Reliability Framework for Characterizing Heat Wave and Cold Spell Events

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Reliability framework for characterizing heat wave and cold spell events

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Abstract

Extreme weather events such as heat waves and cold spells affect people's lives. This study uses a probabilistic framework to evaluate heat waves and cold spells in different regions (Tehran in Iran and Vancouver in Canada). Average daily temperatures of meteorological stations of the two cities from 1995 to 2016 are used to identify four main indicators including intensity, average intensity, duration, and the rate of the occurrence. In addition, average intensities of the events are obtained from the MODIS Land Surface Temperature (LST) in each pixel of the two cities. To include possible uncertainties, the predictive probability distributions of the intensity and duration are derived using a Bayesian scheme and Monte-Carlo Markov Chain (MCMC) method. The probability distributions of the indicators show that the most extreme temperature (lowest temperature) occurs during the cold spell. Results indicate that although Tehran is more probable to experience heat waves than Vancouver, both cities are more likely to be affected by the cold spell than the heat wave. The developed approach can be used to characterize other extreme weather events in any location.

Keywords: Reliability analysis; Bayesian approach; Extreme weather events; Heat wave; Cold spell; Climate indicators

1. Introduction

Extreme events in summer and winter can cause significant consequences on human health (Montero et al., 2010; ul Islam et al., 2009; de'Donato et al., 2013; Barnett et al., 2012; Lee et al., 2018; Sherbakov et al., 2018; Jahangir and Moghim, 2019). The heat wave and cold spell are extreme weather phenomena, which happen when hot or cold extreme temperature lasts for a sequence of days (Barnett et al., 2012 and Ouzeau et al., 2016). Many studies show that high temperature is closely linked to the excess mortality (Semenza et al., 1996; Conti et al., 2005; Anderson and Bell, 2009; Barnett et al., 2012; Xie et al., 2013; etc.). Ahmadnezhad et al. (2013) used time series analysis to detect heat waves from 2001 to 2011 in Tehran and assessed impacts of heat waves on excess mortality. Ho et al. (2017) evaluated risks of

mortality in extremely hot days in Great Vancouver and mapped spatial vulnerability to hot temperatures. They investigated the odds ratio of mortality associated with 1°C increase in daily mean temperature.

Due to the fatal consequences of the heat wave and cold spell, comprehensive analysis of these events is required to provide research-based evidence for policy-making processes. Different studies use various indicators and thresholds to define these extreme weather events (Ouzeau et al., 2016). Many studies attempt to determine heat wave and cold spell events that are mostly characterized by duration, intensity, and maximum or minimum temperature. The extreme temperatures are defined based on the upper and lower quantile of the temperature distribution (e.g. Karl and Knight, 1997; Goldberg et al., 2011 and Ouzeau et al., 2016). The most common thresholds to determine heat wave and cold spell events are 95 to 99 percentiles and 1 to 5 percentiles, respectively (e.g. Goldberg et al., 2011; Barnett et al., 2012; Wolf and McGregor, 2013 and Ahmadnezhad et al., 2013). Zhang et al. (2014) defined heat waves based on the combination of temperature indicators, threshold, and duration that led to the best capture of the mortality consequences of a heat wave in Wuhan, China. Frich et al. (2002) used heat wave duration index (HWDI) to find heat waves when the daily maximum temperature exceeds 5 °C above the average daily maximum temperature of a specific period for at least five consecutive days. The defined climate indexes may not be proper in different regions with varied climate characteristics due to their specific temperature reference (Ouzeau et al., 2016).

Extreme weather events are expected to happen more frequent and intense in the next decades due to global climate change (IPCC, 2007). Frequency and duration of heat waves (as a consequence of climate change) have increased in most parts of the world (McKechnie and Wolf, 2009 and Perkins et al., 2012). The climate models confirm that climate change intensifies heat extremes in many parts of the world (Lelieveld et al., 2016; Qian et al. 2016), which has serious impacts on health system. Ho et al. (2017) quantified temperature-mortality

interaction to indicate high risk regions in Vancouver (Canada). They showed spatial variability of the health risk that is closely tied to the extreme heat and social vulnerability. Nori-Sarma et al. (2019) used Propensity Score Matching (PSM) to identify mortality risk of the heat wave in developing countries. They showed that health risk associated with the heat waves varies by different definitions of the heat wave. An increased temperature can affect strong winds and storms that are bringing warm and cold air masses (Moghim, 2018; Bengtsson et al., 2006).

People particularly the elderly are more vulnerable to health risks of the cold spells (Song et al., 2018; Zhou et al., 2014). The trend and the level of the cold spell impacts varies in different regions. For instance, the frequency, duration, and intensity of cold spells have decreased in western Canada from 1950 to 1998, while east part of Canada has experienced a distinct increase in frequency and duration of cold spells (Shabbar and Bonsal, 2003). Although cold spells can contribute to the environmental health hazards, a limited number of studies has focused on this event.

Many studies have assessed the trend of heat waves using climate models (e.g. Oleson et al., 2015; Perkins-Kirkpatrick et al., 2017; Hayhoe et al., 2004 and Guirguis et al., 2017). Lhotka et al. (2018) analyzed 62 regional climate models (RCMs) to assess possible changes in Central European heat waves under climate change scenarios. Simulations indicated that the frequency of heat waves in the period of 2020 to 2049 will be about two times higher than those from 1970 to 1999. Although GCM is one of the main tools to study future extremes, they contain biases and uncertainties, and their accuracy varies in different models and locations.

Many factors (e.g. data and biases in the modeling procedure) can add uncertainties in heat wave and cold spell assessment. Thus, to consider uncertainties associated with extreme events, a probabilistic approach is required. One of the widely used methods to analyze and

quantify uncertainties in climate studies is the Bayesian approach (Coles and Pericchi, 2003; Jackson et al., 2004; Smith et al., 2009; Siliverstovs et al., 2010, Jahangir and Moghim, 2019). Khaliq et al. (2007) assessed heat waves' occurrences using a Bayesian change-point approach in Montreal, Canada. Results indicated that there is insufficient evidence to show an increase in the rate of heat waves in the 1980s. Bayesian approach calculates posterior distributions of parameters based on the conditional prior distribution. A proper approach to assess posterior distributions is the Monte Carlo Markov Chain (MCMC) method, which is widely used in hydroclimatological and extreme weather assessment (e.g., Elsner et al, 2004; Reis and Stedinger, 2005; Furrer et al., 2007; Zhao and Chu, 2010; Gaume et al., 2010; Gaál et al., 2010; Isikwue et al., 2015; Hauser et al., 2017, Abbaszadeh et al., 2018; among many others). The Bayesian MCMC algorithm can include observations and historical information and also uncertainties to represent extreme events (Reis and Stedinger, 2005).

The characteristics of the extreme weather events (e.g. occurrence rate, intensity, and duration) vary in time and space. To consider uncertainties within the evaluation process, this study assesses heat wave and cold spell events in two different cities, Tehran (Iran) and Vancouver (Canada), using new indicators in a probabilistic framework. We use the developed probabilistic framework for reliability analysis of the heat wave and cold spell events.

2. Case study and dataset

This study aims to assess heat wave and cold spell characteristics in two different regions, Tehran (capital of Iran) and Vancouver (the most populous city in British Columbia province, Canada). Tehran is located in the northern part of Iran in the vicinity of the Alborz Mountains (Fig. 1a). Tehran is the most populated city of Iran (Statistical Center of Iran, 2011), which is extended from the longitudes of 51° to 51°40'E and latitudes of 35°30' to 35°51'N within the elevation of 1032 to 2032m. A wide range of elevation leads to the high variability of

temperature (Habibi and Hourcade, 2005). Likewise, the annual precipitation in Tehran is affected by the topography. This study uses hourly temperature of synoptic stations including Shemiran and Mehrabad to obtain daily temperature from 1995 to 2016 (Fig. 1a).

Greater Vancouver is a metropolitan area located in British Columbia district of Canada. Greater Vancouver is bordered by Fold Mountains on the north, the Pacific Ocean on the west, and the semi-arid Fraser Valley on the east, which leads to complex microclimate in the area (Ho et al., 2016). Although in summer, ocean breeze and winds from the mountain ridges can cool the coastal regions, the Fraser Valley traps low-pressure air masses and creates a relatively hot zone (Ho et al., 2016). On average, Vancouver region is located at lower altitude compared to Tehran (Fig. 1b). Daily temperatures from averaging hourly data of meteorological stations of Vancouver Harbour and West-Vancouver in 1995-2016 are used to characterize the heat wave and cold spell in the Vancouver region.

The average temperatures for the selected stations in Canada and Iran are presented in Table 1. Vancouver and Tehran have different climatic features derived by the adjacent oceans and the Mountain ranges. On average, the weather of Vancouver is less variable than Tehran.

Fig. 1

Table 1

3. Methodology

Heat waves and cold spells are extreme meteorological events characterized mostly by temperature. To evaluate these phenomena, a base threshold (T_b) is defined. This study uses a modified version of the method developed by Ouzeau et al. (2016). The heat wave/cold spell events are defined as a period of at least five consecutive days when the average temperature is larger/smaller than T_b . To estimate T_b , 95th and 5th percentile of the temperature in 1995-2016 are calculated (Table 1). These temperature thresholds are widely used in extreme events

evaluation (e.g. Wolf and McGregor, 2013; Song et al., 2017; Barnett et al., 2012; Ouzeau et al., 2016; Li et al., 2018; Khan et al., 2019; among many others). The extreme events can recur with a small lag between successive events. This study merges two consecutive heat wave (cold spell) events when the temperature does not drop from (exceed) T_b for three consecutive days.

Lack of synoptic stations and long-term air temperature data can affect heat wave/cold spell assessment. Thus, satellites' product and land surface temperature can be an alternative to improve the studies (Jiang et al., 2015). To further validate results, this study uses MODIS Land Surface Temperature (LST) from July 2002 to December 2016 for heat wave and cold spell characterization in both regions. The daily LST product (MYD11A1 version 6) is publicly available at lpdaac.usgs.gov/products/myd11a1v006 (Wan et al., 2015). Furthermore, to address uncertainties of the evaluation (e.g. from data and biases), we apply indicators in a probability framework that is useful for reliability analysis.

3.1 Extreme Weather Indicators

To assess and compare heat wave and cold spell events in two different regions, we use main indicators including intensity, average intensity, and duration. The intensity of the event (I) is defined as (Ouzeau et al., 2016)

$$I = \left| \frac{\Delta t}{2} \sum_{j=1}^D (T_{j-1} + T_j) \right| \quad (1)$$

where Δt is equal to one since daily temperature is used, T_0 is the temperature of the first day of the event ($j=1$), D is the number of the days that the heat wave/cold spell event has lasted. In this equation, T is the difference between the daily temperature and the threshold temperature (T_b) for each event. In other words, the intensity indicator ($^{\circ}\text{C day}$) is defined as the area bounded by the threshold line (e.g. 95th percentile of the temperature data for the heat wave) and the line segments of the temperature time series (corresponding to the $\Delta t = 1$).

146 Another indicator is the duration of the event (D), which is the number of the days that the
 147 event has been observed. The third indicator is the average intensity of the event ($\bar{I}$) as

$$\bar{I} = \frac{I}{D} \quad (2)$$

148 Average intensity ($^{\circ}\text{C}$) can represent the average temperature that is higher/lower than
 149 T_b during a heat wave/cold spell. The maximum values of the defined indicators including
 150 intensity (I), average intensity ($\bar{I}$), and duration (D) are estimated in each year (1995-2016) for
 151 both events (heat wave and cold spell). In addition, total event duration (D_{total}) in each year
 152 and the number of the occurrences per year (n_{occ}) are calculated. These indicators and their
 153 statistics are used to characterize heat wave and cold spell events in the two selected cities
 154 using observations and MODIS LST.

155 This study uses intensity and duration for further investigation since they are two main
 156 indicators that can represent the severity of the events. To include uncertainties (e.g. from
 157 observations and biases) within these indicators, a probabilistic approach is implemented. Log-
 158 Normal and Gamma distributions were selected for the prior probability distributions of the
 159 intensity and duration, respectively as

$$I \sim \text{LogNormal}(i|\mu, \tau) = \frac{1}{i} \sqrt{\frac{\tau}{2\pi}} \exp\left(-\frac{\tau}{2} (\ln(i) - \mu)^2\right) \quad (3)$$

$$D \sim \text{gamma}(d|\omega, \gamma) = \frac{\gamma^{\omega} d^{\omega-1} \exp(-\gamma d)}{\Gamma(\omega)} \quad (4)$$

160 In Eq. (3) i is the random variables for intensity, μ is the location parameter, and τ is the scale
 161 parameter. In Eq. (4) d is the random variables for duration, ω is the shape parameter, γ is the
 162 rate parameter, and Γ is the Gamma function. Parameters in Eqs. (3) and (4) are defined by
 163 their own distributions. To integrate the uncertainty within the results and derive the best

probabilistic model for the events, the parameters' distributions are also considered random and thus they need their own probability distributions. First, the prior uniform distribution is assumed for all four parameters including location and scale parameters in Eq. (3) and shape and rate parameters in Eq. (4). The Bayes' law is used to calculate the posterior distribution of the parameters as

$$f(\boldsymbol{\theta}|x) = \frac{f(x|\boldsymbol{\theta})f(\boldsymbol{\theta})}{f(x)} \quad (5)$$

where $\boldsymbol{\theta}$ is the distribution parameters' vector, $f(\boldsymbol{\theta}|x)$ is the posterior distribution, and $f(x|\boldsymbol{\theta})$ is the likelihood function. $f(\boldsymbol{\theta})$ and $f(x)$ are probability distributions of the parameters and variables, respectively.

MCMC method is used to derive the posterior distribution using PyMC3 (Salvatier et al., 2016) module. The convergence diagnostics of the chain were also handled by PyMC3 module (Salvatier et al., 2016). The MCMC sampling method was introduced by Metropolis et al. (1953) and it was generalized for statistical purposes by Hastings (1970). In this method, the sample is directly taken from the posterior distribution based on the quantiles of the interest (Brooks, 1998). This study uses the Metropolis-Hastings scheme (Hastings, 1970) with a standard normal sampler (Tierney, 1994) to estimate the posterior distribution of the parameters. Thus, the posterior predictive distributions (Sinharay and Stern, 2003) of the indicators including intensity $q'(i)$ and duration $q'(d)$ are calculated as

$$q'(i) = \iint \frac{1}{i} \sqrt{\frac{\tau}{2\pi}} \exp\left(-\frac{\tau}{2}(\ln(i) - \mu)^2\right) q'(\tau, \mu) d\tau d\mu \quad (6)$$

$$q'(d) = \iint \frac{\gamma^\omega d^{\omega-1} \exp(-\gamma d)}{\Gamma(\omega)} q'(\gamma, \omega) d\gamma d\omega \quad (7)$$

where τ , μ , γ , and ω are the distributions' parameters, and $q'(\tau, \mu)$ and $q'(\gamma, \omega)$ are the joint posterior distributions of these parameters. The distributions of these indicators are estimated by the Monte-Carlo (MC) sampling. The derived predictive distributions are then used for

reliability analysis to compare the associated probability of an extreme weather in Tehran and Vancouver.

To evaluate extreme events in each pixel, average intensities are obtained from LST in three periods (2002-2007, 2002 to 2012, and 2002-2016). The confidence interval (95%) for the median of the average intensity values in each pixel is calculated using bootstrapping with 10000 iterations (Efron, 1992). The upper bound of the sample median is used to represent the average intensity for the corresponding pixel.

3.2. Reliability Analysis

The general reliability method consists of series-parallel systems as (Der Kiureghian, 2005)

$$p_f = P\left(\bigcup_{m=1}^M \bigcap_{j \in c_m} (g_j(x) \leq 0)\right) \quad (8)$$

where p_f is the failure probability, g is the limit state function, M is the number of parallel subsystems, and c_m is the number of the cut-sets. An exhaustive review on system reliability methods can be found in the CRC chapter handbook by Der Kiureghian (2005). The reliability method consists of two parallel subsystems that form a series system. The parallel subsystem defines a heat wave or cold spell event when the duration of the event (D) is greater than five days and the average intensity ($\bar{I}$) is larger than one in at least one of the stations located in Tehran and Vancouver. In other words, if the conditions are met ($D > 5$ & $\bar{I} > 1$) in at least one station of the city, “failure” occurs. Thus, the defined failure probability indicates the chance (probability) of the exposure to the extreme events with average intensity larger than 1. The related failure probability for each city is calculated using the derived predictive distributions (see section 3.1) and MC sampling. The failure probability can be represented by the reliability index (β) as

$$\beta = -\Phi^{-1}(p_f) \quad (9)$$

where Φ is the standard normal distribution. A larger reliability index (β) indicates that the mean value of the system is far from the failure criteria, and thus the system is safer. In our evaluation, a larger β indicates a lower chance of exposure to the extreme events. For more details, the reader is referred to Der Kiureghian, 2005; Jahangir and Moghim, 2019; Ketabchi and Jahangir, 2019. MC sampling, failure probabilities, and reliability indexes are evaluated by Rt computer program (Mahsuli and Houkaas, 2013).

4. Results

Time series of the mean annual temperature for all stations is illustrated in Fig. 2a. Results indicate that temperature has been increasing in all stations excluding Vancouver Harbour station. The higher order moments of temperature is further illustrated through cumulative distribution functions (CDF) in Fig. 2b. The different range of temperature and the CDFs in two cities can indicate that Tehran and Vancouver have different climates. The difference can be more significant in the tails of the distributions (see Fig. 2b).

Fig. 2

Temperatures of these stations are used to construct heat-related indicators as the main determinant of heat wave and cold spell events in Tehran and Vancouver. The mean values of these indicators including maximum intensity, maximum average intensity, maximum duration, total duration, and occurrence rate for cold spells and heat waves are summarized in Table 2.

4.1 Heat Wave Evaluation

4.1.1 Heat wave in Tehran

Shemiran and Mehrabad are two synoptic stations in Tehran, where air temperature data are used to determine the heat waves' indicators. Average and 95th percentile of the temperature

(from 1995 to 2016) at Mehrabad synoptic station are higher than Shemiran (Table 1) due to significant difference between elevations of these stations (Fig. 1a). Maximum intensities of heat waves estimated at Shemiran and Mehrabad stations follow the same pattern in 1995 to 2016 excluding 2006-2007 and 2013-2014 (see Fig. 3a). Although the mean temperature is cooler in the northern part of the city (Shemiran station), the maximum intensity of the heat wave is more considerable in Shemiran station (Table 2). In addition, the maximum intensity shows an upward trend (particularly since 2008) in both stations especially in Shemiran station.

Fig. 3

Table 2

The long duration of the heat wave causes high intensity of this extreme event (see Eq.1). The mean values of all estimated indicators for each station are summarized in Table 2. Results show that the mean maximum duration of the heat wave in Shemiran station is more remarkable than that of Mehrabad. Similar to the maximum duration, there is a significant increase in trend of total duration (particularly in Shemiran station) since 2008, when the total duration is mostly more than 10 days (Fig. 3d).

Results reveal that although Mehrabad station has higher temperature than Shemiran station in 22 years of the study (Table 1), Shemiran has been experiencing longer intense heat waves than Mehrabad particularly since 2008 (Fig. 3 and Table 2). While the average number of occurrence is larger in Mehrabad station (Table 2). To find the cycle of the extreme events, the classic periodogram (Pollock, 1999) is used. Results reveal that for heat waves, all indicators excluding average intensity have significant periodic behavior (with a 90% confidence interval). In other words, they have been recurring at constant time intervals (Fig. 3). A significant return period was not observed for any indicator associated with Shemiran station. Indicators of the intensity and duration have different return periods.

4.1.2 Heat wave in Vancouver

Daily temperature data from two meteorological stations of Vancouver Harbour and West Vancouver are used to assess heat waves in Vancouver. In general, Vancouver is located at a lower elevation than Tehran and the elevation difference between the two selected meteorological stations in Vancouver is smaller than Tehran's stations. The average and the 95th percentile of the temperature in 22 years studied data in both stations are close (Table 1). On average, maximum intensity, maximum average intensity, and occurrence rate at West Vancouver station are higher than those of Vancouver Harbour while duration (maximum and total) of the event at Vancouver Harbour station is greater than West Vancouver (Table 2). Although the temperature threshold (95th percentile) is similar for the two stations (Table 1), average heat wave intensity at the West Vancouver station is larger than Vancouver Harbour station. This difference can refer to the physical features of the regions (e.g. topography, land cover/land use) and also atmospheric circulation derived by the adjacent sea-land. Similar to Tehran's stations, all indicators excluding average intensity have significant return periods (Fig. 3). The return period of duration (maximum and total duration) are equal in the two stations of Vancouver Harbour and West Vancouver. While the West Vancouver has a smaller return period of the maximum intensity.

4.2. Cold Spell Evaluation

4.2.1 Cold spell in Tehran

To estimate T_b for the cold spell assessment, 5th percentile of the temperature in 22 years recorded data at Shemiran and Mehrabad synoptic stations are used. The base threshold temperature in Shemiran (close to the Alborz Mountains) is less than half of the temperature measured at Mehrabad station (Table 1). In general, the patterns of the cold spell indicators at both stations (Fig. 4) are more similar than the indicators' pattern in the heat wave events (Fig. 3). While there is a slight difference between the mean values of each indicator at both stations

(see Table 2). Figure 4 shows that the maximum intensity varies between 0 to 50 (°C day) in 22 years excluding year 2008, when maximum intensity at Shemiran and Mehrabad stations are about 170 and 200 °C day, respectively (Fig. 4a). Note that the mean value of maximum intensity at both stations is about 24 °C day.

Fig. 4

Results reveal that although Shemiran station is colder (see Table 2), more severe cold spells have occurred in the Mehrabad station. On the other hand, on average, the duration of the cold spell events in Shemiran station is larger. This indicates that although Shemiran station is located at a higher altitude and has a colder temperature, Mehrabad station has experienced a larger deviation from the threshold temperature (more severe cold spells). All indicators have a significant return period. Although the indicators of the cold spell have the same return period in the two stations (Fig. 4), the duration indicator (maximum and total) has a longer return period (5.5 years) compared to the intensity indicator (2 years).

4.2.2 Cold spell in Vancouver

To assess the cold spell event in Vancouver, daily temperature data of two meteorological stations including West Vancouver and Vancouver Harbour are used. Figure 4 shows that patterns of the estimated indicators of the cold spell at both stations are generally more similar than those related to the heat wave. While there is a slight difference between the values of the maximum intensity estimated at both stations. The mean maximum intensity and maximum average intensity calculated at West Vancouver are greater than those at Vancouver Harbour (see Table 3). We can conclude that cold spells that occurred at West Vancouver station had lower temperatures than related temperature of the cold spells at the Vancouver Harbour station. This is consistent with the result that 5th percentile of the temperature in 22 years at West Vancouver station is lower than those at Vancouver Harbour station (Table 1). The return period of the intensity (maximum and maximum average) in Vancouver is the same as Tehran

(2 years). Although the return period of the maximum duration indicator is larger in West Vancouver, the return period of the total duration is larger in Vancouver Harbour.

4.3 Pixel by Pixel Assessment of the Heat Wave and Cold Spell

Results of the indicators constructed from the synoptic observations confirmed that heat waves and cold spells have been occurring in Tehran and Vancouver. To further evaluate the heat wave and cold spell in each pixel, the daily LST from MODIS is used to estimate average intensities of the events for three time periods (2002-2007, 2002-2012, and 2002-2016). The maximum median of the random samples from the estimated average intensities in each period is considered as the average intensity of the extreme event in each pixel (Fig. 5).

Fig. 5

4.3.1 Heat Wave

The pixel by pixel average intensity of the heat wave is illustrated in the first three rows of Fig. 5 for Tehran (first column) and Vancouver (second column). The 95th percentile of the LST in each pixel, is the base threshold temperature (T_b), which defines heat waves in each pixel (the last row of Fig. 5). Results show that on average T_b is smaller over northern part of Tehran and Vancouver. Figure 5 indicates that the average intensity of the heat wave tends to decrease in Tehran, while this intensity has not changed significantly in Vancouver. The average intensity of the heat wave from LST is larger than those obtained from synoptic data (Table 2).

4.3.2 Cold Spell

Figure 5 (the first three rows) shows the pixel by pixel average intensity of the cold spell in Tehran (third column) and Vancouver (forth column). The 5th percentile of the LST in each pixel, is the base threshold temperature (T_b), which defines cold spells in each pixel (the last row of Fig. 5). On average, T_b is smaller over northern part of Tehran and Vancouver. Results

show that the average intensity of the cold spell has been decreasing in Tehran since 2002, which is more noticeable in the north of the city. Also all pixels of the Vancouver region have experienced a remarkable decrease in average intensity of the cold spell. Similar to the heat wave, the LST based derived average intensity of the cold spell is higher than those obtained from observations (Table 2).

4.4 Reliability Evaluation

4.4.1 Predictive distribution

To include uncertainties of the events for a complete assessment, the predictive distributions of two main indicators including intensity and duration are estimated (Eqs. 6 and 7). The means and standard deviations of the intensity and duration for the estimated predictive distributions are summarized in Table 3. The predictive distributions for intensity and duration for all four selected stations are illustrated in Fig. 6. The predictive distributions of the heat wave intensity in two stations of Vancouver are more similar than those of Iran (see Fig. 6a). Results confirm that although temperature ranges are different in two regions of Tehran and Vancouver (Fig. 2), the defined indicators can be efficiently used to compare and characterize temperature-related extreme events.

Table 3

Fig. 6

The maximum of mean intensity obtained from the predictive distribution occurs in the Shemiran station (Table 3) and the minimum value occurs in the Vancouver Harbour station. Moreover, the derived distribution of the intensity for the Shemiran station is more skewed to the right. The average values of the derived intensity (Table 3) indicate that heat waves in Tehran are more intense than those occurred in Vancouver.

The predictive distributions of the intensity for the cold spell events are illustrated in Fig. 6b. Results indicate that the probability distributions of the cold spell intensity are identical in Shemiran and Vancouver Harbour stations. This can indicate that although temperature ranges are different in these two stations in Tehran and Vancouver, the projected intensity of the cold spell events in Shemiran and Vancouver Harbour can be expected to be identical.

On the other hand, although the mean and the 95th percentile of the temperatures in all stations are different (Table 1), their corresponding projections of heat wave intensities are close. This indicates that extreme weather events (e.g. heat wave and cold spell) in different locations can have similar features. The average intensities obtained from the predictive distributions in all stations are more considerable for the cold spell compared to the heat wave.

The predictive distributions of the heat wave duration for all stations are illustrated in Fig. 6c. The distributions are quite similar for all stations excluding West Vancouver, where minimum duration (maximum and total) occurs (Table 2). In the West Vancouver station, the smaller variance of the duration values leads to a smaller range of this indicator. For both heat wave and cold spell events, the maximum duration obtained from the predictive distributions occurs in the Shemiran station (Table 3). Results reveal that although the estimated mean durations of the heat wave and cold spell events are similar for all stations, the estimated mean intensities of these two events are considerably different. This difference can indicate that during the cold spell event, the deviation of the observed temperature from defined threshold is larger than those in the heat waves.

4.4.2 Failure probability

Derived predictive distributions can form the failure reliability framework for the heat wave and cold spell in two cities. If the estimated duration and the ratio of the intensity to the duration (average intensity) are greater than 5 days and 1°C, respectively, in at least one of the stations in Tehran or Vancouver, the system fails for that city, in other words, that extreme

event occurs. Indeed, this reliability system can determine associated probability of the exposure of the two cities to the heat wave and cold spell and define an index of the severity related to those events. A negative reliability index (Eq. 9) indicates a higher failure probability (a larger change of exposure). Thus, as the failure probability increases, the associated risk of the events increases as well. The reliability indexes and their failure probabilities of Tehran and Vancouver are summarized in Table 4. Results show that the failure probability of the heat waves in Tehran is greater than Vancouver. This higher probability indicates that Tehran is expected to be more at the risk of heat waves than Vancouver. Although Vancouver is more probable to be exposed to the cold spell compared to Tehran, the difference between their associated exposure probabilities is small. The higher exposure probability of the cold spell events relative to the heat wave events indicates that both cities are more likely to have cold spells. These results can be valuable in efficient adaptation and mitigation plans to reduce possible future hazards.

Table 4

5. Discussion and Concluding Remarks

This study aims to use a proper approach and useful indicators to assess heat waves and cold spells in the regions with different climatic features (Tehran and Vancouver). To characterize these extreme weather events, observations from four stations (Shemiran, Mehrabad, West Vancouver, and Vancouver Harbour station) are used to construct main indicators including intensity, average intensity, duration, and the number of occurrences (occurrence rate). In addition, MODIS LST data are used to derive pixel-based average intensity using bootstrapping method in both regions of interest. The defined indicators can provide a new scale for comparison. Note that extreme weather events cannot be completely analyzed by just key climate variables like temperature. To include possible uncertainties (e.g. from observations and biases) the probability distributions of the parameters for the intensity

and duration indicators were updated using MCMC, and consequently, the predictive distributions of these indicators were derived using the Bayesian updating scheme. The predictive distributions were used to define associated reliability index and the failure probability of each event (heat wave and cold spell) in both cities. The developed approach can indicate the chance (probability) of exposure to the extreme events, which can be used in risk analysis and impact assessment.

The mean values of the maximum annual indicators show the heat waves that occurred in the northern part of Tehran (Shemiran station) have a larger intensity, which is mostly due to longer duration of the heat waves. In other words, although more heat waves have occurred in the western part of the city (warmer region), the northern part of the city has experienced more durable and intense heat waves. The average and the 95th percentile values of the temperature in these two stations also indicate that although warmer part of the city has experienced more heat waves, the intensity and especially duration of the event that profoundly affect people's health were more extreme in the cold region of the city. While for the cold spell, the intensity is larger in Mehrabad station. Similar to the heat wave, Mehrabad station (located in the warmer part of the city) has experienced a larger occurrence rate of the cold spell than Shemiran station, while cold spells occurred in the northern part of the city have lasted longer. In other words, cold spells occurred at Mehrabad station were more intense and less durable (shorter) than Shemiran station. Although heat waves have been more examined in past decades, our results revealed that the intensity of the cold spells could be even more considerable (e.g. in Tehran), which asks for more emphasis and investigations on this event.

The indicators of the heat wave in the city of Vancouver showed that heat waves at the West Vancouver station are formed by higher temperatures than those at the Vancouver Harbour. While the heat waves at the Vancouver Harbour had a longer duration. Although the thresholds of the heat waves in two stations of the Vancouver region are similar, West Vancouver station has been more exposed to extreme temperatures during the study period

(1995-2016). On the other hand, results revealed that although the number and the intensity of the cold spell events are larger in the West Vancouver station, the duration of this extreme event is almost the same in both stations. Although, on average, Vancouver is cooler than Tehran, the cold spells occurred in Tehran last longer than those in Vancouver. These differences can reveal the necessity of using different indicators for a complete evaluation of an extreme event.

This study analyzed indicators that are defined based on the 95th and 5th percentile of the daily temperature as upper and lower thresholds for the duration of five days. While higher intensity of the extreme events within the relatively shorter duration can occur and leads to even more serious damages. Note that thresholds for detection of the extreme events can vary in different sectors like agriculture, health, economy, and industry. To evaluate the effect of threshold values, we considered different upper and lower limits including 93th and 97th (3th and 7th) percentile of the temperature for occurrence of the heat wave (cold spell) event. In addition, different intervals including three and seven days for minimum duration of the extreme events are examined. Results showed that an increase in temperature threshold and minimum duration of the heat wave reduces all indicators (maximum intensity, maximum average intensity, maximum duration, and total duration). While an increase in temperature threshold/minimum duration of the cold spell increases/decreases all related indicators. The temperature threshold has more remarkable impact on indicators' values compared to the duration threshold.

Fourier analysis revealed that all indicators of the extreme events excluding average intensity in the heat wave show significant periodic signals. Indicators of the heat wave and cold spell have different return periods. Results show a similar return period in the average intensity of the cold spell in all stations, while the indicators of the heat wave have different return periods. The intensity and duration of the heat waves recorded at Vancouver Harbour

and West Vancouver are larger than those at Mehrabad station. Longer data record can increase validity and accuracy of the results.

To assess extreme weather events pixel by pixel, MODIS LST is used to derive average intensity of the heat waves and cold spells based on the threshold temperature (T_b) in each pixel. Results showed that the northern parts of Tehran and Vancouver have relatively smaller T_b . In general, the average intensity of the cold spell in Tehran and Vancouver region has decreased, which is more remarkable than changes in the heat wave's intensity. The average intensities estimated from the LST is larger than those obtained from observed air temperature. The range for the average intensity of the heat wave in Vancouver is larger than those in Tehran (more than twice). Results indicate that mostly southern parts of the Vancouver region are exposed to the heat waves. Indeed, the larger deviation of the temperature from T_b occurs in heat waves than cold spells in the Vancouver region.

To compare and characterize extreme weather events (e.g. heat wave and cold spell) in different regions a reliability framework was developed. The average and different percentiles (e.g. 5th and 95th) of the temperature in different locations cannot completely characterize the heat-related phenomena, and a proper set of indicators are required to quantify the intensity and duration of the extreme events. Results showed that although Tehran has experienced longer cold spells compared to Vancouver, this event is more extreme (larger temperature deviation from the threshold) in Vancouver. The correlation between intensity and duration is larger than correlation between intensity and the temperature difference, which indicates that the long duration of the events in Tehran and Vancouver caused severe heat wave and cold spell events.

The derived probability distribution of the intensity demonstrated that it is more probable that the cold spells occur with a larger intensity compared to the heat waves in both cities. In general, this probability framework illustrated that Tehran is expected to be more at risk of heat

waves than Vancouver. Furthermore, both cities (Tehran and Vancouver) have a higher chance of exposure to the cold spells than the heat waves. This result shows the importance of further research on the cold spell since there are fewer studies about this event. For a comprehensive evaluation of the extreme weather events, a proper set of indicators is required to provide new metrics for the better interpretation and analysis of the results. Indeed, the probability distributions of the main indicators of the heat wave/cold spell event can determine the possibility (chance) of their occurrence with different intensities and duration, which is vital for impact assessment and management. The developed approach can be used for other extreme weather events in any location.

Extreme heat-related phenomena like heat waves and cold spells have devastating impacts on ecosystem, environment, and people's health. The developed approach for characterizing heat wave and cold spell events provides a robust tool to evaluate and compare these extreme events in different regions. The predictive distribution for the defined indicators can include the uncertainties within the modeling procedure, which is useful for managers and decision makers. Furthermore, the developed reliability approach can be used for risk analysis and severity assessment of the extreme events in different regions for proper resource allocation and emergency actions, which is required in efficient adaptation and mitigation plans.

Declarations

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714 **Table 1** Average, 95th, and 5th percentile of 22 years temperature data in selected stations including
 715 Mehrabad, Shemiran stations in Iran and Vancouver Harbour, West Vancouver stations in Canada

Station name	95 th percentile temperature (°C)	Ave. temperature (°C)	5 th percentile temperature (°C)
Mehrabad	32.56	18.50	2.83
Shemiran	29.82	15.95	1.05
Vancouver Harbour	20.10	11.35	3.00
West Vancouver	20.20	10.61	1.70

716

717 **Table 2** Mean values of the indicators including maximum intensity (I), maximum average intensity
718 ($\bar{I}$), maximum duration in days (D), total duration in days (D_{total}), and occurrence rate (n_{occ}) for cold
719 spells and heat waves in stations of Iran and Canada

Station	I		$\bar{I}$		D		D_{total}		n_{occ}	
	cold spell	heat wave	cold spell	heat wave	cold spell	heat wave	cold spell	heat wave	cold spell	heat wave
Mehrabad	24.51	10.96	1.76	1.06	9.59	8.68	12.82	12.14	1.23	1.23
Shemiran	23.96	14.37	1.62	1.04	10.50	10.91	13.50	14.77	1.18	1.18
Vancouver Harbour	19.68	11.07	2.06	0.97	7.96	9.5	11.18	12.68	1.23	1.23
West Vancouver	22.22	11.27	2.49	1.47	7.86	6.82	11.68	10.55	1.32	1.41

720

721 **Table 3** Mean (μ) and standard deviation (Std) of intensity and duration for the derived predictive
722 distributions in all stations

Station	Intensity				Duration			
	Heat wave		Cold spell		Heat wave		Cold spell	
	μ	Std	μ	Std	μ	Std	μ	Std
Mehrabad	13.15	12.90	24.59	43.42	10.62	5.83	12.50	10.54
Shemiran	14.95	17.08	23.05	29.87	12.82	8.79	12.55	8.62
Vancouver Harbour	12.29	18.70	23.00	29.60	10.73	7.52	10.39	5.98
West Vancouver	12.43	17.03	25.88	37.27	7.14	3.50	10.39	7.90

723

Table 4 Failure probability (p_f) and reliability index (β) for heat wave and cold spell events in
Tehran and Vancouver

	Tehran		Vancouver	
	heat wave	cold spell	heat wave	cold spell
β	-0.42	-1.12	-0.19	-1.16
p_f	0.66	0.87	0.58	0.88

Fig. 1 The study domain and location of the synoptic stations in (a) Tehran (Mehrabad and Shemiran stations) and (b) Vancouver region (Vancouver Harbour and West Vancouver stations)

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