

Assessing agricultural drought vulnerability in the Sanjiang Plain based on an improved projection pursuit model

Wei Pei¹ · Qiang Fu^{1,2,3} · Dong Liu¹ · Tian-xiao Li¹ · Kun Cheng¹

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Abstract Drought is one of the main natural disasters affecting regional agriculture, and regional agricultural drought vulnerability assessment is necessary to establish regional drought forecast, monitoring, and early warning mechanisms. The results can provide a theoretical basis for the identification of drought hazard and disaster prevention. In this study, the concept of the overall dispersion and local aggregation of projection points was proposed by Friedman and Tukey (IEEE Trans Comput 23:881–890, 1974), and improvements to the projection pursuit model are proposed here by measuring discrete projection points according to the information entropy. This improved model was applied to assess the agricultural drought vulnerability of 18 counties located in the Sanjiang Plain for 4 years (2004, 2007, 2010, and 2013). Information entropy was shown to provide improved measurements in the data discreteness relative to standard deviations, and the cutoff radius was defined between 0 and $\ln 2$, thus allowing the use of the exhaustion method to determine the cutoff radius. The overall agricultural drought vulnerability in the Sanjiang Plain area shows a downward trend over time. The main reason for this result is the reduced regional sensitivity and the increased drought resistance ability each year. Economic development speeds up the urbanization process, decreasing the proportion of agricultural population and the proportion of agricultural GDP each year and increasing the irrigation index, per capita GDP, rural per capita net income and other indicators each year. These developments decrease the sensitivity of the agricultural system, improve the adaptive capacity, and reduce the vulnerability. Spatially, the vulnerability of various regions shows some differences. The vulnerabilities of Hulin, Luobei, Youyi, and Fuyuan

✉ Qiang Fu
fuqiang0629@126.com

¹ School of Water Conservancy and 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

are the lowest and showed a downward trend over time. The sensitivities of these regions were also low; the population density, the proportion of agricultural population and other sensitive indicators were significantly smaller than those for other regions. Furthermore, the drought threat is small, the region has many state-owned farms, the economic situation is good, and the drought resistance ability is strong. The vulnerabilities of Baoqing, Muling, Raohe, and Tongjiang are moderate, with high sensitivities but strong adaptive capacity. The vulnerabilities of Yilan, Jidong, Mishan, Fujin, and Boli have changed greatly, mainly due to the rapid economic development in recent years, increasing the agricultural drought resistance. The vulnerabilities of Tangyuan, Suibin, Jixian, Huachuan, and Huanan are the highest, and with little change, these regions are highly sensitive and prone to drought. In addition, the regional economic development level is relatively low, and the agricultural drought resistance is not high.

Keywords Projection pursuit · Information entropy · Agricultural drought · Vulnerability assessment · Sanjiang Plain

1 Introduction

Agriculture relies on natural resources such as land resources, water resources, and climate resources. Therefore, agriculture can be seriously affected by drought, floods, hail, and other natural disasters. Among such disasters, drought is one of the most serious and has the potential to cause enormous economic losses. Many factors, including climate change, natural and geographical factors, and human activities, can affect drought. Agricultural drought vulnerability refers to the nature and state of agricultural production systems that contribute to their likelihood of experiencing drought and loss, especially potential losses that may occur (Chen and Chen 2011; Fontaine and Steinemann 2009). Vulnerability assessment involves many uncertain factors, including regional resources and environmental conditions, economic levels, water conservancy facilities, agricultural technologies and management levels, and population quality (Wu et al. 2013). In recent years, global warming has accelerated, and the frequency and destructive degree of droughts have also shown increasing trends. Droughts may even occur in water-rich areas due to occasional climate anomalies. Drought is the result of the combined effects of disaster factors and vulnerability. Disaster factors are the factors that contribute directly to drought, and vulnerability is the root cause of a drought. China is a drought-prone country, and in 2014 alone, 0.34 billion acres were considered national disaster areas; the direct economic losses reached 91 billion RMB yuan. The lack of drought predictions, early warning and other related management tools led to serious economic losses in certain areas. Assessing agricultural drought vulnerability facilitates in-depth analyses of the factors that affect the drought, including climate, geography, and social economy, according to the likelihood of disaster. Such assessments allow drought vulnerability to be considered in natural resource planning. The evaluation results can be used as the basis for forecasting, monitoring, and early warning mechanisms; thus, they can provide a theoretical basis for evaluating drought risk and disaster prevention.

In recent years, a number of scholars have studied agricultural drought vulnerability and risk assessments from different perspectives. The fuzzy set theory, fuzzy comprehensive evaluation method, and fuzzy clustering iterative algorithm have been introduced to

evaluate agricultural drought vulnerability (Qiu et al. 2011; Wu et al. 2013; Zhang et al. 2011). A regional agricultural drought risk calculation method based on analytic hierarchy processing and fuzzy evaluations has also been presented (Qin et al. 2013). Based on probabilities and statistics, drought loss probability distributions and regression curves between drought loss and drought probability have been plotted (Xu et al. 2013). Empirical orthogonal function (EOF) and multivariate time series model have been proposed to analyze drought in both time and space (Kim et al. 2011). Based on the soil moisture probability density function (PDF), the statistics of the soil moisture condition and its monthly variation were used to assess drought vulnerability (Yoo et al. 2006). Additionally, the spatial characteristics of China's drought risk have been studied by applying natural disaster analysis theory to specific areas (He et al. 2012). This work revealed obvious differences in the agricultural drought risk in China. A spatial assessment model of the agricultural drought risk in the Jinghe River Basin was established with a precision of 1 km (Long et al. 2012). Indicators were selected from the exposure, sensitivity, and adaptability to the evaluation of regional drought vulnerability (Fontaine and Steinemann 2009; Liu et al. 2013; Murthy et al. 2015), and seasonal crop water deficiency, available soil water-holding capacity, and irrigation were identified as the main indicators of agricultural drought vulnerability (Wu et al. 2011). Furthermore, measures based on the quantitative drought hazard index (DHI) and drought vulnerability index (DVI) using hydro-meteorological and socioeconomic data have been proposed (Kim et al. 2015). The integrated drought vulnerability index (IDVI) has been devised as an indicator of vulnerability to drought (Jain et al. 2014). Based on the standardized precipitation index, drought hazard index, and composite drought vulnerability indices, the drought vulnerability of the Tarim River Basin has been studied (Zhang et al. 2014). The agricultural drought in Rajasthan (India) has been assessed using vegetation condition index (VCI) and standardized precipitation index (SPI) (Dutta et al. 2015). Spatially and temporally, the drought vulnerability of Turkey has been evaluated using the standardized precipitation index (Sonmez et al. 2005). Based on the principal component analysis, a new multivariate drought index (MDI) was formulated (Li et al. 2014). According to farmers in Iran, vulnerability is influenced by economic, sociocultural, psychological, technological and infrastructural factors, and the microscopic vulnerability of farmers is influenced by water conservation facilities and income levels (Yan et al. 2012; Zarafshani et al. 2012). This study used the Sanjiang Plain of China as an example and applied the improved projection pursuit model to evaluate regional agricultural drought vulnerability.

Projection pursuit is an effective statistical method that can manage high-dimensional nonlinear and non-normal data. In this method, a projection index that reflects the degree of data clustering projects high-dimensional data to a low-dimensional space, and the index is maximized or minimized to identify the structural features of the high-dimensional data (Kruskal 1969). The choice of projection index is a key step in the projection pursuit method. The difference between the data distribution and the Gaussian distribution is commonly used to define the projection index. For example, the product of total dispersion and local density can be used (Friedman and Tukey 1974), and the influence of outliers on the projection index has been analyzed (Friedman and Jerome 1987). Based on the polynomial asymptotic theory of the projection index, the distance between the density function and the standard normal can be used to measure the projection index (Hall 1989). Based on the work of Friedman, a projection index family has been proposed (Cook and Cabrera 1993). Within this family, the projection index proposed by Friedman and Tukey (1974) is commonly used (Jiang et al. 2006; Wang et al. 2003, 2006; Zhao et al. 2006). In recent years, a number of scholars have studied the projection pursuit proposed by

Friedman and Tukey (1974) from different perspectives. In solving the projection direction, numerous methods are introduced, such as genetic algorithm (GA), real-coded acceleration genetic algorithm (RAGA), chaos accelerating genetic algorithm (CAGA), colony algorithm, firefly algorithm, and simulated annealing algorithm (Feng et al. 2013; Li et al. 2012, 2013; Ma et al. 2015; Wang et al. 2006; Xiao and Chen 2012). Applications of the projection pursuit model include identification of river water pollution characteristics, dynamic risk assessment of flood disaster, optimal utilization of land resources, water quality assessment, and watershed non-point source pollution (Huang and Lu 2014; Jin et al. 2007; Wang et al. 2012; Zhao et al. 2012, 2014). However, the project pursuit of Friedman has certain disadvantages. First, standard deviations are not appropriate for measuring data on different scales. Second, the cutoff radius cannot easily be determined because a universally valid method has not been devised.

Based on the projection index proposed by Friedman and Tukey (1974) and according to the overall dispersion and local aggregation of projection points, this study uses information entropy to measure the data dispersion and determine the cutoff radiuses using the exhaustion method to propose a new projection index and improve the projection pursuit model. This model is then applied to assess the agricultural drought vulnerability of 18 counties located in the Sanjiang Plain. The spatial scale is 18 agricultural counties, and the temporal scale is 4 years (2004, 2007, 2010, and 2013). The relative vulnerability

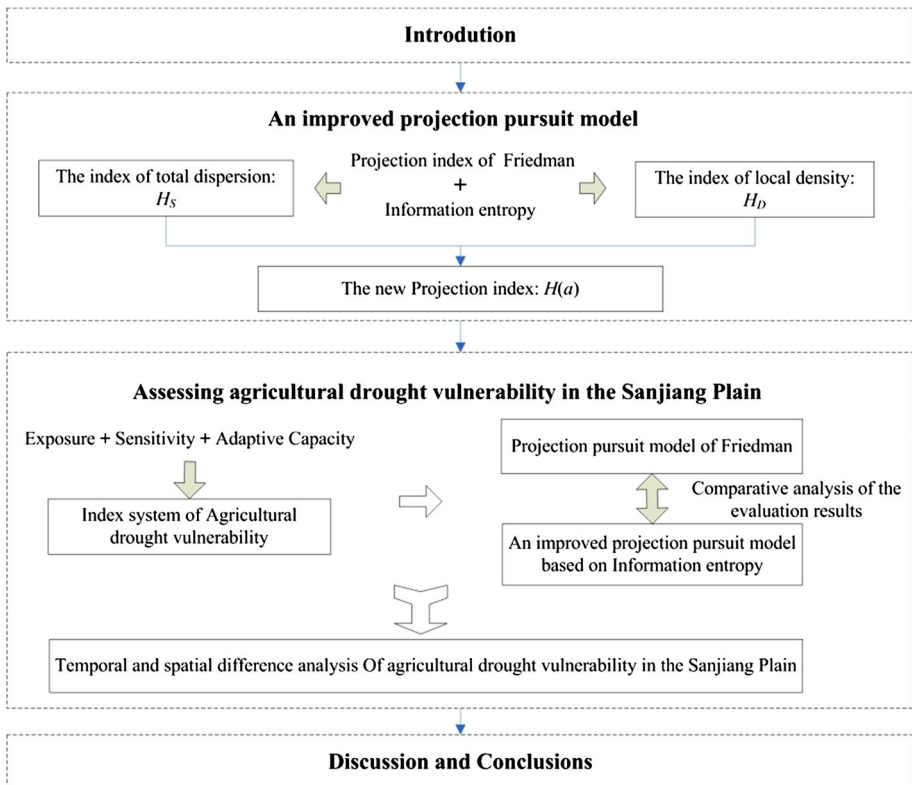


Fig. 1 Schematic diagram of the manuscript structure

values are given, and the reasons for the temporal and spatial differences are analyzed. Finally, policy recommendations are given, which serve as a guide to reduce losses resulting from regional agricultural drought and to improve early warning. The structure of this paper is shown in Fig. 1.

2 Modeling and analysis

2.1 Model concepts

The concept of information entropy was proposed by Shannon in his widely read article “A Mathematical Theory of Communication” in 1948 (Shannon 1948). This method of measuring the uncertainty and discreteness of data has been increasingly applied and has been shown to be useful.

In this study, we refer to the projection index developed by Friedman and Tukey (1974). Based on previous work, we measure the discreteness of data according to the information entropy and thereby propose an improved projection index (Fontaine and Steinemann 2009; Murthy et al. 2015; Wang et al. 2003, 2006).

2.2 Model steps

Step 1 Data normalization.

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

A high index value represents high vulnerability; namely, a large value of $x^*(i, j)$ represents high vulnerability:

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

A low index value represents high vulnerability; namely, a small value of $x^*(i, j)$ represents high vulnerability:

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

where $x_{\max}(j)$ and $x_{\min}(j)$ are the maximum and minimum values of the j th index, respectively, and $x(i, j)$ is the index after normalization, and larger normalized values mean more vulnerability.

Step 2 Projection index $H(a)$.

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

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

The distribution characteristics of $z(i)$ are that the local projection points are as dense as possible and condense into a number of clusters, which are dispersed as much as possible. The projection index is defined as follows:

$$H(a) = \frac{H_S}{H_D} \tag{4}$$

where $H_S = -\sum_{i=1}^n p(i) \ln p(i)$ and $p(i) = \frac{z(i)}{\sum_{j=1}^n z(j)}$. To ensure the maximum dispersion of clusters, H_S should be as small as possible, where $H_D = \sum_{i=1}^n \sum_{j=1}^n (H(i,j) - R) \cdot u(H(i,j) - R)$, $H(i, j) = -q(i) \ln q(i) - q(j) \ln q(j)$, $q(i) = \frac{z(i)}{z(i)+z(j)}$ and $q(j) = \frac{z(j)}{z(i)+z(j)}$. To ensure local aggregation, H_D should be as large as possible.

$u(H(i, j) - R)$ is a unit step function:

$$u(H(i,j) - R) = \begin{cases} 1, & H(i,j) \geq R \\ 0, & H(i,j) < R \end{cases} \tag{5}$$

and R is the cutoff radius. If R is too large, $H(i, j) - R < 0$ and $u(H(i, j) - R) = 0$ for too many projection points; thus, the range will be too narrow, and the projection points in the cluster will be too few. In addition, if R is too small, $H(i, j) - R \geq 0$ and $u(H(i, j) - R) = 1$ for too many projection points; thus, the range will be too wide, and too many projection points will be included in the cluster. According to the nature of information entropy (Shannon 1948), $H(i, j) \in [0, \ln 2]$. For projection points within a cluster, $H(i, j) - R \geq 0$, whereas for projection points between clusters, $H(i, j) - R < 0$. Therefore, R cannot be less than the minimum value of $H(i, j)$. And R is no greater than the maximum value of $H(i, j)$. Therefore, $R \in (0, \ln 2)$, and R can be determined by the exhaustion method.

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

Based on the overall dispersion and local aggregation of projection points, the value of $H(a)$ should be as small as possible.

$$\min H(a) = \frac{H_S}{H_D}, \quad \text{s.t.} \quad \sum_{j=1}^p a^2(j) = 1 \tag{6}$$

The above expression is a nonlinear constrained optimization problem and can be solved by a real-coded genetic algorithm (RGA).

Step 4 Classification evaluation.

If the classification standard is $\{y(l, j) | l = 1, 2, \dots, m - 1; j = 1, 2, \dots, p\}$, where $y(l, j)$ is the normalized l th boundary value of the j th index, and $y(1, j) < y(2, j) < \dots < y(m - 1, j)$, and this standard is combined with the optimal projection direction $a^* = \{a^*(1), a^*(2), \dots, a^*(p)\}$, then the final classification boundary can be obtained:

$$s^*(l) = \sum_{j=1}^p a^*(j)y(l,j) \quad (l = 1, 2, \dots, m - 1) \tag{7}$$

The projection values for each sample are $z^*(i) = \sum_{j=1}^p a^*(j)x(i,j) \quad (i = 1, 2, \dots, n)$. If $z^*(i) < s^*(1)$, the grade is 1; if $s^*(l - 1) \leq z^*(i) < s^*(l)$, the grade is $l \ (l = 2, 3, \dots, m - 1)$; and if $z^*(i) \geq s^*(m - 1)$, the grade is m .

2.3 Theoretical analysis

In this study, the improved method was compared to the Friedman–Tukey projection index, and the most substantial difference was in the method of measuring the data dispersion. The Friedman–Tukey projection index uses standard deviations to measure the degree of dispersion, whereas the improved method uses information entropy. Both information entropy and standard deviations are capable of describing discrete degrees. However, because the standard deviation reflects the average distance between a set of data and its mean, when the mean or order of two groups is not equivalent, it cannot be used to compare the two data sets. Conversely, information entropy has no fixed reference point and instead represents the average distance between the data and a uniform distribution; thus, it is not affected by the mean and data order (Ebrahimi et al. 1999). Standard deviations only reflect the characteristics of the second-order central moment, whereas information entropy can reflect multi-order data. Thus, the latter can better describe the discreteness of data (Ebrahimiet et al. 1999). In addition, when the probability distribution of the raw data is not known, information entropy is more suitable than standard deviations to measure the uncertainty (Maasoumi and Racine 2002). Furthermore, from a local perspective, the Friedman–Tukey projection index uses $r(i, j)$ to describe the local degree of aggregation, whereas $H(i, j)$ is used in the improved method. The disadvantage of $r(i, j)$ is its large range: $r(i, j) \in [0, +\infty)$. However, because $H(i, j) \in [0, \ln 2], R \in (0, \ln 2)$ can be obtained. Thus, information entropy is better able to overcome the range disadvantage and allows for the exhaustion method to be used to determine the cutoff radius.

3 Assessing agricultural drought vulnerability in the Sanjiang Plain

3.1 Study area and data sources

The Sanjiang Plain is situated in northeast Heilongjiang Province in China and is formed by the confluence and alluvial plains of the Heilongjiang, Wusuli, and Songhua rivers, encompassing a total area of 108,900 km². The administrative region consists of 5 prefecture-level cities and 18 counties. The Sanjiang Plain is rich in cultivated land resources, wetland resources, and forest resources; this area is an important food-producing region in China with a regional economy that is strongly dependent on agriculture. Since the 1950s, the wetland and forest areas of the Sanjiang Plain have gradually decreased because of overexploitation, and the cultivated land area has increased rapidly. Since 1960, the forest area has decreased from approximately 48,000 km² to approximately 38,000 km², the wetland area has decreased from approximately 50,000 km² to approximately 15,000 km², and the cultivated land area has increased from approximately 7000 km² to approximately 50,000 km². The reductions in forest and wetland resources have resulted in decreased water and soil conservation, serious water losses, and soil erosion. However, the increased

cultivated land area requires large amounts of water resources. Because of climate change, the temperature increases annually, and the distribution of rainfall is spatially and temporally uneven. Comprehensive factors suggest that the possibility of agricultural drought is elevated in this region. Traditional wetting areas are under a potential threat of drought, and the ecological security and sustainable social and economic development are seriously threatened.

Therefore, the study area was designed to include 18 counties that mainly include agricultural areas, and the 5 prefecture-level cities, which include less cultivated land and a low agricultural population, were excluded. Specifically, the research area included the following counties, as shown in Fig. 2: Yilan, Jidong, Hulin, Mishan, Luobei, Suibin, Jixian, Youyi, Baoqing, Raohe, Huanan, Huachuan, Tangyuan, Fuyuan, Tongjiang, Fujin, Boli, and Muling. The data were primarily collected from the statistical yearbook of Heilongjiang Province (2004, 2007, 2010, and 2014), the water conservancy yearbook of Heilongjiang (2004, 2007, 2010, and 2014), and the official Web sites of relevant departments.

3.2 Index system and evaluation standards

Selecting the indexes used to evaluate agricultural drought vulnerability is a primary step in evaluating regional agricultural drought vulnerability because the selected indexes must be appropriate and directly related to the evaluation results. Agricultural drought vulnerability is related to three aspects: exposure, sensitivity, and adaptive capacity. Exposure is based on frequency and severity of drought; sensitivity is the degree that is susceptible to drought stress, which emphasizes the potential for damage; and adaptive ability is the behavior of reducing the impact of drought. Exposure and sensitivity determine the potential impact. Adaptive capacity determines the portion of the potential impact that becomes an actual (net) impact (Fontaine and Steinemann 2009; Liu et al. 2013; Murthy et al. 2015), and based on the operability principle and system and regional characteristics,

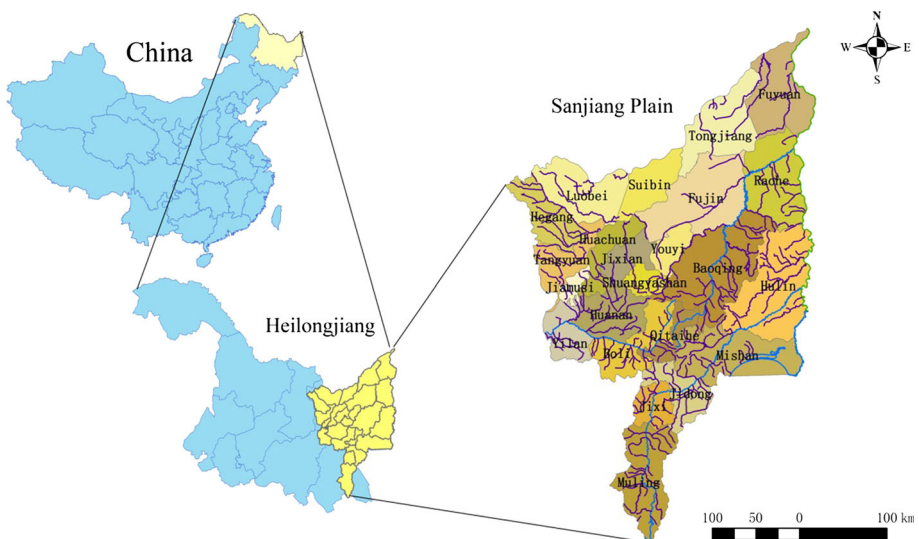


Fig. 2 Regional map of the Sanjiang Plain

12 indicators of the three aspects were selected (Table 1). Exposure is mainly related to the degree of drought; annual precipitation and forest coverage were selected. Sensitivity is concerned with the sensitive degree of the agricultural system structure and population structure. Population density, proportion of agricultural population, proportion of agricultural GDP, food yield per unit area and per capita arable land were selected. Adaptive capacity focuses on reducing the drought effect. The irrigation index, rural per capita net income, fertilizer scalar unit area, per capita GDP and agricultural machinery power per unit area were selected. Together, these factors reflect the disaster status and anti-disaster capability of the agricultural system. According to the classification method reported in relevant literature (Jiang et al. 2006; Liu et al. 2013) and the regional characteristics of the Sanjiang Plain, the indexes were divided into four relative grades. In this system, higher grades indicate increased vulnerability to agricultural drought, as shown in Table 1.

Annual precipitation (X_1) is one of the most important factors affecting the drought, and it is the main factor affecting the growth of crops. If precipitation is greater, the region will be less vulnerable to drought. The forest coverage (X_2) was calculated as the forest area/area, because forests contribute to water and soil conservation, and when the forest coverage is greater, the region will be less vulnerable. The population density (X_3) was calculated as the population/area, and thus, when the population density is higher, more people will be affected and the region will be more vulnerable. The proportion of the agricultural population (X_4) was calculated as the agricultural population/total population, because the agricultural population is more sensitive to drought than the urban population, and it is more susceptible to drought. When the proportion of agricultural population is higher, the region will be more vulnerable. The proportion of agricultural GDP (X_5) was calculated as the agricultural GDP/GDP, reflecting the degree of dependence on agriculture, because agriculture is the most vulnerable to drought; the higher the proportion is, the

Table 1 Evaluation indexes and relative grades of agricultural drought vulnerability in the Sanjiang Plain

Evaluation indexes (X_i)	I	II	III	IV
Exposure				
Annual precipitation (X_1) (ml)	>600	550–600	500–550	<500
Forest coverage (X_2) (%)	>45	30–45	15–30	<15
Sensitivity				
Population density (X_3) (person km ⁻²)	<40	40–60	60–80	>80
Proportion of agricultural population (X_4) (%)	<45	45–55	55–65	>65
Proportion of agricultural GDP (X_5) (%)	<25	25–40	40–55	>55
Food yield per unit area (X_6) (ton ha ⁻¹)	<3	3–4	4–5	>5
Per capita arable land (X_7) (ha person ⁻¹)	>0.6	0.45–0.6	0.3–0.45	<0.3
Adaptive capacity				
Irrigation index (X_8) (%)	>45	45–30	30–15	<15
Per capita GDP (X_9) (RMB yuan)	>26,000	18,000–26,000	10,000–18,000	<10,000
Rural per capita net income (X_{10}) (RMB yuan)	>8000	6000–8000	4000–6000	<2000
Fertilizer scalar unit area (X_{11}) (ton ha ⁻¹)	>0.15	0.1–0.15	0.05–0.1	<0.05
Agricultural machinery power per unit area (X_{12}) (kWh ha ⁻¹)	>3.5	2.5–3.5	1.5–2.5	<1.5

Table 2 Vulnerability assessment results for 18 counties in the Sanjiang Plain

Region	2004			2007			2010			2013		
	Evaluation value	Relative grade	Relative grade	Evaluation value	Relative grade	Relative grade	Evaluation value	Relative grade	Relative grade	Evaluation value	Relative grade	Relative grade
Hulin	1.7290	I	I	1.7252	I	I	1.5383	I	I	1.4266	I	I
Luobei	1.4914	I	I	1.5114	I	I	1.3142	I	I	1.2853	I	I
Youyi	1.6972	I	I	1.4294	I	I	1.4102	I	I	1.3014	I	I
Fuyuan	1.7814	II	II	1.6670	I	I	1.4638	I	I	1.3274	I	I
Baoqing	1.8933	III	III	1.8129	II	II	1.6247	I	I	1.4953	I	I
Muling	1.9838	III	III	1.9634	III	III	1.7303	I	I	1.4989	I	I
Raohu	1.8630	III	III	1.8262	II	II	1.8097	II	II	1.7230	I	I
Tongjiang	1.9537	III	III	1.8635	III	III	1.7986	II	II	1.7606	II	II
Yilan	2.0253	IV	IV	1.9816	III	III	1.8032	II	II	1.6538	I	I
Jidong	2.0317	IV	IV	1.9454	III	III	1.8168	II	II	1.6806	I	I
Mishan	1.9959	III	III	1.9596	III	III	1.8310	II	II	1.6573	I	I
Fujin	2.0079	III	III	1.9689	III	III	1.7519	II	II	1.6143	I	I
Boli	1.9672	III	III	2.0029	III	III	1.8270	II	II	1.7159	I	I
Tangyuan	2.0456	IV	IV	2.0279	III	III	1.9711	IV	IV	1.9637	III	III
Suibin	2.0282	IV	IV	2.0351	IV	IV	2.0221	IV	IV	2.0123	III	III
Jixian	2.3129	IV	IV	2.2428	IV	IV	2.0446	IV	IV	1.9335	III	III
Huanan	2.2410	IV	IV	2.2444	IV	IV	2.1859	IV	IV	2.0248	IV	IV
Huachuan	2.2407	IV	IV	2.2439	IV	IV	2.2144	IV	IV	2.0404	IV	IV

greater the potential loss is. Thus, when this proportion is higher, the region will be more dependent on agriculture, and the region will be more vulnerable. The food yield per unit area (X_6) was calculated as the food yield/area, and when the yield is higher, the potential losses will be greater. The per capita arable land (X_7) was calculated as the cultivated land area/population, and when the per capita arable land area is higher, the land pressure will be lower, and the region's vulnerability will be reduced. The irrigation index (X_8) was calculated as the irrigation area/cultivated area, water conservancy construction has a positive effect on drought resistance, and the degree of agricultural drought is closely related to the degree of water conservancy. This index reflects the drought resistance, and high values indicate low vulnerability. Per capita GDP (X_9) was calculated as GDP/total population, and this factor mainly reflects the level of social and economic development. A higher level of economic development means that there is more capacity to put into the drought, reducing the drought vulnerability. The rural per capita net income (X_{10}) reflects the capability of the region to reduce and recover from disasters, and when the income is higher, the vulnerability is lower. The fertilizer scalar unit area (X_{11}) was calculated as the total amount of fertilizer/cultivated area, because fertilization enhances soil fertility, and it also increases the grain yield and decreases the vulnerability. Agricultural machinery power per unit area (X_{12}) was calculated as agricultural machinery total power/cultivated area, mainly reflecting the level of mechanization in the region. A higher level of mechanization means that the water resources adjustment ability and the development and utilization efficiency are higher, and therefore, the vulnerability is lower.

To analyze the temporal and spatial differences of agricultural drought vulnerability in the Sanjiang Plain, we determined the causes of regional differences and the causes of the changes in vulnerability. Four years of data (2004, 2007, 2010, and 2013) were selected in this study. For each year, the data of 18 counties located in the Sanjiang Plain were selected for a total of 72 samples.

3.3 Model evaluation results and analysis

The data were normalized by substituting X_3 , X_4 , X_5 , and X_6 into Eq. (1) and X_1 , X_1 , X_8 , X_9 , X_{10} , X_{11} , and X_{12} into Eq. (2). After normalization, a higher value of a single index indicated greater vulnerability in the region.

3.3.1 Evaluation results

The following parameters were used to construct the model in this study using MATLAB software (Math Works, Natick, MA, USA) and the RGA of the genetic algorithm toolbox (Sheffield University, UK): The initial population is 20, the generation gap is 0.9, the crossover probability is 0.7, the variation probability is 0.1, and the iteration number is 200. The minimum values of the projection index were $H^*(a) = 5.3027$ and $R = 0.6925$. The optimal projection directions were $a^* = (0.0454, 0.1844, 0.3734, 0.2521, 0.1380, 0.2508, 0.2419, 0.0148, 0.4576, 0.5970, 0.0699, 0.2226)$. The final evaluation values are given in Table 2.

According to the classification standards listed in Table 1, taking the boundary values as samples, the samples were normalized using the primary data. Combined with the optimal projection directions a^* and by applying Eq. (7), three boundary points (2.0135, 1.8392, 1.7384) were obtained, and the counties were then divided into four grades (Table 2).

3.3.2 Comparative analysis of the evaluation results

In this study, the Friedman–Tukey projection index was used as a reference to illustrate the superiority of the improved model. Substituting all of the samples into the original model and taking 2013 as an example, the evaluation results of 2013 obtained using the Friedman–Tukey projection index are given in Table 3.

The evaluation results of the two models are similar, indicating the validity of the model proposed in this work. To quantitatively analyze the differences between the two models, we calculated the differences between the evaluation results and the uniform distribution. Here, the data sequence was as follows: $x = [x_1, x_2, \dots, x_n]$, $p = [p_1, p_2, \dots, p_n]$, where $p_i = x_i / \sum x_i$, the sequence of the uniform distribution is $y = [1/n, 1/n, \dots, 1/n]$, and the Euclidean distance is $T = \sum (x_i - 1/n)^2$. When the T value is larger, the difference between the data distribution and the uniform distribution is also larger, and the classification results are better. The T value of the Friedman–Tukey method was 0.0009, whereas the value obtained using the improved method was 0.0012. Thus, the results obtained using the proposed method were slightly better.

However, when $p = [p_1, p_2, \dots, p_n]$, $H = -\sum_{i=1}^n p_i \ln p_i$ can also be used to determine the data dispersion. In this case, when the H value is larger, the data are more uniform, and the classification results are worse. The H value of the Friedman–Tukey projection index was 2.8822, whereas that of the proposed method was 2.8796. Thus, the results obtained by the improved method were slightly better.

3.3.3 Spatial difference analysis of agricultural drought vulnerability

To directly determine the spatial differences of the agricultural drought vulnerability in the Sanjiang Plain, the visualization function of ArcGIS (Esri, Redlands, CA, USA) was used to map the spatial distribution of the vulnerability level (Fig. 3).

Table 3 Evaluation results of the Friedman–Tukey projection index (2013)

Region	Hulin	Luobei	Youyi	Fuyuan	Baoqing	Muling	Raohe	Tongjiang	Yilan
Evaluation value	1.4875	1.3214	1.4015	1.4178	1.5047	1.5047	1.8475	1.8470	1.7485
Region	Jidong	Mishan	Fujin	Boli	Tangyuan	Suibin	Jixian	Huanan	Huachuan
Evaluation value	1.6475	1.7548	1.6245	1.6574	1.8045	1.8907	1.8475	2.1245	2.0147

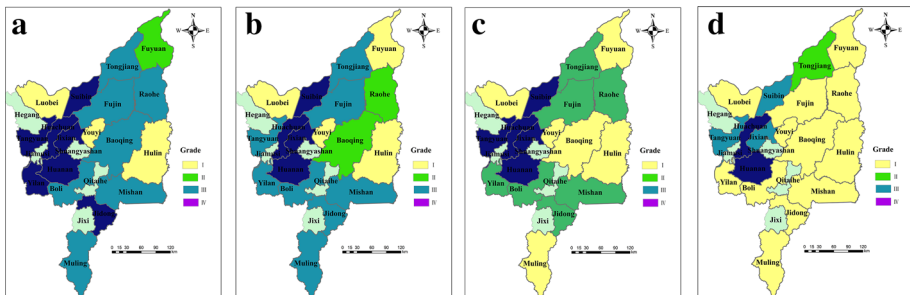


Fig. 3 Spatial distribution of the agricultural drought vulnerability in the Sanjiang Plain **a** 2004, **b** 2007, **c** 2010, and **d** 2013

Figure 3 shows that the vulnerability of agricultural drought in the Sanjiang Plain has gradually decreased overall from 2004 to 2013. The regions that belong to grade IV decreased from 7 to 2, and the regions that belong to grade I increased from 3 to 12. Table 3 shows that mean value of all of the regions was 1.9575 in 2004 and 1.6741 in 2013, so the mean of the grade decreased from 2.94 to 1.78. The agricultural drought vulnerability in the Sanjiang Plain has a downward trend overtime. In exposure, forest cover showed an increasing trend, mainly due to the increasing emphasis on the role of ecological environment at all levels of government. Planting trees, returning farmland to forests and other measures to build forest cover in the Sanjiang Plain increased from 28.35 to 30.1 % in 10 years. In sensitivity, with rapid socioeconomic development and an accelerating urbanization process, the proportion of agricultural population decreased from 54.6 to 51.12 % in 10 years. In adaptive capacity, the reduction in regional drought vulnerability is mainly due to the improvements in drought resistance ability. Irrigation and water conservancy facilities gradually improved, and the irrigation area increased each year. The irrigation index increased from 22 to 46 % in 10 years, and the drought resistance increased significantly. In addition, similar to the Chinese economy, the regional economy developed quickly; the per capita GDP increased from 8303 RMB yuan to 34,616 RMB yuan over 10 years, and the rural per capita net income increased from 2385 RMB yuan to 8367 RMB yuan. Economic development determines the increase in anti-disaster investment. Finally, the efficiency of regional land use also improved. The fertilizer scalar unit area increased from 0.16 to 0.92 tons. The increase in soil fertility was within a reasonable range, and the grain yield was increased, decreasing the vulnerability.

From the local perspective, although the vulnerability of various regions showed a downward trend overtime, obvious differences were shown between regions. Hulin, Luobei, Youyi, and Fuyuan are the least vulnerable areas and are classified as grade I (in addition to Fuyuan, grade II in 2004). The evaluation of the four regions is shown in Fig. 4.

Figure 4 shows that the vulnerability of four regions generally has a downward trend. Among them, the vulnerability of Luobei is lower than that of the other regions. Taking 2013 as an example, the population density of Luobei is 32.87 person km⁻², the mean proportion of agricultural population is 21.5 %, and the mean values of these two factors for all 18 counties are 61.7 person km⁻² and 51.6 %, so the sensitivity is lower. In addition, the forest coverage in Luobei reached 67.9 %, which was the highest in the whole Sanjiang Plain. In adaptive capacity, the irrigation index in the Luobei area was 78.8 %, higher than the mean value of 46.16 %. The regional economy is more developed, and the rural per capita net income reached 12,710 RMB yuan, higher than the regional average of 8637 RMB yuan. From the perspective of time, the vulnerability of Luobei also showed a trend of slow decline, mainly because the regional disaster mitigation ability was enhanced. In 10 years, the irrigation index increased from 32.4 to 78.8 %, the per capita

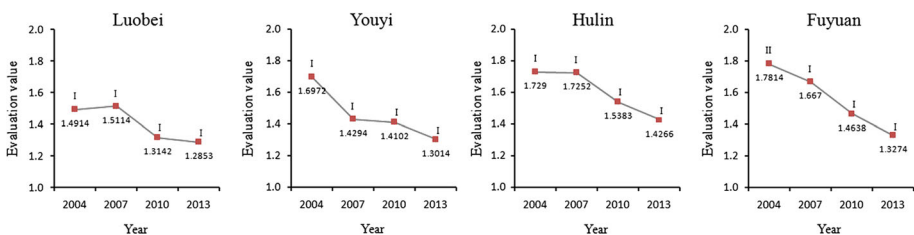


Fig. 4 Vulnerability changes over time (Luobei, Youyi, Hulin, and Fuyuan)

income of farmers increased from 4041 RMB yuan to 12,710 RMB yuan, and the per capita GDP increased from 12,717 RMB yuan to 36,310 RMB yuan. The vulnerability of Youyi is also at a low level. Youyi is less dependent on agriculture. The mean value of the proportion of agricultural GDP for 4 years is 36.18 % with a downward trend each year. The mean value of the proportion of agricultural population for 4 years is 13.23 %, far lower than the regional average. The vulnerability of Youyi also showed a downward trend over time because the adaptive capacity increased. The irrigation index and rural per capita net income also increased. Hulin's vulnerability is slightly higher than that of Luobei and Youyi but is also located in the lower level. In 2013, for example, the region had a low sensitivity. The population density was 30.75 person km⁻², and the proportion of agricultural population was 33.1 %, located in the lower level. Simultaneously, the regional resilience is strong. The irrigation index increased from 25.7 to 56.2 %, and the net income of farmers increased from 2140 RMB yuan to 10,323 RMB yuan. Fuyuan is a county with a large change in vulnerability in four regions. The vulnerability evaluation value decreased from 1.7814 to 1.3274 in 10 years. The proportion of agricultural population decreased from 59.77 to 39.5 %, and the sensitivity was lower. The forest cover was high and the mean value was 60 %. The regional irrigation index increased from 31.4 to 71.3 %. These are the main factors that reduce the vulnerability of the region.

Compared to other regions, the vulnerability of Hulin, Luobei, Youyi, and Fuyuan was lower, mainly because those regions have larger areas with less population, so the sensitivity to drought is lower. The regional economic level is relatively good, with 17 state-owned farms in the region, and the drought resistance of the state-owned farms is significantly higher than the general area.

The vulnerability of Baoqing, Muling, Raohe, and Tongjiang is moderate, showing a downward trend with time, as shown in Fig. 5.

The vulnerabilities of Baoqing and Muling are low and vary with time. The two regions fell from grade III to grade I, significantly reducing the vulnerability. In sensitivity, the average proportion of agricultural population in the two regions in 2004 was 60.11 %, and the value was 49.8 % in 2013. In adaptive capacity, the average irrigation index of the two regions rose from 12.75 to 28.8 %, and the mean values of the rural per capita net income and per capita GDP increased from 3325 RMB yuan and 9422 RMB yuan to 12,616 RMB yuan and 52,301 RMB yuan, respectively. The adaptive capacity was enhanced significantly. Raohe and Tongjiang are moderate vulnerabilities and show a more relaxed downward trend with time. The two regions are more dependent on agriculture. The proportions of agricultural GDP of the two regions are 74.3 and 68.9 %, respectively, but the population density of the region is relatively low at 21.4 and 27.97 person km⁻², respectively. The sensitivity is moderate. The adaptability of the two regions has increased

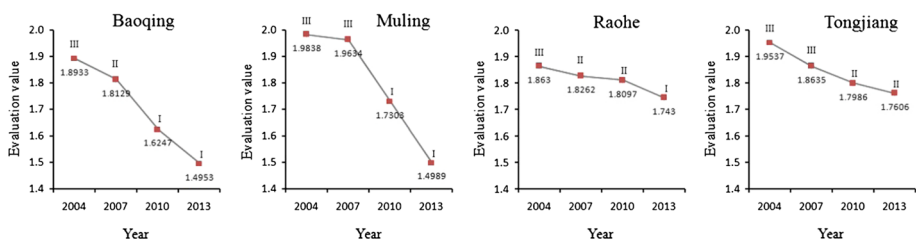


Fig. 5 Vulnerability changes over time (Baoqing, Muling, Raohe, and Tongjiang)

over time, in 10 years, the average irrigation index rose from 33.55 to 64.8 %, and the average per capita GDP increased from 6841 RMB yuan to 43,574 RMB yuan.

The vulnerability of Yilan, Jidong, Mishan, Fujin, and Boli has changed with the time, as shown in Fig. 6.

The vulnerability obviously changed in Yilan and Jidong; this decline is mainly reflected in the resilience of the region. The irrigation index of Yilan was 9.8, 13.15, 17.14, and 16.07 % in 2004, 2007, 2010, and 2013, respectively. The irrigation index of Jidong was 11.2, 17.5, 19.5, and 26.5 % in 2004, 2007, 2010, and 2013, respectively. The two regions significantly improved. The mean value of rural per capita net income in the two regions was 3486 RMB yuan, 4922 RMB yuan, 8249 RMB yuan and 11,869 RMB yuan for 4 years and indicates that the disaster investment capacity was significantly enhanced. Mishan, Fujin, and Boli’s vulnerability also obviously changed, dropping from grade III to grade I because rapid economic development continuously improved adaptability. The mean value of the irrigation index increased from 18.83 to 31.8 % in those regions. The rural per capita net income increased from 3172 RMB yuan to 11,346 RMB yuan, and the per capita GDP increased from 8280 RMB yuan to 30,014 RMB yuan. The anti-disaster investment ability was obviously enhanced.

The vulnerability grades of Tangyuan, Suibin, Jixian, Huanan, and Huachuan were higher and less variable, indicating that these regions are vulnerable to drought threat, as shown in Fig. 7.

The vulnerability of Suibin and Tangyuan has small changes with time, showing a slight downward trend. The rural per capita net income and per capita GDP increased, easing the vulnerability area to a certain extent, but proportion of agricultural GDP is relatively high. Jixian’s vulnerability level is also higher, showing a clear downward trend overtime, mostly because the economy has been greatly developed, enhancing the adaptability. The vulnerability of Huanan and Huachuan changes significantly over time, but the grades of the two regions are still the highest. Taking 2013 as an example, the mean population density in the two regions is 95.72 person km⁻², and the mean proportion of agricultural population is 71.7 %. A comparison showed that the mean values of these three factors for

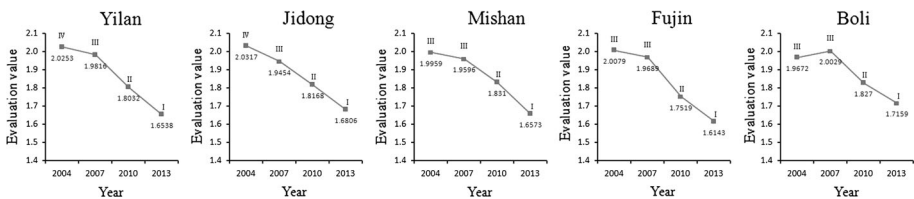


Fig. 6 Vulnerability changes over time (Yilan, Jidong, Mishan, Fujin, and Boli)

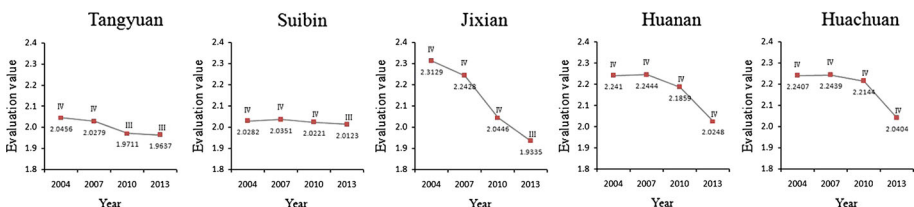


Fig. 7 Vulnerability changes over time (Tangyuan, Suibin, Jixian, Huanan, and Huachuan)

all 18 counties are 61.7 person km⁻² and 51.16 %. Regarding adaptive capacity, the forest coverage value of Huachuan and Huannan is 6.6 and 17.3 %, respectively. Because the forestry coverage is low, the water conservation in these counties is poor and their ability to resist drought is poor. Fewer state-owned farms are in these regions, the drought resistance is less, the irrigation area is insufficient, and the mean irrigation index is 30.2 %. The rural per capita net income is low, with an average of 3659 RMB yuan, much lower than the overall average of 8637 RMB yuan. Thus, the area is vulnerable to drought, and if a drought were to occur, the recovery ability would be poor.

4 Discussion

The above analysis revealed the sensitivity factors and adaptive capacity factors that determine the differences in the regional drought vulnerability. The main sensitivity factors are the proportion of agricultural population and the proportion of agricultural GDP. The Sanjiang Plain is the main grain-producing region in China, and the regional economy is strongly dependent on agriculture. As a result, when drought occurs, the potential losses in this region are relatively serious. The main adaptive capacity factors that contribute to reducing the drought vulnerability include the irrigation index and the rural per capita net income. The irrigation index reflects a region's ability to resist drought, whereas the rural per capita net income is an important indicator of regional agricultural economic development. The agricultural economic level is strongly related to the degree of regional drought vulnerability, and the capacity and potential for disaster reduction are substantially influenced by the agricultural economy.

According to the regional characteristics of the Sanjiang Plain, for the regions with high vulnerability, some suggestions are as follows:

- (1) Reduce the proportion of agricultural population and speed up the process of urbanization. The Sanjiang Plain is mainly based on agriculture, and the proportion of agricultural population is high. A high proportion of agricultural population is one of the reasons for the high vulnerability.
- (2) Develop economic diversification and reduce the proportion of agricultural GDP. The economic dependence on agriculture in Sanjiang Plain is more serious, and agriculture is susceptible to drought. The region should focus on the development of other industries, developing diversified regional economic structure. Diversification of the economy can reduce the risk of drought to a certain extent.
- (3) Take measures adapted to local conditions to cultivate more high economic crop benefits. At present, the main crop in Sanjiang Plain is corn with a single planting structure, and the economic benefit is not high. The region can be based on their own land characteristics, planting more economic crops, such as soybeans, rapeseed, and high-quality rice.
- (4) Promote deep processing of agricultural products and increase the added value of agricultural products. The added value of the finished product or semi-finished product after processing is often higher. Sanjiang Plain should take advantage of its raw materials and actively promote the development of agricultural products processing industry, establishing regional brands, which will also change the regional economic structure and improve the ability to resist drought in the region.
- (5) Increase investment in irrigation and water conservancy facilities, increase the irrigation index, change the traditional irrigation methods, and improve the water

use efficiency. For example, modern irrigation (sprinkling irrigation, drip irrigation, and infiltration irrigation) should replace the traditional irrigation methods (canal irrigation, furrow irrigation, and flood irrigation).

5 Conclusions

This study refers to the projection index developed by Friedman and Tukey (1974). Here, an improved projection pursuit model based on information entropy is proposed and applied to assess the agricultural drought vulnerability of 18 counties for 4 years (2004, 2007, 2010, and 2013) in the Sanjiang Plain. The conclusions are as follows:

- (1) Theoretical analyses revealed that information entropy is more appropriate for measuring the dispersion of data relative to the standard deviation. From a local perspective, the cutoff radius is compressed between 0 and $\ln 2$ by information entropy, which allows for the use of the exhaustion method to determine the cutoff radius.
- (2) Case analyses showed that the results of the improved model and the Friedman–Tukey model are similar, thus confirming the validity of the proposed model. In terms of the classification, the quantitative analysis confirmed the superiority of the proposed model over the original model.
- (3) The overall vulnerability of the Sanjiang Plain shows a decreasing trend over time because the adaptive capacity constantly improved and the drought resistance gradually increased. Specific performance in irrigation index, per capita GDP, and rural per capita net income increased each year. Spatially, obvious differences can be seen in the region. The vulnerabilities of Hulin, Luobei, Youyi, and Fuyuan are the lowest; these regions are less sensitive and more adaptive. The main performance in the population density and the proportion of agricultural population are relatively low, so the potential loss due to drought is smaller. The per capita GDP and rural per capita net income are higher, the regional economy is good, and the ability to invest in the drought is strong. The vulnerabilities of Baoqing, Muling, Raohe, and Tongjiang are moderate. Among them, the vulnerabilities of Baoqing and Muling varied with time. From 2004 to 2013, the proportion of agricultural GDP decreased, and the irrigation index and rural per capita net income significantly increased. The vulnerabilities of Yilan, Jidong, Mishan, Fujin, and Boli are moderate and the change is obvious. Yilan and Jidong rose from IV to I. The change in the vulnerability is obvious, which is mainly reflected in the irrigation index and the rural per capita net income. Mishan, Fujin, and Boli rose from III to I due to the economic development. The gradually increasing per capita GDP and rural per capita net income increased the drought resistance ability. The vulnerability levels of Tangyuan, Suibin, Jixian, Huanan, and Huachuan are the highest and least variable, showing that these areas are vulnerable to drought. These regions are more sensitive to drought, and the potential loss of drought is higher. The regional economic development level is relatively low, so the agricultural drought resistance is not high.

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