

Assessment of Agricultural Drought Vulnerability in the Guanzhong Plain, China

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Abstract The Guanzhong Plain, as an important traditional agricultural area, is suffering from high frequency droughts and a trend towards more serious drought. In this paper, eight factors, precipitation, evapotranspiration, surface water availability, depth to groundwater, well yield capacity, slope, potential water storage of soil, and GDP from agriculture, are integrated into an index to represent drought vulnerability based on the overlay and index method. In this approach, according to the internal connections between factors, precipitation and evapotranspiration are integrated into the moisture index, and depth to groundwater and well yield capacity are integrated into groundwater availability. To improve the rationality and accuracy, normalization is employed to assign rating values, and the analytic hierarchy process is introduced into the weighting scheme. Two local drought monitoring datasets endorse the results of the model. The map removal sensitivity analysis indicates the vulnerability index has low sensitivity in removing each layer. The single-parameter sensitivity analysis indicates the major contribution to the vulnerability index is meteorology followed by groundwater availability and surface water availability. The vulnerability map shows the low vulnerability coincides roughly with irrigation districts on the terraces and floodplains. The northwest tableland generally has moderate vulnerability, due largely to inefficient groundwater withdrawal. The high vulnerability is concentrated at the peripheries of the plain, where agriculture is generally rain-fed without irrigation and groundwater support, and land is rugged with high slopes.

Keywords Drought vulnerability · Overlay and index · Analytic hierarchy process · The Guanzhong plain · The Wei River

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1 Introduction

Reports of severe droughts across the world imply a global vulnerability to drought. On the continent of Asia, the drought occurrence takes up no more than 5% of all natural disasters, with the population affected by drought account for about 30% of population affected by all kinds of disasters (Wilhite and Knutson 2008). According to the statistics from 1970 to 2006, China is one of the countries that have the most reported droughts and the highest number of affected people (CRED 2006). Over the years, the impact of drought has increased significantly (Wilhelmi and Wilhite 2002).

The definition, identification, assessment, mitigation, and management of drought have been studied widely. Based on the different concepts and management objectives of drought, drought is generally grouped into four basic types: meteorological drought, hydrological drought, agricultural drought, and socio-economic drought (AMS 2003; Jha 2010). Various drought indices have been devised to quantify a drought, such as the standardized precipitation index (SPI; Mckee et al. 1993), Palmer drought severity index (PDSI; Palmer 1965), the surface water supply index (SWSI; Shafer and Dezman 1982), the vegetation condition index (VCI; Kogan 1995), and the crop moisture index (CMI; Palmer 1968).

Vulnerability is a complex concept, and there is no universally accepted definition. Initially, vulnerability describes the susceptibility to harm of a physical system (Aller et al. 1987; van Duijvenbooden and van Waegeningh 1987). Drought by itself is not a disaster, and it becomes a disaster only when it has a negative impact on society, including people, economies, and environment (Wilhelmi and Wilhite 2002; Wilhite 2009). Therefore, drought vulnerability is an area's susceptibility to suffer drought in both of its physical and social systems (Adger 2006; Lindoso et al. 2014; Naumann et al. 2014). Understanding drought vulnerability provides information for drought preparedness and resource management, hence facilitating disaster mitigation.

Vulnerability assessment is popular in the field of groundwater contamination and food security. Many countries and organizations have published vulnerability assessment methods for specific regions (Aller et al. 1987; Ribeiro 2000; WFP 2009). The assessment of drought vulnerability started late, but considerable research has been conducted in the last decade (Simelton et al. 2009; Preziosi et al. 2013; Lindoso et al. 2014). This may be attributed to the realization of importance of vulnerability assessment in resource planning and management. Another reason is the emergence of geographic information system (GIS), which has made data analysis easier (Wilhelmi and Wilhite 2002). Nowadays, researchers tend to use integrated assessment methods, as one type of drought does not necessarily lead to another type of drought (Pelling et al. 2004).

Drought occurs in both high and low precipitation areas and virtually all climate regimes (Wilhite 2009). Therefore, it must be considered as a relative phenomenon, and the vulnerability to drought should hence be recognized as a relative measure (Downing and Bakker 2000). As a consequence, it is hard to reach an agreed standard for drought vulnerability assessment. The overlay and index method, which selects factors based on regional conditions and establishes a relative criterion, makes vulnerability assessment easy. This method has been popular for vulnerability assessment in other fields (Shirazi et al. 2012; Pacheco and Sanches Fernandes 2013), and some scholars tried to introduce it to assess drought vulnerability. Wilhelmi and Wilhite (2002) selected four key biophysical and social factors to estimate vulnerability to droughts in Nebraska, US. Pandey et al. (2010) integrated seven hydro-meteorological and physiographic factors based on an experimental weighing scheme to

evaluate drought vulnerability in the Sonar Basin, India. Yuan et al. (2015) selected three factors for exposure, sensitivity, and adaptive capacity indicators respectively to derive a drought vulnerability index for eastern China.

Despite advantages of the overlay and index method for evaluating drought vulnerability, there are still a few issues that need to be discussed and addressed. (1) Many researchers assign all factors an equal weight despite the fact that different factors affect vulnerability to different degrees. Some researchers improve the situation by giving weights based on experience, but subjective weighting scheme leaves room for errors. (2) Many researchers assign rating values to factors based on the criterion with crisp sets. After all, data in the same set are unequal and should not be assigned to the same rating. Additionally, when a value is close to the boundary of a set, a small measuring error may change the rating. (3) Many researchers set a country, state or province, city, or county as an evaluation unit. However, factors may vary enormously in an administrative district.

This paper aims to develop a model for assessing drought vulnerability in the Guanzhong Plain in China. To settle the above issues, the overlay and index method is integrated with normalization, analytic hierarchy process, and other techniques, which are expected to improve rationality and accuracy of results.

2 Study Area

2.1 Geography and Climate

The Guanzhong Plain located in central China lies between 107°01'–110°36'E and 33°57'–35°33'N (Fig. 1a). The plain, covering an area of 20,000 km², extends south to north from the Qinling Mountains to the Bei Mountains, and west to east from Baoji to the Yellow River. The area mainly comprises floodplains, terraces, and loess tablelands (Fig. 1b). The loess tableland is plateau ground formed by loess accumulation on the river terraces. The Guanzhong Plain is dominated by a warm sub-humid continental climate. The mean annual temperature varies from 7.2 °C to 15.2 °C (Wu and Sun 2016). The mean precipitation ranges from 543.6 mm to 863.0 mm per annum, with about half of the precipitation falls in July, August, and September. The annual rate of evaporation is in the range of 900 mm to 1200 mm.

2.2 Irrigation and Historical Droughts

The Guanzhong Plain has more than 20 irrigation districts, accounting for 60% of the study area (Fig. 1b). The fertile fields have been irrigated since the construction of the Zhengguo Canal in 246 BC. In the twentieth century, a large amount of modern hydraulic engineering was constructed leading the nation. Nowadays, although there exist plenty of reservoirs, pumping, and water transfer projects, droughts occur frequently. According to the statistics from 1949 to 1995, droughts occurred almost every year in the plain (DROSP and AMCSP 1999). In the 50 years of the latter half of the twentieth century, the Guanzhong Plain had seen 35 droughts that exceed 20% of the area (Wang 2003). Droughts in the Guanzhong Plain are also particularly long-lasting. In the recent 500 years, more than 10 severe droughts in the area lasted over 1 year. The longest one is the severe or extreme drought from 1627 to 1641 that lasted for 15 years.

There are several hydrologic, socio-economic, and geographic reasons for the drought phenomenon in the Guanzhong Plain. (1) River runoff has decreased seriously. Take the

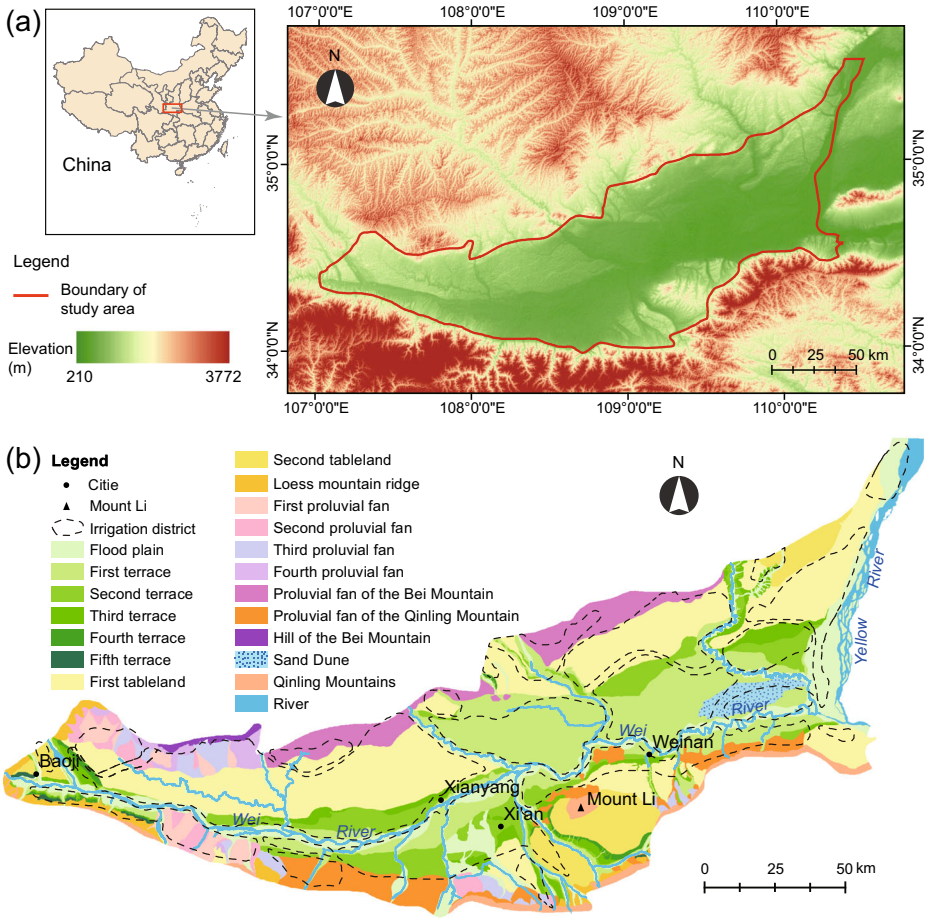


Fig. 1 a Location and digital elevation model (DEM) of the Guanzhong Plain, and b irrigation districts and geomorphological map

example of Linjia County Hydrological Station, where the Wei River enters the plain — the annual runoff has decreased from $3 \times 10^9 \text{ m}^3$ in the 1960s to $1 \times 10^9 \text{ m}^3$ in the 2010s. (2) With growth of economy and population, water demand has been rapidly increasing. Nowadays, the water deficient ratio is about 25% and still on the rise (Wang 2003). (3) It is difficult to develop water resource. In the south of the Wei River, reservoirs are usually small due to the big gradients. In the tablelands, it is hard to pump groundwater because of weak water yield and great depth to groundwater.

2.3 Precipitation Characteristics

2.3.1 Spatial Characteristics of Precipitation

The average annual precipitation in the Guanzhong Plain varies extensively (Fig. 2). The maximum (863.0 mm) is about 1.6 times larger than the minimum (543.6 mm). The south has

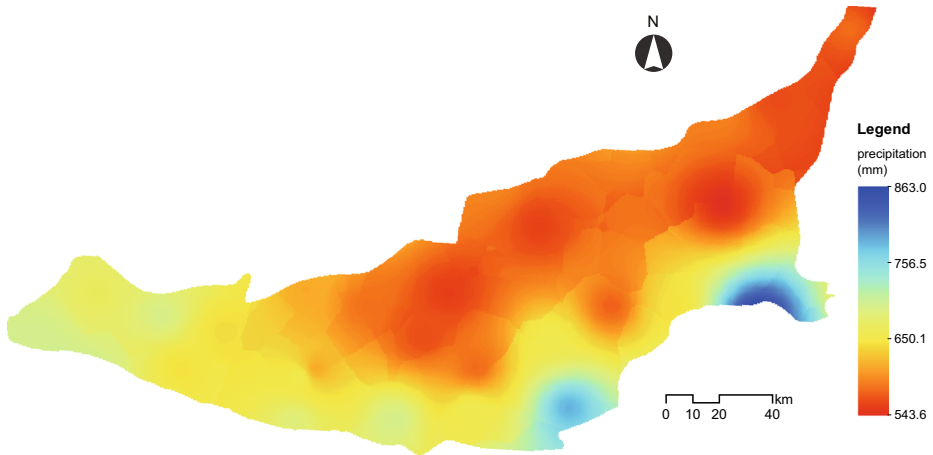


Fig. 2 Average annual precipitation map in the Guanzhong Plain

more precipitation than the north, and the west has more precipitation than the east. The tendency in the direction of latitude is much more prominent than that of longitude.

2.3.2 Multi-Year Characteristics of SPI

The SPI is employed to detect the temporal extents and severity of drought occurrences for multi-timescales. For example, at the National Reference Climatological Station in Xi'an ($34^{\circ}18'N$, $108^{\circ}56'E$), which is in the center of the plain, the SPIs for 1-, 3-, 6-, 9-, 12-, 18-, 21-, 24-month timescales are calculated based on monthly precipitation time series (Fig. 3a). In order to keep confidence of the results, the precipitation series is analyzed from the period of records (Jan. 1951) to station transfer (Dec. 2005).

The results show a remarkable trend towards drought. The linear fittings of 1-, 6-, and 12-month SPIs (Fig. 3b, c, d) show a significant decreased trend ($p < 0.025$). The trend is clearer in 6-month or larger timescales SPIs. According to the definition of drought ($SPI < -1$), the average drought frequency is 26.6% on 1-month timescale before 1977, while the percentage has risen to 32.2% after 1977. Moreover, Fig. 3a implies that droughts in the region have turned longer-lasting, especially evident on larger timescales.

3 Data and Methodology

3.1 Data

The moisture index, soil texture, and GDP from agriculture are raster maps with 1-km spatial resolution. The depth to groundwater is investigated from almost 2000 wells in August 2013, and the grid map was produced by interpolation using kriging with Gaussian variogram model, the optimal method for the case determined by cross-validation. Data of the well yield capacity are obtained from the hydrogeological map made by the First Party of Hydrogeology, Shaanxi Bureau of Geology. The DEM is from ASTER GDEM produced with 30-m postings.

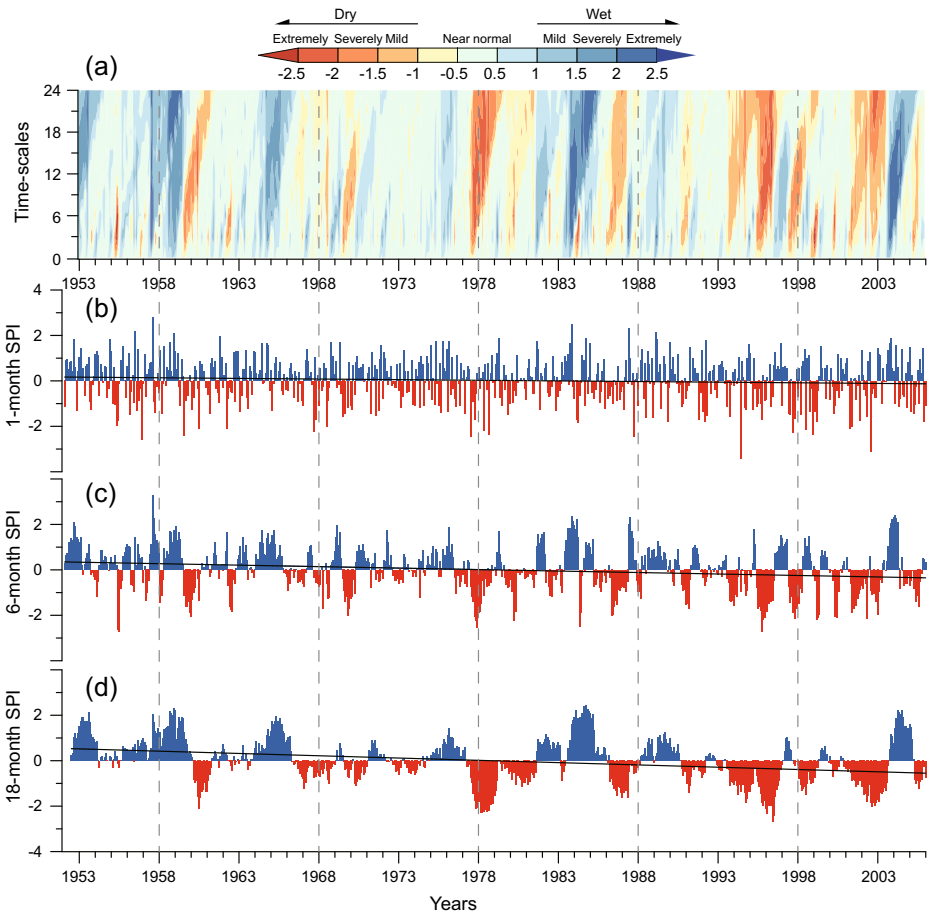


Fig. 3 Time series of SPI for **a** multi-time scale, **b** 1-month time scale, **c** 6-month time scale, **d** 18-month time scale at National Reference Climatological Station in Xi'an

3.2 Drought Vulnerability Model

The key steps of drought vulnerability model can be described as follows.

(1) Selection of factors

According to available data and natural and social conditions associated with drought, 8 key factors (precipitation, potential evapotranspiration, surface water availability, depth to groundwater, well yield capacity, slope, potential water storage of soil, and GDP from agriculture) are singled out to represent meteorology, water availability, geographic feature, and economic indicator. The correlations between factors are considered weak, as 64% of the correlation coefficients are less than 0.20, and the maximum correlation coefficient is 0.35 (between precipitation and surface water availability).

(2) Rating and normalization

Dissecting the area by grids generates thousands of assessment cells. A numerical drought vulnerability index (DVI) derived from ratings and weights assigned to each factor are obtained to represent the drought vulnerability for each cell. The factor ratings are assigned to values to reflect their relative contribution to drought vulnerability. Instead of conventional rating with crisp sets, normalization, a continuous-form classification system, is employed to ensure a continuous DVI that generates precise results. The normalization formula is expressed as follows:

$$X_{Ni} = \begin{cases} \frac{10(X_i - X_{\min})}{X_{\max} - X_{\min}} & \text{positive factors} \\ \frac{10(X_{\max} - X_i)}{X_{\max} - X_{\min}} & \text{negative factors} \end{cases} \quad (1)$$

The higher the value of a positive factor, the more vulnerable the area, and vice versa. Only slope is a positive factor in this case. After normalizing, the ratings are within the range of 0 to 10, with 0 considered to be least vulnerable to drought, and 10 considered to be most vulnerable.

(3) Calculation of DVI

Factors are integrated by different ways (Fig. 4) according to their internal connections. Precipitation and potential evapotranspiration are integrated into the moisture index. The ratings of the depth to groundwater and well yield capacity are compared cell to cell to choose

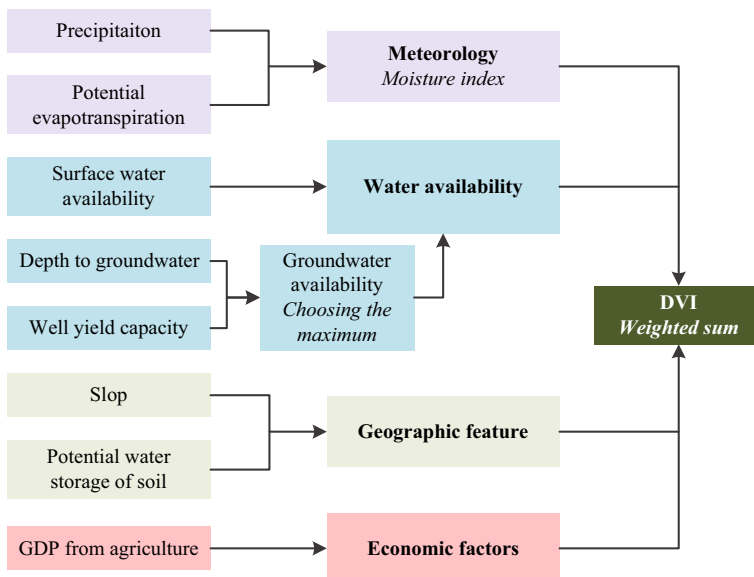


Fig. 4 Modeling framework for calculating DVI

a high rating as groundwater availability. Then, the DVI is derived from a weighted sum of ratings cell by cell as follows:

$$DVI = M_{\omega}M_R + SA_{\omega}SA_R + GA_{\omega}GA_R + S_{\omega}S_R + P_{\omega}P_R + G_{\omega}G_R \quad (2)$$

where, M, SA, GA, S, P, and G are respectively acronyms of meteorology, surface water availability, groundwater availability, slope, potential water storage of soil, and GDP from agriculture, and the subscripts ω and R denote the corresponding ratings and weights, respectively.

3.3 Determination of Weights

The weights, indicating the relative importance of factors, play a crucial role in vulnerability calculation (Qian et al. 2012). In this paper, the analytic hierarchy process (AHP) is used to derive weights from experiential judgments of relative importance of factors. The AHP is a powerful tool to solve multiple criteria decision-making issues. In this approach, problem is decomposed by construction of a hierarchy which places a set of criteria (Sun 2010; Saaty and Shang 2011). The pairwise comparisons, determined by the knowledge and experience of experts, are generated to convey the relative importance of factors. In the present study, 14 experts were surveyed. They are local administrative managers, hydrogeologists, hydrologists or engineers of water resources planning, and are familiar with the Guanzhong Plain. In the pairwise comparison matrix, $a_{ij} = 1$ when the importance of factor i and j are the same, $a_{ij} > 1$ when factor i is more important than factor j , a_{ji} is the reciprocal of a_{ij} . The greater the value of a_{ij} , the more important the factor i is than j . The weight ω_i is derived from pairwise comparisons a_{ij} by formula as follows:

$$\omega_i = \bar{\omega}_i / \sum_{i=1}^n \bar{\omega}_i, \quad \bar{\omega}_i = \sqrt[n]{\prod_{j=1}^n a_{ij}} \quad (3)$$

where ω_i is the weight of factor i and n is the number of factors. To reduce the bias of judgments, the consistency of a comparison matrix must be checked. The consistency ratio for consistency check can be consulted in Saaty (2004) and Saaty and Vargas (2012).

3.4 Sensitivity Analysis

Many factors have a great impact on the final vulnerability map. In the first instance, a high degree of interdependence of factors may increase the probability of misadjustment (Rosen 1994; Rahman 2008). In addition, the imposed errors or uncertainties of a number of input layers (factors) may also have an impact on the final output map (Saha and Alam 2014). Unavoidable subjectivity in the ratings and weights of factors has also raised concerns for accuracy (Kazakis and Voudouris 2015; Wu et al. 2016).

To address these issues, two sensitivity tests are carried out. The first test is the map removal sensitivity analysis introduced by Lodwick et al. (1990). The test identifies the sensitivity of vulnerability map by removing one or more layer maps.

Thus, the sensitivity index reflects the variability of each layer (Gogu and Dassargues 2000). It is calculated as follows:

$$S_i = \frac{|(V_i/N)-(v_i/n)|}{V_i} \times 100 \quad (4)$$

where S_i is the sensitivity index of i th cell, V_i is the DVI of i th cell, v_i is the DVI that excludes one or more input layers, and N and n are the number of layers used to compute V_i and v_i .

The single-parameter sensitivity analysis, introduced by Napolitano and Fabbri (1996), indicates the contribution of individual layers on the resultant vulnerability map (Pacheco et al. 2015). It compares the real or “effective” weight of each input layer with the “theoretical” weight assigned by the AHP model (Rahman 2008; Brindha and Elango 2015). Thus, the test provides helpful information about the impact of weights and ratings assigned to each layer and assists the analyst in determining the significance of subjectivity elements (Huan et al. 2012). The effective weight of an individual factor in an assessment cell is calculated as follows:

$$W = \frac{P_r P_w}{V} \times 100 \quad (5)$$

where W is the effective weight, P_r and P_w are the rating and weight of each input layer, and V is the overall DVI.

4 Factors

4.1 Meteorology

The precipitation, which is the primary cause responsible for a drought occurrence, is the only or core parameter in many meteorological drought indices, e.g. SPI, reconnaissance drought index (RDI; Tigkas and Tsakiris 2015), and percentage of precipitation anomalies (P_a ; Xu et al. 2016). In consideration of the broad range of average annual temperature in the plain (7.2–15.2 °C), the effects of evapotranspiration cannot be neglected. The moisture index recommended by the China Meteorological Administration is chosen as the meteorological factor (CMA 2006). The index with a simple calculation represents the balance between precipitation and evapotranspiration. It can be expressed as (CMA 2006; de Carvalho et al. 2013)

$$I_m = 100 \left(\frac{P}{PE} - 1 \right) \quad (6)$$

where I_m is the moisture index, and P and PE are the precipitation (mm) and potential evapotranspiration (mm) of a certain period respectively. The PE is estimated by the Thornthwaite method (Thornthwaite 1948). The average annual moisture index ranges from -17.5 to 63.89 (Fig. 5a), but the values are negative in 81% of the study area. Compared with the precipitation (Fig. 2), the moisture index has a narrower variation between the north and south, and between the east and west.

4.2 Water Availability

4.2.1 Surface Water Availability

Except a negligible quantity of collected rainwater and treated wastewater, irrigation water is from rivers and groundwater. Benefiting from the construction boom of modern hydraulic engineering in the twentieth century, about two-thirds of farmland is irrigated by rivers diverted by canals. The irrigation is an effective drought mitigation measure to cope with short-term drought conditions (Wilhelmi and Wilhite 2002; Jain et al. 2015). Therefore, the irrigation districts are assigned with a low vulnerability with a rating of 2, while the non-irrigation districts have a high vulnerability with a rating of 8 (Fig. 5b).

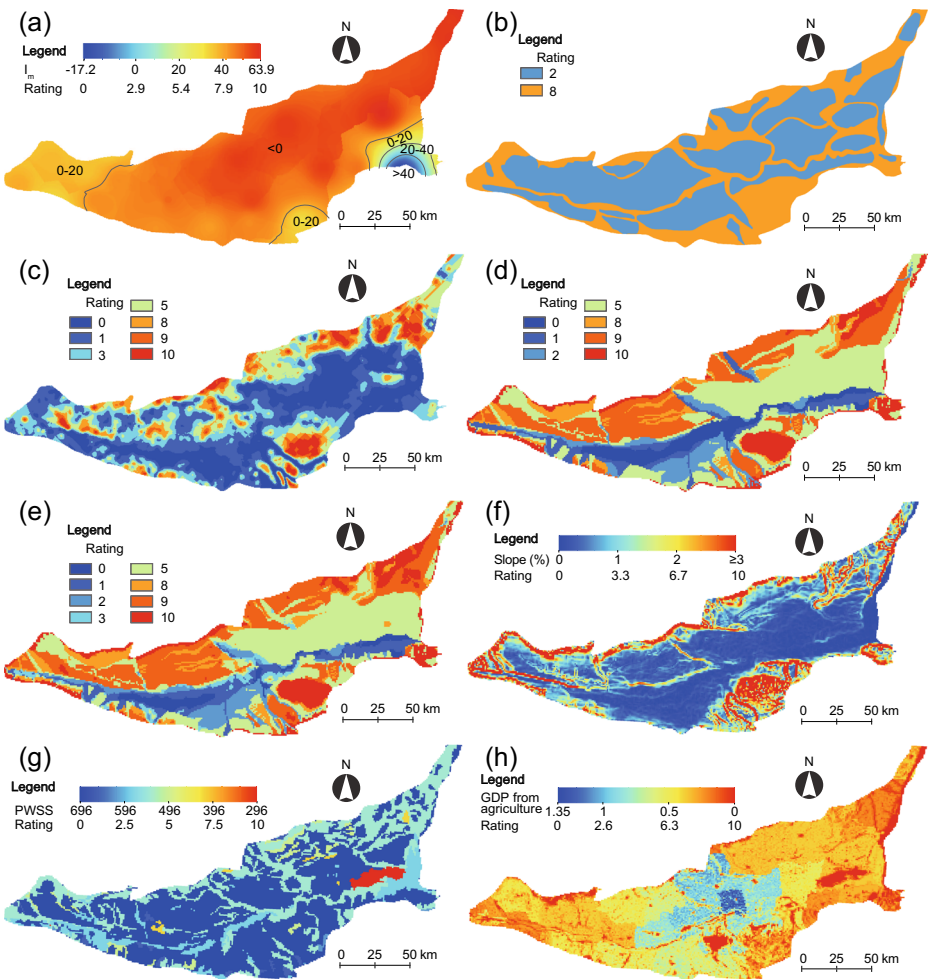


Fig. 5 Maps of the ratings for each of the factors: **a** the moisture index, **b** surface water availability, **c** depth to groundwater, **d** well yield capacity, **e** groundwater availability, **f** slope, **g** potential water storage of soil (PWSS), and **h** GDP from agriculture (million yuan per km²)

4.2.2 Groundwater Availability

According to the Water Statistical Yearbook of Shaanxi from 2008 to 2010, groundwater accounts for, on average, about 40% of irrigation water. From the aspects of space and time, groundwater can be withdrawn almost anywhere at any time, while canals only work in particular areas and at particular times. The easy availability and accessibility of groundwater give it a vital role in coping with drought in the study area.

Well yield and depth to groundwater have an impact on the development of well irrigation (Foster et al. 2015). Under small-scale farming, individuals bear the cost of drilling and pumping, thus the depth to groundwater is closely bound up with the number of wells. Accordingly, the two factors are integrated into account. Each grid cell is assigned the maximum rating of the two factors to get an integrated factor representing the groundwater availability.

According to the investigation of almost 2000 wells in the study area, there are few wells in the area with depth to groundwater exceeding 60 m. Wells are widespread in the area where the depth to groundwater is less than 40 m. The shallower the depth to groundwater is, the lower the costs are, and the more wells there are at that depth. The yield capacity of pumping wells ranges from 0.1 m³/h·m to 40 m³/h·m. In general, wells in the floodplains and terraces have good yield capacities (>1 m³/h·m), while in the loess tableland, the yield capacity is low (<0.5 m³/h·m).

The ratings assigned to the depth to groundwater and well yield capacity are given in Table 1. The maps of depth to groundwater, well yield capacity, and groundwater availability are shown in Fig. 5c–5e. The groundwater availability map shows a close similarity with the well yield capacity map, which is consistent with the research of Foster et al. (2015) that found that well yield capacity has a greater impact on agriculture.

4.3 Geographic Feature

4.3.1 Slope

The slope accelerates runoff of surface and subsurface flows, which leads to a fast delivery of water (Woo 2012; Şen 2015). Therefore, it is adverse to water infiltration, storage, and soil moisture retention. Soil moisture is available for a longer time in an area with mild slopes than steep slopes (Jain et al. 2015). Thus, steep slope areas are considered highly prone to drought followed by gentle slope areas and flat areas. The slopes are calculated from the DEM data using ArcGIS 10. The map (Fig. 5f) shows that slopes range between 0 and 15.2% in the study

Table 1 Ranges and ratings for depth to groundwater and well yield capacity

Depth to groundwater		Well yield capacity	
Range (m)	Rating	Range (m ³ /h·m)	Rating
<10	0	20–40	0
10–20	1	10–20	1
20–30	3	5–10	2
30–40	5	1–5	5
40–50	8	0.5–1	8
50–60	9	0.1–0.5	9
>60	10	bedrock	10

area. However, slopes are less than 0.5% over half of the area (52.9%), and less than 3.0% in most area (90.4%). A gentle slope may lead to significant water loss (Zehetner and Miller 2006; Hounsell 2015), so the maximum slope for normalization is set to 3%, and any slope exceeding 3% is assigned a rating value of 10.

4.3.2 Potential Water Storage of Soil

The soil root zone can retain moisture and supply it to crops, which is critical to plant growth during periods of deficient water. The water holding capacity of soil is mainly determined by soil texture (Parry et al. 1988; Wilhelmi and Wilhite 2002). For example, sand loses water fast due to high porosity, and is therefore considered vulnerable to drought. The water storage capacity of soil (Webb and Rosenzweig 1993) can be estimated as

$$2 \times [\text{sand}] + 7 \times [\text{clay}] + 10 \times [\text{silt}] \quad (7)$$

where $[\cdot]$ is the relative percentage of sand (0.05–2 mm), silt (0.002–0.05 mm) or clay (<0.002 mm). The results (Fig. 5g) indicate soil texture is considered relatively low vulnerable to drought, except in the small-scale sand in the east.

4.4 Economic Indicator

Economic status is closely related to hazard severity or adaptive capacity of many disasters, e.g. flood, earthquake, and tropical cyclone (Pelling et al. 2004). With respect to drought, Simelton et al. (2009) demonstrated that GDP is consistently correlated with drought vulnerability across China. It is believed that government institutions or farmers are able to provide powerful investments to reduce risk in rich areas (Yang et al. 2007; Simelton et al. 2009). However, in an area with a low GDP, a small economic loss is critically important (Pelling et al. 2004). Thus, an area with a high GDP has a high adaptive capacity, hence low vulnerability to drought. GDP from agriculture (Fig. 5h) is employed as an assessment factor, as it has an intimate relationship with agriculture.

5 Results and Discussion

5.1 Weights and Vulnerability Map

Precipitation, rivers, and groundwater are the direct sources for irrigation water. Hence meteorology, surface water availability, and groundwater availability are considered to be the most important factors. The geographic factors (slope and potential water storage of soil), which have an effect on diversion and storage of water, are of secondary importance. The economic indicator works only if drought occurs, so it is considered of marginal importance. The AHP with the 1–3 scale is used to decide weights. Accordingly, the pairwise comparisons, showing the relative importance of factors, are constructed as formula (8). The last column of formula (8) lists the weights of the six factors calculated by formula (3). The consistency ratio of the comparison matrix is 0.002 (less than the threshold 0.1), thus the matrix is considered to be reliable. The resultant vulnerability is shown by a color map with grids of 1×1 km (Fig. 6). The DVI varies from 1.24 to 8.55, with an average of 5.00 and a standard deviation (SD) of

1.13. To highlight the extreme values, the standard deviation stretch is applied to produce the vulnerability map. More specifically, the map applies a linear stretch between two SDs of the average and pushes values falling outside the range to the ends (Freedman et al. 2007; ESRI 2016). The frequency of DVI and operation of the SD stretch refer to Fig. 7.

$$Q = \begin{pmatrix} A & M & SA & GA & S & P & G & \bar{\omega}_i & \omega_i \\ M & 1 & 1 & 1 & 2 & 2 & 3 & 1.51 & 0.23 \\ SA & 1 & 1 & 1 & 2 & 2 & 3 & 1.51 & 0.23 \\ GA & 1 & 1 & 1 & 2 & 2 & 3 & 1.51 & 0.23 \\ S & 1/2 & 1/2 & 1/2 & 1 & 1 & 2 & 0.79 & 0.12 \\ P & 1/2 & 1/2 & 1/2 & 1 & 1 & 2 & 0.79 & 0.12 \\ G & 1/3 & 1/3 & 1/3 & 1/2 & 1/2 & 1 & 0.46 & 0.07 \end{pmatrix} \quad (8)$$

5.2 Validation of Drought Vulnerability

It is difficult to evaluate the reliability of the drought vulnerability map due to a lack of a well-established monitoring system. Nevertheless, two datasets from local monitoring can be used for validation. The first dataset refers to Jia (2015). It calculated mean drought-affected rates from 1990 to 2007, but confined to the northwest of the study area. The second dataset was obtained from the China Meteorological Data Service Center, which provided drought information every ten days from 1991 to 2011. Likewise, average drought-affected rates are employed.

The first dataset shows, in the northwest tableland, the west is less likely to be affected by droughts than the east. Correspondingly, the vulnerability map shows the west has moderate to low vulnerability, while the east almost always has moderate vulnerability. The dataset also implies terraces are less affected by droughts than the tableland, which coincides with the

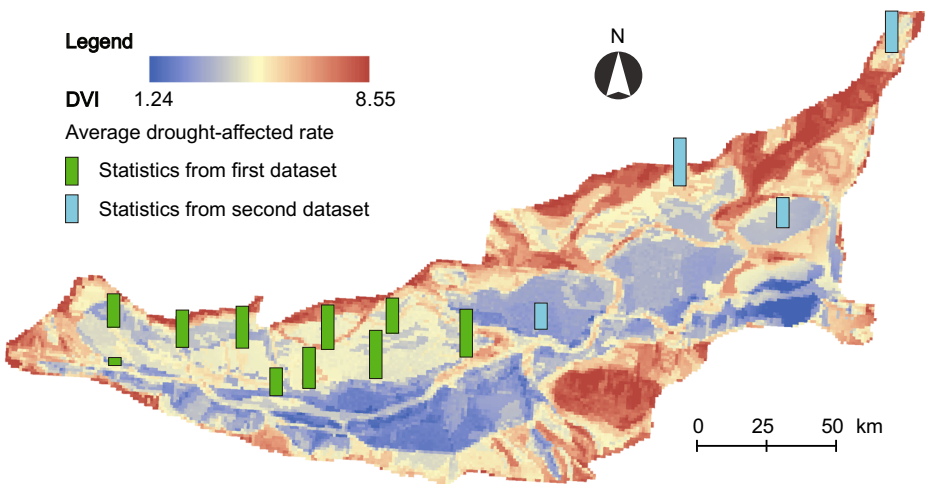


Fig. 6 Drought vulnerability map and historical drought statistics used for validation. Red, yellow, and blue stand for high, moderate, and low vulnerability, respectively

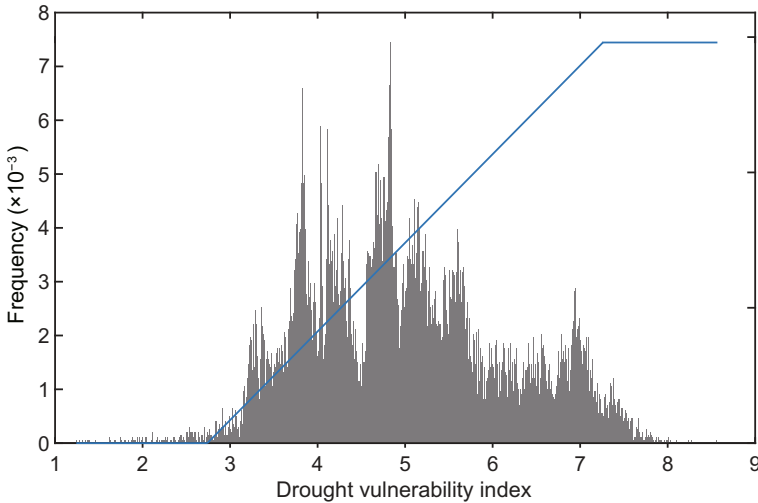


Fig. 7 Frequency of DVI. The polyline shows the operation of the standard deviation stretch

vulnerability map. The second dataset also corresponds to the vulnerability map, which further endorses the vulnerability map.

5.3 Sensitivity Analysis of Vulnerability Index

The variations of the DVI as a result of removing one layer at a time are presented in Table 2. The table shows the mean variation indices are less than 5%, which indicates a minor variation of the DVI is expected upon the removal of each layer. The DVI seems to be most sensitive to the removal of the meteorology layer as the mean variation index is 4.9%. The vulnerability variation index seems to be moderately sensitive to the removal of the slope (3.0%), potential water storage of soil (2.7%), and groundwater availability layers (2.3%). The smallest variation index was seen after removing the surface water availability (1.8%) and the GDP from agriculture layers (1.3%).

Table 2 also shows the results of the single-parameter sensitivity analysis. The analysis reveals the meteorology layer dominates the DVI, as its average effective weight is the maximum, reaching as high as 41.1%. This is partly caused by its high theoretical weight

Table 2 Statistics of map removal sensitivity analysis and single-parameter sensitivity analysis

Factor	Map removal sensitivity analysis (%)		Single-parameter sensitivity analysis (%)		
	Mean	SD	Theoretical weight	Effective weight	
				Mean	SD
M	4.9	2.2	23	41.1	10.5
SA	1.8	1.1	23	19.5	10.8
GA	2.3	1.7	23	24.2	10.3
S	3.0	0.5	12	1.6	1.9
P	2.7	0.8	12	3.3	4.5
G	1.3	0.7	7	10.5	3.5

(23.0%), and partly caused by widespread high ratings of the meteorology layer, whose average value is 8.5. The high rating also results in larger effective weights than its theoretical weight. The groundwater availability and surface water availability also tend to be fairly effective factors in the vulnerability assessment, as their average effective weights are 24.2% and 19.5%, respectively. They are not much different than their theoretical weights (23.0%). This would imply that the theoretical weights are the principal cause of their high effective weights. The least effective factors are the slope and potential water storage of soil, as their effective weights are 1.6% and 3.3%, respectively. The smaller influence could be attributed to their low theoretical weights (12.0%), but it is likely rather due to their low ratings. The mean ratings for the slope and potential water storage of soil layers are 0.75 and 1.43, respectively, implying geography is in favor of tolerating drought.

5.4 Discussion

The low vulnerability coincides roughly with irrigation districts on the river terraces and floodplains. In these areas, irrigation water supply is generally guaranteed during the irrigation periods; even during the non-working periods of canals, crops can be watered by groundwater. A small area in the southeast, where precipitation is more abundant than other areas, has extremely low vulnerability.

The moderate vulnerability is mainly concentrated in the northwest tableland. In contrast to the irrigation districts of low vulnerability, it is hard to pump groundwater there. One of the reasons for this is the considerable depth to groundwater due to the thick loess covering river terraces. More importantly, the well yield is too poor to utilize. Thus, water diversion and reservoirs play a crucial role in coping with drought. The west of the tableland is less vulnerable than the eastern part, due largely to its higher precipitation.

The dominance of high vulnerability areas is on the peripheries of the Guanzhong Plain, including proluvial fans, hills, Mount Li and its adjacent tablelands, and tablelands in the northeast. The geography is generally unfavorable for farming due to rugged landscape and precipitous slopes. In the northeast tablelands, groundwater withdrawal is also tough, and canals are not built in the second tableland. As a result, precipitation is an important water resource; however, it is scarce. In the tablelands adjacent to Mount Li (south center), precipitation is relatively abundant. However, the land is rather rugged, canals are not built, and groundwater cannot be pumped.

6 Conclusions

The overlay and index method, which is popular in assessing vulnerability of groundwater and food security, were employed to assess the drought vulnerability of the Guanzhong Plain. The developed model involves meteorological, hydrologic and geohydrologic, geographic, and economic indicators, including eight factors. Two datasets of historical droughts endorsed the reliability of the drought vulnerability map.

The map removal sensitivity analysis showed that the DVI has a low sensitivity to the removal of each layer. The single-parameter sensitivity analysis revealed that the meteorological factor is the leading contributor (41.1%) on the DVI. The availability of groundwater and surface water also make significant contributions to the DVI (24.2% and 19.5%, respectively).

The vulnerability map reveals that the irrigation districts on the river terraces and floodplains have low vulnerability, while the irrigation districts on the northwestern loess tableland have moderate vulnerability, as thick loess make it hard to pump groundwater, which might be pivotal resource in withstanding droughts during the non-working periods of canals. The high vulnerability areas are mainly on the peripheries of the Guanzhong Plain. In the northeast tablelands, groundwater withdrawal is tough, there is no irrigation support in the second tableland, and precipitation is relatively scarce. In the tablelands adjacent to Mount Li, despite relatively abundant precipitation, it is hard to tolerate drought due to rugged land and rain-fed agriculture without irrigation and groundwater support.

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