Theor Appl Climatol (2018) 133:151–164
DOI 10.1007/s00704-017-2182-x

ORIGINAL PAPER

Spatiotemporal analysis of the agricultural drought risk in Heilongjiang Province, China

Wei Pei[1] · **Qiang Fu**[1,2,3] · **Dong Liu**[1] · **Tian-xiao Li**[1] · **Kun Cheng**[1] · **Song Cui**[1]

Received: 14 July 2016 / Accepted: 22 May 2017 / Published online: 7 June 2017

Abstract Droughts are natural disasters that pose significant threats to agricultural production as well as living conditions, and a spatial-temporal difference analysis of agricultural drought risk can help determine the spatial distribution and temporal variation of the drought risk within a region. Moreover, this type of analysis can provide a theoretical basis for the identification, prevention, and mitigation of drought disasters. In this study, the overall dispersion and local aggregation of projection points were based on research by Friedman and Tukey (IEEE Trans on Computer 23:881–890, 1974). In this work, high-dimensional samples were clustered by cluster analysis. The clustering results were represented by the clustering matrix, which determined the local density in the projection index. This method avoids the problem of determining a cutoff radius. An improved projection pursuit model is proposed that combines cluster analysis and the projection pursuit model, which offer advantages for classification and assessment, respectively. The improved model was applied to analyze the agricultural drought risk of 13 cities in Heilongjiang Province over 6 years (2004, 2006, 2008, 2010, 2012, and 2014). The risk of an agricultural drought disaster was characterized by 14 indicators and the following four aspects: hazard, exposure, sensitivity, and resistance capacity. The spatial distribution and temporal variation characteristics of the agricultural drought risk in Heilongjiang Province were analyzed. The spatial distribution results indicated that Suihua, Qigihar, Daqing, Harbin, and Jiamusi are located in high-risk areas, Daxing'anling and Yichun are located in low-risk areas, and the differences among the regions were primarily caused by the aspects exposure and resistance capacity. The temporal variation results indicated that the risk of agricultural drought in most areas presented an initially increasing and then decreasing trend. A higher value for the exposure aspect increased the risk of drought, whereas a higher value for the resistance capacity aspect reduced the risk of drought. Over the long term, the exposure level of the region presented limited increases, whereas the resistance capacity presented considerable increases. Therefore, the risk of agricultural drought in Heilongjiang Province will continue to exhibit a decreasing trend.

✉ Qiang Fu
fuqiang0629@126.com

[1] School of Water Conservancy & Civil Engineering, Northeast Agricultural University, Harbin 150030, China

[2] Collaborative Innovation Centre of Promote Grain Production in Heilongjiang Province, Harbin 150030, China

[3] Key Laboratory of Water-saving Agriculture of Regular Institutions of Higher Education in Heilongjiang Province, Harbin 150030, China

1 Introduction

Drought is a major natural disaster that affects human societies, the environment, and regional economies. Drought not only affects agriculture but also affects industrial production, urban water supplies, and the environment, and these disasters directly threaten regional economic development, food security, ecological security, etc. Because of the impact of human activities and other factors, global climate change, increased temperatures, and rainfall variability probabilities have become increasing concerns. Even in areas with steady rainfall patterns, drought may occur because of extreme weather, and the frequency and intensity of droughts in these areas are increasing. Freshwater resource deficits are a direct cause of drought disasters in water circulation systems. In recent years, climate change and environmental degradation have increased the seriousness of water shortages, and the risk of drought hazards has subsequently increased. Social economic development and population expansion increase the risk of exposure to drought, and a greater potential for loss is observed for these factors when a disaster occurs. A drought disaster develops when a disaster factor develops into a drought loss because of vulnerability to a disaster body (Chen and Chen 2011), with vulnerability represented by exposure, sensitivity, and resistance capacity. Exposure refers to the quantity and value of the disaster body and exposure to drought hazard, sensitivity refers to the loss response of different disaster bodies after a drought, and resistance capacity refers to the ability and capacity of a region to resist drought (Jin et al. 2014). Agricultural drought risk represents the comprehensive interactions between natural factors and social attributes, including disaster factor hazards, disaster body exposure, and resistance capacities. Hazards represent the direct cause of damage, exposure and sensitivity determine the potential loss or impact, and the resistance capacity determines the portion of the potential impact that becomes an actual (net) impact (Fontaine and Steinemann 2009). Since the beginning of the twenty-first century, a shift has been observed from traditional passive to active drought and drought risk management, and drought risk analyses are the core concept of drought risk management (Wilhite et al. 2000). A drought risk analysis is a quantitative process used to determine the risk of drought by assessing the potential for drought using a comprehensive evaluation method. The spatial and temporal components of an agricultural drought risk analysis are helpful for understanding differences in the regional drought risk and the law of variation of drought risk in different regions. This type of analysis can be used as a guideline for decision making to establish forecasting, monitoring, and early warning mechanisms and as a theoretical basis for identifying drought disasters and determining disaster prevention and mitigation measures.

In recent years, an increasing number of studies have focused on drought risk (Dutta et al. 2015; Waseem et al. 2015; Zhang et al. 2015b), and the relevant indexes for analyzing drought risk have been quantified. Based on GIS and remote-sensing technology, a VCI (Vegetation Condition Index) and a SPI (Standardized Precipitation Index) were applied to assess the drought risk of Rajasthan (India) (Dutta et al. 2015). In addition, a drought hazard assessment index was proposed based on the VIC (Variable Infiltration Capacity), which is used to simulate the hydrological process of a basin, and the PDSI (Palmer Drought Severity Index), which is used to evaluate and analyze the degree of drought (Zhang et al. 2013). A new MDI (Multivariate Drought Index) was proposed using a principal component analysis and a cumulative distribution function (Li et al. 2015a). Using example data, MDI results were compared with SPI and PDSI results. Moreover, a SPI was used to analyze the spatial and temporal drought risk in the Huaihe River Basin according to a bias interpolation method (Duan et al. 2014). A DHI (Drought Hazard Index), which reflects precipitation, and a DVI (Drought Vulnerability Index), which reflects social and economic conditions, were used to evaluate the drought risk in 229 administrative regions of South Korea (Kim et al. 2015). Based on an SDI (Streamflow Drought Index), the hydrological drought conditions in northern Iran were assessed (Tabari et al. 2013). An Integrated Index was developed to evaluate the vulnerability to drought based on the hydrology, meteorology, land use, and other factors of a region (Safavi et al. 2014). Using precipitation, runoff, evaporation, soil water content and other indicator data, an MDI was proposed based on entropy theory (Rajsekhar et al. 2015). The drought risk of the coastal semi-arid region of south Texas was analyzed based on a SPI and SPEI (Standard Precipitation Evaporation Index) (Hernandez and Uddameri 2014). A weighted similarity measure that considered the agriculture, hydrology, and meteorological drought of a region was used to propose a multivariate composite drought index (CDI) (Waseem et al. 2015). A PNPI (Percent of Normal Precipitation Index) was used to analyze the spatial pattern of drought risk in a study area in Iran (Masoudi and Hakimi 2014). Based on a PDI (Perpendicular Drought Index) and an MPDI (Modified Perpendicular Drought Index), the performances of two remote sensing droughts were evaluated in Iran (Shahabfar and Eitzinger 2011). Additional studies have analyzed drought risks from the perspective of hazard factors and disaster bodies. Based on a fuzzy clustering iterative model, the vulnerability to agricultural drought in the Yellow River Basin was evaluated from the two aspects sensitivity and adaptation capacity (Wu et al. 2013). Three aspects of exposure, sensitivity, and adaptability were selected to evaluate the risk of drought (Fontaine and Steinemann 2009; Liu et al. 2013; Murthy et al. 2015). Furthermore, regional meteorological, hydrological, social, and economic data have been used to select four aspects, i.e., hazard, exposure, sensitivity, and resilience, to evaluate the risk of drought (Zhang et al. 2011; Qin et al. 2013; Han et al. 2016). Scholars have combined different mathematical models and methods to analyze drought risk. Using a DEA (data envelopment analysis) and the AHP (analytic hierarchy process), the risk of drought in four provinces in eastern China was analyzed (Yuan et al. 2015b). The AHP and fuzzy comprehensive evaluation method were used to analyze the risk of agricultural drought in China using quantitative calculations and qualitative assessments. The results indicated that the risk of drought in northern areas was higher than that in southern areas and that the risk in the central and eastern areas was higher than that in western areas (Qu et al. 2015). Based on a two-stage method, a drought risk assessment was conducted in 31 provinces of China based on spatial and temporal perspectives (Yuan et al. 2015a). Using the information diffusion model, the spatial and temporal characteristics of the agricultural drought and flood disaster risk in Henan Province, China, were studied (Zhang 2012). This model resolves the problem of insufficient sample data and improves the accuracy of information processing. Additional research into multivariate frequency analyses led to the introduction of the Copula method into the analysis of drought risk (Huang et al. 2015; Li et al. 2015b; Weng et al. 2015; Zhang et al. 2015b), and this research into drought risk analyses coincided with the increasing popularity of drought risk as a study subject.

Projection pursuit is an effective statistical method that can manage high-dimensional, non-linear, and non-normal data. The product of the total dispersion and local density was used as a projection index by Friedman and Turkey (1974). This projection index required a generally dispersed and locally aggregated distribution law of the projection point. In recent years, a number of scholars have conducted extensive research on the projection pursuit model proposed by Friedman and Turkey. Model-solving methods have been used to generate a genetic algorithm and improved genetic algorithm (Wang et al. 2006; Xiao and Chen 2012), a simulated annealing algorithm (Feng et al. 2013), a bee colony algorithm (Li et al. 2013), and a firefly algorithm (Ma et al. 2015) to solve the projection pursuit model. This model has been applied using a flood disaster risk assessment (Zhao et al. 2014), river water pollution evaluation (Huang and Lu 2014), water quality assessment (Zhao et al. 2012), and watershed non-point source pollution evaluation (Jin et al. 2007). Currently, studies on the Friedman projection pursuit model are primarily focused on methods of solving and applying the model, although few studies have sought to improve the model itself. Moreover, the Friedman projection index presents certain deficiencies, including a difficult-to-determine cutoff radius, which is crucial for the distribution of the projection point.

This paper applies the index selection method as detailed in the relevant literature (Fontaine and Steinemann 2009; Zhang et al. 2011; Wu et al. 2013; Murthy et al. 2015; Sehgal and Dhakar 2016). This index was selected based on four aspects: the hazard of the disaster factors, the exposure of the disaster body, the sensitivity of the disaster body, and the resistance capacity of the region. Combined with a cluster analysis and a projection pursuit model, the high-dimensional data were processed using a cluster analysis, and the results were represented by a cluster matrix. By using the cluster matrix, the local density index was determined; thus, the cutoff radius did not have to be determined, and an improved projection pursuit index was proposed. The improved model was applied in a risk analysis of the agricultural drought in Heilongjiang Province. Thirteen prefecture-level cities were used as the spatial scale, and 6 years (2004, 2006, 2008, 2010, 2012, and 2014) were used as the timescale, and the spatial differences in the regional agricultural drought risk and the time variation of the agricultural drought risk were analyzed. Moreover, a further analysis was conducted to understand the reasons for the spatial and temporal differences. Finally, relevant suggestions have been provided based on the results of the analysis to serve as a guide for reducing the losses caused by regional agricultural droughts and improving early warning systems.

2 Study area and data

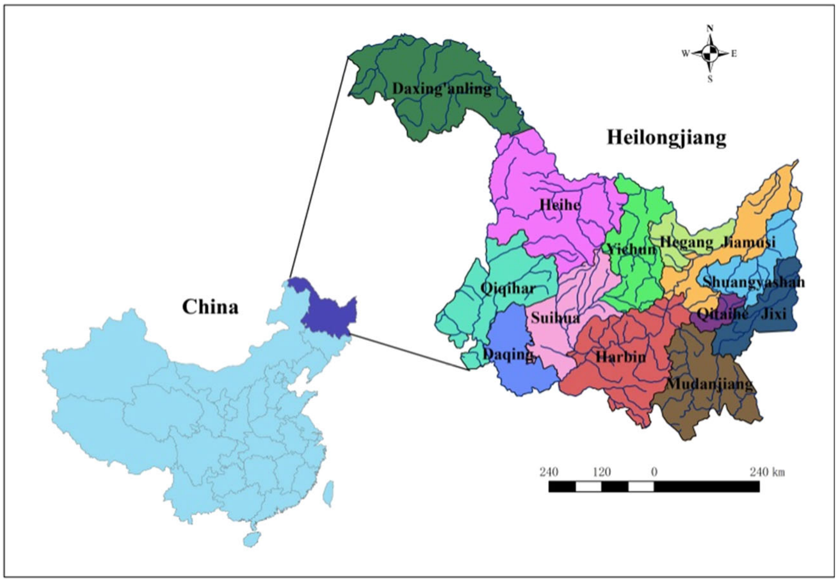
Heilongjiang Province is located in northeastern China, and it is the highest-latitude province in China. The north and east of the province are bordered by the Heilongjiang and Wusuli rivers and Russia, the west is adjacent to Inner Mongolia, and the south is bordered by Jilin Province. The north-south distance is 1120 km, and the east-west width is 930 km. The terrain of the northwest, north, and southeast is higher than that of the northeast and the south, which is relatively low. The region has a cold temperate continental monsoon climate. The drainage area includes 2881 rivers that are more than 50 km^2. The average total water resources are 810.33 billion m^3. The total area of Heilongjiang Province is 452,540 km^2, the total population is 38.33 million, and the agricultural population is 16.95 million. Heilongjiang Province is a major agricultural province that is rich in land resources. The cultivated land area covers 158,660 km^2 and accounts for 11.75% of the country's arable land area, representing a per capita arable land area of 0.41 ha. The cultivated land area and per capita arable land area are the largest in the country. Heilongjiang Province is one of the most important commodity grain production bases in China, and the output of grain is the highest in the country. A regional overview is shown in Fig. 1.

This paper selected 13 cities in Heilongjiang Province as the study area (Fig. 1): Harbin, Qigihar, Jixi, Hegang, Shuangyashan, Daqing, Yichun, Jiamusi, Qitaihe, Mudanjiang, Heihe, Suihua, and Daxing'anling. A comparative analysis is presented of two samples for Heilongjiang Province and China. The data were primarily collected from the statistical yearbook of Heilongjiang Province, the water conservancy yearbook of Heilongjiang, and the official websites of the relevant departments.

3 Methodology

Based on the regional disaster theory and the actual situation in Heilongjiang Province, this study constructs evaluation indexes of the agricultural drought risk in Heilongjiang Province. Based on the index system, a combined cluster analysis and the Friedman projection pursuit model were developed to improve a projection pursuit model for evaluating the regional agricultural drought risk.

Fig. 1 Regional map of Heilongjiang Province



3.1 Index system

In recent years, many scholars have constructed drought risk index systems from different aspects: examples including risk indexes based on the two aspects of sensitivity and adaptation capacity (Wu et al. 2013); the three aspects of exposure, sensitivity, and adaptability (Murthy et al. 2015; Sehgal and Dhakar 2016); and the four aspects of hazards, exposure, sensitivity, and resistance capacity (Zhang et al. 2011). Hazards represent the direct cause of damage, exposure and sensitivity determine the potential loss or impact, and resistance capacity determines the portion of the potential impact that becomes an actual (net) impact (Fontaine and Steinemann 2009). Based on previous studies, in the present study, the index was selected according to the following four aspects: the hazard of the disaster factors, the exposure of the disaster body, the sensitivity of the disaster body, and the resistance capacity of the region. Hazard factors represent the necessary conditions for drought, and hazards refer to the possibility of damage to agricultural production and human life, and the annual precipitation and water resources per unit area were included in the hazard evaluation index. Exposure refers to the magnitude of the disaster body that is affected by the disaster and includes the quantity, density, distribution, and value of the disaster body, and the proportion of the cultivated land area, per capita arable land area, and food yield per unit area were included in the exposure evaluation index. Sensitivity refers to the drought loss response, and the population density, agricultural population proportion, and agricultural GDP proportion were included in the sensitivity evaluation index. The resistance capacity represents the necessary conditions for reducing the drought hazard and the ability to withstand disasters, and the irrigation index, rural per capita net income, agricultural irrigation machinery power per unit area, rural labor per unit area, investment in water conservancy facilities, and reservoir capacity per unit area were included in the resistance capacity evaluation index. In summary, 14 indexes in four topic areas are used to evaluate the risk of agricultural drought in Heilongjiang Province. Certain indexes represent an increased drought risk, and in these indexes, greater agricultural drought values indicate greater risks. The abovementioned indexes are considered positive indexes. Other indexes represent a reduced risk of agricultural drought; in these indexes, greater agricultural drought values indicate smaller risks. The remaining indexes are considered reverse indexes. The positive and reverse indexes are described in Table 1.

3.2 Model steps

Step 1. Data normalization

The data are normalized as follows: $\{x^*(i,j)|i = 1,2,..,n; j = 1,2,.., p\}$, where $x^*(i,j)$ is the jth index of the ith sample and n and p represent the number of samples and indexes, respectively.

For positive indexes,

$$x(i,j) = \frac{x^*(i,j) - x_{\min}(j)}{x_{\max}(j) - x_{\min}(j)} \tag{1}$$

For reverse indexes,

$$x(i,j) = \frac{x_{\max}(j) - x^*(i,j)}{x_{\max}(j) - x_{\min}(j)} \tag{2}$$

where $x_{\max}(j)$ and $x_{\min}(j)$ are the maximum and minimum values of the jth index, respectively, and $x(i,j)$ is the index after normalization. The data were normalized by substituting X_3, X_4, X_5, X_6, X_7, and X_8 into Eq. (1) and X_1, X_2, X_9, X_{10}, X_{11}, X_{12},

Table 1 Evaluation indexes for the agricultural drought risk assessment in Heilongjiang Province

	Evaluation indexes (X_i)	Computing method	Description	Positive or reverse
Hazard	Annual precipitation (X_1) (mm)	Daily precipitation summation	The main factor impacting crop growth. Greater rainfall represents a lower probability and lower risk of drought.	Reverse
	Water resources per unit area (X_2) ($m^3\ ha^{-1}$)	Total water resources/cultivated area	Important natural resources in agricultural production. The greater the amount of water resources, the lower the drought risk.	Reverse
Exposure	Proportion of cultivated land area (X_3) (%)	Cultivated area/total area	Reflects the size of the agricultural production area exposed to drought. A higher ratio indicates a greater number of threats and a greater risk of drought.	Positive
	Per capita arable land (X_4) (ha person^{-1})	Cultivated area/population	Represents the agricultural production conditions and number of threats. A higher value indicates greater potential losses, a higher degree of exposure, and a greater risk of drought.	Positive
	Food yield per unit area (X_5) (t ha^{-1})	Food yield/area	Represents the level of agricultural production. A higher yield indicates a greater relative loss from the disaster and a greater risk.	Positive
Sensitivity	Population density (X_6) (person·km^{-2})	Population/area	A higher population density indicates a greater number of affected people, greater potential losses, and a higher risk under drought conditions.	Positive
	Proportion of the agricultural population (X_7) (%)	Agricultural population/total population	The agricultural population is the most sensitive to drought and most easily affected by drought. A higher proportion of the agricultural population indicates a greater drought risk.	Positive
	Proportion of agricultural GDP (X_8) (%)	Agricultural GDP/GDP	Agriculture is most vulnerable to the impact of the drought. A higher value indicates a higher proportion of potential losses and a greater drought risk.	Positive
Resistance capacity	Irrigation index (X_9) (%)	Irrigation area/cultivated area	A higher degree of water conservancy indicates an area with a strong ability to resist drought and a low drought risk.	Reverse
	Rural per capita net income (X_{10}) (RMB Yuan)	Obtained directly from the yearbook	Represents the ability to invest in disaster reduction and disaster recovery. A higher income indicates a lower drought risk.	Reverse
	Agricultural irrigation machinery power per unit area (X_{11}) (kWh ha^{-1})	Total power/cultivated area	A higher mechanization level indicates higher water resources adjustment ability and utilization efficiency and a lower risk.	Reverse
	Rural labor per unit area (X_{12}) (person ha^{-1})	Rural labor/cultivated area	Represents the agricultural drought resistance of the labor input level. A higher labor input value indicates a lower drought risk.	Reverse
	Investments in water conservancy facilities (X_{13}) (10^3 RMB Yuan·km^{-2})	Total investment in water conservancy facilities/area	Ensures the efficient use of agricultural water resources. A higher number of water conservancy facilities indicates a lower drought risk.	Reverse
	Reservoir capacity per unit area(X_{14}) ($m^3\ ha^{-1}$)	Reservoir capacity/cultivated area	Represents the regional water storage capacity that can effectively guarantee irrigation water. A greater reservoir capacity indicates a lower drought risk.	Reverse

X_{13}, and X_{14} into Eq. (2). After normalization, a higher value of a single index indicated a greater drought risk in the region.

Step 2. Projection index $Q(a)$

$a = \{a(1), a(2),\ldots, a(p)\}$ is a p-dimensional unit vector, and $z(i)$ is the projected characteristic value of $x(i,j)$. The projection is described as follows:

$$z(i) = \sum_{j=1}^{p} a(j)x(i,j) \qquad (i = 1, 2, \cdots, n) \tag{3}$$

where n samples are divided into m classes via k-means clustering and denoted as $A_1,\ A_2,\ \cdots,\ A_m$. Assuming that the ith sample belongs to the A_k class, then the jth sample belongs to the A_l class and the cluster matrix is defined as $D = (d_{ij})_{n\times n}$,

$$d_{ij} = \begin{Bmatrix} 1 & k = l \\ 0 & k \neq l \end{Bmatrix} \tag{4}$$

If the ith sample and the jth sample belong to the same class, $d_{ij} = 1$; otherwise, $d_{ij} = 0$. For samples of the same class, the local density determined by the clustering matrix preserves the projection point information; for those of different classes, the local density discards the projection point information.

The projection index is defined as follows:

$$Q(a) = S_z D_z \tag{5}$$

where $D_z = \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{n} r(i,j)d_{ij}}$, d_{ij} is the element in the cluster matrix, and $r(i,j) = |z(i) - z(j)|$, $(i,j = 1,2,\ldots, n)$. S_z is the standard deviation, $S_z = \frac{1}{n-1}\sum_{i=1}^{n} \left(z(i)-\overline{z}\right)^2$, $\overline{z} = \frac{1}{n}\sum_{i=1}^{n} z(i)$. For samples in the same cluster, $\sum_{i=1}^{n}\sum_{j=1}^{n} r(i,j)d_{ij}$ retains $r(i,j)$ (for the same class of projection points, the corresponding element in the clustering matrix is equal to 1), and for different clusters of samples, $\sum_{i=1}^{n}\sum_{j=1}^{n} r(i,j)d_{ij}$ abandons $r(i,j)$ (for the projection points between different classes, the corresponding element in the clustering matrix is equal to 0). The local projection points are as dense as possible, $\sum_{i=1}^{n}\sum_{j=1}^{n} r(i,j)d_{ij}$ is smaller, and D_z is greater. For the overall dispersion of the projection point, S_z is greater.

In conclusion, when the projection index $Q(a)$ is large, it can guarantee that S_z and D_z are large. A high S_z value guarantees overall dispersion, and a higher D_z value guarantees local aggregation. The projection index $Q(a)$ satisfies the idea of projection pursuit proposed by Friedman and Turkey (1974).

Step 3. Projection index $Q(a)$ optimization

According to the above expressions, the value of $Q(a)$ should be as large as possible:

$$\max \quad Q(a) = S_z D_z, \qquad \text{s.t.} \ \sum_{j=1}^{p} a^2(j) = 1 \tag{6}$$

Equation (6) is a non-linear constrained optimization problem and can be solved by a real-coded genetic algorithm (RGA).

Step 4. Classification evaluation

By inputting the optimal projection direction a into Eq. (3), the final evaluation value of each area can be obtained.

In this paper, an improved projection pursuit model is introduced by the combination of cluster analysis and the projection pursuit model. k-means clustering is a traditional and effective clustering method that can effectively classify high-dimensional samples. The projection pursuit model is used to project high-dimensional data into low-dimensional space, and samples are classified or evaluated according to the distribution of projection points. In this study, cluster analysis was used to construct the local density D_z. The high-dimensional samples are classified by k-means clustering. The clustering results are represented by the clustering matrix, and the local density D_z is constructed based on the clustering matrix. The improved projection pursuit model combines cluster analysis and the projection pursuit model, which offer advantages for classification and assessment, respectively. The improved model enriches the theory of projection pursuit and has theoretical significance.

4 Results

To analyze the spatial and temporal differences of the agricultural drought risk in Heilongjiang Province and compare this result with the agricultural drought risk in China, we determined the cause of regional differences in the agricultural drought risk and the underlying mechanisms for these changes. Data from the six studied years (2004, 2006, 2008, 2010, 2012, and 2014) were selected. For each year, we selected 13 prefecture-level cities as well as Heilongjiang Province and China as examples and produced 90 samples. According to the methods of model construction in Sect. 3.2, we obtained an evaluation value of the agricultural drought risk in Heilongjiang Province. In this paper, the final evaluation value was decomposed according to the direction of the projection, and the comprehensive agricultural drought risk decomposition was based on four previously defined aspects (hazard, exposure, sensitivity, and resistance capacity), which were separately analyzed.

4.1 Spatial difference analysis

To directly determine the spatial differences of the agricultural drought risk in Heilongjiang Province, a visualization function in ArcGIS (Esri, Redlands, CA, USA) was used to map the spatial distribution of the drought risk. Figure 2 shows the spatial distribution of the hazard, exposure, sensitivity, and resistance capacity

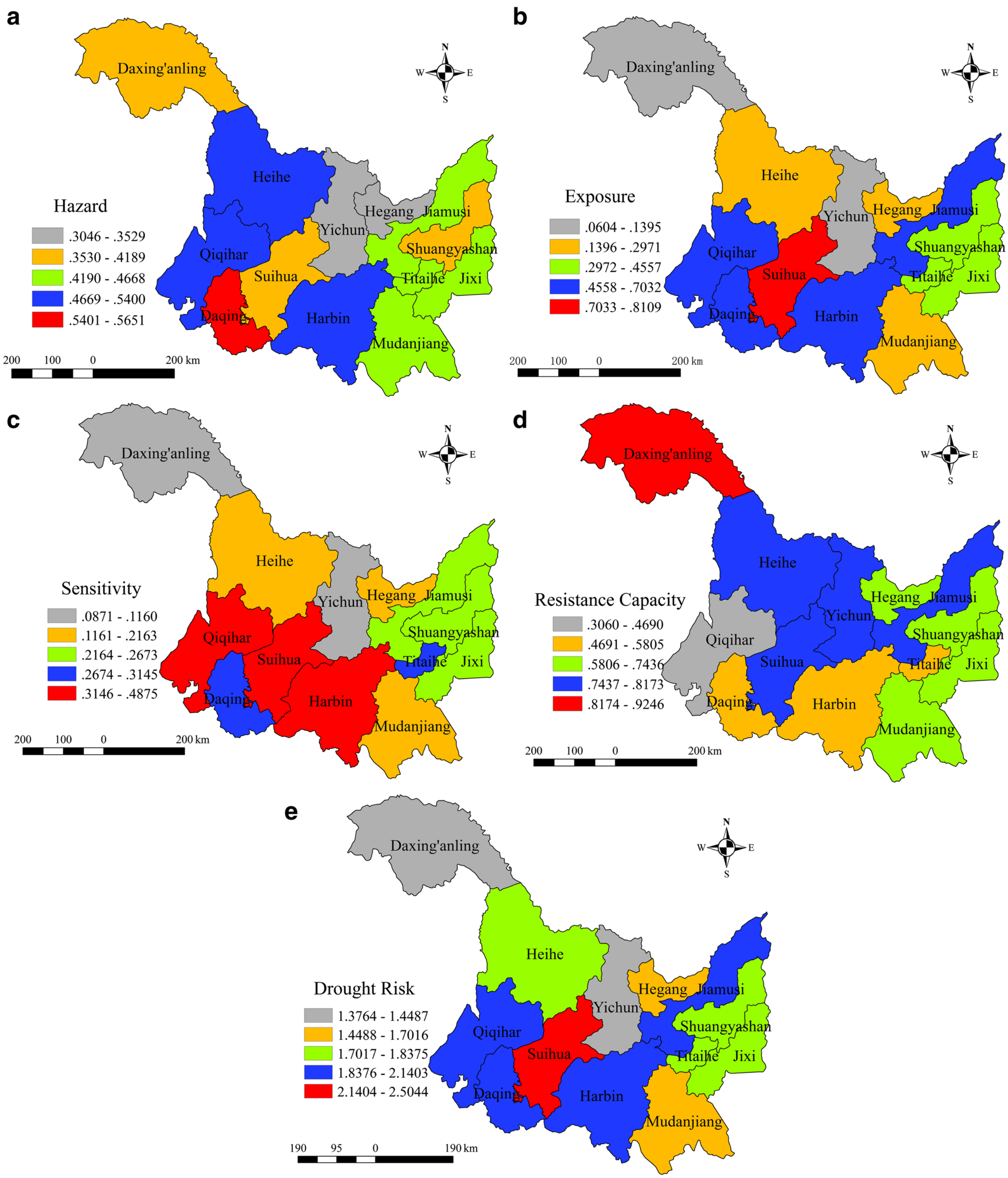


Fig. 2 Spatial distribution of the agricultural drought risk in Heilongjiang Province (2014): **a** hazard, **b** exposure, **c** sensitivity, **d** resistance capacity, and **e** drought risk

aspects and the integrated drought risk in Heilongjiang Province (2014).

To analyze the reasons for the spatial differences, we constructed a stacked column chart that showed the percentages of the 14 indexes according to region as shown in Fig. 3.

4.1.1 Spatial difference analysis of the hazard level

Figure 2a shows that the hazard levels in Daqing, Harbin, Qigihar, and Heihe are high, and Fig. 3 shows that the annual precipitation in these areas is relatively low at less than 450 mm, which is far below the province's average of 559 mm. The hazard levels in Hegang and Yichun are low, and the annual precipitation in these two regions is greater than 700 mm, which indicates that the water resource supply capacity is strong in these areas. The average water resources in these two regions are equivalent to 32,886 m^3 ha^{-1}, which is much higher than the value of 5468 m^3 ha^{-1} in Heilongjiang Province. The water resource reserves and the water resource supply capacity are the main causes of the differences in the regional hazard levels (Fig. 3).

4.1.2 Spatial difference analysis of the exposure level

Figure 2b shows that the exposure of Daxing'anling and Yichun was low, which indicates that the extent of agricultural production exposed to drought conditions in the two regions is relatively low. The two regions are located in forested areas that have less arable land; furthermore, the regions belong to the alpine zone, where the grain yield is low (Fig. 3). The exposure levels in Suihua, Qigihar, Daqing, Jiamusi, and Harbin are relatively high. These areas represent the main grain-producing areas of Heilongjiang Province. Western Qigihar, southern Harbin, eastern Jiamusi, and central Suihua are the main soybean-producing areas in Heilongjiang Province; Harbin, Jiamusi, Suihua, and Qigihar are the major rice-producing areas and account for approximately 45% of the total output of the province; and Harbin, Suihua, and Qigihar are the primary maize-producing areas and account for approximately two thirds of the maize production area of the province (Yun et al. 2005).

4.1.3 Spatial difference analysis of the sensitivity levels

Figure 2c shows that Daxing'anling and Yichun are low-sensitivity areas, and the primary cause of this low sensitivity is the sparse and small population of the rural communities. Suihua, Qigihar, and Harbin have the highest sensitivity, and the population density in these three areas is relatively high (Fig. 3) at 159, 131, and 186 person·km^{-2}, respectively. Furthermore, the proportion of the agricultural population is larger in these regions (Fig. 3) at more than 50% of the total population. The population, especially the agricultural population, has a higher response to the sensitivity of agricultural drought, which is the main reason for the difference in regional sensitivity (Fig. 3).

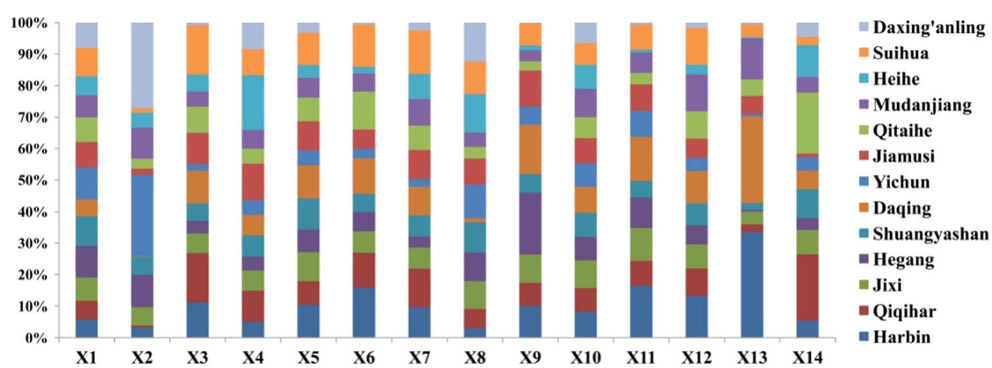
4.1.4 Spatial difference analysis of the resistance capacity level

Figure 2d indicates that the resistance capacity of Qigihar, Daqing, Harbin, and Qitaihe is strong and that the reservoir capacity of Qigihar and Qitaihe is relatively large; therefore, the drought-resistant water resources in these areas are more abundant (Fig. 3). The irrigation index of Daqing and Harbin is large, and the rural per capita net income of these two regions is higher than that of the other areas (Fig. 3). The resistance capacity of Heihe, Suihua, Yichun, and Jiamusi is relatively low, and the resistance capacity indexes in these areas are lower than those of the other regions (Fig. 3). Comparatively, the resistance capacity of Daxing'anling is the lowest. This region is located in a cold zone, and the level of economic development is low. The irrigation index is only 1.11%, and it is the only region with a per capita net farmer income less than 10,000 RMB Yuan (9994 RMB Yuan). The level of economic development is the main reason for the difference in regional resistance capacity (Fei et al. 2013).

4.1.5 Spatial difference analysis of the drought risk level

The comprehensive drought risk is composed of the hazard, exposure, sensitivity, and resistance capacity aspects. Figure 4

Fig. 3 Stacked column chart showing the percentages of the 14 indexes according to the region (2014)



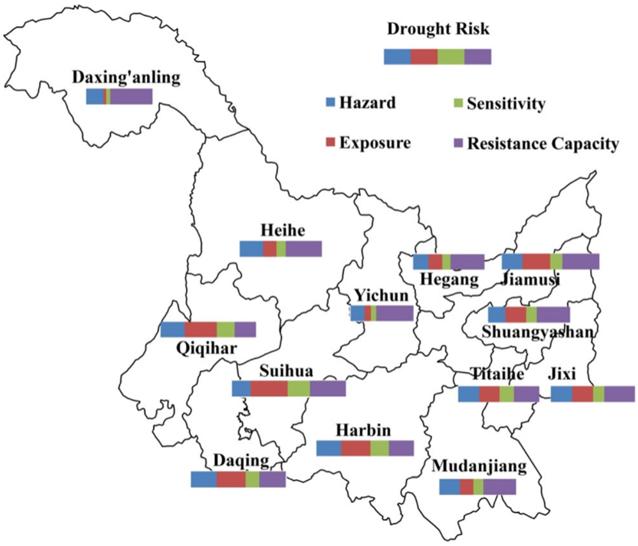


Fig. 4 Spatial distribution of the drought risk; a *longer drought risk bar chart* represents a higher risk. For each area, the bar was composed of the four aspects hazard, exposure, sensitivity, and resistance capacity. For each aspect, a *longer bar* represents a higher risk

describes the risk and composition of the various regions; longer bar charts indicate a greater drought risk.

Figures 2e and 4 show that the drought risk of Daxing'anling and Yichun is relatively low. In addition, the resistance capacity of the two areas is weak, although the exposure and sensitivity of the two areas are relatively low, and the number of exposed in the disaster environment is reduced under the same impact factors; therefore, the potential losses are low. The drought risk in Suihua, Qigihar, Daqing, Harbin, and Jiamusi is relatively high. The resistance capacity of the two areas is strong; however, these areas are the main grain-producing areas of Heilongjiang Province and their exposure and sensitivity are higher, and the number of production materials that are threatened by drought indicates a large number of potential losses. The levels of exposure and sensitivity are the main reasons for the differences in regional agricultural drought risk.

4.2 Temporal variation analysis

To analyze the temporal variations in the hazard, exposure, sensitivity, and resistance capacity levels and the comprehensive drought risk, we drew a mosaic map to illustrate the agricultural drought risk (Fig. 5).

4.2.1 Temporal variation analysis of the drought hazard

Figure 5a shows that the overall agricultural drought hazard in Heilongjiang Province and each prefecture-level city is higher than the national value. Heilongjiang has a shortage of water resources, and the rainfall and water resources are lower than the national average; thus, regional hydrological droughts are easily induced (Zhang et al. 2015a). In various regions, the regularity of the hazard pattern, which is primarily determined by the regional climate and hydrological conditions, is not obvious.

4.2.2 Temporal variation analysis of the exposure

Figure 5b shows that the overall exposure levels in Heilongjiang Province have a tendency to increase and are slightly higher than the national average. The main reason for increases in the exposure level is the significantly increased proportion of cultivated land area and per capita arable land in each area (Fig. 6). Driven by economic benefits, the area of cultivated land increases each year (Song and Chen 2012). For more than 10 years, the area of cultivated land and per capita cultivated land area has increased, the proportion of cultivated land area in Heilongjiang Province has increased from 21.32 to 32.65%, and the per capita arable land increased from 0.253 to 0.394 ha·person^{-1}. Moreover, the amount of agricultural production materials exposed to a disaster environment has significantly increased.

4.2.3 Temporal variation analysis of the sensitivity

Figure 5c shows that the sensitivity of the trend of drought changes is not obvious, which is primarily because the three indicators of sensitivity showed minimal changes over time. In areas where the population density showed almost no change, the proportion of the agricultural population and the proportion of agricultural GDP exhibited a decreasing trend, although the change was not large. However, the sensitivity in most parts of Heilongjiang Province was slightly lower than the national value.

4.2.4 Temporal variation analysis of the resistance capacity

Figure 5d shows that the resistance capacity of various regions exhibits an increasing trend, although the overall resistance capacity is lower than the national level. The increase of resistance capacity is mainly caused by economic development and the construction of agricultural water conservancy facilities. From 2004 to 2014, the irrigation index, rural per capita net income, and investment in water conservancy facilities in various regions significantly increased (Fig. 7). The rural economy in the Heilongjiang Province developed rapidly, and the rural per capita net income increased from 2725 RMB Yuan in 2004 to 10,453 RMB Yuan in 2014. In addition, the investment in water conservancy facilities increased from 12900 RMB Yuan/km^2 to 204600 RMB Yuan/km^2, and the irrigation index increased from 11.83 to 35.91%.

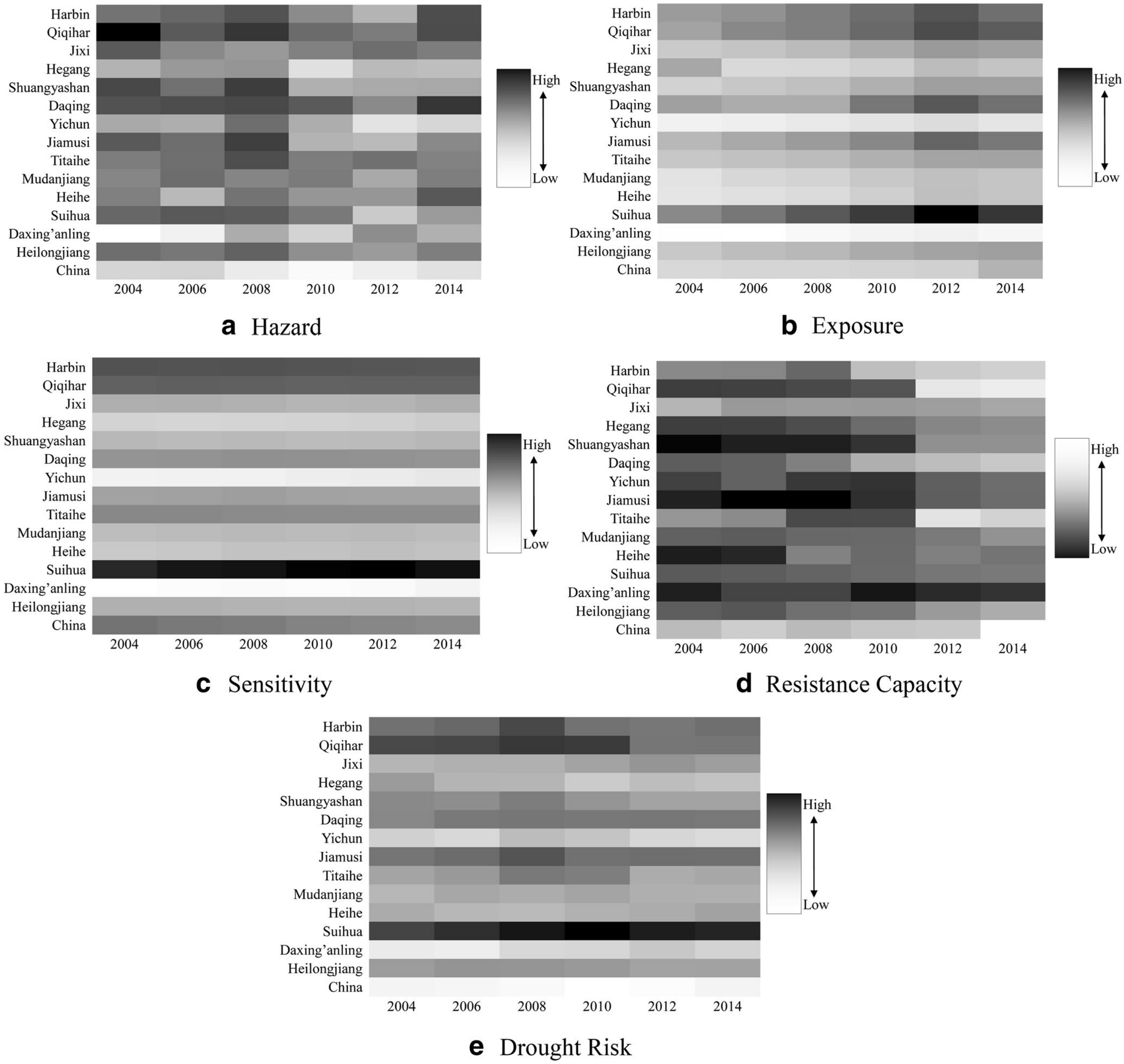


Fig. 5 Temporal variation of risk: **a** hazard, **b** exposure, **c** sensitivity, **d** resistance capacity, and **e** drought risk. *Darker colors* represent higher risk, and *lighter colors* represent lower risk

4.2.5 Temporal variation analysis of drought risk

From the previous analysis, it is clear that changes in the integrated drought risk are mainly caused by the exposure and resistance capacity levels. Figures 5b and 8a indicate that before 2012, there was an increasing trend of exposure in each area, although after 2012, a stable and even lower trend is observed. This change was primarily caused by the policy of returning farmland to forest and grassland in Heilongjiang Province in recent years, which has led to stable or decreasing amounts of cultivated land (Song and Chen 2012). Because of improvements in the regional economic development and agricultural water conservancy facilities, the resistance capacity in various regions has exhibited an increasing trend (Figs. 5d and 8b). In this study, smaller values represent a greater resistance capacity. Based on the comprehensive effects, the risk of agricultural drought in Heilongjiang Province initially exhibits an increasing trend and then a decreasing trend (Figs. 5e and 8c). Currently, the development of cultivated land in Heilongjiang Province is stable, and the development of the economy and the improvement of water conservancy facilities will continue to increase the resistance capacity of the region. Therefore, the risk of drought in Heilongjiang Province will exhibit a further declining trend.

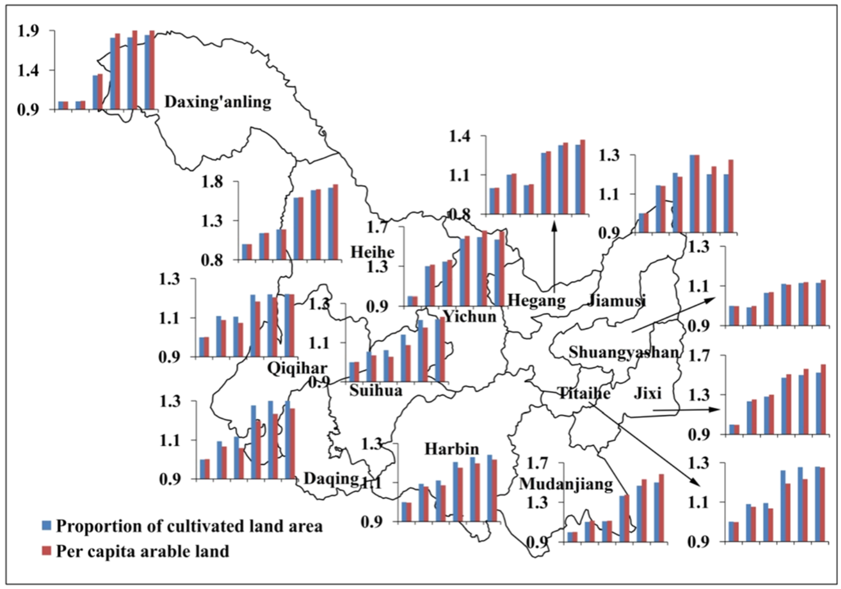


Fig. 6 Temporal variation in the proportion of cultivated land area and per capita arable land

5 Discussion

The previous analysis indicates that although the risk of agricultural drought in Heilongjiang Province exhibits a decreasing trend, the overall trend is higher than that in China in general. Moreover, the difference in the drought risk in different regions is greater in Heilongjiang Province and indicates a greater number of high-risk areas relative to the national average. According to the regional characteristics of Heilongjiang Province, the following suggestions are provided for the high drought risk areas:

1. The area of cultivated land and the conversion of cropland to forest and grassland should be strictly controlled. Heilongjiang Province is a major agricultural province, and because of the need for agricultural development, a large amount of forestland and grassland has been reclaimed for arable land. Long-term land cultivation and neglectful maintenance indicate the increasing conflict between human activity and ecological conservation. Soil water conservation has decreased gradually, and soil desertification is becoming increasingly serious. These issues further intensify the risk of agricultural drought.
2. Non-agricultural industries and economic diversification must be promoted, and the proportion of agricultural output must be reduced. Heilongjiang's economic dependence on agriculture is relatively strong, and the risk of agricultural drought is relatively large. The region should focus on the development of a third industry to diversify the regional economic structure and reduce the

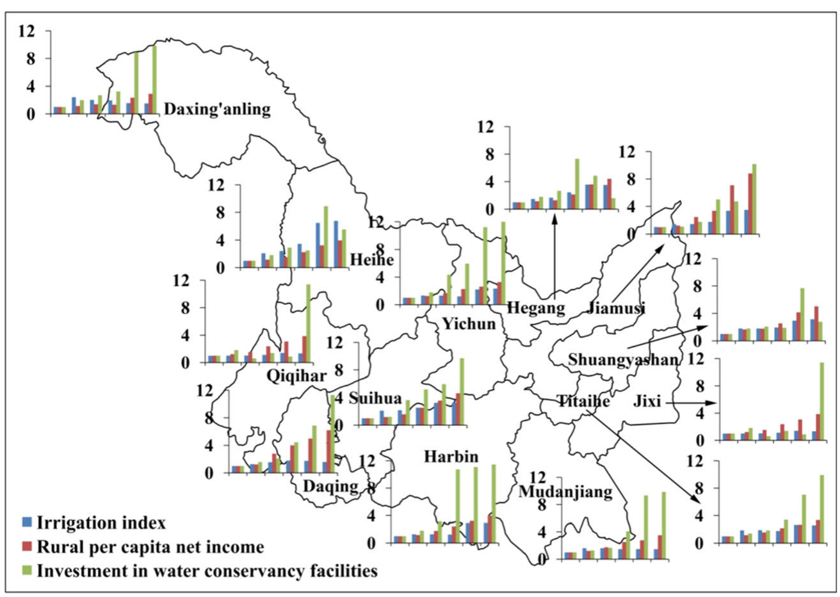


Fig. 7 Temporal variation of the irrigation index, rural per capita net income, and investment in water conservancy facilities

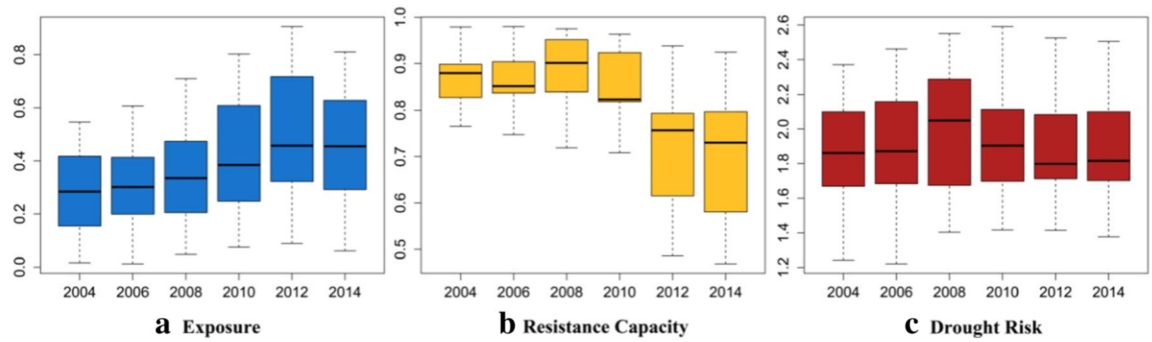


Fig. 8 Boxplot of the exposure, resistance capacity, and drought risk for each year: **a** exposure, **b** resistance capacity, and **c** drought risk

dependence of the regional economy on agriculture, which would help avoid the risk of agricultural drought hazards.

3. The deep processing of agricultural products should be promoted, and the added value of agricultural products should be improved. The economic value of agricultural raw materials is often low, and the added value of finished or semi-finished products is often higher. Heilongjiang Province should take advantage of its raw materials to actively promote the development of the agricultural product processing industry and establish a regional brand. This will also change the region's economic structure and improve the region's ability to resist drought damage.
4. Investments in irrigation and water conservancy facilities should be increased, and the water use efficiency should be improved. The flat terrain in Heilongjiang Province is conducive to the construction of irrigation and water conservancy facilities, and this geographical advantage should be exploited in Heilongjiang Province to increase the irrigation area, improve the irrigation methods, improve the water use efficiency, and reduce the risk of regional agricultural droughts. For example, modern irrigation methods (drip irrigation, infiltration irrigation, and sprinkle irrigation) should replace traditional irrigation methods (furrow irrigation, flood irrigation, and canal irrigation).

6 Conclusions

This paper combines a clustering analysis with the Friedman projection pursuit model to improve the projection pursuit model. The improved model was applied in a risk analysis of the agricultural drought hazard in Heilongjiang Province, and the spatial differences and change trends of the agricultural drought risk in Heilongjiang Province were analyzed from a spatial and temporal perspective. The conclusions are listed as follows.

1. In this study, the overall dispersion and local aggregation of projection points were based on research by Friedman and Turkey (1974). The variance S_z was used to measure the degree of scatter of the projected points, and the improved local density D_z was used to measure the degree of local aggregation. Cluster analysis was used to construct the local density D_z. The high-dimensional samples were classified by *k*-means clustering. The clustering results are represented by the clustering matrix, and the local density D_z is constructed based on the clustering matrix. The method avoids the problem of determining the cutoff radius. An improved projection pursuit model was proposed that combines cluster analysis and the projection pursuit model, which offer advantages for classification and assessment, respectively. The improved model enriches the theory of projection pursuit and has theoretical significance.
2. A spatial analysis of the drought hazard indicated that the hazard level in Daqing, Harbin, Qigihar, and Heihe was higher relative to Yichun, Hegang, Daxing'anling, Shuangyashan, and the remaining regions, and the main reason for these differences was the difference in regional precipitation and total water resources. The trend analysis indicated that the overall hazard level in Heilongjiang Province was higher than that of the whole country, and the regularity of the hazard pattern was not obvious.
3. A spatial analysis of the exposure levels indicated that Suihua, Qigihar, Daqing, Jiamusi, and Harbin had a relatively high degree of exposure and Daxing'anling and Yichun had a relatively low degree. The main reason for these differences was the different proportion of cultivated land in these regions. A trend analysis indicated that the exposure of each area presented an increasing trend.
4. A spatial difference analysis of the sensitivity levels indicated that Suihua, Qiqihar, and Harbin had higher levels and Daxing'anling and Yichun had lower levels. The main reason for these differences was the agricultural population and GDP. A trend analysis indicated that the sensitivity changes in the various regions are not obvious.
5. A spatial difference analysis of the resistance capacity indicated that Qiqihar, Daqing, Harbin, and Qitaihe had a stronger capacity than Heihe, Suihua, Yichun, Jiamusi, and Daxing'anling. The main reasons for these

differences were differences in agricultural water conservancy facility investments and water resource utilization efficiencies, which were related to differences in the economic development of the different regions. A trend analysis indicated that the resistance capacity of all regions has improved, and the construction of agricultural water conservancy facilities has increased; consequently, the water resource utilization efficiency has significantly improved.

6. A spatial difference analysis of the comprehensive drought risk indicated that Suihua, Qigihar, Daqing, Harbin, and Jiamusi had a higher risk, and Yichun, Hegang, Mudanjiang, and Daxing'anling had a lower risk. A trend analysis indicated that the overall risk in Heilongjiang Province was higher than the national trend, and the drought risk in various regions exhibited an initially increasing trend followed by a decreasing trend. This trend was caused by the exposure and resistance capacity levels.

Acknowledgements The authors thank the National Natural Science Foundation of China (Nos. 51279031, 51479032, 51579044), the Province Natural Science Foundation of Heilongjiang (No. E201241), the Yangtze River Scholars Support Program of Colleges and Universities in Heilongjiang Province, the Heilongjiang Province Water Conservancy Science and Technology project (Nos. 201318, 201503), and the Prominent Young Person of Heilongjiang Province (No. JC201402).

References

Chen P, Chen XL (2011) Evaluating drought vulnerability of agricultural system in Poyang Lake ecological economic zone, China. Trans CSAE 27:8–13 (in Chinese)

Duan K, Xiao W, Mei Y, Liu D (2014) Multi-scale analysis of meteorological drought risks based on a Bayesian interpolation approach in Huai River basin, China. Stochast Environ Res Risk Assess 28: 1985–1998. doi:10.1007/s00477-014-0877-4

Dutta D, Kundu A, Patel NR, Saha SK, Siddiqui AR (2015) Assessment of agricultural drought in Rajasthan (India) using remote sensing derived Vegetation Condition Index (VCI) and Standardized Precipitation Index (SPI). Egypt J Remote Sens Space Sci 18:53–63. doi:10.1016/j.ejrs.2015.03.006

Fei ZY, Zhou YL, Jin JL, Jiang SM (2013) Construction of evaluation index system and model for regional drought resistance ability. J Catastrophol 28:197–204 (in Chinese)

Feng YX, Gao YC, Song X, Tan J-R (2013) Equilibrium design based on design thinking solving: an integrated multicriteria decision-making methodology. Adv Mech Eng 5:953–956. doi:10.1155/2013/125291

Fontaine MM, Steinemann AC (2009) Assessing vulnerability to natural hazards: impact-based method and application to drought in Washington state. Nat Hazards Rev 10:11–18. doi:10.1061/(ASCE)1527-6988(2009)10:1(11)

Friedman JH, Turkey JW (1974) A projection pursuit algorithm for exploratory data analysis. IEEE Trans Comput 23:881–890

Han LY, Zhang Q, Ma PL, Jia JY, Wang JS (2016) The spatial distribution characteristics of a comprehensive drought risk index in southwestern china and underlying causes. Theor Appl Climatol 124:517–528. doi:10.1007/s00704-015-1432-z

Hernandez EA, Uddameri V (2014) Standardized precipitation evaporation index (SPEI)-based drought assessment in semi-arid south Texas. Environ Earth Sci 71:2491–2501. doi:10.1007/s12665-013-2897-7

Huang H, Lu J (2014) Identification of river water pollution characteristics based on projection pursuit and factor analysis. Environ Earth Sci 72:3409–3417. doi:10.1007/s12665-014-3247-0

Huang S, Huang Q, Chang J, Chen Y, Xing L, Xie Y (2015) Copulas-based drought evolution characteristics and risk evaluation in a typical arid and semi-arid region. Water Resour Manag 29:1489–1503. doi:10.1007/s11269-014-0889-3

Jin JL, Hong TQ, Wei YM (2007) Projection pursuit based correspondence factor analysis method of watershed non-point source pollutio. J Hydraul Eng 38:1032–1037 (in Chinese)

Jin JL, Li JQ, Zhou YL, Fei ZY, Jiang SM, Yuan XC, He J (2014) Research on the theoretical framework of drought risk assessment. J Catastrophol 29:1–10 (in Chinese)

Kim H, Park J, Yoo J, Kim T (2015) Assessment of drought hazard, vulnerability, and risk: a case study for administrative districts in South Korea. J Hydro-Environ Res 9:28–35. doi:10.1016/j.jher.2013.07.003

Li H, Li J, Kang F (2013) Application of the artificial bee colony algorithm-based projection pursuit method in statistical rock mass stability estimation. Environ Earth Sci 68:2337–2345. doi:10.1007/s12665-012-1912-8

Li Q, Li P, Li H, Yu M (2015a) Drought assessment using a multivariate drought index in the Luanhe River basin of Northern China. Stochast Environ Res Risk Assess 29:1509–1520. doi:10.1007/s00477-014-0982-4

Li Y, Gu W, Cui W, Chang Z, Xu Y (2015b) Exploration of copula function use in crop meteorological drought risk analysis: a case study of winter wheat in Beijing, China. Nat Hazards 77:1289–1303. doi:10.1007/s11069-015-1649-2

Liu X, Wang Y, Peng J, Braimoh AK, Yin H (2013) Assessing vulnerability to drought based on exposure, sensitivity and adaptive capacity: a case study in middle Inner Mongolia of China. Chin Geogr Sci 23:13–25. doi:10.1007/s11769-012-0583-4

Ma Y, Zhao Y, Wu L, He Y, Yang XS (2015) Navigability analysis of magnetic map with projecting pursuit-based selection method by using firefly algorithm. Neurocomputing 159:288–297. doi:10.1016/j.neucom.2015.01.028

Masoudi M, Hakimi S (2014) A new model for vulnerability assessment of drought in Iran using Percent of Normal Precipitation Index (PNPI). Iran J Sci Technol Trans A Sci 38:435–440

Murthy CS, Laxman B, Sesha Sai MVR (2015) Geospatial analysis of agricultural drought vulnerability using a composite index based on exposure, sensitivity and adaptive capacity. Int J Disaster Risk Reduction 12:163–171. doi:10.1016/j.ijdrr.2015.01.004

Qin Y, Xu XY, Xu K, Li A, Yang D (2013) Fuzzy evaluation system of agriculture drought disaster risk and its application. Trans CSAE 29: 83–91 (in Chinese)

Qu Y, Gao H, Lü J, Su Z, Cheng X (2015) Agricultural drought disaster risk assessment in China based on the regional disaster system theory. J Hydraul Eng 46:908–917 (in Chinese)

Rajsekhar D, Singh VP, Mishra AK (2015) Multivariate drought index: an information theory based approach for integrated drought assessment. J Hydrol 526:164–182. doi:10.1016/j.jhydrol.2014.11.031

Safavi HR, Esfahani MK, Zamani AR (2014) Integrated index for assessment of vulnerability to drought, case study: Zayandehrood River Basin, Iran. Water Resour Manag 28:1671–1688. doi:10.1007/s11269-014-0576-4

Sehgal VK, Dhakar R (2016) Geospatial approach for assessment of biophysical vulnerability to agricultural drought and its intraseasonal variations. Environ Monit Assess 188:197. doi:10.1007/s10661-016-5187-5

Shahabfar A, Eitzinger J (2011) Agricultural drought monitoring in semi-arid and arid areas using MODIS data. J Agric Sci 149:403–414. doi:10.1017/S0021859610001309

Song G, Chen L (2012) Analysis and system construction of safety early warning for cultivated land resources in Heilongjiang Province. Trans CSAE 28:247–252 (in Chinese)

Tabari H, Nikbakht J, Hosseinzadeh Talaee P (2013) Hydrological drought assessment in northwestern Iran based on streamflow drought index (SDI). Water Resour Manag 27:137–151. doi:10.1007/s11269-012-0173-3

Wang S, Zhang X, Yang Z, Ding J, Shen Z (2006) Projection pursuit cluster model based on genetic algorithm and its application in karstic water pollution evaluation. Int J Environ Pollut 28:253–260. doi:10.1504/IJEP.2006.011210

Waseem M, Ajmal M, Kim T (2015) Development of a new composite drought index for multivariate drought assessment. J Hydrol 527:30–37. doi:10.1016/j.jhydrol.2015.04.044

Weng B, Zhang P, Li S (2015) Drought risk assessment in China with different spatial scales. Arab J Geosci 8:10193–10202. doi:10.1007/s12517-015-1938-9

Wilhite DA, Hayes MJ, Knutson C, Smith KH (2000) Planning for drought: moving from crisis to risk management. J Am Water Resources Assoc 36:697–710. doi:10.1111/j.1752-1688.2000.tb04299.x

Wu D, Yan D, Yang G, Wang X, Xiao W, Zhang H (2013) Assessment on agricultural drought vulnerability in the Yellow River basin based on a fuzzy clustering iterative model. Nat Hazards 67:919–936. doi:10.1007/s11069-013-0617-y

Xiao F, Chen J (2012) Fractal projection pursuit classification model applied to geochemical survey data. Comput Geosci 45:75–81. doi:10.1016/j.cageo.2011.10.019

Yuan X, Tang B, Wei Y, Liang X, Yu H, Jin J (2015a) China's regional drought risk under climate change: a two-stage process assessment approach. Nat Haz 76:667–684. doi:10.1007/s11069-014-1514-8

Yuan XC, Wang Q, Wang K, Wang B, Jin JL, Wei YM (2015b) China's regional vulnerability to drought and its mitigation strategies under climate change: data envelopment analysis and analytic hierarchy process integrated approach. Mitigation Adaptation Strateg Glob Change 20:341–359. doi:10.1007/s11027-013-9494-7

Yun YR, Fang XQ, Wang Y, Tao JD, Qiao DF (2005) Main grain crops structural change and its climate background in Heilongjiang Province during the past two decades. J Nat Resour 2005:697–705 (in Chinese)

Zhang JJ (2012) Risk assessment and spatial-temporal distribution haracteristics of flood and drought disasters in Henan Province. Trans CSAE 28:98–106 (in Chinese)

Zhang D, Wang G, Zhou H (2011) Assessment on agricultural drought risk based on variable fuzzy sets model. Chin Geogr Sci 21:167–175. doi:10.1007/s11769-011-0456-2

Zhang B, Wu P, Zhao X, Wang Y, Gao X, Cao X (2013) A drought hazard assessment index based on the VIC–PDSI model and its application on the Loess Plateau, China. Theor Appl Climatol 114:125–138. doi:10.1007/s00704-012-0826-4

Zhang Q, Gu X, Singh VP, Kong D, Chen X (2015a) Spatiotemporal behavior of floods and droughts and their impacts on agriculture in China. Glob Planet Change 131:63–72. doi:10.1016/j.gloplacha.2015.05.007

Zhang D, Yan D, Lu F, Wang Y, Feng J (2015b) Copula-based risk assessment of drought in Yunnan Province, China. Nat Hazards 75:2199–2220. doi:10.1007/s11069-014-1419-6

Zhao J, Jin J, Zhang X, Chen Y (2012) Dynamic risk assessment model for water quality on projection pursuit cluster. Hydrol Res 43:798–807. doi:10.2166/nh.2012.095 (in Chinese)

Zhao J, Jin J, Guo Q, Liu L, Chen Y, Pan M (2014) Dynamic risk assessment model for flood disaster on a projection pursuit cluster and its application. Stochast Environ Res Risk Assess 28:2175–2183. doi:10.1007/s00477-014-0881-8