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Estimating the Aquifer's Renewable Water to Mitigate the Challenges of Upcoming Megadrought Events

Ameneh Mianabadi[1] · Seyed Majid Hasheminia[2] · Kamran Davary[2] · Hashem Derakhshan[2] · Markus Hrachowitz[3]

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Abstract

In arid and semi-arid regions of the world, the occurrence of prolonged drought events (megadroughts) associated with climate change can seriously affect the balance between water supply and demand, thereby severely increasing the susceptibility of such regions to adverse impacts. In this study, a simple framework is introduced to estimate renewable water volumes (RW) to mitigate the challenges of megadrought events by managing the groundwater resources. The framework connects a weighted annual hydrological drought index (wSPEI) to RW, based on the short time-scale precipitation volume. The proposed framework, which was in a proof-of-concept case study applied to the Neishaboor watershed in the semi-arid part of Iran, showed that developing the weighted drought index can be valuable to estimate RW. The results suggested that the wSPEI, aggregating hydrological drought index (HSPEI) with the time scale $k=5$ days and the regional coefficient $s=1.3$ can be used to estimate RW with reasonable accuracy ($R^2=0.73$, RMSE $=11.5$ mm year^{-1}). This indicates that in the Neishaboor watershed, the best estimation of RW can be determined by precipitation volumes (or the lack thereof) falling over 5-day aggregation periods rather than by any other time scales. The accuracy of the relationship was then investigated by cross validation (leave-one-out method). According to the results, the proposed framework performed fairly well for the estimation of RW, with $R^2=0.75$ and RMSE $=12.2$ mm year^{-1} for $k=5$ days. The Overall agreement between the wSPEI, the RW derived from water balance calculations, and the estimated RW by the proposed framework was also assessed for a period of 34 years. It showed that the annual RW followed closely the wSPEI, indicating a reasonable relationship between wSPEI and the annual RW. Accordingly, the proposed framework is capable to estimate the renewable water of a given watershed for different climate change scenarios.

✉ Seyed Majid Hasheminia
s.m.hasheminia@gmail.com; Hasheminia@um.ac.ir

1 Department of Ecology, Institute of Science and High Technology and Environmental Sciences, Graduate University of Advanced Technology, Kerman, Iran

2 Water Science & Engineering Department, College of Agriculture, Ferdowsi University of Mashhad, P. O. Box: 91779-1163, Mashhad, Iran

3 Department of Water Management, Faculty of Civil Engineering and Geosciences, Delft University of Technology, P. O. Box: 5048, Delft, The Netherlands

Keywords Renewable water · Weighted drought index · Megadrought · Neishaboor

1 Introduction

In recent years, prolonged drought events due to climate change have increasingly caused serious adverse impacts on ecosystems, societal and economic instability of communities (Roodari et al. 2021). These prolonged droughts which are referred to as "megadroughts" may last for two decades or longer. The occurrence of megadrought events triggers more water use and exacerbates the extraction of water resources, especially in arid and semi-arid regions of the world which mainly rely on groundwater as their major water resource. Therefore, it is important to establish sustainable water planning and management strategies to better understand the future probability of occurrence and potential impacts of megadroughts (Coats et al. 2015; Şen 2021). Development of arid and semi-arid areas by exploiting groundwater resources has led to a considerable decline in the water level of aquifers in these regions. During prolonged drought events (megadroughts) the low levels of rainfall, exacerbated by climate change, have a serious impact on groundwater recharge and have the potential to cause devastating pressure on these resources.

Therefore, there is a serious urgency to manage water withdrawals from aquifers with an adaptation plan so that parts of the groundwater are set aside as an emergency resource for extraction during megadrought events. This part of groundwater is typically referred to as a fraction of "Strategic Groundwater Reserve" which is considered as a crucial "emergency" water resource during megadrought events (D_s). In arid and semi-arid regions, where groundwater extraction is often the key resource to meet water demands, D_s has been already or will be eventually reduced (Mianabadi et al. 2020), since the demand for water exceeds supply, intensifying the problem even more and causing considerable water shortages during megadrought events. Thus, it is of great importance to identify the sustainable amount of groundwater extraction so that a reliable D_s could be ensured and be available for water management during a probable megadrought event (Mianabadi et al. 2020).

D_s for a certain megadrought event with a duration of d years is defined as the difference in annual renewable water as compared to its long-term average (Eq. 1).

$$D_s = \sum_{j=1}^{d} (\overline{\mathrm{RW}} - \mathrm{RW}_j) \tag{1}$$

where $\overline{\mathrm{RW}}$ is the long-term mean annual RW, j is the index for the water year ($j = 1$ is the first year of a megadrought event) and d is the duration of the megadrought event (Mianabadi et al. 2020).

According to Eq. (1), estimating the RW is the primary step of megadrought management and a key element to identify the sustainability challenges of a region (Yan et al. 2010). By assessing the amount of RW, water resources managers along with policymakers can develop appropriate strategies for reserving adequate water in the aquifers to enhance the resilience of sustainable development and to cope with the effects of any probable megadrought event. The RW is often estimated in accordance with groundwater recharge (Wada et al. 2011; Brauman et al. 2016). While some water balance and hydrological models are developed to quantify groundwater recharge (e.g., Arnold et al. 1998; Alcamo et al. 2003), these models need sufficient input data and/or calibration parameters which may not be available for many watersheds (Schuol et al. 2008; Hrachowitz et al. 2013). Therefore, the long-term groundwater recharge, and consequently, the amount of RW is difficult to be estimated and often poorly unknown (Zammouri and Brini 2020). For example, Xu et al. (2019) applied the estimation of annual percolation flow proposed by USGS (Reitz et al. 2017) as a proxy for annual groundwater recharge. However, in recent decades, with an increase in the availability of remote sensing data, constraints on hydrological components' estimation, especially at the regional scale, are being reduced (e.g., Nijzink et al. 2018; Dembélé et al. 2020). Nevertheless, estimating the amount of groundwater recharge by using complex models requiring vast data is still a tedious task, accompanied by considerable uncertainties of these models (e.g., Hulsman et al. 2021). Besides, techniques developed for estimating groundwater recharge in areas with high amounts of rainfall are often not appropriate for arid and semi-arid regions (Edmunds 2003). Furthermore, it is not possible to assess the future water balance of a region to estimate the effects of the worst future megadrought event on groundwater recharge. Thus, developing a simple and reliable framework for estimating the RW with lower data requirements could be a valuable tool in sustainable megadrought management and to cope with its consequences. In this study, a novel simple framework is introduced to estimate the renewable water of groundwater resources. The framework establishes a simple relationship between the RW and the annual drought indices (i.e., RW = f(DI), where DI is the drought index) as aggregated from weighted drought indices over shorter time scales, i.e., shorter than a season. To evaluate the proposed framework, it was applied to a watershed in Iran, which currently is struggling with severe groundwater challenges and limited data availability, hindering the application of complex hydrological models for estimating the RW.

2 Methods

2.1 The Study Area

The Neishaboor watershed, covers an area of 7330 km^2 in Iran's Central Desert basin, in the northeast part of Iran (Fig. 1). The maximum and the minimum elevation of the watershed are 3,300 and 1,050 m above sea level at Binalood Mountains and Hoseinabad (the outlet of the watershed), respectively. The climate of the watershed is classified as semi-arid to arid, with a mean annual precipitation of 265 mm year^{-1} and a mean annual temperature of 13 °C in the mountainous area and 13.8 °C in the lower basin area (Izady et al. 2015). The mean annual minimum and maximum temperature of the watershed are about 6 and 21 °C, respectively. The mean annual potential evaporation is estimated at around 2335 mm year^{-1} (Velayati and Tavassoli 1991). Note that "evaporation" in this study is defined as the sum of interception evaporation, soil evaporation, plant transpiration, and open water body evaporation as mentioned by Shuttleworth (1993) and Savenije (2004).

Like many other watersheds all over the country, Neishaboor is subjected to serious water challenges. Throughout history, Iranians could deal successfully with the limited water availability in the arid regions by implementing techniques such as Qanats (Madani et al. 2016). However, during the last few decades, the increase in water demand due to rise in population, exhaustive water consumption owing to intensive agricultural activities, coupled with recurrent of severe droughts has caused the water resources in many parts of Iran to experience serious pressures (Roodari et al. 2021), much of it linked to groundwater overexploitation (Ashraf Vaghefi et al. 2014). The situation is more serious in central and eastern parts of the country, where the Neishaboor watershed is located. The occurrence of prolonged drought events may cause water shortages and even frequent water cuts, resulting in disruptions to the quality of life components for millions of citizens in these areas.

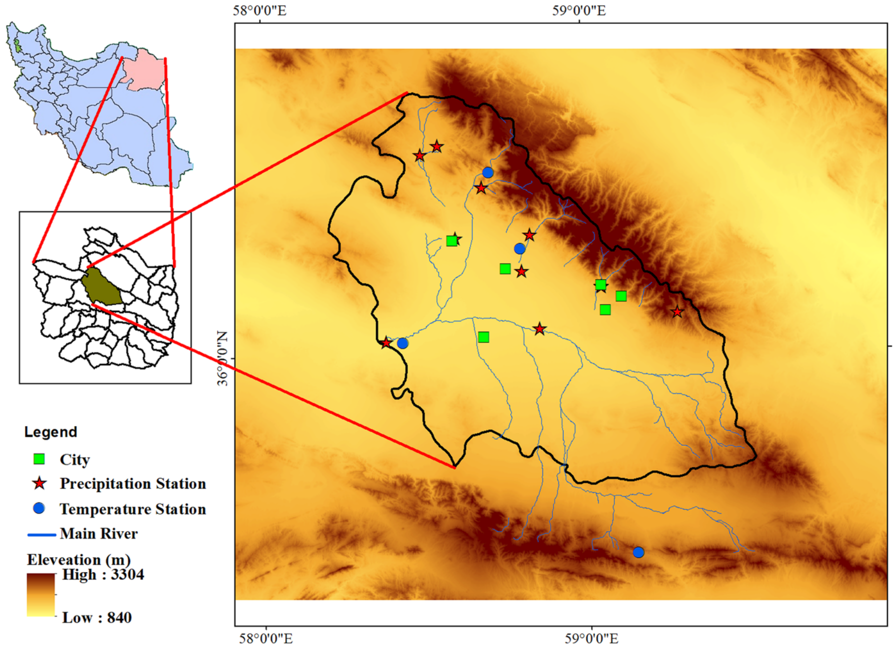

Fig. 1 Geographical location of the Neishaboor watershed

In the agricultural sector, this may lead to a serious decline in crop production, agricultural losses, and severe food supply shortages. Declining groundwater levels along with drying Qanats, wetlands, lakes and rivers, have led to several profound water-related challenges. Madani (2014) and Roodari et al. (2021) have identified the foremost reasons for causing increasing water shortages in many basins of Iran as: 1) rapid population growth and its inappropriate spatial distribution, 2) a growing but inefficient agricultural sector and its mismanagement, and 3) a great aspiration for development.

In arid and semi-arid regions including the Neishaboor watershed, expanding the irrigated agriculture and construction of different factories with high water consumption, have led to over-drafting of groundwater resources. With the expectation that prolonged drought events will happen with increased frequency in the future due to exacerbating effects of climate change, the arid and semi-arid regions of Iran are currently ill-prepared and ill-equipped to face the pertaining consequences. In light of this issue, there is a serious urgency to introduce and implement strategies to cope with the consequences of mega-drought events through effective groundwater management (Hasheminia 2021). To deal with this concern, a reliable estimation of the RW is introduced in order to provide appropriate plans for using groundwater resources in a sustainable way.

2.2 Data

The required data are precipitation, and the maximum and minimum temperatures. These daily data were acquired from 10 precipitation and 4 temperature stations for 34 years from 1982 to 2015. The location of the stations is illustrated in Fig. 1. To interpolate daily precipitation and temperature, the study area extent was divided into 25 homogeneous regions in terms of dimension, where each region included 2500 (50×50) cells. Daily precipitation was interpolated over the watershed by the inverse distance weighted (IDW) method. IDW coefficients for each region versus 10 precipitation stations (C_{Pr}) and 4 temperature stations (C_T) were determined for further daily interpolations. Equation (2) shows how the daily precipitation for each region (Pr_R) is estimated.

$$Pr_{R(j)} = \Sigma(C_{pr(ij)} \times Pr_i) \tag{2}$$

where i and j represent the ID of each station and region, respectively. In this equation, Pr is daily precipitation for each station and C_{pr} represents each region's IDW coefficient versus each precipitation station.

Due to the inadequate state of temperature data, daily laps rates of average temperature for the whole basin were estimated, considering the daily ratio of precipitation by the multiplication of reference evaporation and the daily antecedent effective days parameter ($LR = Pr/(E_0 \times eD)$), for each temperature station. The eD parameter is defined as the number of days that moisture left in the soil by previous rain events can affect evaporation, where it varies between 2 days in summer and 9 days in winter. The mentioned daily ratio was used to indicate lapse rates for daily average temperatures through a conditional function, in which they were interpolated between 3.5×10^{-3} and 6×10^{-3}. To determine the regional coefficient of average temperatures (CT_R), the lapse rates (for four stations) were multiplied by each station and region height difference (dH) (Eq. 3).

$$CT_{R(ij)} = LR_i \times dH_{ij} \tag{3}$$

CT_R was then added to the daily average temperatures of each station to estimate regional station-wise average temperatures (SRT_{av}). As Eq. (4) illustrates, each region would have one SRT_{av} per temperature station (4 stations).

$$SRT_{av(ij)} = CT_{R(ij)} + T_{av(i)} \tag{4}$$

The addition of SRT_{av} and the mean of differences between daily maximum and average temperatures (dT_{mx}) as well as daily minimum and average temperatures (dT_{mn}) for each station, generated station-wise regional maximum (SRT_{mx}) and minimum (SRT_{mn}) temperatures. As shown in Eqs. (5)–(7), the same method was applied to estimate regional daily average, minimum, and maximum temperatures (rT_{av}, rT_{mn}, and rT_{mx} respectively) as well as for estimation of the regional amount of precipitation.

$$rT_{av(j)} = \Sigma_{i=1}^{4}(\Sigma_{j=1}^{25}(C_{T(ij)} \times SRT_{av(ij)})) \tag{5}$$

$$rT_{mx(j)} = \Sigma_{i=1}^{4}(\Sigma_{j=1}^{25}(C_{T(ij)} \times SRT_{mx(ij)})) \tag{6}$$

$$rT_{mn(j)} = \Sigma_{i=1}^{4}(\Sigma_{j=1}^{25}(C_{T(ij)} \times SRT_{mn(ij)})) \tag{7}$$

2.3 A General Overview of the Framework

To develop a framework for the RW estimation in terms of drought indices, two important factors need to be considered. Firstly, the fact that drought indices are usually analyzed over time scales of more than one month (e.g., Jain et al. 2015; Stagge et al. 2015; Fluixá-Sanmartín et al. 2018; Ali et al. 2019; Pei et al. 2020). Using these time scales, the drought indices are only related to the amount of precipitation and not to the duration and intensity of individual precipitation events which, however, are critical factors for aquifer recharge. For example, two years which have the same precipitation amounts would be classified in the same category of a drought index, while the intensity and duration of precipitation, which considerably affect the hydrological response of a catchment, are not taken into account. Therefore, it is important to interpret the drought events over a shorter time scale (Vicente-serrano 2006; Van Loon 2013). In addition to the intensity and duration of a precipitation event, the amount of RW is considerably dependent on the soil moisture content at that moment. All these factors indicate that RW should preferably be analyzed over shorter time scales, *k*. Secondly, to provide a reliable relationship between drought indices and precipitation amount and to estimate their role on RW, the intra-annual timing of drought occurrence needs to be considered. For example, if the magnitude of a drought index in two months with high and low precipitation (e.g., March and August, respectively) is the same, it would mean that these two months exhibit the same drought severity, while due to the different amounts of precipitation, their contribution to the RW and runoff would be considerably different. Therefore, it is necessary to put a weighting function into effect by which a standard drought index is converted to a weighted drought index (wDI), so that the probability of occurrence of precipitation is included. Such a weighting function gives a higher weight to any *k* with a high amount of precipitation and a lower weight to any other *k* with a low amount of precipitation. For example, in dry months when precipitation is low the RW is negligible, and therefore, the weighting function reduces the drought index value. In contrast, the weighting function enhances the effect of periods with higher amounts of precipitation.

It should be emphasized that in the areas where precipitation and evaporation are out of phase, the available water of each period and its contribution to the annual RW depends mostly on precipitation and the timing thereof, i.e., shorter time periods should be considered in order to find wet periods where precipitation exceeds evaporation. Therefore, it is postulated that in such regions the weighting function is largely determined by precipitation. In contrast, in the areas where precipitation and evaporation are more in phase, both precipitation and evaporation rates considerably affect the available water of each period and its contribution to the annual RW, and thus, both variables should be considered for determining the weighting function.

The framework developed in this study (Fig. 2), connects a wDI to RW which hereafter is referred to wDI-RW. The description of each step of the framework is presented as follows.

2.3.1 Calculating the Annual RW

As mentioned earlier the framework establishes a simple relationship between renewable water and drought indices. Accordingly, reliable approximations of the RW in a given catchment over the past are required. The annual RW can be assessed through watershed water balance. The accuracy of the calculated RW (cRW) depends on the data availability, the time scale used, and the water balance period. Obviously, the more available data with sufficient accuracy and the longer the study period, the RW would be evaluated more accurately. Then, the annual calculated RW amounts assessed in this way (cRW) are used to validate the RW estimated by the wDI-RW relationship (eRW).

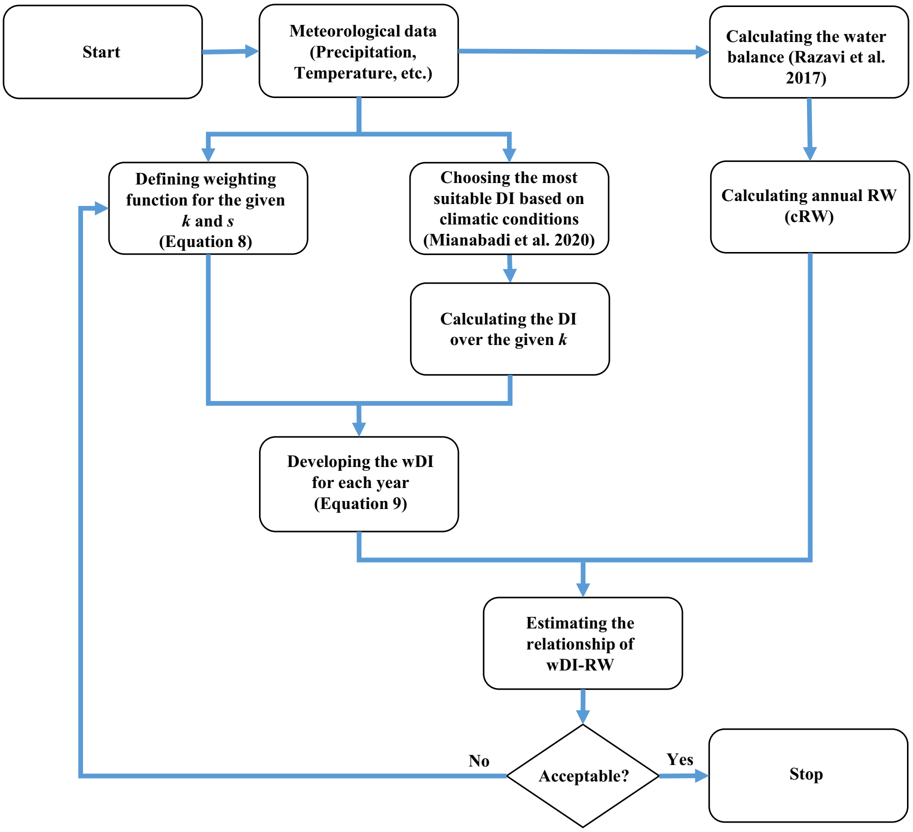

Fig. 2 The wDI-RW framework developed by the authors for this research

2.3.2 The Appropriate Drought Indices

The second step is choosing the most appropriate drought index based on the climatic conditions of a region. For this purpose, the drought indices which are not exclusively based on precipitation, but on other climatic variables affecting the drought severity, such as temperature, wind speed, and humidity (Stagge et al. 2015), might be taken into consideration.

2.3.3 Calculating the DI Over the Time Scale of *k*

In this step, the selected drought index is calculated over short time scales k, varying from 1 to 30 days. The time scale, k, is defined such that to fit precisely to the number of days per month, meaning that often the last k-day of each month is not precisely k days. For example, for $k=10$ days for the month of January, the first k-day refers to 1–10, the second to 11–20, and the third to 21–31 of January. Therefore, the third k-day covers 11 days. The first time scale for starting the flowchart is determined by the user.

2.3.4 The Weighting Function for the Time Scale (*k*) and the Regional Coefficient (*s*)

In the next step, the time series of the RW and the climatic variables are analyzed, and afterwards the weighting function ($W_{k,j,i}$) is determined based on the climatic variables affecting the RW.

$$W_{k,j,i} = f\left(\left(\frac{x_{1,k,j,i}}{\sum_{i=1}^{m} x_{1,k,j,i}}\right)^{s_{1,k,j,i}}, \left(\frac{x_{2,k,j,i}}{\sum_{i=1}^{m} x_{2,k,j,i}}\right)^{s_{2,k,j,i}}, \ldots, \left(\frac{x_{n,k,j,i}}{\sum_{i=1}^{m} x_{n,k,j,i}}\right)^{s_{n,k,j,i}}\right) \quad (8)$$

In this equation, x_1, x_2, …, x_n are the climatic variables which have more effects on the amount of and change in RW, for *i*th *k*-day period of the water year of *j*, and the time scale of *k*; *m* is the maximum value of *i*, which is determined as $m = 360/k$; and s_1, s_2, …, s_n are regional coefficients which should be calibrated for each region. Based on the pre-mentioned reasoning, to determine the best relation between the climatic condition of any short time period of the year (e.g. $k = 5$, 10, 15, or 30 days) and the amount of produced RW during the pertaining period, the parameter *s* should be calibrated for each region. It should be reminded that Eq. (8) is assumed to be a power relation, with *s* being the power ($s > 0$) which can be representative of each given region.

It is worth noting that the effective climatic variables can be determined for each region through a forward or backward method to find which variable has a significant contribution to the RW. However, as mentioned earlier, the most effective variable for dry regions is precipitation and that for wet regions is precipitation as well as evaporation.

2.3.5 Developing the wDI

Thereafter, the wDI is developed based on the weighting function and the selected drought index as follows:

$$\mathrm{wDI}_{k,j} = \sum_{i=1}^{\mathrm{m}} \left(\mathrm{DI}_{k,j,i} \times W_{k,j,i}\right) \quad (9)$$

In which $\mathrm{wDI}_{k,j}$ is the drought index for the *j*th water year and the time scale of *k*.

2.3.6 wDI-RW Relationship

The relationship between wDI and the cRW was analyzed for different time scales *k* and different regional coefficients *s*. For each pair of *k* and *s*, the regression is developed. Then the equation with least error (e.g. least RMSE) with an appropriate amount of *k* and *s* can be applied to find the eRW_i in terms of $\mathrm{wDI}_{k,j}$ as follows:

$$\mathrm{eRW}_i = f(\mathrm{wDI}_{k,j}) \quad (10)$$

Otherwise, another time scale/ regional coefficient has to be chosen and the process should be iterated until the best time scale and regional coefficient are identified for estimating the RW.

3 Application of the wDI-RW Framework for the Neishaboor Watershed

Due to the high correlation of potential evaporation with drought conditions, it is suggested that the indices which include potential evaporation is preferred to be used for drought monitoring in arid and semi-arid regions of Iran (Yosefi et al. 2017). Accordingly, the RDI (Reconnaissance Drought Index), and SPEI (Standardized Precipitation Evapotranspiration Index) were suggested for this study. The RDI was the first index taking into consideration the potential evaporation (Tsakiris and Vangelis 2005; Tsakiris et al. 2007). The basic form of the RDI uses the ratio of the cumulative precipitation to potential evapotranspiration for a specified reference period. Its wide acceptance worldwide gave the opportunity to other scientists to propose similar indices such as SPEI. Furthermore, the RDI was later improved by other researchers (e.g., Tigkas et al. 2013, 2016, 2017; Vangelis et al. 2013).

The SPEI uses the difference between precipitation and potential evaporation (P-E_P), instead of considering precipitation (P) alone as suggested for SPI (Standardized Precipitation Index) (Vicente-Serrano et al. 2010). Taking (P-E_P) into account as the climatic water balance (Thornthwaite 1948), leads to a comparison between the available water (P) and the atmospheric evaporative demand (E_P), providing a more reliable measure of drought severity than considering the precipitation amount alone (Begueria et al. 2014). Among these two indices, SPEI was chosen as the most appropriate drought index for the Neishaboor watershed (Derakhshan 2017). For calculation of the SPEI at different time scales, a three-parameter probability distribution was needed (Vicente-Serrano et al. 2010). The results of Vicente-Serrano et al. (2010) showed that the Log-logistic distribution adapted very well to the series (P_i-E_{Pi}) compared to Pearson III, Log-normal, and General Extreme Value. Our results also indicated that the Log-logistic (Eq. 11) is the most appropriate distribution function for the study area.

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1}\left[1+\left(\frac{x-\gamma}{\alpha}\right)^{\beta}\right]^{-2} \tag{11}$$

In Eq. (11), α, β, and γ are scale, shape, and origin parameters, respectively.

Due to low data requirements, the Hargreaves-Samani method (Hargreaves and Samani 1982) was applied to estimate potential evaporation. Afterwards, the SPEI index was analyzed for four short time scales, including 5, 10, 15, and 30-day scales (i.e., $k=5$, $k=10$, $k=15$, and $k=30$).

RW was calculated from a simple daily quasi-distributed daily water balance model (QDWB) ran for 34 water years from 1982 to 2015 (Razavi et al. 2017). QDWB is a process-based hydrological model that has been developed to assess the parameters of water balance equation for semi-arid regions. This model simulates hydrologic processes at the basin scale and estimates soil water content in daily time steps. QDWB's concept for the soil profile is a three-layer column that consists of a thin evaporative layer, the root zone, and the vadose zone.

The term quasi-distributed is adopted due to the model's aspect for different parameters. While most of the variables are generated in a distributive matrix-wise perspective, few are limited to particular regions such as runoff that is not routed. By this approach, specific cells are allowed to generate runoff and coefficients related to geological characteristics are used to correct this parameter. For the rainfall-runoff process, it uses the SCS curve number method and after determining daily runoff, the amount of initial infiltration to the soil profile will be derived considering the water content left from the previous day for each layer. Excessive amount of moisture is reflected as percolation to deep layers by considering soil texture moisture limits. In terms of evaporation, the two-step FAO method is used where daily meteorological parameters are interpolated through the region to provide the required data.

As mentioned earlier, in dry regions where precipitation and evaporation are out of phase, the RW is mostly under influence of precipitation rather than evaporation. Thus, in this study, precipitation ($P_{k,j,i}$) was chosen as the most effective variable on the RW in order to determine the weighting function, which is as follows:

$$W_{k,j,i} = \left(\frac{P_{k,j,i}}{\sum_{i=1}^{m} P_{k,j,i}} \right)^{s_{k,j,i}} \tag{12}$$

Then, the weighted drought index for the Neishaboor watershed (according to the SPEI) was determined as follows:

$$\mathrm{wSPEI}_{k,j} = \sum_{i=1}^{\mathrm{m}} \left(\mathrm{SPEI}_{k,j,i} \times \left(\frac{P_{k,j,i}}{\sum_{i=1}^{m} P_{k,j,i}} \right)^{s_{k,j,i}} \right) \tag{13}$$

By considering $k=5$, $k=10$, $k=15$, and $k=30$ days, m will have the values of 72, 36, 24, and 12, respectively. The amount of s was also chosen by trial and error ($s>0$). In our study, s was chosen between 0.5 and 2. Among the time scales of k and regional coefficients of s, the scale and the coefficient with the highest correlation coefficient between wSPEI_{kj} and the RW were chosen as the best choice.

For the sake of validation of the above relationships, a cross-validation analysis (leave-one-out method) was performed. In order to achieve that, N separate times (N is the number of data points in the set, here $N = 34$), the regression relationship was trained and developed on all the data except for one point. Then a prediction was made for the left out point. This process was conducted for each set of k and s. Then the average error was computed and used to evaluate the regression.

4 Results and Discussion

This research was aimed to develop and apply a practical method to assess the renewable water by utilizing the universally available weather data (temperature and rainfall). The RW is normally obtained from water balance models which are cumbersome and time-consuming, costly, requiring plenty of detailed data, and yet faces many uncertainties. Besides, in the majority of the underdeveloped or developing countries, some of the required data either does not exist at all or are difficult or impossible to obtain.

The importance of this research relies on the fact that arid and semi-arid regions of the world mostly depend on groundwater as their main water resource. In addition, the applicability of this method is based on the fact that the occurrence of prolonged droughts due to climate change and the subsequent decline in rainfall has a direct impact on groundwater recharge and can seriously upset the balance between water supply and demand, severely increasing the susceptibility of such regions to destructive consequences.

In this paper, it is shown that the developed method is capable of estimating the RW by using the temperature and rainfall data series, which can be used for the past and present data series as well as future climate change scenarios. Hereafter, the results of applying the framework to the Neishaboor watershed are presented and discussed.

It is well known that there exists an exponential relationship between precipitation and renewability of water resources (i.e. deep percolation and runoff), meaning that at low rainfalls the majority of rain is intercepted and captured by soil surface as moisture which evaporates eventually. By increasing the amount of rainfall the storage capacity of the soil will be exceeded, providing more opportunity for deep percolation and runoff occurrence. Figure 3 shows the exponential relationship between annual wSPEI and the RW over four time scales for the Neishaboor watershed and the time period of 1982–2015. This figure shows that by increasing the annual wSPEI, the annual RW increases accordingly. Indeed, the SPEI index is a drought index which its increase is translated to a wet year (increased rainfall), which accordingly leads to more deep percolation and runoff.

As mentioned before two core concepts of this novel method includes: A) Choosing short period time scales for analyzing the drought indices; B) Recognizing the necessity of putting a weighting function into effect by which a standard drought index is converted to a weighted drought index (wDI), so that the probability of occurrence of precipitation is included. Considering the latter two concepts, the best relationship was found by trial and error to be $k=5$ days and $s=1.3$ ($R^2=0.73$, RMSE = 11.5 mm year^{-1}, Fig. 3a). This means that in the Neishaboor watershed, the RW would be largely controlled by 5-day aggregated precipitation volumes (or the absence thereof). RW can thus be expressed for the Neishaboor watershed as:

$$\mathrm{RW} = 2.8 * \mathrm{Exp}(1.9 * wSPEI_{k=5}) \tag{14}$$

According to the cross-validation results (Fig. 4), the framework performs fairly well for eRW, with $R^2=0.75$ and RMSE = 12.2 mm year^{-1} for $k=5$; which simply means an average error of about 17%.

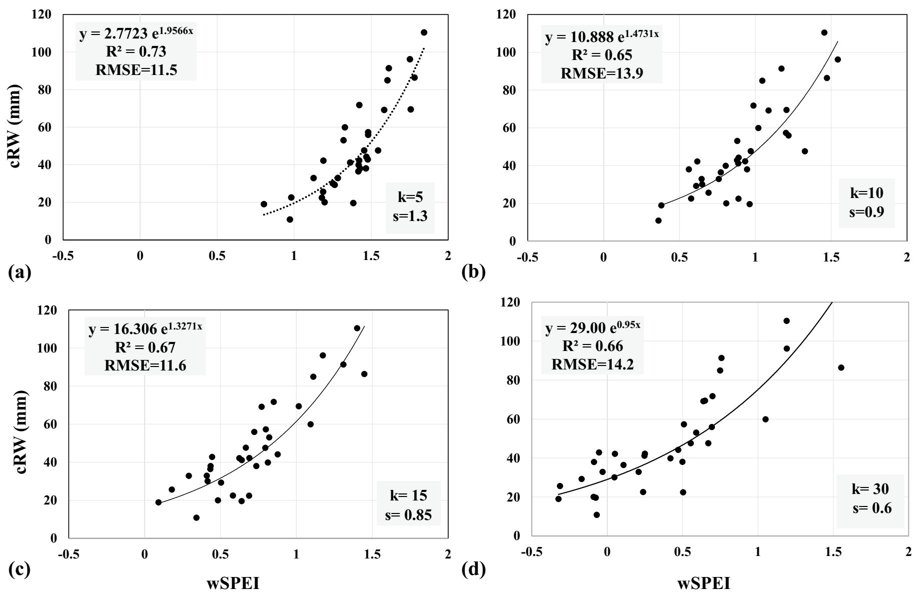

Fig. 3 The relationship between the RW and the wSPEI for four time scales of **a**) $k=5$, **b**) $k=10$, **c**) $k=15$, and **d**) $k=30$ days. The dots are cRW and the regression lines represent eRW

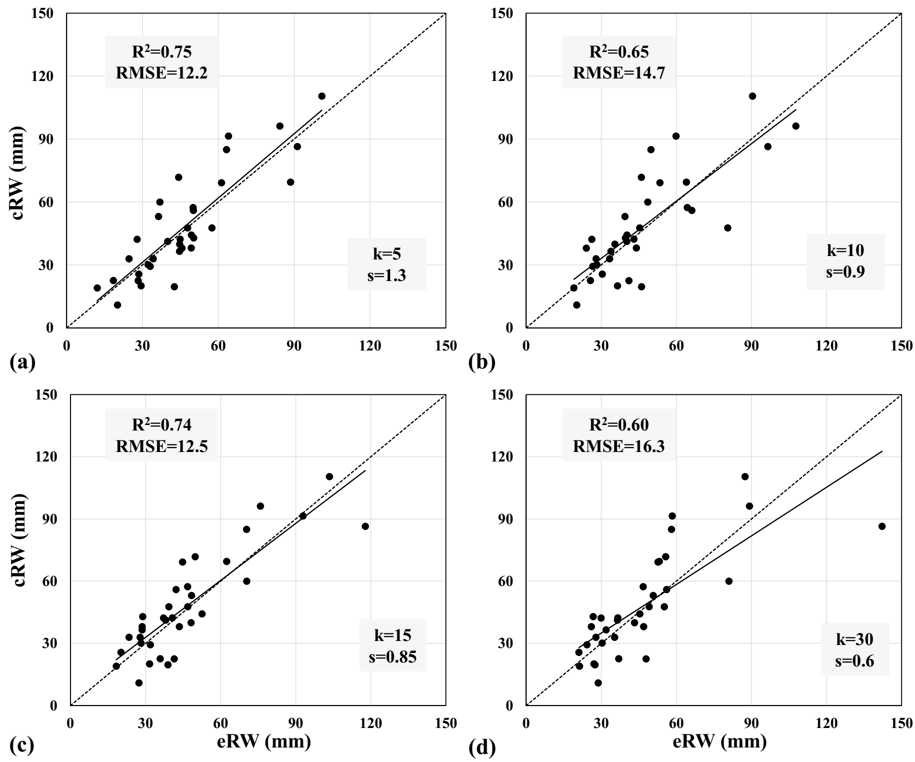

Fig. 4 The correlation between the cRW and the eRW for different time scales: **a**) $k=5$, **b**) $k=10$, **c**) $k=15$, and **d**) $k=30$ days

Figure 5 shows the wSPEI for the period of 34 years. In addition, it shows the annual RW obtained from both cRW and the eRW (wDI-RW framework). This figure demonstrates that

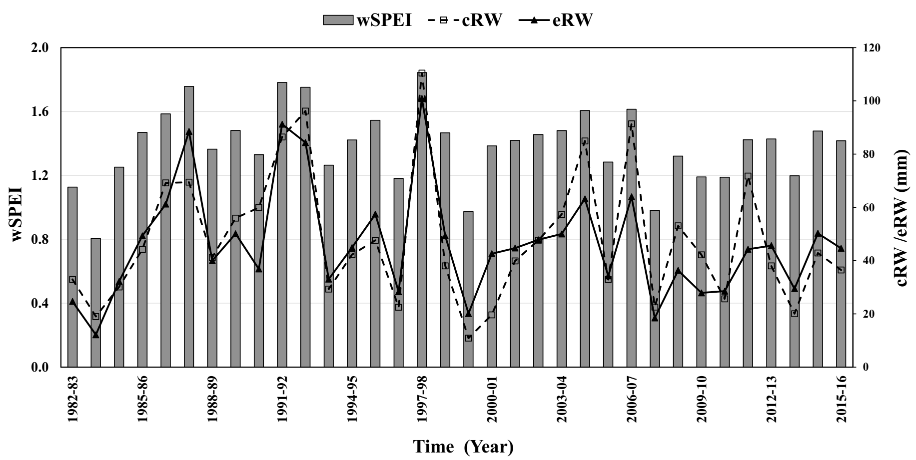

Fig. 5 Overall agreement of the wSPEI, the cRW and eRW

the annual RW follows closely the wSPEI, indicating that a reasonable correlation exists between the two.

5 Conclusions

In this study, a simple framework was introduced to estimate the aquifer's renewable water in order to mitigate the challenges of megadrought events by managing the groundwater resources. The proposed framework which estimates the RW in terms of hydrological drought indices is easy to use and requires less detailed data, being available almost universally. The proposed framework was then applied to the Neishaboor watershed located in the northeastern part of Iran, as it is one of the regions currently facing groundwater overexploitation, water scarcity, and continuous increasing demand for water. The results showed that a hydrological drought index for the time scale of $k=5$ days and the regional coefficient of $s=1.3$ can estimate the RW with reasonable accuracy ($R^2=0.73$, RMSE = 11.5 mm year^{-1}). This indicates that in the Neishaboor watershed, the best estimation of RW can be determined by precipitation volumes (or the lack thereof) falling over 5-day aggregation periods rather than by any other time scale. The estimated RW was then compared to the RW derived from other pertinent water balance calculations. According to the results, the proposed framework performed fairly well for the estimation of RW, with $R^2=0.75$ and RMSE = 12.2 mm year^{-1}. The Overall agreement between the wSPEI, cRW, and eRW indicated a reasonable relationship between wSPEI and the annual RW.

This framework is capable to estimate the RW of a given watershed for different climate change scenarios. This can help the groundwater resources' managers and policymakers to estimate the crucial strategic groundwater reserves, and then prepare and apply appropriate strategies for mitigating the challenges of probable megadrought events in the future through effective groundwater management. For further expansion and qualification of this idea, we suggest that this method be conducted for various regions of the world with diverse climatic conditions having more available and extended hydrometeorological data.

Author Contribution The novel idea was initially developed and proposed by K. Davary and was performed in part as a MSc thesis by H. Derakhshan in which K. Davary and S. M. Hasheminia were major professors. The idea was further expanded and completed by K. Davary, and afterwards, A. Mianabadi prepared the first version of the manuscript with considerable contribution from H. Derakhshan. The manuscript was further revised and completed by S. M. Hasheminia and M. Hrachowitz.

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Data Availability All data were made available by the Regional Water Company of Khorasan Razavi and the authors have restrictions on sharing them publicly.

Code Availability The codes are available from the corresponding author by request.

Declarations

Ethics Approval Not applicable.

Consent to Participate Not applicable.

Consent to Publish Not applicable.

Conflicts of Interest The authors declare no conflicts of interest.

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