Agricultural Drought Disaster Risk Assessment in Shandong, China

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Abstract

Shandong Province, the main grain-producing area in China, has ranked first in China in terms of total agricultural output value for many years. However, droughts with high frequency and long duration have been hindering local agricultural production. This paper aims to assess the risk of drought disaster in Shandong Province. Based on the natural disaster system theory, an agricultural drought disaster risk assessment model is developed. This model is applied to assess the agricultural drought hazard, exposure, vulnerability, emergency response and recovery capability, and comprehensive agricultural drought disaster risk year by year from 2012 to 2019. The results show that: (1) There is an aridity trend in Shandong Province. The interannual variation of drought hazard is obvious, and the areas with high drought hazard levels are largely located in the eastern part. (2) Agricultural exposure and vulnerability are mainly concentrated in the western part of Shandong Province. With the decrease in the proportion of the rural population, there is a slight downward trend of agricultural exposure. (3) The interannual variation of emergency response and recovery capability in Shandong Province is relatively stable. Agricultural insurance premiums in all regions have a clear upward trend, which is helpful for disaster risk reduction. (4) Rizhao has been in a high-risk area, moreover, Binzhou, Dezhou, and Liaocheng have gradually become high-risk areas in recent years. The interannual variation characteristics and spatial zoning of agricultural drought risk are explored, it is instructive for risk decision-makers to better develop drought response measures and improve drought resilience.

1. Introduction

Drought is a phenomenon in which the precipitation is significantly less than the multi-year average precipitation during a certain period (Dracup et al., 1980). When the water supply is insufficient to meet the water needs of the population and causes economic losses and human casualties, which is called a drought disaster (Bi et al., 2021). Drought disasters pose a serious threat to climate-sensitive economic sectors, especially the agricultural sector (Simelton et al., 2012, Liu et al., 2018). More than 7% of global crop output loss comes from drought (Lesk et al., 2016). In recent years, with the uneven spatiotemporal distribution of precipitation, changes in land surface factors, and human activities, drought disasters have occurred frequently in China (Zhang et al., 2020). Shandong Province leads the rest of China in arable land rate, which has long ranked first in agricultural growth value. However, the drought disaster has been affecting the local agricultural development (Wang et al., 2019). From the China Drought and Water Disaster Bulletin, the agricultural drought-affected area in Shandong Province reached 570,000 hectares in the past four years, of which 36,300 hectares were in extinction. Therefore, it is necessary to develop risk assessment work to promote regional drought planning and improve drought mitigation capacity, thus reducing the risk of drought disasters.

Drought disaster risk assessment can be divided into three main categories (Yanping et al., 2018), i.e., the mathematical and statistical-based assessment method, the assessment method based on the physical formation mechanism, and the indicator system method. The mathematical and statistical-based assessment method can analyze and refine historical data to calculate trends of disaster evolution and

risk probabilities (Sun et al., 2020). The method is limited by the availability of data information and requires a high length and accuracy of historical data. E.g., through the statistics of the main hydrological disaster data in Urumqi from 1949-2015, Li et al. (Li et al., 2019) identified and analyzed the risk characteristics and integrated distribution of hydrological disasters in the city. Bahrami et al. (Bahrami et al., 2021) assessed the spatial and temporal distribution of drought severity in the Iranian region from 1967 to 2014 by using a standardized reconnaissance drought index (RDIst), and further assessed the trend by parametric and non-parametric statistical tests. By using the improved linkage number and entropy information diffusion method, Chen et al. (Chen et al., 2020) assessed the risk of agricultural drought disasters in the Huabei Plain. The assessment method based on the physical formation mechanism can describe the physical process of drought disaster formation. The internal linkages and evolutionary processes among the components of drought disaster risk can be obtained, however, this method requires high spatial resolution of the data and is complicated to operate. Zhu et al. (Zhu et al., 2021) used the AquaCrop model to simulate the yield of maize under different irrigation scenarios, furthermore, vulnerability curves (a function of DHI and yield loss rate) were developed for the entire growing season and each growth stage. Li et al. (Li et al., 2020) used the partial least squares regression method to analyze the effects of climate change and non-climatic factors on NDVI dynamics and drought risk, thus exploring the key drivers of risk formation. The indicator system method is the most commonly used in drought disaster risk assessment. The method often uses regional disaster system theory and natural disaster system theory to construct the indicator system. The regional disaster system theory can be used to divide disaster risk sources into disaster-formative factors, disaster-formative environment, disaster-affected bodies, and emergency response and recovery capability (Yang et al., 2021). The natural disaster system theory can be used to divide disaster risk sources into hazard, exposure, vulnerability, and emergency response and recovery capability (Jia et al., 2016). Then we get specific indexes based on the source of risk, the indicator weights are determined by the analytic hierarchy process (AHP) (Palchaudhuri and Biswas, 2016), entropy weight method (Yi et al., 2018), and CRITIC weight method (Krishnan et al., 2021), etc. And further, the index data are weighted to obtain the risk assessment value. Zarei et al. (Zarei et al., 2021) used the AHP and geographic information systems (GIS) to assess the sensitivity to the occurrence of different types of drought, such as meteorological drought, hydrological drought, and agricultural drought. Guo et al. (Guo et al., 2021) assessed the degree of agricultural drought vulnerability in China by using the entropy weight method and the weighted composite score method, moreover, the contribution of the influencing factors was analyzed by the contribution model.

The previous indicators of drought hazard assessment include precipitation, temperature, evaporation, etc. However, these indicators do not provide a good description of the extent of drought hazards. Drought indices have been used to quantify drought, and a combination of drought indices and Run theory (Yevjevich, 1967) can be used to identify elements such as the duration, intensity, and peak of the drought. Therefore, we use the drought index to assess the hazard level of drought. Drought indices can be generally categorized into drought indices based on ground climate data and remote sensing monitoring. The indices based on ground climate data are used to quantify the drought situation through statistical analysis of the observed data, e.g., the precipitation anomaly percentage (Zhao et al., 2019),

the Palmer Crop Moisture Index (CMI) (Ahammed et al., 2020), and the Standardized Runoff Indicator (SRI) (Shukla and Wood, 2008), etc. Remote sensing has the advantages of high timeliness and wide coverage, which can realize the dynamic monitoring of drought. Drought indices based on remote sensing monitoring include the Normalized Difference Vegetation Index(NDVI) (Chu et al., 2019), the Vegetation Temperature Condition Index (VTCI) (Zhou et al., 2020), and the Perpendicular Drought Index (PDI) (Nie et al., 2020), etc. The most common drought indices are the Palmer Drought Severity Index (PDSI) (Wang et al., 2015, Yan et al., 2016), the Standardised Precipitation Index (SPI) (Karimi et al., 2019, Bhunia et al., 2020), and the Standardised Precipitation-Evapotranspiration Index (SPEI) (Zhang et al., 2020a, Musei et al., 2021). PDSI has been widely used as a more mature drought monitoring indicator, but the fixed time scale is its limitation. The SPI only considers the effect of precipitation on drought but ignores the effect of temperature on drought. Since SPEI compensates for the shortcomings of these two drought indices (Wang et al., 2017), we choose SPEI to assess the drought hazard level.

Currently, drought disaster risk assessments based on indicator systems are relatively mature(Dabanli, 2018, Hoque et al., 2021), but most of them are assessed only for a particular year, and few studies have assessed the variation of drought disaster risk in interannual units. Due to the complexity of agricultural drought formation and the variability of the human social environment, the risk of agricultural drought disaster in each region varies significantly from year to year. Therefore, we develop a risk assessment of agricultural drought disasters for the last eight years, and the changes in drought hazard, agricultural exposure and vulnerability, and emergency response and recovery capability over the eight years are analyzed. Moreover, we count the changes of indicators in different regions in different years, which can reflect the sources of risk in different regions.

The rest of the paper is organized as follows. Section 2 describes the study area and data. Section 3 introduces the calculation method of SPEI, the process of implementing the run theory, the calculation steps of the indicator system method, and the method of Comprehensive Percentage of Production Loss. In section 4, we lay out the results and discussion. The paper ends with the conclusions in Section 5.

2. Study Area And Data

Shandong Province is a coastal province in East China (longitude 114°47.5’ - 122°42.3’E and latitude 34°22.9’ to 38°24.01’N), which is 721.03 km long from east to west and 437.28 km long from north to south (Fig. 1). Shandong Province is a largely agricultural province (Yanlin et al., 2020). The province becomes the first province in China with a total agricultural output value of more than one trillion yuan in 2020, reaching 1019.06 billion yuan. However, the drought disaster has been hindering the local agricultural development (Wang et al., 2019). The climate of Shandong Province is a warm-temperate monsoon climate, with low precipitation in spring and winter, and prone to drought disasters. With the increasing population and water demand, Shandong Province is more vulnerable to drought (Zuo et al., 2018). Therefore, it is instructive to develop an agricultural drought disaster risk assessment for Shandong Province to protect the local agricultural development.

Monthly average temperature and monthly cumulative precipitation data of different meteorological stations are got from China Meteorological Data Network. Agricultural insurance premium data from 2012 to 2019 are obtained from the “China Insurance Yearbook”. Road mileage data from 2012 to 2019 are derived from the “statistical yearbooks” of each prefecture-level city. Food loss data from 2012 to 2019 are derived from the “China Water and Drought Disaster Bulletin". The data of the agricultural land area and surveyed land area from 2012 to 2018 are got from the “Shandong Province Statistical Yearbook”. The data of the agricultural land area and surveyed land area for 2019 has not been announced. Since the data has not changed much in recent years, the data of the agricultural land area and surveyed the land area for 2019 is adopted from 2018. All other data from 2012 to 2019 are taken from the “Shandong Provincial Statistical Yearbook”.

3. Methodology

3.1 Standardized Precipitation Evapotranspiration Index

SPEI is an index to analyze the trend of drought evolution, which is obtained by normal normalizing the cumulative probability distribution values of difference value series of precipitation and potential evapotranspiration. SPEI was developed in 2010, and it can show the wet and dry conditions of a region(Vicente-Serrano et al., 2010). This index not only considers the effect of temperature on drought variation but also has a multi-time scale character. The calculation steps of this index are as follows:

Step 1: Calculate the potential evapotranspiration by the Thornthwaite method. After obtaining the temperature and latitude data of each meteorological station, we can calculate the potential evapotranspiration (PET).

$$PET = 16K\left(\frac{10T}{H}\right)^{A},$$

1

$$H = \sum_{mon=1}^{12}\left(\frac{T_{mon,ave}}{5}\right)^{1.514},$$

2

where *K* is the correction factor of a function of latitude and month, *T* represents the average monthly temperature, *H* represents the annual temperature efficiency index, *A* represents a function of the heat index, $A = 6.75 \times 10^{-7}H^{3} - 7.71 \times 10^{-5}H^{2} + 1.79 \times 10^{-2}H + 0.492.$

Step 2: Get the difference values D_i between monthly precipitation and evapotranspiration.

$$D_i = P_i - PET_i,$$

3

where P_i is monthly precipitation, PET_i represents monthly evapotranspiration.

Step 3: Compute the SPEI index series. The log-logistic probability distribution is used to normalize the *D* series, thus obtaining the SPEI index series.

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

4

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where *α*, *β*, and *γ* are scale, shape, and origin parameters, respectively. The parameters *α*, *β*, and *γ* can be obtained by the linear moment (L-moment) method.

The probability distribution function of D is given in Eq. (5).

$$F(x) = \left[1+\left(\frac{\alpha}{x-\gamma}\right)\right]^{-1}$$

5

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Step 4: Obtain the SPEI value. *P* is the probability that a given *D* value will be exceeded, $P = 1 - F(x)$. If $P \leqslant 0.5$, then $W = \sqrt{-2\ln(P)}$; otherwise $W = \sqrt{-2\ln(1-P)}$, and multiply the resulting SPEI value by -1.

$$SPEI = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3}$$

6

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where C_0 = 2.515517, C_1=0.802853, C_2=0.010328, d_1 = 1.432788, d_2=0.189269,and d_3 =0.001308.

3.2 Run theory

Run theory can be used to identify drought events (Yevjevich, 1967), and a drought event includes drought duration, drought severity, and drought peak. Set the drought threshold as -0.5, i.e., when SPEI value is less than -0.5, the month is in drought. Dd, the cumulative duration of all drought events in year *i*, is the count of months with SPEI values less than -0.5 in year *i*. Ds, the cumulative intensity of all drought events in year *i*, is the sum of the SPEI values less than -0.5 in year *i*. Dp, the peak value of a drought event, is the minimum SPEI value in year *i*.

3.3 The indicator system method

The calculation steps of the indicator system method are as follows:

Step 1: Construct the assessment indicator system. According to the four elements theory of natural disaster risk formation, natural disaster risk is composed of natural disaster hazard, exposure and vulnerability of the disasterbearing body, and emergency response and recovery capability. According to this theory, the index system we constructed is shown in Table 1.

The disaster hazard indicates the severity of meteorological drought, drought hazard is strongly related to both precipitation and temperature, therefore, SPEI can be used to describe it (Pei et al., 2018). Since SPEI with a three-month timescale (SPEI-3) can reflect the meteorological drought, we use the SPEI-3 values to calculate the drought duration (Dd), drought severity (Ds), and drought peak (Dp) for each year. SPEI with a twelve-month timescale (SPEI-12) can reflect the drought situation throughout the year, thus we use it to measure the overall hazard of drought each year. The values of Ds, Dp, and SPEI-12 are less than zero, so the smaller their values, the greater the hazard. Moreover, the larger the value of Dd, the more harmful the disaster. In this paper, we first calculate the values of SPEI-3 and SPEI-12 by using the temperature and precipitation data from 19 meteorological stations. Then, based on the inverse weight interpolation method in ArcGIS software, we process the values of SPEI-3 and SPEI-12 corresponding to each meteorology station as raster data. Finally, by using the prefecture-level city as the boundary, the average value of all raster points within each region is computed, i.e., the SPEI value of each prefecture-level city.

Exposure of the disaster-bearing body indicates the number or value of disaster-bearing bodies exposed to the drought disaster, and the disaster-bearing body studied in this paper is agriculture. Both Agricultural land (% of survey land) and grain crop sown area (% of the total sown area) are positive indicators (Zeng et al., 2019), i.e., the larger the proportion, the bigger the exposure of agriculture. Likewise, the rural population (% of the total population) is a positive indicator.

Vulnerability of the disaster-bearing body indicates the extent of crop damage caused by drought disasters in a given region, and it synthetically reflects the extent of drought disaster damage. Agricultural films play an important role in moisturizing and insulating crops during the planting period, it can effectively reduce the impact of drought on crops. The larger the grain crops output per hectare, the higher the grain output value per hectare, and the greater the potential loss (Luo et al., 2020).

Emergency response and recovery capability indicate the extent that the affected area recovers from the disaster in the long or short term. The total power of agricultural machinery per hectare determines the level of agricultural mechanization in the region, which determines the level of agricultural development. Therefore, the higher the total power of agricultural machinery per hectare, the higher the level of agricultural development, the greater the resistance to adversity (Liu et al., 2019). Disposable income of rural households and agricultural insurance premiums can effectively reduce the risk of drought disaster, both of which are negative indicators (Hagenlocher et al., 2019). The greater the density of the road network, the more conducive to do disaster relief work in the event of a disaster (Duan et al., 2021).

Step 2: Calculate indicator weights. To eliminate the influence of different physical dimensions on decision-making, we standardize the positive indicator data with Eq. (7) and standardize the negative indicator data with Eq. (8).

$$A_{ij}=\frac{X_{ij}-\min\left\{X_{1j},\cdots,X_{nj}\right\}}{\max\left\{X_{1j},\cdots,X_{nj}\right\}-\min\left\{X_{1j},\cdots,X_{nj}\right\}}$$

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$$A_{ij}=\frac{\max\left\{X_{1j},\cdots,X_{nj}\right\}-X_{ij}}{\max\left\{X_{1j},\cdots,X_{nj}\right\}-\min\left\{X_{1j},\cdots,X_{nj}\right\}}$$

8

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Table 1
Indicator system and weights

Factors	Indicator	Number	Correlation	W_j^+	W_j^-	W_j
Hazard	Dd	R_1	Positive	0.1138	0.0592	0.0810
	Ds	R_2	Negative	0.1119	0.0758	0.0902
	Dp	R_3	Negative	0.0916	0.0238	0.0509
	SPEI-12	R_4	Negative	0.0452	0.0913	0.0728
Exposure	Agricultural land (% of survey land)	E_1	Positive	0.0303	0.0714	0.0550
	Grain crop sown area (% of total sown area)	E_2	Positive	0.0881	0.1429	0.1210
	Rural population (% of total population)	E_3	Positive	0.0719	0.0357	0.0502
Vulnerability	Use of agricultural plastic film per hectare (t/hm^2)	V_1	Negative	0.0289	0.0623	0.0489
	Grain crops output per hectare (kg/hm2)	V_2	Positive	0.0639	0.0849	0.0765
	Grain output value per hectare (ten thousand yuan/hm2)	V_3	Positive	0.1009	0.1028	0.1020
Emergency Response and Recovery	Disposable income of rural households (yuan/person)	B_1	Negative	0.0757	0.0536	0.0624
	Agricultural insurance premiums (million yuan)	B_2	Negative	0.0664	0.0893	0.0801
	Road density (km of road per km2 of land area)	B_3	Negative	0.0807	0.0357	0.0537
	Total power of agricultural machinery per hectare (kw/hm2)	B_4	Negative	0.0307	0.0714	0.0551

Then, we can calculate the objective weight W_j^+ by the entropy weight method. Next, the AHP is used to quantify the expert's professional judgment and to obtain subjective weights W_j^-. The comprehensive

indicator weight W_j is computed by Eq. (9), *q* indicates the preference coefficient. After consulting experts, set the preference coefficient *q* as 0.4. The weights of each indicator are shown in Table 1.

$$W_j = qW_j^+ + (1-q)W_j^-, i = 1, \cdots, n,$$

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where W_j^+ represents objective weight, and W_j^- represents subjective weight.

Step 3: Calculate the assessment value and determine the assessment level. With the indicator weights obtained, we can compute the meteorological risk assessment values since the 21st century by the WAA algorithm. Let R be the drought hazard index, E be the agricultural exposure index, V be the agricultural vulnerability index, B be the emergency response and recovery index, Z be the drought disaster risk index, where

$$R = Y_{R1}W_{R1} + Y_{R2}W_{R2} + Y_{R3}W_{R3} + Y_{R4}W_{R4},$$

10

$$E = Y_{E1}W_{E1} + Y_{E2}W_{E2} + Y_{E3}W_{E3},$$

11

$$V = Y_{V1}W_{V1} + Y_{V2}W_{V2} + Y_{V3}W_{V3},$$

12

$$B = Y_{B1}W_{B1} + Y_{B2}W_{B2} + Y_{B3}W_{B3} + Y_{B4}W_{B4},$$

13

$$Z = R + E + V + B,$$

14

Y_i represents the standardized indicators value, W_i represents the weight value of each assessment indicator.

To provide a uniform classification of hazard, exposure, vulnerability, emergency response and recovery capability, and comprehensive agricultural drought disaster risk separately, we use the average value of the indicators from 2012 to 2019 as the classification criteria. The natural breakpoint method is used to classify the indicator values, which can maximize the spatial differences. The levels classification table is shown in Table 2.

Table 2
Levels classification table

Level	Low	Lower	Moderate	Higher	High
Hazard	0.045100-0.052100	0.052101-0.106200	0.106201-0.120600	0.120601-0.180200	0.180200-0.276200
Exposure	0.029600-0.060400	0.060401-0.093700	0.093701-0.105600	0.105601-0.114800	0.114801-0.210400
Vulnerability	0.050300-0.057700	0.057701-0.096000	0.096001-0.135400	0.135401-0.167100	0.167101-0.197800
Emergency Response and Recovery	0.040400-0.042000	0.042001-0.082200	0.082201-0.118200	0.118201-0.148500	0.148501-0.168000
Drought disaster risk	0.394400-0.424200	0.424201-0.502700	0.502701-0.543500	0.543501-0.581700	0.581701-0.655700

3.4. The method of Comprehensive Percentage of Production Loss

The method of Comprehensive Percentage of Production Loss was derived from the “Drought Assessment Criteria”, which was issued by the Office of State Flood Control and Drought Relief Headquarters in China.

C is agricultural drought disaster assessment values(%). The larger its value, the more severe the drought disaster loss.

$$C = I3 \times 90\% + (I2 - I3) \times 55\% + (I1 - I2) \times 20\%,$$

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where $I1$ is the affected area (more than 10% yield reductions) as a percentage of the sown area, $I2$ represents the damaged area (more than 30% yield reductions) as a percentage of the sown area, $I3$ represents extinction area (more than 80% yield reductions) as a percentage of the sown area.

4. Results And Discussion

4.1 Drought hazard analysis

Based on the meteorological data from 19 meteorological stations, we calculate the SPEI values for a 3-month time scale (SPEI-3) and for a 12-month time scale (SPEI-12). The changes of SPEI-3 and SPEI-12 in Shandong Province by year are shown in Fig. 2. In the last 8 years, the SPEI in Shandong province showed a decreasing trend, with a linear propensity rate of -0.048/8 years for SPEI-3 values and -0.72/8 years for SPEI-12 values. There is an aridity trend in Shandong Province.

Based on ArcGIS software, we get a map of drought hazard levels for 2019 (Fig. 3 (a)), maps of average drought hazard levels over the last four and eight years (Fig. 3 (b) and (c)), a map of spatial variability levels (Fig. 3 (d)), maps of average annual precipitation over the last four and eight years (Fig. 3 (e) and (f)), and maps of annual mean temperature over the last four and eight years (Fig. 3 (g) and (h)).

The high hazard area of drought is largely concentrated in the eastern part of Shandong. In the past four years, high hazard droughts mostly occurred in Weihai, Yantai, Qingdao, Rizhao, and Dezhou. Moreover, high hazard droughts mainly occurred in Yantai, Qingdao, Weifang, Rizhao, and Linyi in the past eight years. By comparing the spatial hazard distribution from 2012 to 2019, it is clear that the degree of interannual variation in drought hazard is significant. The overall drought hazard level was high in 2014 and 2018, with high hazard areas located in Dongying, Weifang, Rizhao, and Linyi in 2014, and in Yantai, Dezhou, and Liaocheng in 2018.

Although the average value can reflect the average level of a region over time, it alone can not reflect the drought characteristics of the place. Therefore, we calculate the change in levels for each region from 2012 to 2019, the degree of spatial variability is shown in Fig. 3 (d). Weihai has a high average value and a high degree of variation in the drought hazard level, thus it is necessary to pay more attention to the agricultural drought in this region. Weifang has a high average value and a low degree of variation in the drought hazard level, which indicates that the area is affected by drought all year round.

Over the past eight years, the spatial distribution of precipitation and temperature in Shandong Province has not changed much. High-intensity precipitation is mainly distributed in Tai'an, Jinan, Linyi, etc., attention should be paid to prevent floods in the area. The eastern part of Shandong Province has low annual precipitation, which is the reason for the high drought hazard in the region. Weihai and Tai'an have low annual average temperatures, which cause less evapotranspiration and are more conducive to crop water retention. Parts of Yantai have significantly high average annual temperatures, and the area is prone to drought disasters in agriculture.

4.2 Agricultural exposure analysis

The degree of agricultural exposure is calculated by Eq. (11), then we produce a map of agricultural exposure levels for 2019, maps of average agricultural exposure levels over the last four and eight years, a map of spatial variability levels, and a map of the change in indicators (Fig. 4).

From Fig. 4, we can conclude that the areas with high agricultural exposure are largely concentrated in the western part of Shandong Province. The western region is located in the interior and is mostly engaged in agriculture. From Fig. 4 (a), the regions with high agricultural exposure in 2019 are mainly located in the western part of Shandong Province, of which, Dezhou has the highest agricultural exposure. From Fig. 4 (b) and (c), the agricultural exposure levels across Shandong Province from 2012 to 2019 do not change much.

Then we compute the change in levels for each region from 2012 to 2019, the degree of spatial variability is shown in Fig. 4 (d). In the last eight years, the agricultural exposure level in Zibo, Dezhou, Liaocheng,

Binzhou, and Heze has been High, and the variance value for these five areas is zero. In 2012, 2013, and 2014, every city in Shandong Province except Dongying had a high level of agricultural exposure. Moreover, the exposure to agriculture started to decrease in 2015 in most areas. The agricultural exposure level in Dongying has been Low level from 2012 to 2016, which increased from 2017 to reach the High level in 2019.

Figure 4 (e) shows the changes in the agricultural exposure indicators in Shandong Province for the past eight years by region. The western part of Shandong Province has a high percentage of the rural population, which is the reason why the high agricultural exposure level is concentrated in the western part of Shandong Province. Except for Dongying, the percentage of agricultural land in each region is above 60%, and the ratio has remained almost unchanged for eight years. Due to the increase in the percentage of the total sown area of grain crops in Dongying, the agricultural exposure level of the area has gradually increased. The percentage of grain sown area in Dezhou, Zibo and Binzhou also increased gradually, with a ratio close to 90%, so it is important to focus on the conservation of agriculture in this area.

4.3 Agricultural vulnerability analysis

The degree of agricultural vulnerability is calculated by Eq. (12), then we produce a map of agricultural vulnerability levels for 2019, maps of average agricultural vulnerability levels over the last four and eight years, a map of spatial variability levels, and a map of the change in indicators (Fig. 5).

From Fig. 5 (a), the regions with high agricultural vulnerability in recent years are Liaocheng, Zaozhuang, Jinan, and Tai'an. From Fig. 5 (b), the agricultural vulnerability levels in Taian and Jining were high in the last four years. Taian's agricultural vulnerability level reached a High level in 2017 and has remained unchanged since then. The agricultural vulnerability level in Jining has always been high. From Fig. 5 (c), the agricultural vulnerability in Jining has been high in the last eight years, while the agricultural exposure level in the area is high, and attention should be paid to local food security.

Then we compute the change in level for each region from 2012 to 2019, the degree of spatial variability is shown in Fig. 5 (d). The degree of level variation in Rizhao is at a high level, moreover, the agricultural vulnerability of this place starts to increase year by year. Three areas in Shandong Province have remained unchanged in terms of their agricultural vulnerability levels, namely Jining, Dezhou, and Binzhou. The agricultural vulnerability of Jining has been at a high level, that of Dezhou has been at a higher level, and that of Binzhou has been at a moderate level.

Fig. 5 (e) shows the changes in the agricultural vulnerability indicators in Shandong Province for the past eight years by region. The western part of Shandong Province has a higher grain output value than the eastern part, so the high agricultural vulnerability area is located in the western part of Shandong. Furthermore, there was a continuous upward trend in grain output value across Shandong Province until 2016, it suddenly dropped in 2017 and then resumed its growth trend. Over the years, the largest use of plastic film per unit area in Shandong Province has been in Weifang, which has greatly reduced the

agricultural vulnerability of the area in drought conditions. Jining has a high grain output value per unit area, with an average of 64,600 yuan per hectare over the past eight years, which indicates the high agricultural vulnerability of the region. Both Weihai and Dongying have low grain output and grain output value, and thus the agricultural vulnerability of the two areas has been at a low level for eight years.

4.4 Emergency response and recovery capability analysis

The capability of emergency response and recovery is calculated by Eq. (13), then we produce a map of emergency response and recovery levels for 2019, maps of average emergency response and recovery levels over the last four and eight years, a map of spatial variability levels, and a map of the change in indicators (Fig. 6).

The area with the highest emergency response and recovery capacity in Shandong Province is Weifang, which has been at a high level for the past eight years. Rizhao and Zaozhuang have low disaster prevention and mitigation capacity. Although the emergency response and recovery capacity in these two regions have improved, the rate of improvement has been slow. Especially, Zaozhuang has high agricultural exposure and vulnerability, so it is important to focus on food security work in this area.

From Fig. 6 (d), overall, there has been little change in the emergency response and recovery levels across Shandong Province over the past eight years. There has been no change in the emergency response and recovery capability level in Weifang, Yantai, Dongying, and Liaocheng. Weifang and Yantai have always been strong in disaster prevention, and the level of agricultural technology in these two areas is also strong. Dongying and Zaozhuang should strengthen the disaster prevention capacity of the area, thus reducing the damage caused by drought.

Figure 6 (e) shows the changes in the emergency response and recovery capacity indicators in Shandong Province for the past eight years by region. The indicator values in different parts of Shandong Province are different, of which, Weifang has a high value of all indicators and has a strong drought mitigation ability. The disposable income per capita of rural residents in the eastern part of Shandong Province is more than that in the western part, and the indicator has a clear trend of growth. The trend of agricultural insurance premium growth is fierce, with premiums in Dezhou, Weifang, Linyi, Jining, and Heze all exceeding 300 million in 2019. Weifang, Dezhou, Heze, and Linyi have a high-density road network, which is conducive to disaster response and relief work in the event of a disaster. Since the low agricultural insurance premiums and underdeveloped roads in Rizhao and Zaozhuang, the emergency response and recovery capacity in both places are low. Of which, Zaozhuang has a low level of agricultural mechanization, with an average of 0.81kw/hm^2 for eight years.

4.5 Drought disaster risk analysis

The assessment values of drought disaster risk are calculated by Eq. (14), then we produced a map of drought disaster risk levels for 2019, maps of average drought disaster risk levels over the last four and eight years, and a map of spatial variability levels (Fig. 7). From Fig. 7 (a), the high-risk areas for

agricultural drought disasters in 2019 are located in Binzhou and Qingdao. The high risk in Binzhou is a result of the high level of agricultural exposure at that location in 2019, and the high risk in Qingdao is a result of the high level of drought hazard at that location in 2019. From Fig. 7 (b). In the past four years, high-risk areas for agricultural drought disasters are located in Liaocheng, Dezhou, Binzhou, and Rizhao. From Fig. 7 (c), the high-risk area of agricultural drought disaster is located in Rizhao for the past eight years.

From Fig. 7 (d), Qingdao has high variability in levels, with the region being at high risk in 2015 and 2019, but a low risk of agricultural drought disasters in other years. The risk levels of Liaocheng and Zaozhuang have not changed much, and the risk of drought disasters in both places has been high.

4.6 discussion

This paper presents a detailed analysis of the overall components of agricultural drought disaster risk in Shandong Province. By calculating the drought hazard, agricultural exposure and vulnerability, disaster prevention and mitigation capacity, and comprehensive risk in 2019, it is clear to get the distribution and composition of recent agricultural drought disaster risks in Shandong Province. Moreover, we computed the average situation in the last four years and eight years and the change degree in levels in each place over eight years, which facilitates the analysis of changes in the sources of drought disaster risk in each region. We also give the changes in each indicator over eight years, thus allowing us to find the influencing factors for each source of risk. With the above information, it is convenient for risk decision-makers to find out the shortcomings of the drought work in each city and propose corresponding drought strategies.

To further verify the ability of this paper to assess drought disaster risk, we compared the drought disaster risk and drought disaster loss derived from each year's assessment. Years with many high-risk and higher-risk cities may cause heavy overall losses in Shandong Province in that year. We count cities with drought disaster risk at the Higher and High levels from 2012 to 2019 and further calculate their percentages of all cities in that year. At the same time, we calculate the year-by-year drought loss values by using the method of Comprehensive Percentage of Production Loss (Fig. 8). By comparing them, we find that the trends are almost the same.

Since the assessment results in this paper are reasonable, we can use the assessment content to make recommendations for drought response in the corresponding areas. From the eight-year average, Rizhao has been at a high-risk level for agricultural drought disasters, and the agricultural exposure and vulnerability of the area are at a low level. The source of drought disaster risk in this area is the high hazard of drought and the low capacity for emergency response and recovery. In the emergency response and recovery capacity factor, the area has a low road network density and low agricultural insurance premiums, and the values of these two indicators have increased slowly over the past eight years. Rizhao's next key points of drought relief work include: (1) The monitoring and forecasting of meteorological drought in agricultural planting areas should be further strengthened, and drought supplies should be scientifically dispatched. (2) The water conservancy project is vigorously constructed

to store water for irrigating farmland. (3) The roads in this area should be built reasonably, thus improving the disaster resistance efficiency of this area. (4) Agricultural insurance coverage should be expanded moderately, and the level of agricultural insurance coverage should be improved.

The assessment method in this paper is simple and easy to implement, and it has some reference value for drought prevention and drought relief work in agriculture in the future. With the improvement of statistical data, the scientificity and completeness of the agricultural drought risk assessment system are expected to be further enhanced.

5. Conclusion

This paper had analyzed the risk components of drought disasters and explored them from four aspects: hazard, exposure, vulnerability, and emergency response and recovery capacity. The spatial and temporal evolution characteristics of risk components were analyzed, moreover, cities in Shandong Province were zoned. The findings of the study are as follows:

(1) From the spatial scale, the eastern part of Shandong Province had low precipitation, therefore, the area had been at a high drought hazard level. The western part of Shandong Province had a significantly larger proportion of rural people than the eastern part, which had resulted in the western part of Shandong Province having been a highly exposed area for agriculture. The western region of Shandong Province had high grain output per unit area and high grain output value per unit area, which made the agricultural vulnerability of the region high. For eight years, Weifang had had a strong emergency response and recovery capacity. Rizhao and Zaozhuang had a low drought mitigation capacity, which needs to be further improved to reduce the losses caused by drought disasters. In a comprehensive view, Rizhao had been in a high-risk area for drought disasters, in recent years, Binzhou, Dezhou, and Liaocheng had gradually become high-risk areas.

(2) From the temporal scale, precipitation and temperature were highly variable from year to year, which is the reason for the significant interannual variation of drought hazards in Shandong Province. Weihai had a high interannual variability of drought hazards and had been at a high hazard level for many years, so it is necessary to strengthen the agricultural drought monitoring in the region. The percentage of the rural population in Shandong Province had a clear downward trend and the percentage of agricultural land had a small change, which led to a slight downward trend in the exposure to agriculture. In recent years, grain output per unit area had changed little across Shandong Province, and grain output value per unit area had increased little, so the interannual variation in agricultural vulnerability had been relatively stable. With the growth of the economy, the per capita disposable income of rural residents and agricultural insurance premiums had increased significantly in most parts of Shandong Province. However, the growth rate of agricultural insurance premiums in Rizhao and Weihai was slow, and the coverage of agricultural insurance should be expanded, thus improving the ability to cope with agricultural drought disasters. Over the past eight years, the risk varied widely from year to year in

different places. Qingdao had the greatest interannual variation in drought disaster risk levels, reaching high levels in 2015 and 2019, with other years at lower levels.

Declarations

Authors contributions

Wentong Yang: Conceptualization, Methodology, Modelling, Writing-original draft. Liyuan Zhang: Funding acquisition, Supervision, Writing - review & editing. Chunlei Liang: Validation, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Figures

Figure 1

Geographical location of the study area and meteorological stations

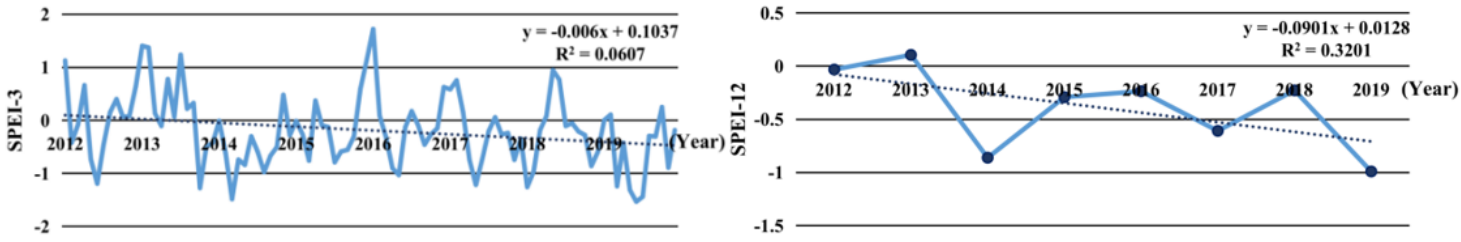

Figure 2

SPEI on a 3-month time scale and a 12-month time scale

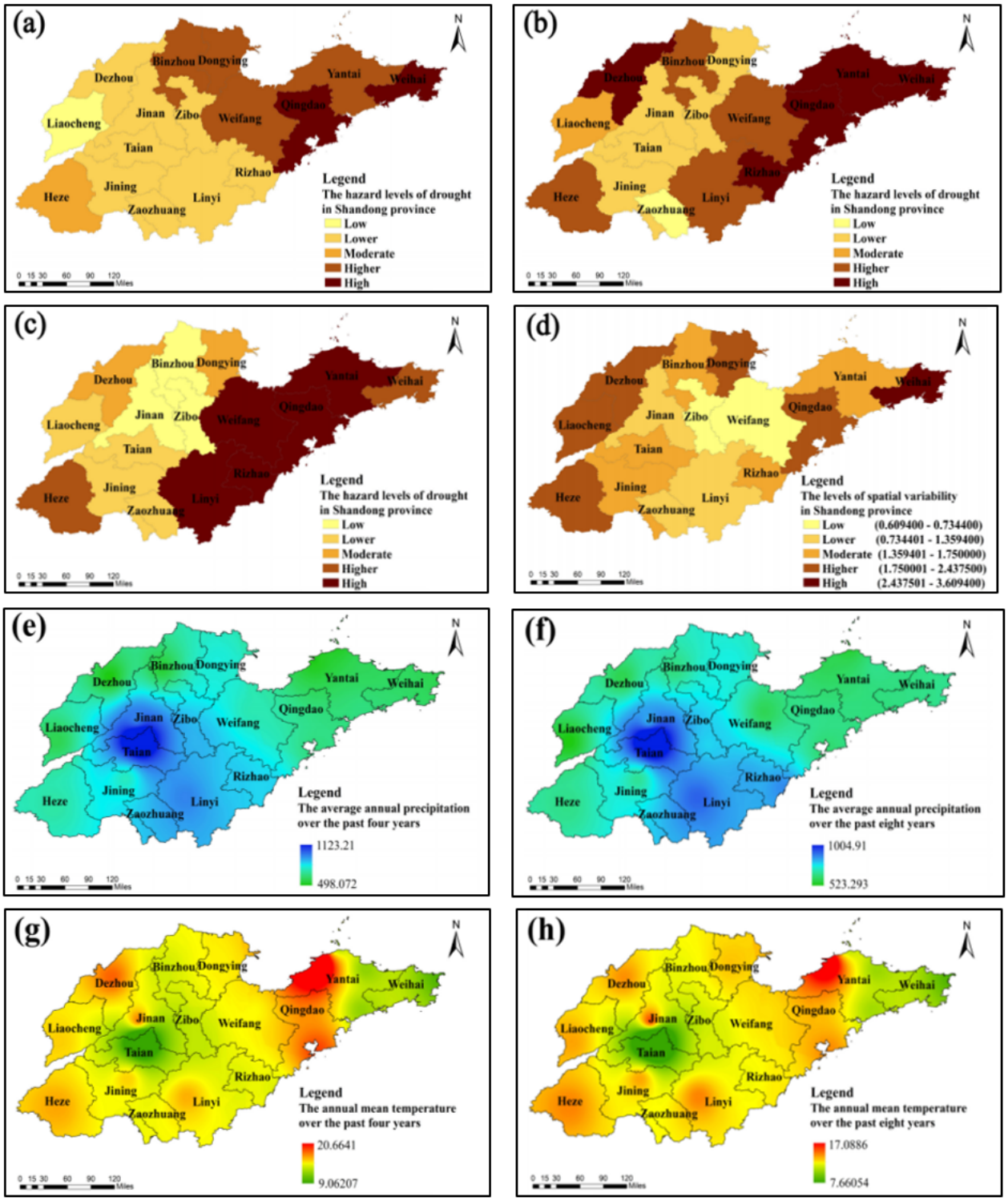

Figure 3

Agricultural drought hazard in Shandong

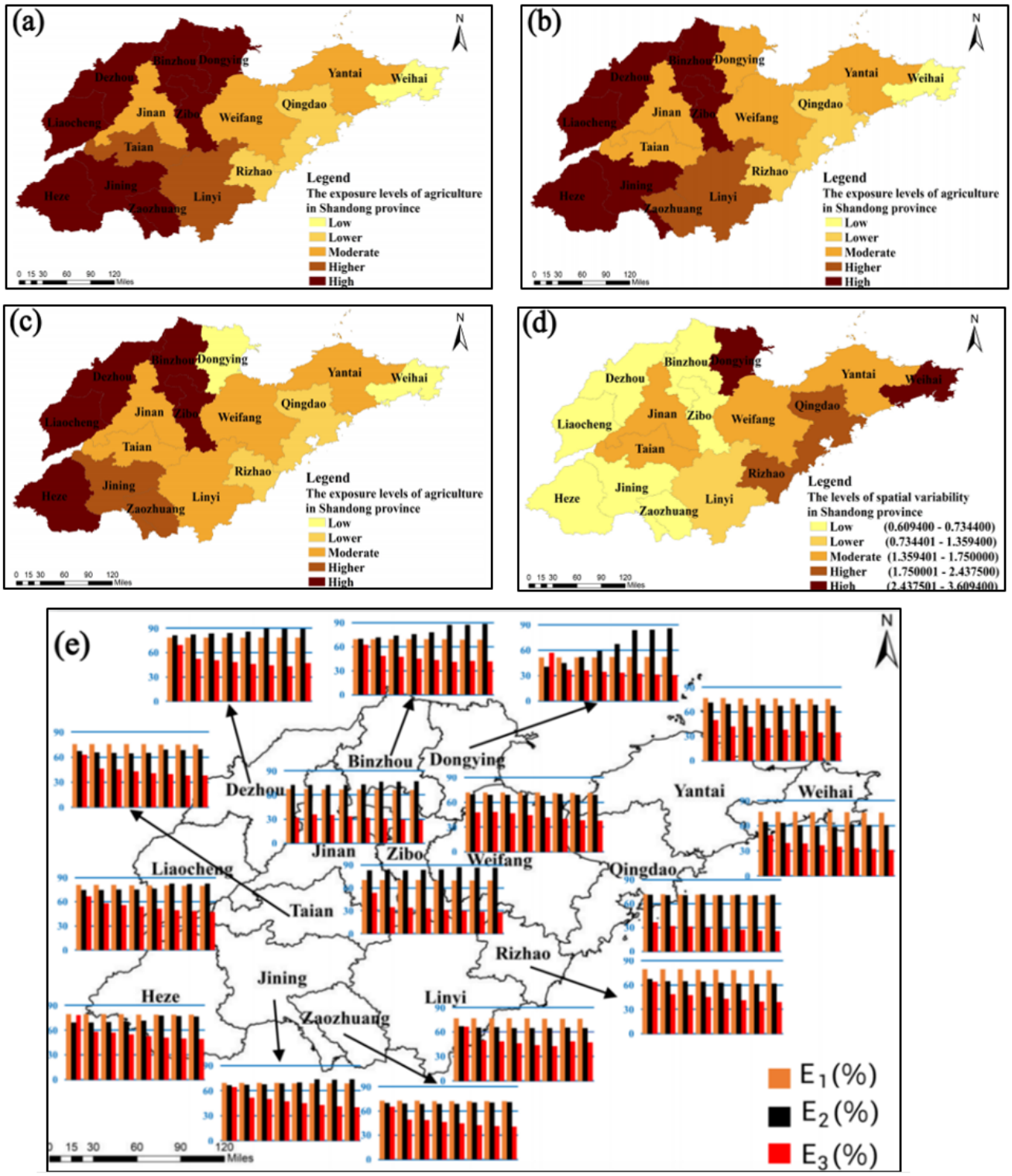

Figure 4

Agricultural exposure in Shandong Province

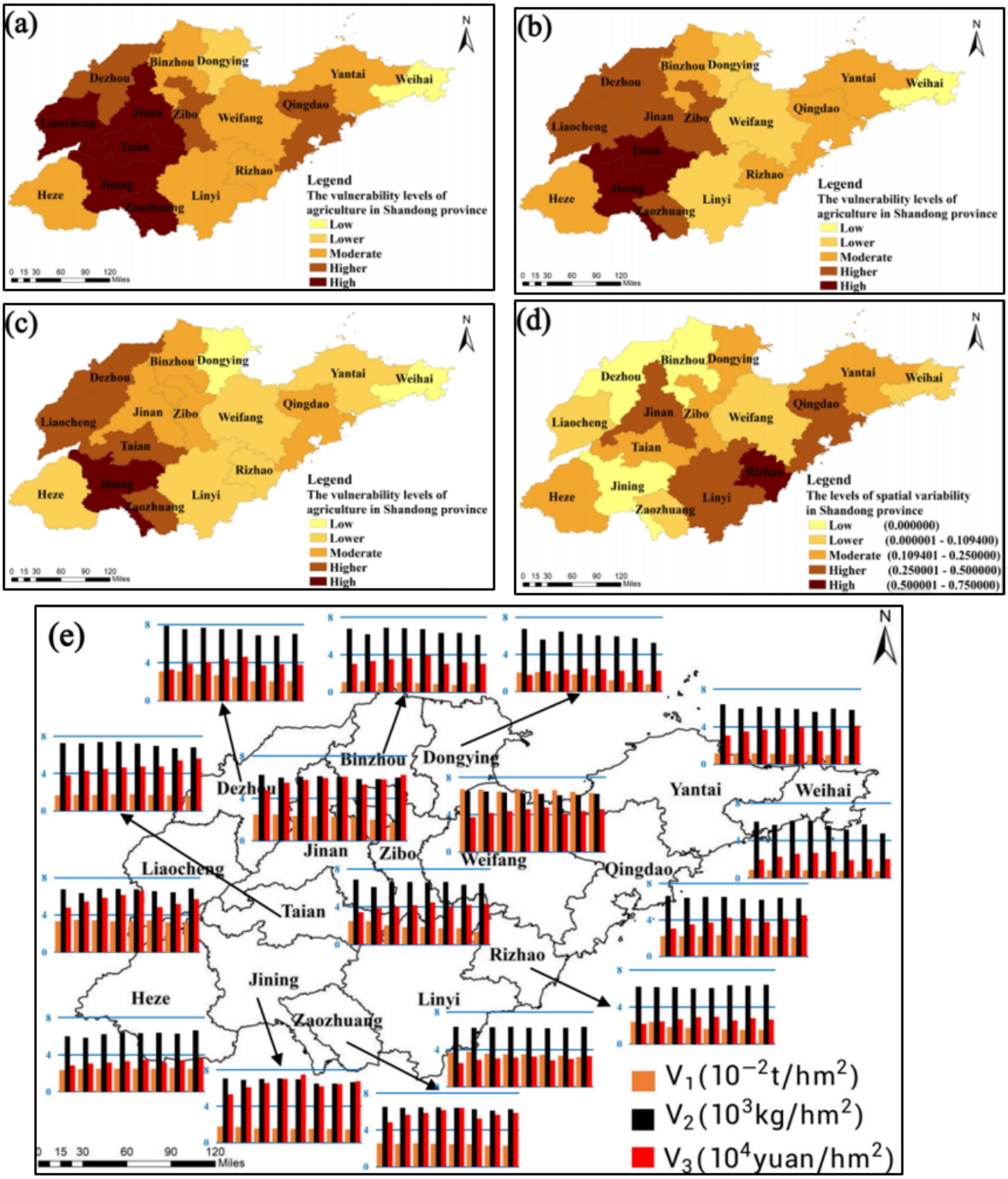

Figure 5

Agricultural vulnerability in Shandong Province

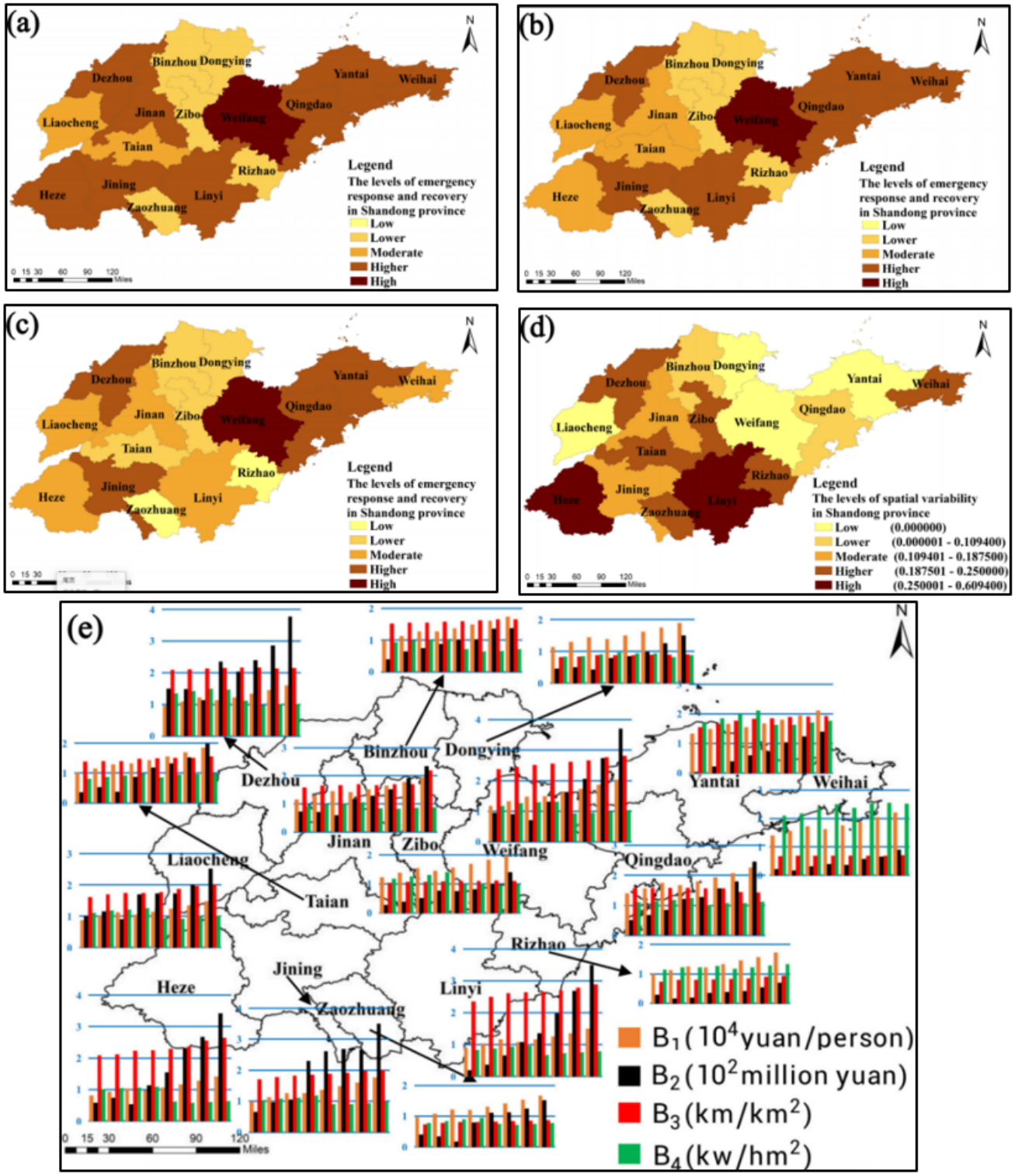

Figure 6

Emergency response and recovery capability in Shandong Province

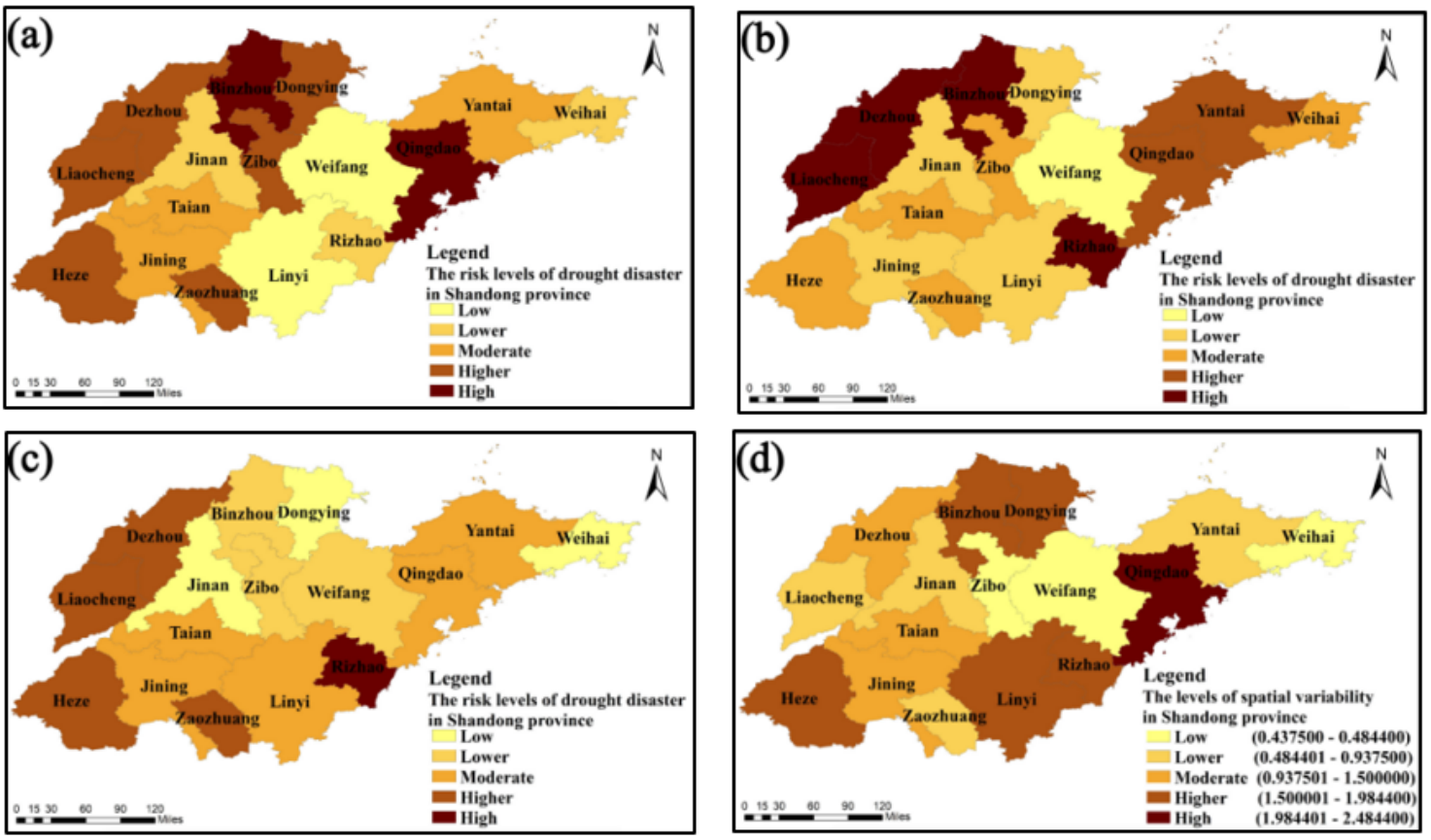

Figure 7

Agricultural drought disaster risk in Shandong Province

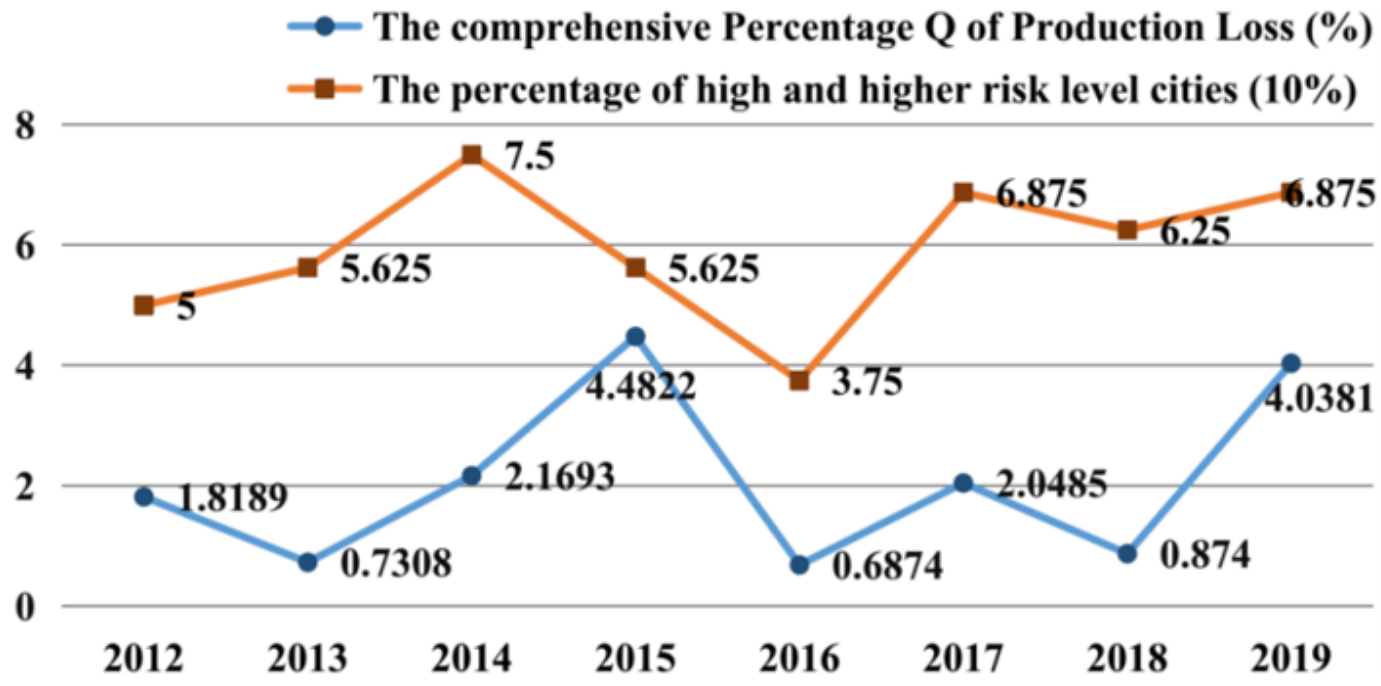

Figure 8

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