramabad	-	-	-	-	0.0	0.5	1.2	1.1	0.0	0.0	-	-	10	3	15
Khoy	-	-	-	-	0.0	0.9	1.5	2.0	0.5	-	-	-	4	5	9
Mashhad	-	-	-	0.1	0.8	2.1	2.2	2.1	1.0	0.0	-	-	-1	9	6
Urmia	-	-	-	-	-	0.3	0.5	0.6	0.0	-	-	-	9	2	11
Qazvin	-	-	-	-	0.0	0.5	0.6	0.6	0.4	0.0	-	-	5	2	8
Ramsar	-	-	-	-	0.1	1.1	1.5	2.0	1.3	0.1	-	-	1	6	7
Rasht	-	-	-	0.0	0.3	1.1	1.4	1.7	0.9	0.1	-	-	0	5	5
Sabzevar	-	-	-	0.3	1.2	1.8	1.9	1.8	1.5	0.3	-	-	-1	9	7
Sanandaj	-	-	-	-	0.0	1.1	1.1	1.2	0.4	-	-	-	-3	4	1
Shahrekord	-	-	-	-	-	-0.3	-0.5	-0.8	-0.1	-	-	-	13	-2	12
Shahrud	-	-	-	0.0	0.5	1.3	1.5	1.1	1.0	0.0	-	-	1	6	7
Shiraz	-	-	-	0.0	0.9	1.5	1.7	1.4	1.2	0.2	-	-	-1	7	5
Tabriz	-	-	-	-	0.1	1.1	1.5	1.8	0.7	-	-	-	7	5	12
Tehran	-	-	-	0.1	0.8	1.3	1.2	1.3	1.4	0.4	-	-	-3	7	4
Torbat H.	-	-	-	0.0	0.1	0.4	0.5	0.4	0.2	0.0	-	-	5	2	7
Yazd	-	-	0.0	0.6	1.7	2.1	2.3	1.9	2.2	0.8	-	-	1	12	11
Zahedan	-	-	0.0	0.5	1.3	1.0	1.1	0.9	0.9	0.3	-	-	-3	6	3
Zanjan	-	-	-	-	-	0.2	0.3	0.5	0.1	-	-	-	-3	1	-2

	Significant trend at 0.001	Significant trend at 0.01	Significant trend at 0.05	Insignificant trend (0.05 < p-value)
Positive				
Negative				

Table 5 The number (and percentage) of stations with positive and negative annuall trends across the period 1960–2019 as well as the number (and percentage) of stations with upward and downward abrupt changes. Numbers in parenthesis represent percentages. The values are calculated based on a 0.05 significance level

Variable	Mann–Kendall Trend Test		Pettitt Test	
	Significant positive trend (%)	Significant negative trend (%)	Upward abrupt change (%)	Downward abrupt change (%)
HDD	3 (10%)	3 (10%)	15 (49%)	6 (19%)
CDD	26 (84%)	1 (3%)	30 (97%)	1 (3%)
HDD + CDD	25 (81%)	0 (0%)	29 (94%)	0 (0%)

turning point in the trend and made it positive. It should also be mentioned that both Shiraz and Shahrekord stations experienced positive trends before breakpoints, but their trends after the breakpoints were approximately zero.

As explained before, HDD + CDD trends for all the studied stations (except Zanjan) over a 60-year period (1960–2019) are positive; however, the trends before and after the abrupt change were negative at 14 stations. In fact, upward abrupt change caused a positive trend for the period at these stations, while the trend was negative before and after the abrupt change. Anyhow, for some stations in different parts of the country, the trend line slope after the abrupt change was approximately zero (< 1.5 °C-days). Only charts with an intense trend line slope after and before abrupt changes are shown. It seems that the HDD + CDD trend for most of the stations in the southern half of the country is positive before and especially after abrupt changes. In contrast, the majority of the stations with a negative HDD + CDD trend after abrupt changes are located in the northern half. At some stations, a turning point in trends occurred in HDD + CDD series.

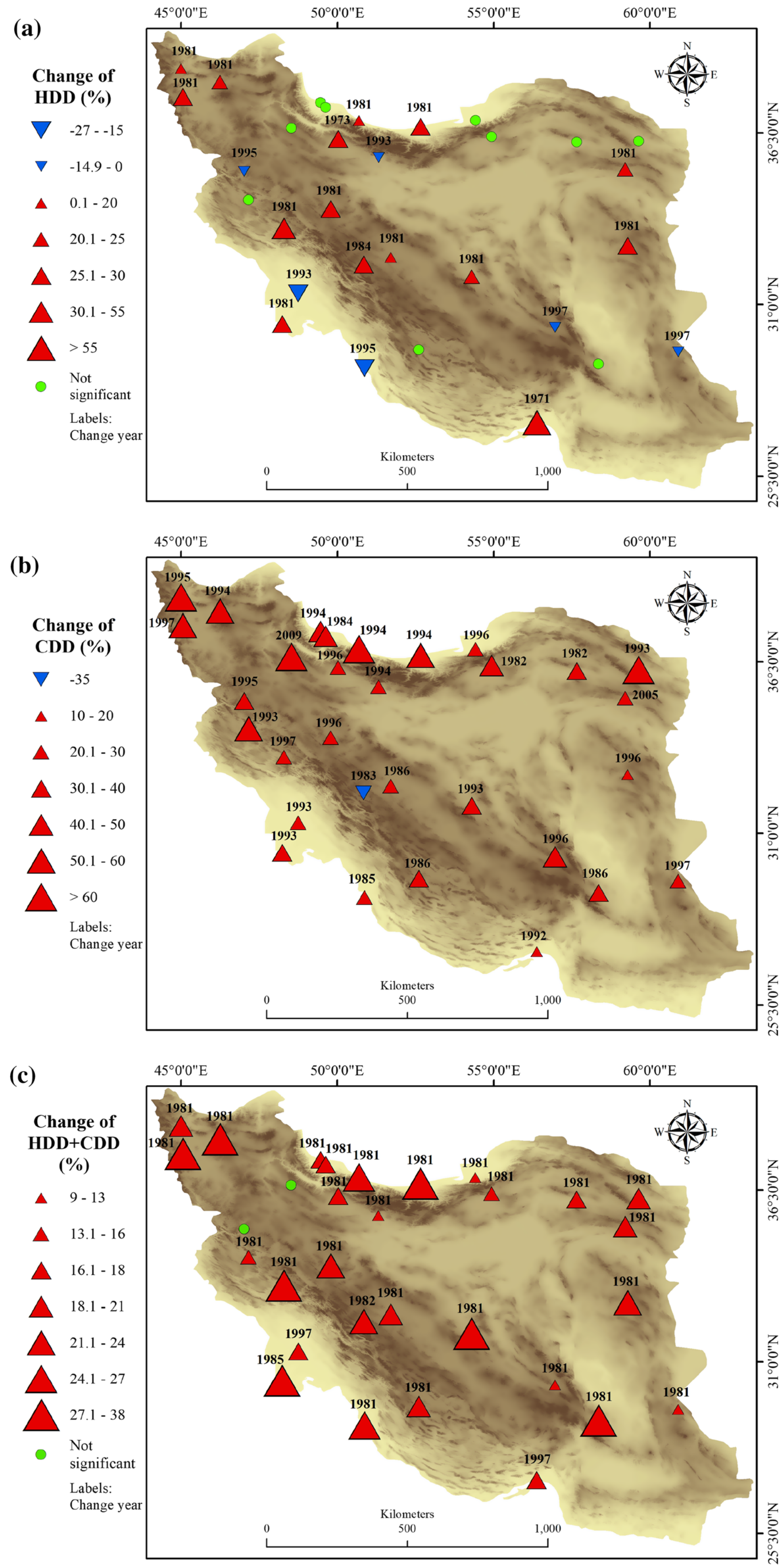
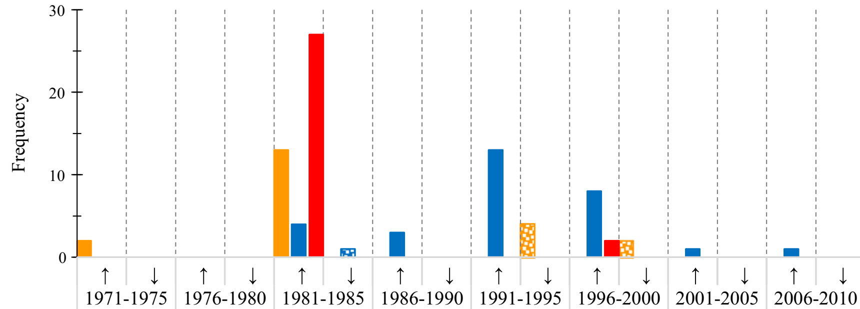


Fig. 5 Percentage changes between post-breakpoint and pre-breakpoint series for **a** HDD, **b** CDD and **c** HDD + CDD. Labels show abrupt change year. Up and down pointing triangles denote upward and downward abrupt changes ($p < 0.05$), respectively. Solid circles indicate the stations experiencing no statistically significant changes ($p > 0.05$)



	1971-1975 ↑	1971-1975 ↓	1976-1980 ↑	1976-1980 ↓	1981-1985 ↑	1981-1985 ↓	1986-1990 ↑	1986-1990 ↓	1991-1995 ↑	1991-1995 ↓	1996-2000 ↑	1996-2000 ↓	2001-2005 ↑	2001-2005 ↓	2006-2010 ↑	2006-2010 ↓
HDD	2	0	0	0	13	0	0	0	0	4	0	2	0	0	0	0
CDD	0	0	0	0	4	1	3	0	13	0	8	0	1	0	1	0
HDD+CDD	0	0	0	0	27	0	0	0	0	0	2	0	0	0	0	0

Fig. 6 Frequency of abrupt change year in 5-year periods. Downward abrupt changes are shown using white dots inside the bar

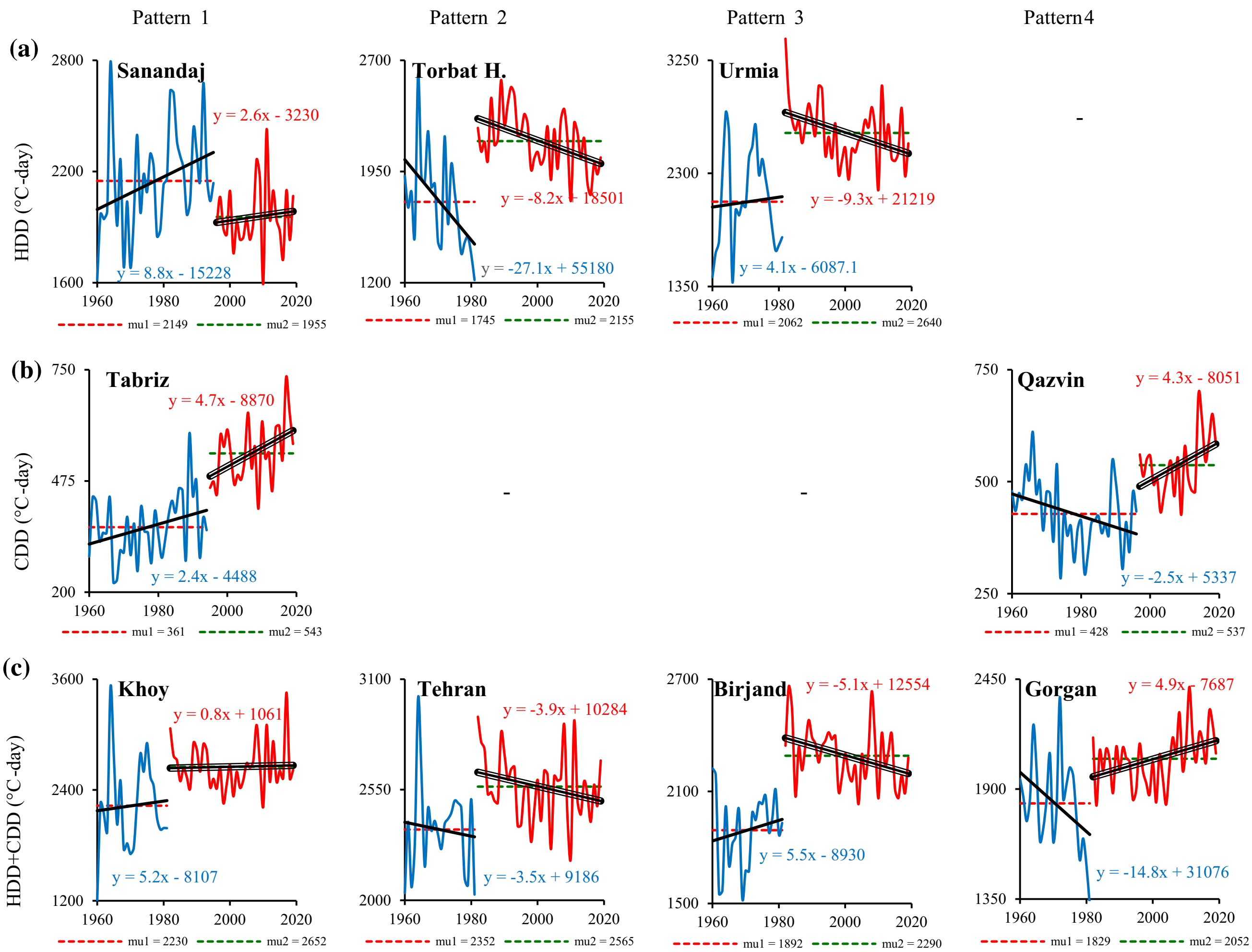


Fig. 7 Time series trends before and after the abrupt change for **a** HDD, **b** CDD and, **c** HDD + CDD at some stations. The first case is for the stations that had positive trends in both pre- and post-breakpoint sub-series. The second one is for the stations that had negative trends in both pre- and post-breakpoint sub-series. The third case is for the series had a positive trend before the breakpoint and a negative trend afterwards. The fourth case is the opposite form of the third case. Mu denotes the average of sub-series

3.3.2 Multiple abrupt changes in time series

The stations experiencing more than one abrupt change are investigated using a modified Pettitt test. Table 6 shows the year of abrupt changes and direction of changes for the stations experiencing more than one breakpoint. HDD time series had more than one breakpoints at 9 stations. The first abrupt change for all 9 stations occurred in 1981 and had an

Table 6 Abrupt change year and direction for stations experiencing more than one breakpoint

Station name	HDD Breakpoint (year)			CDD Breakpoint (year)			HDD+CDD Breakpoint (year)		
	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd
Abadan				1981 ↑	1993 ↑	2007 ↑	1985 ↑	1998 ↑	
Ahvaz				1978 ↑	1993 ↑		1981 ↑	1997 ↑	
Anzali				1994 ↑	2009 ↑		1972 ↓	1981 ↑	
Arak	1981 ↑	1997 ↓		1996 ↑	2012 ↑				
Babolsar	1981 ↑	1997 ↓		1994 ↑	2009 ↑				
Bam				1986 ↑	2004 ↑		1981 ↑	1998 ↑	
Bandarabbas							1981 ↑	1997 ↑	
Birjand	1981 ↑	1997 ↓							
Bushehr				1976 ↑	1985 ↑				
Esfahan				1986 ↑	2007 ↑				
Gorgan							1981 ↑	2005 ↑	
Kerman	1981 ↑	1997 ↓							
Kermanshah				1978 ↑	1993 ↑		1968 ↓	1981 ↑	
Khorramabad	1981 ↑	1995 ↓		1979 ↓	1997				
Khoy				1995 ↑	2009 ↑				
Mashhad				1982 ↑	1993 ↑	2009 ↑	1981 ↑	1997 ↓	
Urmia	1981 ↑	1993 ↓		1969 ↓	1997 ↑				
Qazvin				1973 ↓	1996 ↑				
Ramsar	1981 ↑	1997 ↓		1994 ↑	2009 ↑		1981 ↑	1993 ↓	
Rasht				1974 ↑	1984 ↑	2004 ↑			
Sabzevar				1972 ↑	1982 ↑				
Sanandaj				1995 ↑	2005 ↑				
Shahrekord									
Shahrud									
Shiraz							1968 ↓	1981 ↑	
Tabriz									
Tehran				1974 ↑	1994 ↑				
Torbat H.	1981 ↑	1997 ↓					1981 ↑	1997 ↓	
Yazd	1981 ↑	1997 ↓		1981 ↑	1993 ↑	2007 ↑			
Zahedan									
Zanjan									

upward direction. The second abrupt change was downward and generally occurred in 1997. Based on the results of Table 6, CDD time series in four stations experienced three breakpoints. At almost all stations experiencing more than one breakpoint in CDD, the direction of abrupt changes was upward. In other words, CDD increased step by step at these stations. The exceptional stations located in the west and northwest of the country experienced a downward first abrupt change. Concerning HDD + CDD, both abrupt changes were upward for most of the stations, while stations in different parts of the country, the first abrupt change was downward and the second one was upward. Conversely, what happened in Ramsar in the north and Mashhad, and Torbat Heydariyeh in the northeast of the country was an upward first abrupt change and downward second one.

In the late 1990s, Lake Urmia—the second largest hypersaline lake in the world—began to dry up mainly due to anthropogenic development and water overuse (Agha-Kouchak et al. 2015; Alizade Govarchin Ghale et al. 2018;

Chaudhari et al. 2018; Pouladi et al. 2021), which has adversely affected the environment in the Urmia basin. According to the results of this research, the mean air temperature in Iran has generally increased, but no evidence was found that the changes in HDD and CDD in the Urmia basin were distinct from other parts of the country. Although a few studies from all over the world have been found to discuss and analyse HDD and CDD trends, no researches are found to investigate abrupt changes in HDD and CDD time series for comparing with the findings of this paper.

3.4 Return period

A total of 19 distributions out of 65 distributions were found to be suitable fits for the studied indices in Iran (Fig. 8). Wakeby and Johnson SB distributions accounted for about 60% of the best-fitted distributions, and they were used for estimating return periods. After a consecutive analysis procedure applied for the calculation of return periods, the spatial distribution of the magnitudes with respect to the four return periods are plotted in Fig. 9. The frequency and return period analyses of HDD indicated that the southern coastal strip of the country had the highest degree-days increase (hereafter defined as a deviation from the average value of the baseline period) in return period. On average, HDD values of 10-, 25-, 50- and 100-year return periods for all over the country increased by 20%, 28%, 33% and 38%, respectively. Analyses of frequency and return periods for CDD showed that stations located in the northwestern part of the country experienced the largest increase with respect to their return periods among the other stations. The smallest increase in CDD return periods was calculated for southern tropical regions where about 20% increase is for CDD of a 100-year return period. The joint HDD + CDD index value sharply increases from 10- to 100-year return periods, while it is less the case for the two single indices.

4 Discussion

This study estimated the thermal energy demand of buildings by using the degree-day method. The technique calculates the buildings' thermal energy demand based on monitoring changes in outdoor temperature. There are,

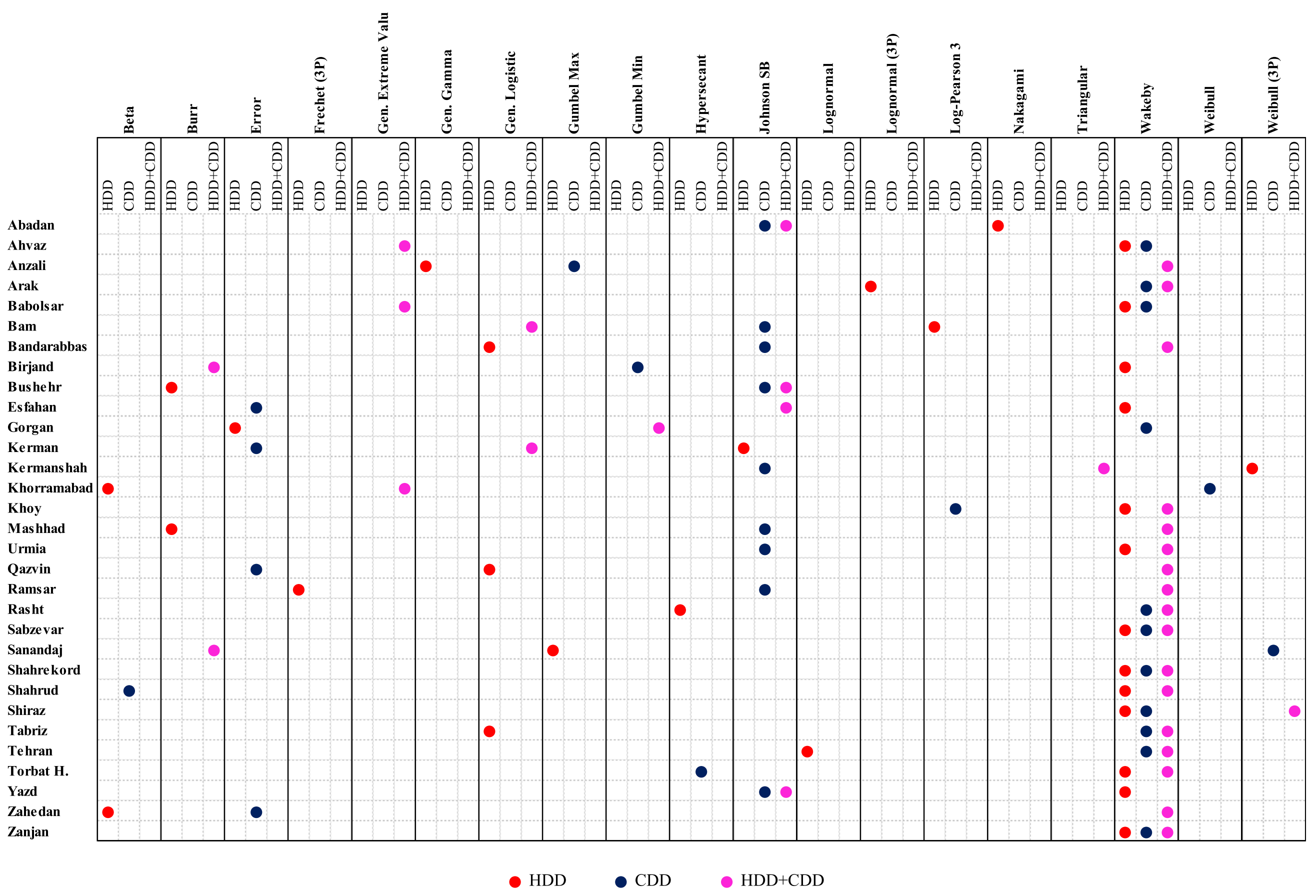


Fig. 8 The best fitted cumulative distribution functions to the studied indices

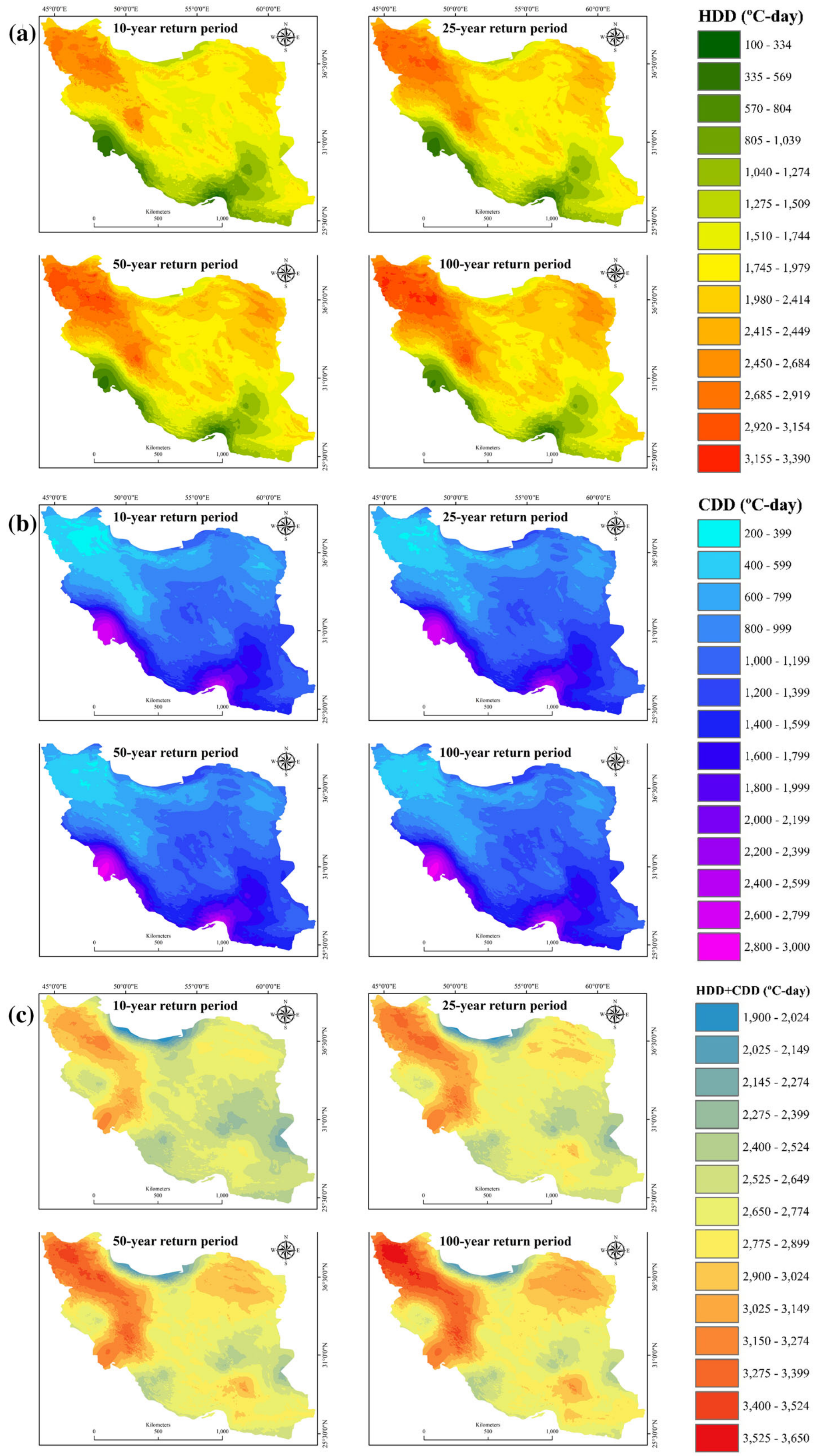


Fig. 9 Spatial distributions for 10-, 25-, 50- and 100-year return periods of **a** HDD, **b** CDD, and **c** HDD + CDD

however, some drawbacks to this method. Some relevant factors such as the architecture, construction materials, insulation, and internal thermal system of buildings are not taken into account in this method. However, the main advantage of the degree-day method is that it can be applied to a large area because of its facility and the availability of meteorological parameters needed to conduct the analyses. Unlike full thermal simulation models, degree-day calculations can be carried out within computer spreadsheets; they have transparency and repeatability that full simulation models may not provide (Day 2006). Since degree-days incorporate outdoor temperature fluctuations and remove those periods when thermal systems do not need to operate, they can seize extreme events in a way that other methods cannot. This makes them more reliable when estimating energy demand, particularly in milder months as well as in periods of extreme cold snaps, when they capture both the magnitude and duration of an event. For future studies, it is recommended to analyse three examples of typical buildings in Iran, and consider the thermal system, insulation, and interior design of thermal energy consumption and compare the results with the findings of this study.

The results of this study show an increase in the cooling demand in Iran by an average magnitude of 70 °C-days per decade, which can be attributed to anthropogenic influences (e.g., climate change, urbanization). In contrast, HDD didn't change significantly. HDD + CDD shows a considerable increase due to the CDD increase. If global warming continues with the current trend, the demand for the energy supply of the residential sector will increase over the next decades. At a significant number of stations, the temporal trend of in the time series of the studied indices (especially HDD) before the abrupt change point was different from their trend afterwards. The results showed that the average annual CDD experienced three significant abrupt upward changes in their time series at some stations. The present study has similar results with You et al. (2014), De Rosa et al. (2015), Cvitan and Sokol Jurković (2016), Anjomshoaa and Salmanzadeh (2017) and Tavakol et al. (2020).

Although urban areas cover a small portion of Earth's surface, they generally have the highest energy consumption. Energy consumption is in turn one of the main reasons of climate change, although a large portion of energy greenhouse gas emissions. Population growth in Iran has been very rapid consumed for heating and cooling is due to climate change as well as unplanned development and efficiency (Wachs and Singh 2020). Besides, growing urbanization has made heat islands and led to significantly increased energy demands and. In the first official census in 1956, the population of Iran was 19 million, while it reached 80 million in the last census in 2016. Also in 1995, only 32% of the population lived in cities which increased to 74% in 2016. These anthropogenic influences can have led to significant changes in the energy demand.

In developing countries such as Iran that use less renewable energies and rely on their fossil fuels, this level of increase in the demand for energy supply will cause various problems in the energy supply and impose great expenses to the country. Energy consumption in Iran is much higher than the global standards (Gorjian et al. 2019). Lack of renewal and enhancement of old, inefficient heating and cooling systems in buildings, a rapid population growth and continuation of global warming trend can cause an energy supply crisis in Iran. The country may encounter critical problems in energy supply, despite being one of the major energy (oil and gas) exporters. However, heating comes normally from using gas or other fossil fuels while cooling generally requires electrical power. It is also necessary to note that since Iran has enormous gas and oil sources, using fossil fuels for generating electricity is more economical, as 93% of the resources for electricity power plants in the country are supplied by fossil fuels (gas, gasoline and mazut), and the rest is supplied by hydropower. The use of low quality gases the electricity generation plants are highly noxious to the environment.

Any increase in the energy consumption, whether for heating or cooling, practically causes more emission of greenhouse gasses. Changing demand from fossil fuels to electricity can have considerable outcomes for energy policies and the environment (Li et al. 2012). So if renewable energies are used to supply electrical power, not only can prevent more greenhouse gas emissions and thus global warming, but also can conserve the natural environment and mitigate climate change. It should also be pointed that Iran has a great potential for the solar energy, as the annual rate of solar energy in Iran estimated to be 4.5–5.5 kWh/m^2 (Gorjian et al. 2019). To clarify the importance of solar energy, Alamdari et al. (2013) reported that if only 10% of received solar energy on Earth's surface transforms to electricity with 10% efficiency, the generated power would be 4 times more than the energy consumed globally in a year. Hence, investing on this section can solve various problems regarding energy supply in Iran while it can also prevent excessive emission of greenhouse gas, which is the main reason of global warming.

To mitigate global warming impacts according to the contents of the Paris Climate Agreement, Iran promised to reduce its greenhouse gas emissions at least by 4% by 2030. But no practical and effective actions have been taken in the country to reach this goal. Unfortunately, so far in Iran, when a president ends his term (the maximum presidential term of 8 years). The next president, who is often elected from a rival party, does not follow the environmental policies of the previous one. It is even customary for a new president to select new ministers and senior executives, which hampers long-term planning policies to tackle environmental problems. Iran has suffered from a symptom-based management paradigm, which focuses mainly on treating the symptoms of problems rather than dealing with their root causes (Madani 2014). Although Iran has great potential for renewable energies such as solar, wind and geothermal, its strong dependence on oil and gas has made Iran, which accounts for 1.1% of the world's population, one of the top ten greenhouse gas emitters countries. It is hoped that changing the approach of policy-makers and environmental planners, paying special attention to renewable energies and repairing worn-out and inefficient infrastructure will solve environmental problems in Iran.

5 Conclusions

This study investigated historical changes in heating degree-days (HDD), cooling degree-days (CDD), and their simultaneous combination. The results revealed that the highest heating demand and the lowest cooling demand belong to cold and mostly mountainous regions in the northwestern part of the country where the annual average HDD goes beyond 2380 °C-days while annual average CDD is 276 °C-days. On the other hand, for southern tropical regions, the coasts, the Lut desert and the central region of Iran (regions around Yazd), observations showed the lowest heating demand and the highest cooling demand. In Ahvaz and Abadan that located in the southwest of the country, the cities with the highest cooling demand, this demand has increased up to 3000 °C-days due to global warming over recent years.

The temporal changes and their spatial distribution in HDD, CDD and HDD + CDD indices in Iran were also investigated in this study. HDD changes at the studied stations represent different patterns; some stations experienced upward abrupt changes, while others had downward abrupt changes. Although for the majority of the stations with abrupt changes, post-breakpoint series trend was negative, pre-breakpoint series trend was positive for some stations and negative for some others. 32% of the stations also experienced no significant abrupt changes in HDD series, while all the studied stations except Shahrekord experienced upward abrupt changes in CDD values. It is noteworthy that 94% of the stations experienced upward abrupt changes in HDD + CDD time series. Investigating CDD values, the trends for the majority of the stations were positive after abrupt changes. Regarding pre-breakpoint trends, with except of 6 out of 29 stations that had a negative pre-breakpoint trend, the trend line slope for the other stations were positive or approximately zero. The statistical significance level of 90% of the stations that experienced abrupt changes in CDD time series was the 0.001. All abrupt changes that happened in HDD + CDD series were upward and 93% of them occurred in the 80 s. Most of the stations with a negative HDD + CDD trend after abrupt changes were located in the northern half of the country. By modifying Pettitt test, it was found that 29% and 65% of the stations experienced more than one abrupt change in HDD and CDD series, respectively. Also, in almost 35% of the studied stations, more than one breakpoint was observed in HDD + CDD time series.

In Iran, energy is mainly supplied from fossil fuels and the country's average energy consumption is fourfold the global average. The findings showed that the energy demand for buildings' cooling significantly increased due to global warming. If global warming trend continues, electricity demand will therefore increase in the future. Taking the advantage of solar energy which has high potentials in Iran for generating electric power instead of fossil fuels can lead to reduced emissions of greenhouse gasses as well as controlling negative effects of climate changes. In addition, renewal and enhancement of buildings' energy sector in Iran that are generally old and low-efficient can play an important role in achieving an optimum energy consumption and reducing air pollution. The results of this study are beneficial for investors, designers and managers in the residential sector, as it provides a basis for analysis and prediction of buildings' energy performance. They can also be used for a better understanding of the impact of global warming on buildings' energy consumption.

Appendix A

Mann–Kendall trend test

The Mann–Kendall (M–K) trend test is a rank-based non-parametric test for determining the statistically significant trend in time series. The correlation between the rank order of the observed values and their chronological order are considered in this test. In other words, the M–K test is an approach to compare each value of the time series with the remaining values in a sequential order (Araghi et al. 2017; Mullick et al. 2019). The original Mann–Kendall trend test statistic (S) is given by (Mann 1945; Kendall 1975):

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{sgn}\left(x_j - x_i\right) \tag{8}$$

$$\operatorname{sgn}\left(x_j - x_i\right) = \begin{cases} +1 & x_j > x_i \\ 0 & x_i = x_j \\ -1 & x_j < x_i \end{cases} \tag{9}$$

where n is the length of the time series, and x_i and x_j are the sequential data amounts, respectively. For $n > 10$, given that x_i is independent and randomly ordered, the statistic S is approximately normally distributed with a mean of zero and variance as follows:

$$Var\,(S) = \frac{1}{18}\left[n(n-1)\,(2n+5) - \sum_{i=1}^{m} t_i\,(t_i-1)\,(2t_i+5)\right] \tag{10}$$

where m is the number of tied groups, and t_i is the number of data points in the i^{th} group. Then, the test statistic Z is calculated using the following formula:

$$Z = \begin{cases} S-1/\sqrt{Var(S)} & if \quad S>0 \\ 0 & if \quad S=0 \\ S+1/\sqrt{Var(S)} & if \quad S<0 \end{cases} \tag{11}$$

The null hypothesis H_0 would be rejected if in a two-tailed test, $|Z| \geq Z_{1-\alpha/2}$ at α significance level, then the trend can be considered significant. In this research study, $\alpha = 0.05, \alpha = 0.01$, and $\alpha = 0.001$ significance levels were performed for the M–K trend test, so increasing or decreasing trend will be accepted at 95%, 99%, and 99.9% confidence intervals. The M–K test is carried out for each station separately.

It has been found that the positive serial autocorrelation in time series increases the trend's chance of significance in the M–K test. So if autocorrelation of data is significant, the positive or negative autocorrelation will change *Var (S)* value to be less or more than the actual value. Hamed and Rao (1998) proposed the modified M–K trend test to remove the effect of serial correlation. The modified version of the M–K test can be calculated using the following equation:

$$Var(S)^* = Var(S)\;\frac{n}{n_s^*} \tag{12}$$

$$\frac{n}{n_s^*} = 1 + \frac{2}{n\,(n-1)\,(n-2)} \sum_{i=1}^{n-1} (n-i)\,(n-i-1)\,(n-i-2)\;\rho_s(i) \tag{13}$$

where n/n_s^* represents a correction due to the autocorrelation in the data, and $\rho_s(i)$ is the autocorrelation function of the ranks of the observed data.

Sen's slope estimator

Sen's slope estimator is a non-parametric linear regression slope that is a better alternative to simple linear regression. In this method, the effects of outlier data points on the results of the trend are negligible which can be considered as a major advantage over other parametric methods. The Sen's slope (β) is presented by (Sen 1968):

$$\beta = Median\left[\frac{x_j - x_i}{j-i}\right] \quad for\, i = 1 \ldots n, \quad and\; \forall j > i \tag{14}$$

Pettitt change point test

The Pettitt test was utilized for identifying potential abrupt changes in the time series for each of the considered indices and calculates their statistical significance. This test is non-parametric rank-based and distribution-free, which means it is insensitive to outliers. The Pettitt statistic K_T obtained using the following formula (Pettitt 1979):

$$K_T = \max_{1<t\leq n} |S| \tag{15}$$

where S corresponds to Eq. (8) and the p-value of the Pettitt test defined as:

$$p = 2\;\exp\left[\frac{-6\;K_T^2}{n^3+n^2}\right] \tag{16}$$

With a given significance level α, if $p < \alpha$, then a change point can be statistically significant. In this study, 95% and 99% confidence intervals ($\alpha = 0.05$ and $\alpha = 0.01$) were performed for analysing abrupt change detection.

Kolmogorov–Smirnov (K-S) Test

This test is used to decide if a sample comes from a hypothesized continuous distribution. It is based on the empirical cumulative distribution function (ECDF). Assume that there is a random sample $x_1, \ldots, x_n$ from some distribution with CDF $F(x)$. The empirical CDF is denoted by:

$$F_n(x) = \frac{1}{n}\,[Number\,of\,observations \leq x] \tag{17}$$

The K-S statistic (D) is based on the largest vertical difference between the theoretical and the empirical cumulative distribution function (Smirnov 1939; Kolmogorov 1941; Nikiforov 1994):

$$D = \max_{1\leq i\leq n}\left(F(x_i) - \frac{i-1}{n}\,,\,\frac{i}{n} - F(x_i)\right) \tag{18}$$

The null and the alternative hypotheses are:

H_0: the data follow the specified distribution.

H_a: the data do not follow the specified distribution.

The hypothesis regarding the distributional form is rejected at the chosen significance level (α) if the test statistic, D, is greater than the critical value obtained from a table. The fixed values of α (0.01, 0.05 etc.) are generally used to evaluate the null hypothesis (H_0) at various significance levels.

Grubbs test for outliers

Grubbs (Grubbs and Beck 1972) developed a tests in order to determine whether the greatest value or the lowest value are outliers. In statistics, an outlier is a value recorded for a given variable, that seems unusual and suspiciously lower or greater than the other observed values.

Let $x_1, \ldots, x_i, \ldots, x_n$ be a sample that is extracted from a population that we assume is following a normal distribution $N(\mu, s^2)$. Parameters μ and s^2 are respectively estimated by:

$$x = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{19}$$

$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n} (x_i - \overline{x})^2 \tag{20}$$

$$x_{\max} = \arg \max_{i=1\ldots n} (x_i) \tag{21}$$

$$x_{\min} = \arg \min_{i=1\ldots n} (x_i) \tag{22}$$

$$G_{\min} = \frac{\overline{x} - x_{\min}}{s} \tag{23}$$

$$G_{\max} = \frac{x_{\max} - \overline{x}}{s} \tag{24}$$

$$G = \max(G_{\min}, G_{\max}) \tag{25}$$

For the two-sided test, the null (H0) and alternative (Ha) hypotheses are given by:

H_0: The sample does not contain any outlier.

H_a: The lowest or the greatest value is an outlier.

An approximation of the critical value G_{crit} giving the threshold above which, for a given significance level α, one must reject the null hypothesis is given by:

$$G_{crit}(n, \alpha) \approx \frac{(n-1)\, t_{n-2,\,1-\alpha/k}}{\sqrt{n - 2 + t^2_{n-2,\,1-\alpha/k}}} \tag{26}$$

where $n-2,\ 1-\alpha/k$ is the value of the inverse of the Student cumulative distribution function at $1-\alpha/k$ with $n-2$ degrees of freedom, and where k equals n for one-sided tests and 2n for the two-sided test. This value can be compared with the G statistic computed for the sample, and deduce that one can keep H_0 if G_{crit} is greater than G (or G_{min} or G_{max}) and reject it otherwise. From the G_{crit} approximation, it can be also deduced an approximation of the p-value that corresponds to G.

Appendix B

To evaluate the results of the spatial modelling three error metrics were used: Normalized Root Mean Square Error (NRMSE), Mean Absolute Percentage Error (MAPE) and Mean Bias Error (MBE). The mentioned performance criteria defined as:

$$NRMSE = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n} (F_t - A_t)^2}}{\max\,(A_t) - \min\,(A_t)} \times 100 \tag{27}$$

$$MAPE = \left(\frac{1}{n}\sum_{t=1}^{n} \left|\frac{F_t - A_t}{A_t}\right|\right) \times 100 \tag{28}$$

$$MBE = \frac{1}{n}\sum_{t=1}^{n} F_t - A_t \tag{29}$$

where n is the number of observations, A_t and F_t are observed and estimated values, respectively. The range of NRMSE and MAPE is 0 to $+\infty$, and the range of MBE is $-\infty$ to $+\infty$. The best performance for the three criteria is zero.

Acknowledgements The Authors considerably appreciate the reviewers who have dedicated their precious time and expertise to review our article. The authors greatly acknowledge Vahid Karimi Khosrowshahi and Ali Asghar Rostami for their kind contributions and supports for performing the statistical anlyses.

Author contribution Amin Sadeqi: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing—original draft. Hossein Tabari: Data curation, Supervision; Validation, Writing—Review & Editing. Yagob Dinpashoh: Conceptualization, Data curation, Supervision, Writing—Review & Editing.

Funding This research did not receive any grant from a funding institution either in governmental, commercial or non-profit sectors.

Availability of data and material Data used in the present study are available on the website of Iran Meteorological Organization, IRIMO (https://data.irimo.ir/).

Declarations

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

Consent for publication Informed consent to publish has been obtained from each participant.

Consent to participate All authors give their consent for participate of this paper.

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