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Development and Assessment of a Hybrid Index for Groundwater Drought, Case Study: Zayandehrood River Basin, Iran

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Abstract

Drought is one of the most complex and damaging natural hazards, particularly in arid and semi-arid regions where increasing dependence on groundwater has intensified pressure on already vulnerable water resources. Groundwater drought develops differently from meteorological and surface-water drought and may persist for longer periods due to the delayed response of groundwater systems to climatic variability. Therefore, comprehensive assessment of groundwater drought requires consideration of multiple hydrogeological, climatic, environmental, and anthropogenic factors. This study develops a Hybrid Groundwater Drought Index for the spatial and temporal assessment of groundwater drought vulnerability in the Zayandehrood River Basin, central Iran. A 21-year dataset covering the period 2000–2020 was analyzed using a Geographic Information System. The proposed index integrates ten static and dynamic indicators, including land use, surface, saturated and unsaturated soil layers, hydraulic conductivity, groundwater level, precipitation penetration, electrical conductivity, saturated-layer thickness, and reservoir releases. Each indicator was classified according to its vulnerability to groundwater drought and assigned a rating from 0 to 10. Greater weights were assigned to precipitation penetration and saturated-layer thickness because of their critical roles in groundwater recharge and storage. The resulting spatial layers were integrated in GIS to produce annual groundwater drought maps and define drought triggers. Results indicated that the Zayandehrood River Basin experienced 15 dry years, 2 normal years, and 4 wet years during the study period. The year 2000 was identified as the wettest year, whereas 2020 represented one of the most severe drought conditions, with very extreme drought occurring in the eastern and western parts of the basin and extreme drought in the central and southern areas. Comparison with the Groundwater Resource Index demonstrated that HGDI provides a more comprehensive representation of drought severity and spatial variability because it incorporates multiple groundwater-related and external controlling factors rather than relying primarily on groundwater storage changes. The proposed HGDI can therefore serve as an effective tool for groundwater drought monitoring, early warning, vulnerability assessment, and sustainable groundwater management in drought-prone regions.

Keywords:
Groundwater Drought, Hybrid Index, Static Indicators, Dynamic Indicators, Zayandehrood Basin.

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1. Introduction

In recent decades, natural hazards have posed serious threats to human societies, ecosystems, and economic activities in many regions of the world. Among these hazards, drought is one of the most complex and damaging phenomena, particularly in arid and semi-arid regions and developing countries. Unlike many other natural hazards, drought develops gradually over time, may persist for extended periods, and can affect large spatial areas. Despite its widespread occurrence and significant impacts, there is no universally accepted definition of drought. Its definition varies depending on the geographical region, climatic conditions, sector of interest, and the perspective of the user (Wilhite and Glantz, 1985).

In general, drought can be described as a prolonged period of below-normal water availability resulting from insufficient precipitation and/or an imbalance between water supply and demand. Such conditions can generate considerable stress on soil moisture, water quality, surface-water systems, groundwater resources, and water-dependent economic sectors (Valivand and Katibeh, 2022).

The consequences of prolonged or recurrent severe droughts can be particularly destructive in arid and semi-arid environments. Persistent drought may reduce water availability, threaten food security, adversely affect agricultural production, and increase pressure on available water resources. In severe and prolonged cases, the degradation of productive lands may contribute to desertification and the transformation of fertile areas into less productive or desert-like environments (Mishra and Singh, 2010). Because drought propagates through different components of the hydrological cycle, its impacts are not limited to a single environmental or socioeconomic sector. The American Meteorological Society[1] (AMS, 1997) classified drought into four major categories: meteorological, agricultural, hydrological, and socioeconomic drought. Meteorological drought is generally associated with a deficiency in precipitation, while agricultural drought is related to inadequate soil moisture for crop development. Hydrological drought is reflected in reduced surface-water and groundwater availability, whereas socioeconomic drought occurs when water shortages begin to affect the supply of goods and services and human activities.

In addition to these conventional categories, groundwater drought[2] has increasingly been recognized as an important and distinct dimension of drought. Mishra and Singh (2010) emphasized that groundwater drought should be considered as an independent type of drought rather than merely a subcategory of the conventional drought classes. Groundwater is one of the most important components of the hydrological system and plays a particularly critical role in arid and semi-arid regions, where it frequently serves as a reliable source of water for domestic and productive purposes, including agriculture, livestock production, mining, and other economic activities. Because groundwater storage can buffer short-term fluctuations in precipitation and surface-water availability, groundwater is often considered a drought-resilient water source. Nevertheless, groundwater itself is vulnerable to prolonged drought, especially when natural recharge is reduced and groundwater abstraction increases in response to water shortages.

The relationship between drought and groundwater is complex and potentially reciprocal. On the one hand, prolonged meteorological and hydrological droughts can reduce groundwater recharge and consequently lead to declining groundwater levels and storage. On the other hand, excessive groundwater abstraction during drought periods can intensify groundwater depletion and prolong the hydrological consequences of drought.

Consequently, groundwater drought may develop more slowly than meteorological drought but can persist for a substantially longer period. The quantification of groundwater drought is therefore challenging because groundwater systems are characterized by complex processes of recharge, storage, flow, and interaction with surface-water systems. Eltahir and Yeh (1999) noted that groundwater drought is commonly identified through reductions in groundwater levels, although such reductions may not directly represent changes in groundwater storage or recharge. The term groundwater drought was first introduced by Rutulis (1989), and subsequent studies have highlighted the importance of understanding its characteristics and impacts. Kumar (2012), for example, provided a comprehensive review of the effects of climate change on groundwater resources, while Mall et al. (2006) emphasized the need for further research into the effects of drought on groundwater systems.

Effective drought management requires not only an understanding of drought impacts but also appropriate systems for drought monitoring, early warning, and response. A drought management plan should establish how drought conditions are identified and how appropriate responses are triggered as drought severity increases. The effectiveness of such a plan depends largely on two fundamental components: indicators and triggers. Drought indicators are variables used to characterize, monitor, and assess drought conditions and may be based on meteorological, hydrological, agricultural, or water-supply and demand-related information. Common indicators include precipitation, streamflow, soil moisture, snowpack, groundwater levels, and reservoir storage. Triggers, in contrast, are

[1] American Meteorological Society (AMS)

[2] Groundwater Drought (GWD)

predefined threshold values of drought indicators that signal the onset or intensification of drought and initiate specific management responses. Therefore, indicators and triggers provide the essential link between the identification of drought conditions and the implementation of appropriate mitigation and response measures (Steinemann and Cavalcanti, 2006).

Despite the important role of groundwater in drought mitigation, groundwater development and management have often received inadequate attention from the perspective of drought resilience. In many cases, groundwater drought management has relied primarily on ad hoc emergency measures, such as deepening existing wells or developing new wells in response to declining water availability (Calow et al., 1997, 2010). Moreover, conventional drought monitoring and early-warning systems have generally focused on meteorological, agricultural, and surface-water conditions and have not fully accounted for the drought-mitigating capacity of groundwater resources (Mendicino et al., 2008). This limitation is particularly important in regions where groundwater is the principal source of water supply and where increasing abstraction during drought can result in long-term depletion of groundwater resources. Consequently, incorporating groundwater conditions into drought monitoring and management frameworks is essential for developing more comprehensive and sustainable drought-risk management strategies.

A variety of drought indices have been developed to characterize, monitor, and forecast drought conditions. These indices generally focus on one or more components of the hydrological cycle and are commonly classified according to the type of drought they represent. Tsakiris et al. (2007a) noted that drought indices are among the most widely used approaches for drought characterization. To overcome the limitations of single-variable or single-sector indices, several hybrid and composite drought indices have subsequently been developed. Examples include the hybrid approaches proposed by Tsakiris et al. (2007b), Smith and Maidment (2008), and Karamouz et al. (2009). Pandey et al. (2010, 2012) developed drought vulnerability index (DVI) methodologies for spatial assessment of drought vulnerability. Safavi et al. (2017) proposed the Hybrid Drought Index[1], a nonparametric composite indicator designed to monitor multiple components of the hydrological cycle. These developments demonstrate a gradual shift from single-dimensional drought assessment toward integrated approaches capable of representing the complex nature of drought.

Several approaches have also been specifically developed for groundwater drought assessment. Mendicino et al. (2008) proposed the Groundwater Resource Index[2] for groundwater drought monitoring and forecasting based on a simple water-balance model. Hassan et al. (2003) and Lowry et al. (1995) introduced the Groundwater Drought Risk Mapping and Management System[3], which evaluates groundwater drought risk using relative indicators and composite spatial analysis within a Geographic Information System[4] framework. Villholth et al. (2013) subsequently applied GRiMMS for integrated groundwater drought-risk mapping in the Southern African Development Community[5] region. These studies demonstrated the potential of GIS-based approaches for identifying spatial variations in groundwater drought risk and supporting groundwater management.

Other researchers have proposed indices based directly on groundwater observations and model-based estimates. Li and Rodell (2014) developed a Groundwater Index[6] using the Catchment Land Surface Model[7] together with in situ groundwater observations. Their results showed strong regional agreement between the CLSM-based and observation-based groundwater indices. Both groundwater indices also exhibited stronger relationships with the Standardized Precipitation Index[8] at 12- and 24-month timescales, indicating the importance of considering longer temporal scales when investigating groundwater drought. Similarly, Babre et al. (2022) introduced the Standardized Groundwater Level Index[9] for assessing groundwater drought episodes in the Baltic States. More recently, Zavareh et al. (2023) developed the Groundwater Quantity-Quality-based Drought Index[10], which integrates groundwater quantity and quality indicators using multivariate copula analysis. Such approaches emphasize that groundwater drought cannot always be adequately represented by groundwater-level variations alone and that multiple characteristics of groundwater systems may need to be considered.

In parallel with groundwater-specific indices, significant progress has been made in the development of drought indices for different applications and temporal and spatial scales. Tsakiris et al. (2007a) reviewed the application of drought indices for drought characterization, while Zargar et al. (2011) provided a comprehensive review of drought indices covering meteorological, agricultural, and hydrological drought.

[1] Hybrid Drought Index (HDI)

[2] Groundwater Resource Index (GRI)

[3] Groundwater Drought Risk Mapping and Management System (GRiMMS)

[4] Geographic Information System (GIS)

[5] Southern African Development Community (SADC)

[6] Groundwater Index (GWI)

[7] Catchment Land Surface Model (CLSM)

[8] Standardized Precipitation Index (SPI)

[9] Standardized Groundwater Level Index (SGI)

[10] Groundwater Quantity-Quality-based Drought Index (GQQI)

Safavi et al. (2014) developed a GIS-based methodology for identifying areas susceptible to drought in both spatial and temporal dimensions. Tigkas et al. (2015) developed a software tool for drought analysis based on drought indices, particularly the Reconnaissance Drought Index[1]. Subsequently, Tigkas et al. (2016) introduced a modified Reconnaissance Drought Index incorporating effective precipitation for agricultural drought assessment, followed by an enhanced effective Reconnaissance Drought Index for improved characterization of agricultural drought (Tigkas et al., 2017).

Recent developments have further expanded the use of advanced statistical and machine-learning techniques for groundwater drought assessment. Kashani and Safavi (2025) investigated the application of machine-learning methods for downscaling and forecasting groundwater storage anomalies[2] in order to derive a GRACE Groundwater Drought Index[3] and examine the relationship between teleconnection indices and groundwater drought in Iranian basins. More recently, Popat et al. (2026) introduced the Groundwater Level Deficit Anomaly Index[4], which combines the anomaly and deficit characteristics of groundwater levels. In this index, the deficit component is quantified as the relative difference between the required groundwater level, representing potential monthly groundwater demand, and the observed monthly groundwater level, representing groundwater supply.

Overall, the evolution of drought assessment methodologies demonstrates a transition from conventional single-variable indices toward integrated, composite, and groundwater-specific indicators. Nevertheless, important challenges remain in accurately identifying groundwater drought, particularly because groundwater systems respond to climatic forcing with considerable temporal lags and are strongly influenced by geological, hydrological, and anthropogenic factors. Furthermore, the increasing dependence on groundwater during drought may provide short-term resilience while simultaneously increasing long-term groundwater depletion. Therefore, an effective groundwater drought assessment framework should consider not only groundwater-level anomalies but also the temporal persistence, severity, water demand, recharge conditions, and interactions between groundwater and other components of the hydrological cycle.

Given the increasing importance of groundwater in drought-prone regions, the development of reliable groundwater drought indicators and appropriate drought thresholds is essential for improving monitoring, early warning, and management. In this context, integrating groundwater-related indicators with suitable drought triggers can provide a more effective basis for identifying the onset, evolution, and severity of groundwater drought and for supporting timely management responses. Such an integrated approach can contribute to reducing the vulnerability of groundwater-dependent communities and ecosystems and can provide a scientific basis for sustainable groundwater management under increasing climatic and water-resource pressures.

Despite considerable advances in drought monitoring and the development of numerous meteorological, hydrological, agricultural, socioeconomic, and groundwater drought indices, important limitations remain. Conventional drought monitoring frameworks often treat drought categories independently and provide limited representation of groundwater, despite its critical role in buffering drought impacts in arid and semi-arid regions. Existing groundwater drought indices, generally focus on individual aspects of groundwater conditions, such as groundwater-level anomalies, storage, quantity, quality, or supply–demand deficits, and therefore may not adequately capture the interactions between groundwater drought and other components of the hydrological cycle. Although several hybrid drought indices have been proposed to integrate multiple drought dimensions, the explicit incorporation of groundwater conditions into a comprehensive drought assessment framework remains limited. This limitation is particularly significant in the Zayandehrood River Basin, where recurrent drought, declining surface-water availability, and increasing dependence on groundwater have intensified pressure on groundwater resources. Consequently, there is a need for an integrated drought assessment approach that considers the interconnected meteorological, hydrological, agricultural, socioeconomic, environmental, and groundwater dimensions of drought and provides a more comprehensive basis for drought monitoring and management in the basin.

This study proposes a hybrid index considering main factors of drought and applied to the Zayandehrood river basin in the central Iran plateau as a case study. A hybrid index consists of several indicators like meteorological, hydrological, agricultural, socio-economic and environmental drought. In recent years, declining surface water resources have led to increasing groundwater use in the study area, resulting in a substantial reduction in groundwater resources. As in many other regions of Iran, various drought indices have been developed over the years for drought monitoring and forecasting; However, only a limited number of these indices specifically address the groundwater resources for this basin.

[1] Reconnaissance Drought Index (RDI)
[2] Groundwater Storage Anomalies (GWSA)
[3] Groundwater Drought Index (GGDI)
[4] Groundwater Level Deficit Anomaly Index (GLDAI)

In this paper, a hybrid groundwater drought index[1] is presented as a reliable and useful tool in a multi-analysis approach for monitoring drought conditions. The long-term climate data (2000-2020) is used for assessment. In designing the proposed hybrid index, we have used a combination of static and dynamic layers of information. Static layers include indicators that do not change in a short study period, such as three types of soil (surface, saturated and unsaturated), hydraulic conductivity and land use. Dynamic layers are considering indicators with time-variable data such as penetration of precipitation, groundwater levels, thickness of saturated layer, released water from upstream dams, and electrical conductivity[2]. All static and dynamic layers which represent spatial maps of different factors, were prepared and compiled via (Arc-GIS). Each factor has been grouped into several sub-groups to determine their rate of vulnerability to drought. They were then used as the inputs of our proposed weighing scheme.

2. Study area

The Zayandehrood River basin has an area of 26,900 Km^2 with the district of Isfahan contributing to more than 90% of it; the district of Chaharmahal-va-Bakhtiari completes the remaining area (Fig. 1). The four-digit numbers in Fig. 1 indicate, from the left, the number of the watershed, sub-basin, third-degree sub-basin, and finally the study area. Zayandehrood is the longest river basin in central Iran plateau with an annual average natural flow of about 900 MCM, average rainfall of 130 mm and a monthly average temperature of 3 °C to 29 °C. The Zagros Mountains with an altitude of 3,974 m, are the headstream of this river. It flows 350 km to the Gavkhuni wetland with an altitude of 1,466 m. According to the 1975 Convention on Wetlands (Ramsar), the Gavkhuni is one of the most important wetlands in Iran. The basin comprises 2,700 Km^2 of irrigated land, with water derived from the deep and shallow wells, qanat, and springs in lateral valleys.

In recent decades, precipitation reduction was significantly observable in the Zayandehrood basin. Due to limited surface water resources, groundwater use has increased in the study area, leading to a severe reduction in groundwater resources. Existing signs of drawdown in wells and phreatic declines in all sub-basins have proved this reduction, too. Nevertheless, the increasing number of deep wells and the intensification of groundwater extraction will exacerbate groundwater drought in the coming years. Isfahan Regional Water Company and Chaharmahal-va-Bakhtiari Water Company in Iran national statistics records in 1990 recorded the total number of annual groundwater exploitations as 15155 deep and shallow wells (estimated 1138 MCM withdrawal) in the Zayandehrood river basin; In 2000 this record increased to 1699 MCM (22326 wells). In 2020, this number increased to 3952 MCM with 49523 deep and shallow wells. The reduction in groundwater resources caused from the mentioned exploitations clearly indicates their extreme vulnerability and the need for this crisis to be managed (Isfahan Regional Water Company, 2020).

Therefore, this study proposes a HGDI as a reliable and efficient tool in a multi-analysis approach for monitoring drought conditions. The long-term climate data (2000-2020) are used for further assessments.

3. Methodology

3.1. Recognition of groundwater drought vulnerability indicators

A groundwater indicator, static or dynamic, describes a specific aspect of a groundwater system and processes that based on aggregation of selected variables. Static indicators do not change with time. Nonetheless, they vary in local scales and dynamic indicators can change in both time and space domains. Indicators can be combined into index, which provides condensed and intended information for groundwater planning, policy-making and management. An index is a dimensionless quantity and is constructed by various weightings and rating systems. The HGDI is defined to clarify some unclear features of drought indices. This proposed index (HGDI) is based on measurable and observable data and it provides information about groundwater quantity and quality.

The static indicators engaged in HGDI do not actually contain any drought information. They are the background geographic indicators corresponding to the whole system; but they are used to provide a platform to clarify drought factors. The static indicators include: three types of soil (surface, saturated and unsaturated), hydraulic conductivity and land use. Dynamic indicators include: penetration of precipitation, groundwater levels, thickness of saturated layer, released water from upstream dam, and electrical conductivity. Fig. 2 presents the schematic diagram showing the indicators category included in this study.

The proposed HGDI in this study produces ten layers of data based on each of the corresponding indicators. Therefore, using these layers spatial maps, a composite mapping analysis technique in a traditional GIS environment (ArcGIS) produces the pertaining GIS-ready maps. Hence, using GIS results in the accurate evaluation of groundwater drought vulnerability in the aquifers of Zayandehrood river basin presented in the spatial merging of the mentioned indicators.

[1] Hybrid Groundwater Drought Index (HGDI)

[2] Electrical Conductivity (EC)

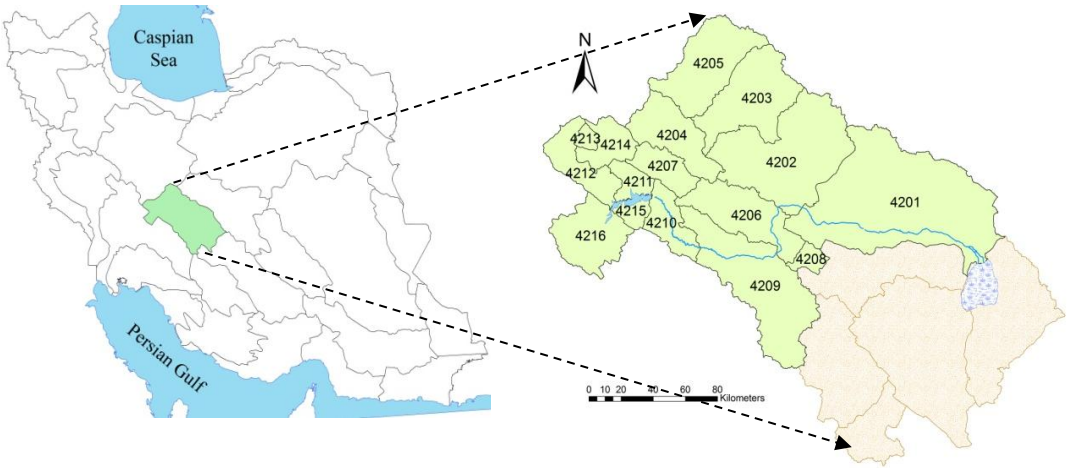

Fig. 1. Location of the Zayandehrood River Basin in Iran

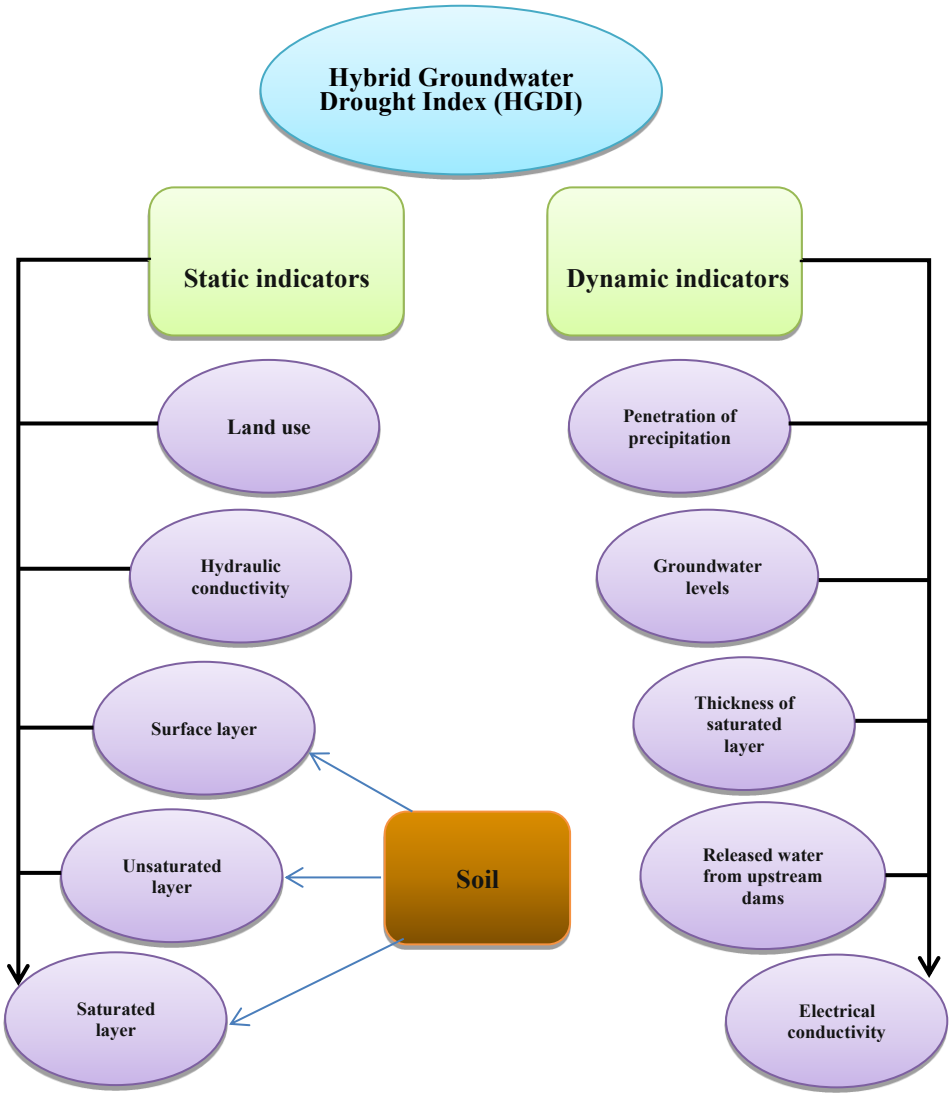

Fig. 2. Indicators category schematic diagram, used in HGDI

In the present study, the result of 21 years of observation, from 2000 to 2020, by Isfahan Regional Water Company and Chaharmahal-va-Bakhtiari Water Company in Iran was used.

To develop the HGDI and generate hybrid groundwater drought maps for the aquifers in the study area, different layers (static and dynamic) representing various parameters were arranged via GIS software. These layers were classified as static or dynamic according to their variability. Static layers represent hydraulic conductivity, soil in three layers (surface, saturated and unsaturated) and land use. Thedynamic layers represent penetration of precipitation, groundwater levels, thickness of saturated layer, released water from upstream dam, and electrical conductivity. All these layers were processed and integrated by GIS software.

The DRASTIC method that was established by the United States Environmental Protection Agency[1] and American Water Works Association[2] is one of the most applicable methods for evaluating the vulnerability of aquifers (Saidi et al., 2010 and Qian et al., 2012). This method is defined as an approach considers all the major geologic and hydrologic factors simultaneously that affects and control the groundwater movement flowing into, through, and out of an area". The acronym DRASTIC is derived from the initials of seven parameters used in the model, namely, Depth to water, net Recharge, Aquifer media, Soil media, Topography, Impact of vadose zone, and hydraulic Conductivity (Babiker et al., 2005).

An inverse rating method to DRASTIC model was used for weighting some hydrogeological parameter values like soil layers and hydraulic conductivity. As in the DRASTIC method, more soil permeability results in more water contaminating possibility, whereas in its inverse rating version, more groundwater recharges from precipitation penetration can be derived from higher soil permeability. This can lead to less vulnerability against drought.

Altogether, in this study the rating value of 1 indicates that the given factor belongs to the subclass of "least vulnerable to groundwater drought". Same way in this assessment, the rating value of 10 indicates that the factor belongs to "highly vulnerable to groundwater drought" subclass. The rating tables specified for each static and dynamic layer are assigned to various ranges.

4. Spatial representations of physiographic indicators

4.1. Hydraulic conductivity

The ability of the aquifer to convey water is called hydraulic conductivity. This parameter indicates water conveyance by the aquifer features, generally their porosity. In order to prepare the hydraulic conductivity layer of the Zayandehrood plain, the pumping tests data of 185 exploration wells prepared by Esfahan Regional Water Organization were used. This layer was divided into different thicknesses of saturated zones, and then points were extracted from this layer and shifted to ArcGIS. According to inverse DRASTIC model, a rating was done in MATLAB, then the data was transferred to ArcGIS by an interpolation and the final hydraulic conductivity layer was produced (Rezaei et al., 2013). The hydraulic conductivity ratings and ranges are illustrated in Table 1.

This layer is shown in Fig. 3 and indicates that, hydraulic conductivity decreased in a west to east direction in the study area as witnessed by ratings of 8 to 10 in the eastern sub-basins and ratings lower than 6 in the west.

Table 1. Hydraulic conductivity ratings and ranges according to inverse DRASTIC model

Rating	Range (m/day)
10	0.4-4
8	4.1-12
6	12.1-28
4	28.1-40
2	40.1-80
1	>80

4.2. Saturated layer

Boundaries of a saturated zone are called a saturated layer. A saturated layer with coarse grains and high porosity can transmit more precipitation penetrations to aquifer.

In this study, 294 well logs were used and the category of each soil layer was determined based on the information presented in Table 2. This table is prepared according to the mentioned inverse DRASTIC rating method. The harmonic mean used was as follows:

$$I_r = \frac{T}{\sum_{i=1}^{n} \frac{T_i}{I_{r_i}}} \quad (1)$$

Where,

I_r is the harmonic mean of the ratings of saturated layer, T_i is the thickness of the layer i, and I_{r_i} is the rating of the layer I (Umar et al., 2009).

The equivalent rating of the saturated layer at every point was obtained in ArcGIS. In this layer, the lowest ratings belong to the northern and western areas of the Zayandehrood river basin consisting of river alluvia. The highest ratings are seen in the east and certain parts in the center of the basin whose saturated zone is made up of fine soils such as clay.

[1] United States Environmental Protection Agency (USEPA)

[2] American Water Works Association (AWWA)

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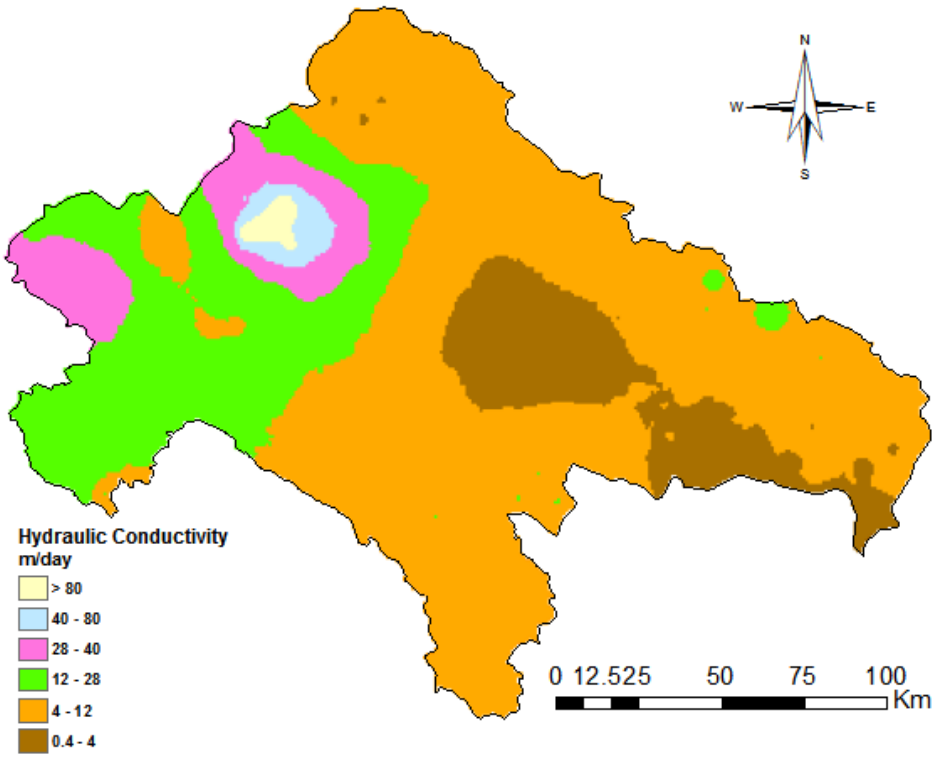

Fig. 3. Hydraulic conductivity categories in the Zayandehrood River basin

Table 2. Soil rating layers according to invers DRASTIC model

Surface layer		Saturated layer		Unsaturated layer	
Range	**Rating**	**Range**	**Rating**	**Range**	**Rating**
Thin or absent	1	Karst limestone	2	Karst limestone	1
Gravel	1	Basalt	2	Basalt	2
Sand	2	Sand and gravel	3	Sand and gravel	3
Peat	3	Massive limestone	3	Metamorphic/igneous	7
Shrinking and/or aggregated clay	4	Massive sandstone	5	Sand and gravel with significant silt and clay	5
Sandy loam	5	Bedded sandstone, limestone and shale sequence	5	Bedded limestone, sandstone and shale	5
Loam	6	Glacial till	6	Sandstone	5
Silty loam	7	Weathered metamorphic/igneous	7	Limestone	5
Clay loam	8	Metamorphic/igneous	8	Shale	8
Muck	9	Massive shale	9	Silt/Clay	8
Non-shrinking and non-aggregated clay	10			Confining layer	10

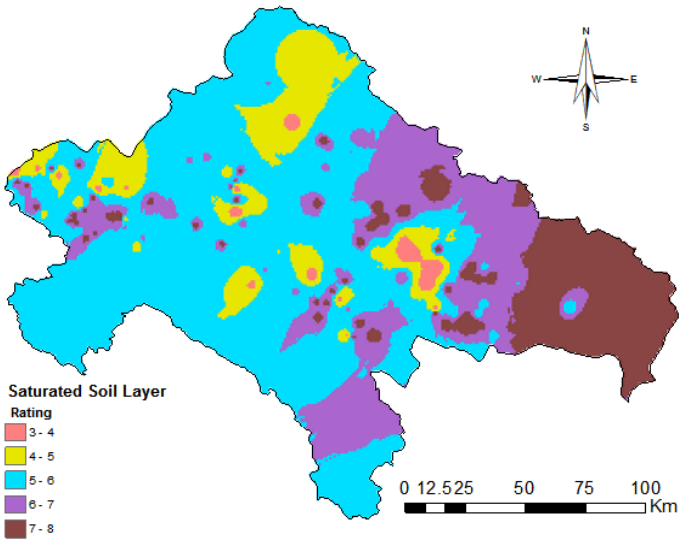

Fig. 4. Saturated soil layer in the Zayandehrood River basin

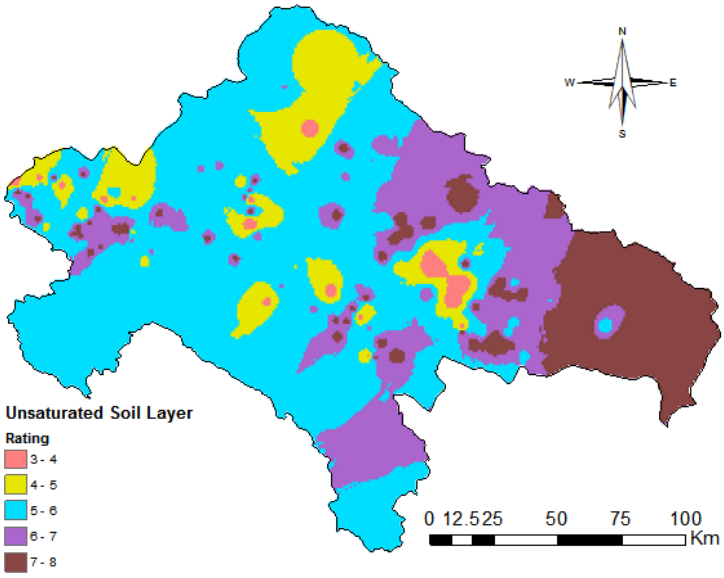

Fig. 5. Unsaturated soil layer in the Zayandehrood River basin

This layer is similar to aquifer media in DRASTIC model. Rating method for this layer is similar to hydraulic conductivity according to inverse of rating method in DRASTIC model. This layer was rated according to Table 2 and the saturated soil layer is shown in Fig. 4.

4.3. Unsaturated layer

This parameter refers to the distance between the bottom of the surface layer (topsoil) and the groundwater level. Data for this layer was achieved by using well logs mentioned in the previous sections. The harmonic mean equation was used to prepare data in this layer like saturated layer. The highest ratings in this layer were found in regions consisting of silt and clay in the eastern parts of the Zayandehrood river basin and the lowest ratings were observed in the northern and northwestern parts of this area consisting of sand, gravel and basalt.

This layer is similar to impact of vadose zone in DRASTIC model. Rating method for this layer is similar to hydraulic conductivity according to inverse of rating method in DRASTIC model. Finally, this layer was rated according to Table 2 and the unsaturated soil layer in the basin is shown in Fig. 5.

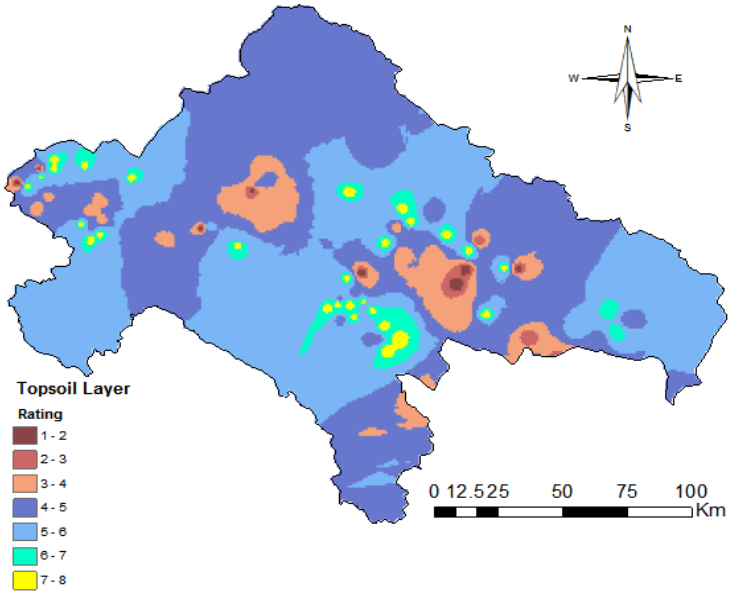

Fig. 6. Topsoil layer in the Zayandehrood River basin

4.4. Surface layer

Surface layer or topsoil exhibits external parts of lithosphere of the earth, known as upper weathered zone. This layer includes a mean depth of about 2 meters or less. To rate this layer, data was collected from previously available geological information based on 294 drilled well logs and then merged with ArcGIS. The surface layer with the appearance of sandy loam and shrinking or aggregated clay (rating between 4 and 5) represented the predominant type of topsoil in this region.

This layer is similar to soil media in DRASTIC model. Rating method for this layer is similar to hydraulic conductivity according to inverse of rating method in DRASTIC model, but unlike the aforementioned method, the higher soil permeability makes it suitable for this research (Aller et al., 1987). Finally, this layer was rated according to Table 2 and the surface layer of soil or topsoil layer in the basin is shown in Fig. 6.

4.5. Land use

The land use is considered as a static layer. Different land use in the basin of the Zayandehrood River can be categorized as: urban and industrial zones, orchards and forests, dry farming lands, agricultural lands, ranges, wetlands, deserts and salt lands, mountainous and rocky terrains, rivers, and reservoirs. Based on the fact that inhabitation regions, agricultural and orchard lands demand for water is more than other categories of land use and the majority of their needs are provided from groundwater, these regions are more vulnerable to groundwater drought. Conversely, other land use categories, like desert and salty lands, mountainous and rocky terrains with low rates of industrial and rural activities are less prone to drought, so lower rates are assigned to them. Rating of this layer in the range of 2 to 10 is based on each subclass area illustrated in Table 3. This layer was introduced in ArcGIS by considering both the rate and the area of all subclasses. The land use layer and its subclasses in the Zayandehrood River basin are shown in Fig. 7.

Table 3. Land use ratings and subclasses layers

Rating	Subclasses
2	Rivers and reservoirs
3	Mountainous and rocky terrains
4	Desert and salt lands
5	Wetlands
6	Ranges
7	Agricultural lands
8	Dry farming lands
9	Orchards and forests
10	Urban and industrial lands

4.6. Groundwater level

The groundwater level is one of the dynamic layers for assessing the drought hazard. This parameter refers to the distance between the land surface and the groundwater table. In this study, annual groundwater level was obtained from monthly depth of groundwater table data at observation wells for a period of 21 years (2000–2020). For preparing groundwater layer, the well level elevation and the water level mean elevation for each observation well were fed into ArcGIS and both elevations were separately interpolated. For instance,

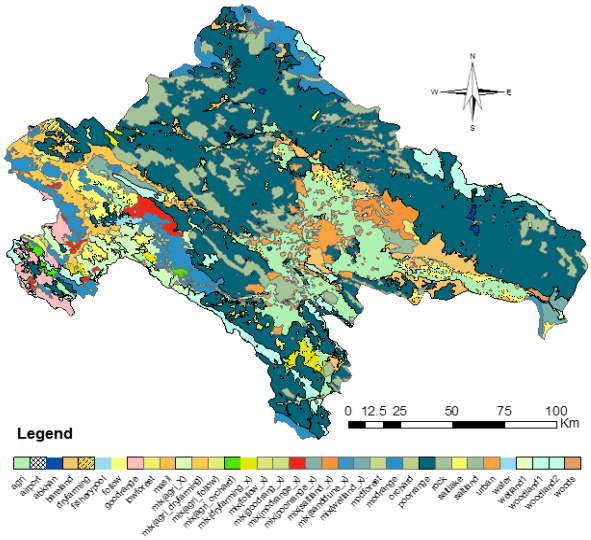

Fig. 7. Land use in the Zayandehrood River basin

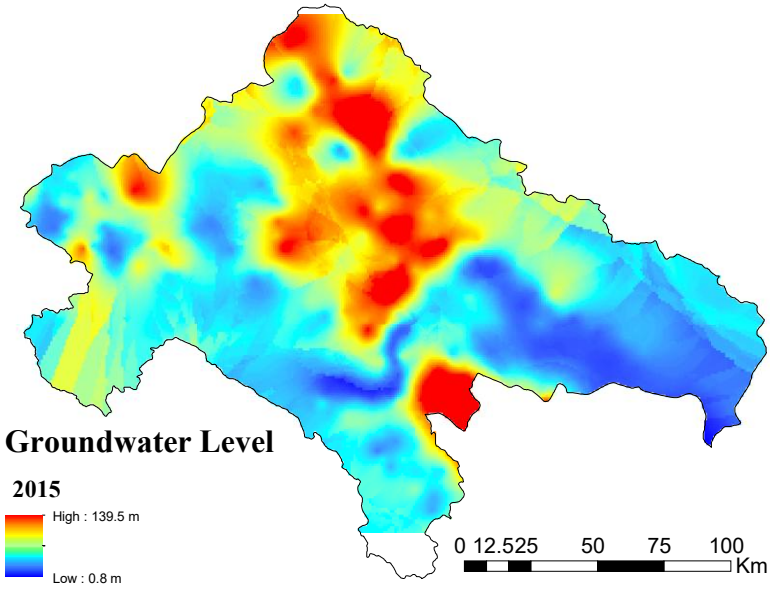

Fig. 8. Groundwater level map for 2015 in the Zayandehrood River basin

groundwater level map just for 2015 is shown in Fig. 8. As groundwater level elevation drop increases, more vulnerability to drought is observed. Rating of this indicator was done based on the percentage of groundwater level deviation from long term average over a period of 21 years. A higher positive percentage of groundwater table deviation indicates greater groundwater vulnerability to drought. According to equation (2), the percentage of deviation from average groundwater table can be calculated.

$$R = \frac{X - \bar{X}}{\bar{X}} \times 100 \qquad (2)$$

Where,

X is mean of groundwater level in each water year, $\bar{X}$ is mean of average groundwater level over a period of 21 years for each basin, R is percentage of static groundwater table deviation in each water year from average long term static groundwater levels. In Table 4 eachsubclass of groundwater level layer and its ratings are shown.

This layer indicates that the east of the Zayandehrood basin has the lowest rating and the highest water table, whereas the central and northern areas have the highest rating and lowest water table. Groundwater level map and groundwater contour are shown in Figs. 8 and 9.

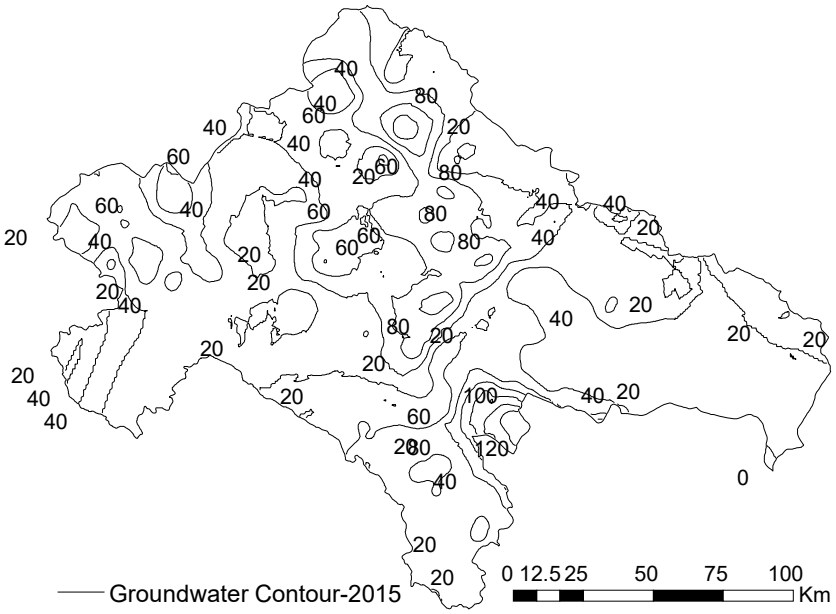

Fig. 9. Groundwater contour for 2015 in the Zayandehrood River basin

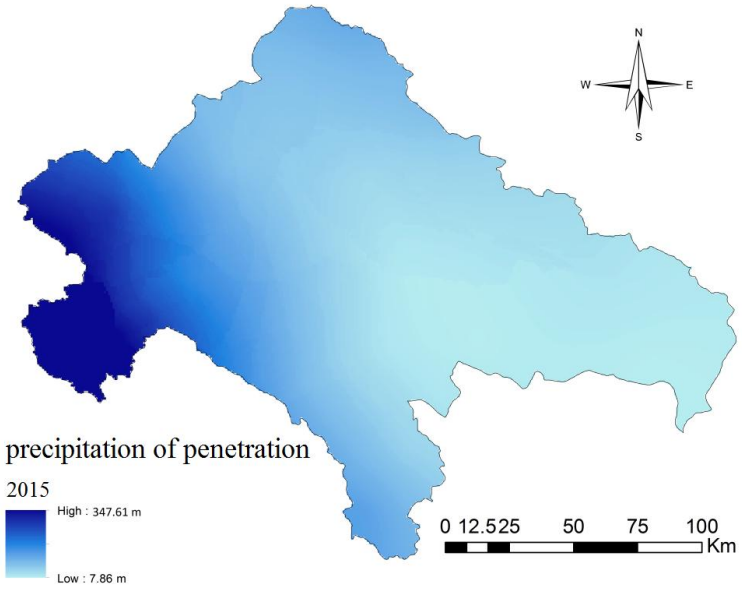

Fig. 10. Precipitation penetration map for 2015 in the Zayandehrood River basin

Table 4. Groundwater level ratings and subclasses layers

Rating	Range
0	<4 %
2	4 % to 8 %
4	8 % to 12 %
6	12 % to 16 %
8	16 % to 20 %
10	>20 %

4.7. Penetration of precipitation

The most important dynamic layer to estimate the risk of groundwater drought in an area is the penetration of precipitation. In the present study, data were gathered using the daily precipitation amounts of 21 years (2000 to 2020) to elicit annual average precipitation data for all of the stations in the study area. The penetration of precipitation layer was prepared by calculating the minimum, maximum, and mean values of penetration of precipitation using Guttman equations (Guttman, 2000) as follows:

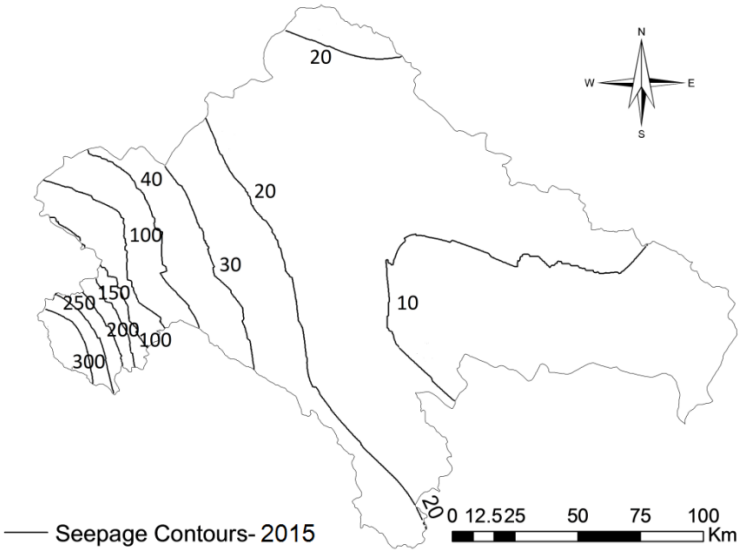

Fig. 11. Seepage contour for 2015 in the Zayandehrood River basin

$$R = 0.15P \qquad P < 300$$
$$R = 0.534(P - 216) \qquad 300 \le P \le 650 \qquad (3)$$
$$R = 0.8(P - 360) \qquad P > 650$$

where,
R is annual average recharge and P is annual average precipitation, both in millimeters.

The mean values of penetration of precipitation were spatially interpolated using Krigging interpolation method in ArcGIS to obtain average precipitation penetration range map for each year. After that, the penetration of precipitation contour was drawn spatially using Krigging map and contour method in ArcGIS to obtain contour maps for each year. As an example, penetration of precipitation map and contour for 2015 in the Zayandehrood River basin is shown in Figs. 10 and 11. Most clearly, regions with lower penetration of precipitation are generally more susceptive to drought than those with higher amount of penetration of precipitation.

As groundwater recharge decreases, vulnerability to drought will increase. Rating of this indicator was done based on the percentage of precipitation penetration deviation from long term average over a period of 21 years. More obtained negative percentage of precipitation penetration deviation will lead to more groundwater vulnerability to drought. According to equation (2), the percentage of deviation can be calculated from average penetration of precipitation. In Table 5, each subclass of net recharge layer and their ratings are shown.

This layer indicates that the average net recharge decreases from west to east direction in the Zayandehrood River basin. With respect to the significance of penetration of precipitation in the vulnerability draught assessment, the importance of the current layer as a factor was considered to be twice as much as the other layers..

Table 5. Penetration of precipitation ratings and subclasses layers

Rating	Range
1	0 % to -10 %
2	-10 % to -20 %
4	-20 % to -40 %
6	-40 % to -60 %
8	-60 % to -80 %
10	> -80 %

4.8. Electrical conductivity

Groundwater Electrical Conductivity is known as a qualitative criterion which is another dynamic layer in designing HGDI, representing some water qualitative properties like salinity. EC groundwater data from the Zayandehrood River basin over a period of 21 years (2000-2020), were used in current investigation. Initially, these data were classified into annual files, then they were fed into ArcGIS as point data, interpolating in this basin by Kriging method spatially (Chang and Teoh, 1995).

The EC layer of groundwater for the year 2015 is illustrated in Fig. 6. Similar to the procedure of the previous layer, the EC contour was drawn spatially using Kriging map and contour method in ArcGIS to obtain contour maps for each year. EC map and contour map for 2015 in the Zayandehrood River basin is shown in Figs. 12 and 13. EC was averaged by Zonal Analysis in the whole Zayandehrood River basin. It is clear that the

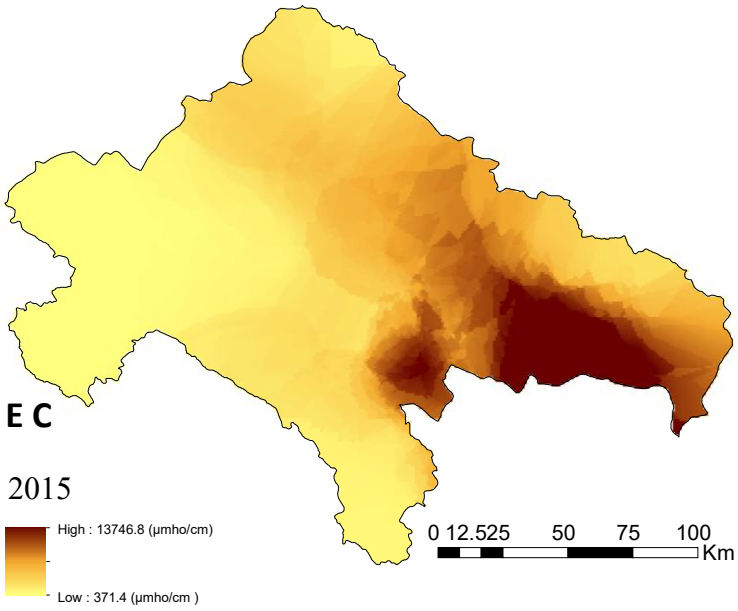

Fig. 12. Electrical conductivity map for 2015 in the Zayandehrood River basin

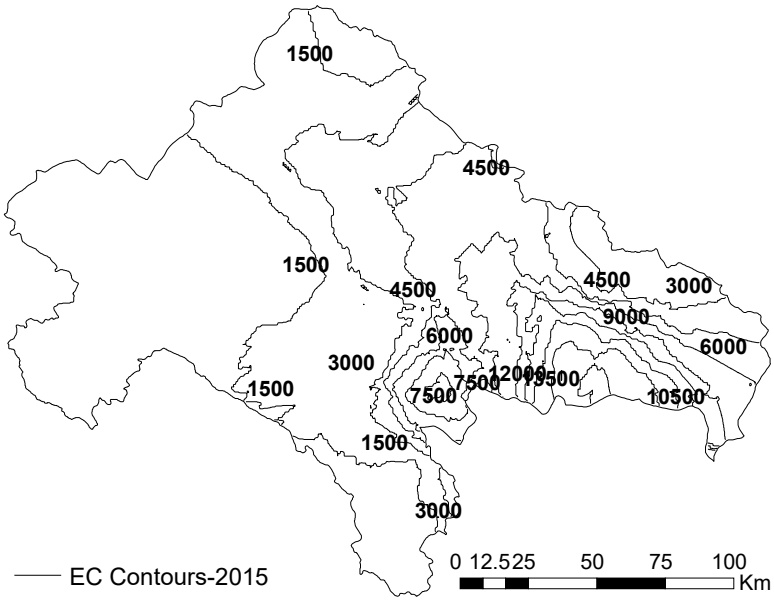

Fig. 13. Electrical conductivity contours map for 2015 in the Zayandehrood River basin

average EC increases from west to east direction. As groundwater EC increases, vulnerability to drought will increase. Rating of this indicator was done based on the percentage of EC deviation from long term average over a period of 21 years. A higher positive percentage of EC deviation will lead to more groundwater vulnerability to drought. According to equation (2), the percentage of deviation can be calculated from the average groundwater EC. In Table 6 each subclass of EC layer and their ratings are shown.

Table 6. EC ratings and subclass layers

Rating	Range
0	< 0 %
2	0 % to 20 %
4	20 % to 40 %
6	40 % to 60 %
8	60 % to 80 %
10	> 80 %

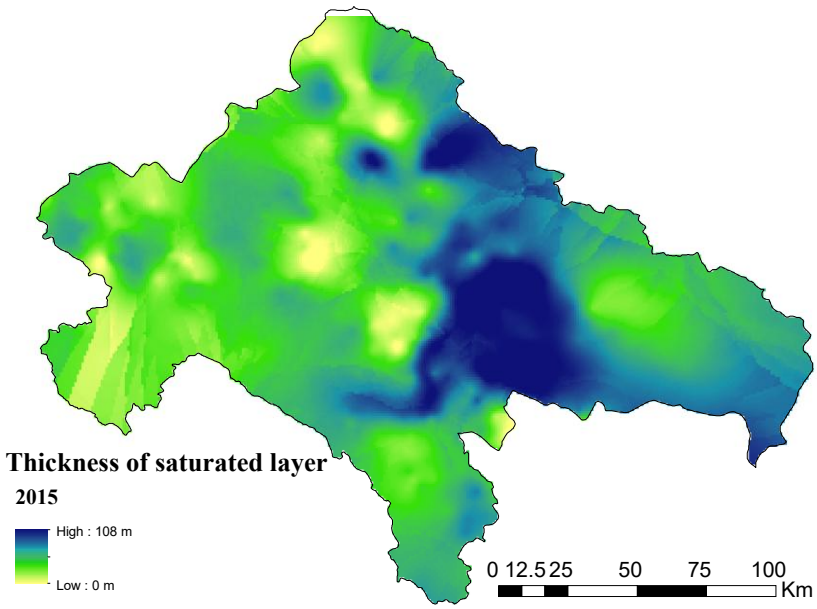

Fig. 14. Thickness of saturated layer map for 2015 in the Zayandehrood River basin

4.9. Thickness of saturated layer

Saturated layer thickness is one of the more important dynamic layers in designing HGDI. Thickness data were imported into ArcGIS as point data. In order to determine the thickness of bedrock for each pixel in the study areas, Kriging command was used. Eventually, thickness of saturated layer can be obtained by subtracting the bedrock thickness layer from groundwater level using Raster Calculator command. The saturated layer just for the year 2015 is shown in Fig. 14. The thickness of saturated layer contour was drawn spatially like the aforementioned approach in previous layers to obtain contour maps for each year. For example, thickness of saturated layer contour map just for 2015 in the Zayandehrood River basin is shown in Fig. 15. Thickness of saturated layer was averaged by zonal analysis in the whole Zayandehrood River basin.

According to Fig. 14, the thickness of the saturated layer decreases from the east to west direction. As the thickness decreases, vulnerability to drought will increase because of diminished groundwater storage. Rating of this indicator was done based on the percentage of thickness of saturated layer deviation from the long-term average over a period of 21 years. A greater negative percentage of thickness indicates more groundwater vulnerability to drought. According to equation (2), the percentage of these deviations can be calculated from average thickness of saturated layer of groundwater. In Table 7 each subclass of thickness of saturated layer and their ratings are shown. With respect to the significance of saturated layer thickness in the vulnerability draught assessment, the importance of the current layer as a factor was considered to be twice as much as the other layers.

Table 7. Thickness of saturated ratings and subclass layers

Rating	Range
2	0 % to -10 %
4	-10 % to -20 %
6	-20 % to -30 %
8	-30 % to -40 %
10	> -40 %

4.10. Reservoir released

The reservoir released is another dynamic layer to estimate the groundwater drought vulnerability. The daily released water data were set on an annual chronological order from 2000 to 2020. The volume of released water for this span is shown in Table 8 for the Zayandehrood Dam.

As the volume of released water increases, vulnerability to drought will decrease because of the greater penetration area. This layer represents the same rating for the whole basin and its sub-basin regions during a particular water year.

Rating of this indicator was done based on the deviation percentage of water released volume layer from a long-term average over a period of 21 years. A greaternegative percentage of deviation indicates a higher vulnerability to drought. According to equation (2), the percentage of water released volume deviation

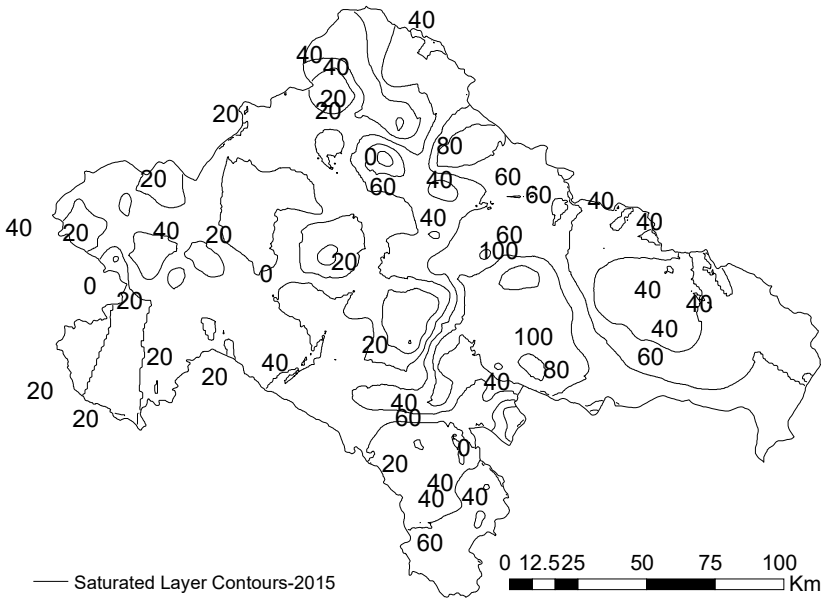

Fig. 15. Thickness of saturated contours map for 2015 in the Zayandehrood River basin

Table 8. Volume of dam released from the Zayandehrood Dam in a period of 21 years (2000–2020)

Year	Dam released (MCM)	Year	Dam released (MCM)	Year	Dam released (MCM)
2000	1367	2007	1676	2014	1400
2001	1102	2008	1706	2015	802
2002	568	2009	1838	2016	1231
2003	1188	2010	1891	2017	1080
2004	1454	2011	1422	2018	1432
2005	1549	2012	1284	2019	1630
2006	1546	2013	750	2020	1208

can be calculated from average water released volume. In Table 9 each subclass of storage volume and their ratings are shown.

Table 9. Dam released ratings and subclass layers

Rating	Range
2	0 % to -20 %
4	-20 % to -40 %
6	-40 % to -60 %
8	-60 % to -80 %
10	> -80 %

5. Groundwater drought triggers

Each of the static and dynamic layers was defined and rated in previous sections. In general, there are 10 indicators which possess a rate between 0 and 10. Based on the results obtained from questionnaires completed by experienced experts, a coefficient equal to 1 was allocated to all layers except penetration of precipitation layer and thickness of saturated layer, which have a coefficient equal to 2 because of their importance. By adding up all of the rates of each factor in the Zayandehrood River basin, a value between 0 and 120 was obtained. Based on the drought experience during the last two decades around the Zayandehrood River basin, the obtained value was classified into different ranges to ascertain drought triggers. Trigger ranges are

Table 10. Triggers for HGDI

Triggers	Type	Value
Drought	Very extreme	> 60
	Extreme	50-60
	Moderate	45-50
	Negligible	40-45
Normal		35-40
Wet	Negligible	30-35
	Moderate	25-30
	Extreme	15-25
	Very extreme	0-15

revealed in Table 10.

Hybrid groundwater drought maps for each year including the 10 mentioned layers (static and dynamic) in the Zayandehrood River basin were produced based on several drought vulnerability factors. The layers were combined for analysis by the 'union' command in ArcGIS and the rated maps were cumulated in GIS. The Union command on the Editor toolbar creates a new feature in the Target layer by combining the currently selected features. The command is used to combine either polylines or polygons and the Target layer geometry must match the geometry type of the selected features. Overlay analysis, a fundamental spatial analysis technique that allows users to combine two or more layers to identify relationships and create new information, was also used. Overlay analysis is a technique for applying a common scale of values to diverse and dissimilar inputs to create an integrated analysis.

6. Results and discussion

Devise of hybrid groundwater drought maps which were in spatial and temporal dimension, was performed by combining dynamic and static maps with ArcGIS software annually.

The derived maps show the vulnerability of groundwater drought for a 21-year period from 2000 to 2020. The average and summation of the ten drought factors (statically and dynamically) for the Zayandehrood River basin during the research period are shown in Table. 11.

Table 11 shows that the Zayandehrood basin has experienced 15 dry years, 2 normal years and 4 wet years, during the 21-year study. With respect to Figs. 16 and 17, the wettest and the driest years were 2000 and 2020, respectively. Fig. 16 clearly shows that in 2000, the aquifers in the western part of the basin were normal, the north and northwest were moderate wet, and the center and east of the basin were negligible wet. Fig. 17 also shows that in 2020, there was a very extreme drought in the eastern and western parts of the basin, an extreme drought in the central and southern parts, and a moderate drought in the northern part.

The results of this study confirm that groundwater drought in the Zayandehrood River Basin is controlled by the combined effects of climatic variability, groundwater recharge, aquifer storage, groundwater-level fluctuations, water quality, land use, and surface-water availability. This finding is consistent with the general understanding that groundwater drought develops through the propagation of meteorological and hydrological anomalies into groundwater systems and is further modified by hydrogeological characteristics and human water use. Unlike meteorological drought, which can develop relatively rapidly following precipitation deficits, groundwater drought generally exhibits a delayed response and may persist after meteorological conditions have returned to normal. Nevertheless, the superiority of HGDI should not be interpreted as proof that a composite index is inherently more accurate than a physically based groundwater model. Rather, its principal advantage is its ability to integrate multiple dimensions of groundwater vulnerability into a spatially explicit and relatively simple management tool. This characteristic is particularly useful for drought monitoring and decision-making in data-limited regions where fully coupled groundwater and climate models may be difficult to develop and maintain.

7. Comparison between GRI and HGDI in the Zayandehrood river basin

One of the most important indices introduced in recent years is GRI (Mendicino et al. 2008), which is based on groundwater detention values. GRI can be calculated as:

$$GRI_y = \frac{D_y - \mu_D}{\sigma_D} \quad (4)$$

Where,

GRI_y and D_y are, respectively, the values of the index and the groundwater detention values for the year y, while μ_D and σ_D are the mean and the standard deviation of groundwater detention values, respectively, during the defined 21-year period of time. It should be noted that there always exists a lag between meteorological drought indices and groundwater drought data which normally takes about 2 to 3 years.

By comparing GRI and HGDI in Table 12, it can be concluded that despite the two-year lag between the groundwater drought data and the meteorological drought indices, both indicators are able to show this appropriately, but GRI is unable to show the real intensity of drought in the Zayandehrood River basin and its sub-basin regions according to real observations, which HGDI can. The comparison between HGDI and

Table 11. Average of ranks and summation of the ten drought factors in Zayandehrood River basin

Year	Rank of land use	Rank of saturated layer	Rank of unsaturated layer	Rank of surface layer	Rank of hydraulic conductivity	Rank of groundwater level	Rank of penetration of precipitation *	Rank of electrical conductivity	Rank of thickness of saturated layer *	Rank of dam released	Total rank
2000	6	6.1	5.8	5	6.5	0	0	0	0	1	30.4
2001	6	6.1	5.8	5	6.5	3	4	0	0	3	43.4
2002	6	6.1	5.8	5	6.5	4	5	0	1	5	50.4
2003	6	6.1	5.8	5	6.5	2	6	0	2	7	54.4
2004	6	6.1	5.8	5	6.5	2	4	0	3	4	49.4
2005	6	6.1	5.8	5	6.5	4	0	0	3	2	41.4
2006	6	6.1	5.8	5	6.5	3	0	0	3	0	38.4
2007	6	6.1	5.8	5	6.5	2	0	1	2	0	36.4
2008	6	6.1	5.8	5	6.5	2	0	1	1	0	34.4
2009	6	6.1	5.8	5	6.5	2	0	1	1	0	34.4
2010	6	6.1	5.8	5	6.5	0	0	1	0	0	30.4
2011	6	6.1	5.8	5	6.5	0	4	1	1	2	42.4
2012	6	6.1	5.8	5	6.5	1	7	1	3	3	54.4
2013	6	6.1	5.8	5	6.5	4	3	1	4	5	53.4
2014	6	6.1	5.8	5	6.5	6	1	1	6	1	51.4
2015	6	6.1	5.8	5	6.5	8	5	1	7	6	68.4
2016	6	6.1	5.8	5	6.5	7	2	1	7	4	50.4
2017	6	6.1	5.8	5	6.5	6	0	1	6	4	46.4
2018	6	6.1	5.8	5	6.5	5	2	1	5	2	44.4
2019	6	6.1	5.8	5	6.5	3	5	2	7	2	48.4
2020	6	6.1	5.8	5	6.5	7	4	3	6	4	53.4

* The layers with a double significance.

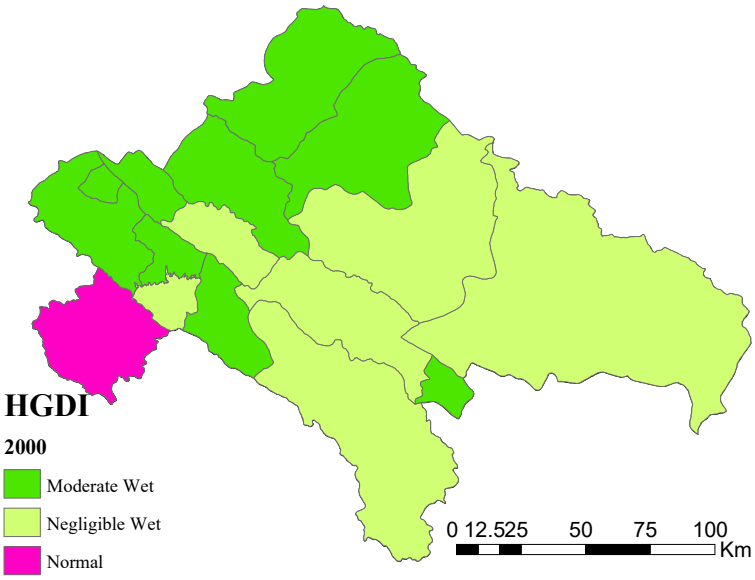

Fig. 16. Hybrid groundwater drought map of the Zayanderood River basin (2000)

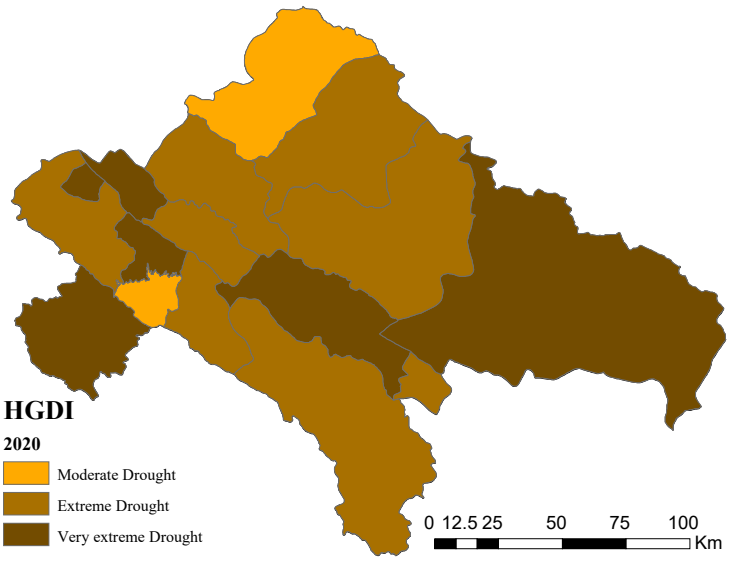

Fig. 17. Hybrid groundwater drought map of the Zayanderood River basin (2020)

GRI provides further insight into the performance of the proposed index. GRI is based primarily on groundwater storage or detention anomalies and is therefore useful for identifying deviations from long-term groundwater conditions. However, the comparison presented in this study shows that GRI tends to classify several years as normal even when the combined hydrogeological and hydrological conditions indicate substantial drought vulnerability. For example, the GRI classified 2002 as normal, whereas HGDI classified the same year as extreme drought. Similarly, GRI identified 2015 as negligible drought, while HGDI identified it as very extreme drought. These differences suggest that a single-variable index may not adequately represent drought severity where groundwater conditions are simultaneously affected by reduced recharge, declining groundwater levels, reduced saturated thickness, water-quality deterioration, and changes in surface-water availability.

Table 12. Comparison between GRI and HGDI indices in Zayandehrood River basin

Year	HGDI	Drought conditions	GRI	Drought conditions
2000	30.4	Negligible wet	0.45	Normal
2001	43.4	Negligible drought	-0.11	Normal
2002	50.4	Extreme drought	-0.50	Normal
2003	54.4	Extreme drought	-0.82	Near to normal (Drought)
2004	49.4	Moderate drought	-0.46	Normal
2005	41.4	Negligible drought	-0.14	Normal
2006	38.4	Normal	0.07	Normal
2007	36.4	Normal	0.14	Normal
2008	34.4	Negligible wet	0.28	Normal
2009	34.4	Negligible wet	0.51	Near to normal (wet)
2010	30.4	Negligible wet	0.26	Normal
2011	42.4	Negligible drought	0.03	Normal
2012	54.4	Extreme drought	-0.11	Normal
2013	53.4	Extreme drought	-0.25	Normal
2014	51.4	Extreme drought	-0.68	Near to normal (Drought)
2015	68.4	Very extreme drought	-1.14	Negligible drought
2016	50.4	Extreme drought	-0.85	Near to normal (Drought)
2017	46.4	Moderate drought	-0.26	Normal
2018	44.4	Negligible drought	-0.52	Normal
2019	48.4	Moderate drought	-0.69	Near to normal (Drought)
2020	53.4	Extreme drought	-1.25	Negligible drought

8. Conclusions

This study developed a HGDI to provide an integrated framework for assessing the spatial and temporal variability of groundwater drought vulnerability in the Zayandehrood River Basin, central Iran. Unlike conventional drought indices that mainly rely on a single variable or a specific component of the hydrological cycle, the proposed approach integrates a combination of hydrogeological, climatic, environmental, water-quality, land-use, and surface-water indicators. Analysis of the 2000–2020 period showed that the Zayandehrood River Basin experienced predominantly dry conditions, with 15 dry years, 2 normal years, and 4 wet years. The results indicate an overall increase in groundwater drought vulnerability during the latter part of the study period. The year 2000 was identified as the wettest year, whereas 2020 represented one of the most severe drought conditions. In 2020, very extreme drought conditions occurred in the eastern and western parts of the basin, while the central and southern regions experienced extreme drought. These findings demonstrate the increasing pressure on groundwater resources resulting from the combined effects of climatic variability, reduced recharge, declining groundwater levels, and intensive groundwater exploitation.

The results also indicate that precipitation penetration, saturated-layer thickness, groundwater level, electrical conductivity, and reservoir releases are important factors influencing groundwater drought vulnerability. In particular, precipitation penetration and saturated-layer thickness were assigned greater weights because of their importance for groundwater recharge and storage. The spatially distributed HGDI maps demonstrate that groundwater drought is highly heterogeneous across the basin and that different areas may respond differently to similar climatic conditions because of variations in hydrogeological properties, land use, groundwater availability, and water demand.

Comparison with the GRI showed that although both indices can identify general groundwater drought conditions and the delayed response of groundwater to climatic forcing, GRI has limitations in representing the actual intensity and spatial variability of groundwater drought in the study area. The HGDI provides a more comprehensive representation by incorporating multiple factors that control groundwater drought vulnerability. Therefore, the proposed index can be considered a useful tool for groundwater drought monitoring, spatial vulnerability assessment, early warning, and supporting sustainable groundwater management.

Nevertheless, several limitations and sources of uncertainty should be acknowledged. First, the analysis was based on a 21-year observation period (2000–2020).

Although this period provides valuable information on recent drought variability, a longer record would be preferable for more robust characterization of drought frequency, persistence, recurrence, and long-term trends. Second, some spatially distributed variables, including hydraulic conductivity, soil characteristics, groundwater level, groundwater quality, and recharge, were derived from observation points using spatial interpolation. Consequently, the density and spatial distribution of monitoring wells and the selected interpolation method may introduce spatial uncertainty into the resulting maps. This uncertainty may be particularly important in areas with limited observational coverage.

Another important limitation is related to the weighting and rating scheme used in the HGDI. The relative importance of the indicators was determined largely through expert judgment and questionnaire-based assessment, while only precipitation penetration and saturated-layer thickness were assigned higher weights. Although this approach provides a practical and transparent framework, the resulting weights may contain a degree of subjectivity and may not fully represent the nonlinear interactions among groundwater drought drivers. Similarly, the classification of indicators into vulnerability classes and the associated rating values influence the final HGDI values and drought categories. Consequently, the index results should be interpreted as an integrated measure of groundwater drought vulnerability rather than as a direct measurement of groundwater storage deficit.

There are also uncertainties associated with the representation of groundwater recharge and storage. Precipitation penetration was estimated using an empirical relationship between precipitation and recharge, which may not fully capture the spatial and temporal complexity of recharge processes. Groundwater systems are also affected by pumping, evapotranspiration, geological heterogeneity, surface-water–groundwater interactions, and groundwater flow between sub-basins. These processes were not explicitly simulated in the current HGDI framework. In addition, electrical conductivity was used as an indicator of groundwater quality and drought vulnerability; however, groundwater quality is influenced by several geochemical and anthropogenic processes that cannot necessarily be attributed solely to drought.

The definition of drought triggers represents another source of uncertainty. The HGDI thresholds were established based on the drought experience of the study area and expert assessment. Although these thresholds provide a practical basis for drought classification, their transferability to other basins or climatic settings cannot be assumed without independent validation. Moreover, the present study primarily evaluates drought vulnerability and does not explicitly quantify the socioeconomic consequences associated with each drought category. Therefore, the relationship between HGDI classes and actual impacts on agriculture, domestic water supply, ecosystems, and economic activities requires further investigation.

Future research should therefore focus on several important areas. First, longer-term and higher-frequency groundwater, precipitation, streamflow, pumping, and groundwater-quality datasets should be incorporated to improve the characterization of drought persistence, propagation, and recovery.

Second, physically based groundwater-flow and recharge models should be coupled with the HGDI framework to better represent groundwater storage changes, recharge processes, groundwater abstraction, and surface-water–groundwater interactions.

Third, uncertainty and sensitivity analyses should be systematically incorporated to quantify the influence of indicator selection, weighting schemes, spatial interpolation, and drought thresholds on HGDI results. Data-driven approaches, including machine learning and probabilistic methods, could also be explored to develop less subjective weighting and classification schemes.

Furthermore, future studies should consider groundwater abstraction and water demand explicitly, particularly because increased pumping during drought may provide short-term resilience while accelerating long-term groundwater depletion. Integrating climate-change projections would also allow assessment of future groundwater drought risk under different climate and water-demand scenarios. The inclusion of socioeconomic and environmental impact indicators could further transform HGDI from a primarily hydrogeological vulnerability index into a more comprehensive drought-risk assessment framework.

Finally, independent validation of HGDI against observed groundwater storage changes, well failures, ecological impacts, agricultural losses, and other documented drought impacts is necessary to evaluate its predictive and operational performance. Application of the proposed framework to other arid and semi-arid basins would also help determine its transferability and identify which indicators, weights, and thresholds need to be adapted to local hydrogeological and socioeconomic conditions.

In conclusion, despite the aforementioned limitations and uncertainties, the proposed HGDI provides a useful and flexible framework for integrating the multiple dimensions of groundwater drought. Its principal advantage is the ability to combine spatially variable hydrogeological characteristics with temporally varying drought-related conditions within a single GIS-based framework. The approach can therefore support the identification of vulnerable areas, development of drought early-warning systems, prioritization of groundwater management actions, and transition from reactive drought response toward proactive and

sustainable groundwater-resource management. Future improvements in data availability, process-based modeling, uncertainty quantification, and independent validation will be essential for increasing the reliability and operational applicability of the HGDI.

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