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Risk analysis and influencing factors of drought and flood disasters in China

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Abstract: The risk analysis of flood and drought disasters and the study of their influencing factors enhance our understanding of the temporal and spatial variation law of disasters and help identify the main factors affecting disasters. This paper uses the provincial administrative region of China as the research area. The statistical distribution of flood and drought disasters was optimized from 10 alternative distributions by the KS test, and the disaster risk was analyzed. Thirty-five indicators were selected from nature, agriculture and the social economy as alternative factors. The main factors affecting flood and drought disasters were selected by Pearson, Spearman and Kendall correlation coefficient test. The results demonstrated that the distribution of floods and drought is right skewed, and the beta distribution is the best statistical distribution for fitting disasters. In terms of time, the risk of flood and drought disasters in all regions showed a downward trend. Economic development and the enhancement of the ability to resist disasters were the main reasons for the change in disasters. Spatially, the areas with high drought risk were mainly distributed in Northeast and North China, and the areas with high flood risk were mainly distributed in the south, especially in Hubei, Hunan, Jiangxi and Anhui. The distribution of floods and drought disasters was consistent with the distribution characteristics of precipitation and water resources in China. Among the natural factors, precipitation was the main factor causing changes in floods and drought disasters. Among the agricultural and socioeconomic factors, the indicators reflecting the disaster resistance ability and regional economic development level were closely related to flood and drought disasters. The research results have reference significance for disaster classification, disaster formation mechanisms and flood and drought resistance.

Key words: drought; flood; risk analysis; influencing factors; china

1 Introduction

Flood and drought disasters are major natural disasters that affect human society, the ecological environment and the regional economy and directly threaten regional economic development, food security and ecological security (Jia et al., 2019; Narasimhan and Srinivasan, 2005; Wijitkosum, 2018). Under the background of global warming, the uncertainty of temperature, precipitation and other natural factors increases in local areas (Grubler, 2014; WILLIAMSON, 2013). In addition, human activities have changed the underlying surface, further increasing the possibility of extreme weather events. Traditional humid areas may experience droughts due to extreme meteorological factors, while arid and semiarid areas may experience floods due to short-term heavy rainfall (Chen et al., 2019a). Agriculture is the industry most affected by flood and drought disasters, which directly lead to reductions in crop yield or even crop failure; these changes seriously undermine the safety of agricultural ecological environments and restrict food production (Parsons et al., 2019; Zhang et al., 2015). China is a large agricultural country and has frequent floods and droughts. In five years (2013-2017), the average drought-affected area was 1,1337,000 ha, and the flood-affected area was 6,609,000 ha. The average annual losses from each type of disaster were 60.4 billion yuan and 177.6 billion yuan, respectively. The analysis of flood and drought disaster risk and the study of its influencing factors are helpful for identifying the occurrence risk of flood and drought disasters in China, understanding the temporal and spatial variation law of flood and drought disasters, identifying the coupling relationship between natural, economic and social factors and flood and drought disasters, and optimizing the main influencing factors of flood and drought disasters in China.

Both flood and drought disasters are related to "water". The surplus or deficit of water is the most direct cause of flood and drought disasters; thus, "water" is the common perspective used in this study. For drought, it is common to define the drought index by considering precipitation, temperature, radiation and soil water holding capacity; examples include the palmer drought severity index (PDSI) (Palmer, 1965; Yang et al., 2018b), standardized precipitation index (SPI) (McKee et al., 1993; Zuo et al., 2019), standardized precipitation evapotranspiration index

(SPEI) (Guo et al., 2018; Vicente-Serrano et al., 2010), standardized precipitation crop evapotranspiration index (SPCEI) (Pei et al., 2019) and soil water deficit index (SMDI) (Narasimhan and Srinivasan, 2005; Yang et al., 2017). Flood disasters are usually related to extreme precipitation, and the intensity and coverage area of extreme precipitation are one aspect of flood risk studies (Yang et al., 2018a; Yuan et al., 2019). In addition, a comprehensive evaluation method based on an index system is a common method used to study flood and drought disaster risk. In terms of drought, physical factors such as climate, soil, land use and water resources represent one perspective for selecting a drought risk index system (Wijitkosum, 2018). Based on the social attributes of drought disasters, the impacts of climate change, population growth and socioeconomic vulnerability on drought disasters are comprehensively considered (Ahmadalipour et al., 2019). More studies choose indicators from the perspectives of hazard, exposure, sensitivity and resistance capacity to measure the risk of drought (Pei et al., 2018; Prabnakorn et al., 2019). Similar to drought, a flood risk assessment can establish an index system from the perspective of flood-related factors. For example, indicators are selected to measure the flood risk from the perspective of the disaster environment, the subject bearing the flood and the ability to resist the flood(Jia et al., 2019). Hazard, exposure and vulnerability factors are also commonly used index systems for flood risk assessment(Cai et al., 2019).

Drought index and extreme precipitation are the direct causes of flood and drought disasters. They mainly emphasize the natural attributes of disaster risk but fail to consider the social attributes of disaster(Guo et al., 2018; Pei et al., 2018; Yang et al., 2018b; Zuo et al., 2019). The index system method considers the natural and social attributes of disasters; additionally, this method considers that disasters are transformed from hazard factors to disaster risks through the vulnerability of disaster bodies, hazard factors are direct causes, and vulnerability is the root cause(Fontaine and Steinemann, 2009; Luh et al., 2015; Murthy et al., 2015). This method shows that flood and drought disasters have dual attributes related to nature and society. However, the differences in the index selection and weight determination methods will affect the results, showing the limitations of this method (Mishra and Singh, 2010; Tanago et al., 2016). The disaster area, population and economic loss are the result of flood and

drought disasters and can be used as a good index to measure the risk of flood and drought disasters (Nafarzadegan et al., 2012; Shi et al., 2017; Wu et al., 2016). Among them, the size of the affected crop area and the proportion of production reduction due to disasters can reflect the extent of the impact of disasters on the region. The fitting distribution of disaster areas is one way to study flood and drought disaster risk. However, limited by the availability of data and other factors, there are few studies on large-scale flood and drought disaster risk and multi-angle influencing factors from the perspective of disaster area.

In this paper, the flood and drought disaster risk and its influencing factors in China are studied, and the proportion of disaster area is regarded as the index to measure the disaster risk. The risk of flood and drought disasters in China is considered as a statistical population. Based on the samples from 1989 to 2017, the optimal statistical distribution of the disaster was selected, the trend of risk change was analyzed, and the risk level of different regions was determined. Furthermore, 35 indicators were selected from the perspective of nature, agriculture and the social economy, the correlation coefficients between flood and drought disaster area and indicators were calculated, and the main influencing factors were determined from the perspective of correlation.

The framework of this paper is shown in Figure 1.

Fig.1 about here

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2 Data

In this paper, the area proportion of flood and drought disasters is used as the sample data in 31 provincial administrative regions of China from 1989 to 2017 (Taiwan Province is not included in the study area because the data could not be obtained). At the same time, from the perspective of nature, agriculture and the social economy, the factors related to flood and drought disasters were preliminarily selected, and the relationship and statistical significance between disasters and factors were analyzed. The provincial administrative regions (e.g., provinces,

106 municipalities, and autonomous regions) of China are shown in Figure 2.

107 ---

108 Fig.2 about here

109 ---

110 2.1 *Flood and drought disaster areas*

111 China's meteorological disaster yearbook defines disaster area coverage, disaster areas that are affected and
112 disaster areas without output according to the proportion of crop yield reduction caused by disasters. Among them,
113 the disaster area coverage was reduced by more than 10% as a result of disasters, the disaster areas affected were
114 reduced by more than 30%, and the disaster areas without output were reduced by more than 80%. The area of 100%
115 reduction as a result of disasters was estimated from three types of disaster areas (Xiao et al., 2017).

$$DA_{ij} = DA3_{ij} \times 0.9 + \left(DA2_{ij} - DA3_{ij}\right) \times 0.55 + \left(DA1_{ij} - DA2_{ij}\right) \times 0.2 \quad (1)$$

116 where $i = 1,2$ represent drought and flood, respectively, $j = 1,2,\ldots,31$ represent the 31 provincial
117 administrative regions. DA is the disaster area with 100% yield reduction, $DA1$ is the disaster area coverage; $DA2$
118 is the disaster area affected; and $DA3$ is the disaster area without output. Because of the difference in sowing area
119 in different provinces of China, the disaster areas were not comparable. Therefore, the proportion of disaster area
120 was used as the sample data to fit the distribution of flood and drought disasters. The calculation method is as
121 follows.

$$PDA_{ij} = \frac{DA_{ij}}{SA_j} \quad (2)$$

122 where PDA is the proportion of disaster area, and SA is the total sown area. The definition of disaster area
123 type and disaster data are from China's civil affairs statistical yearbook and China's meteorological disasters
124 yearbook.

125 2.2 *Influencing factor data*

126 Disaster risk is the result of disaster factors acting on the vulnerability of disaster-bearing bodies, which have

both natural and social attributes (Fontaine and Steinemann, 2009; Luh et al., 2015; Murthy et al., 2015; Pei et al., 2018). In this paper, 35 indicators were selected as alternative factors from the perspectives of nature, agriculture and the social economy. Natural factors mainly include meteorological and water resource factors, agricultural factors are mainly related to crop planting, and social and economic factors are mainly related to disaster resistance (see Table 1 for details). The data on influencing factors were from the Chinese statistical yearbook and provincial administrative region statistical yearbook.

3 Methods

The research of this paper is divided into two parts. In the first part, according to the sample data obtained from Equation 2, the distributions of flood and drought are fitted. The histogram shows that the distribution of flood and drought disasters is skewed; therefore, 10 common skew distributions were selected as alternative distributions. They included the normal distribution, lognormal distribution, chi-squared distribution, gamma distribution, beta distribution, exponential distribution, power function distribution, inverse Gaussian distribution, Pearson-III distribution, and three-parameter log-logistic distribution. The statistical distribution of flood and drought disasters was determined by the KS test, and the risk level of flood and drought disasters in China was classified. In the second part, according to 35 indicators and disaster area, the Pearson, Spearman and Kendall correlation coefficients and the p value of the test were calculated. Statistical significance of a correlation was obtained at the level of $\alpha = 0.05$. The average value of the three correlation coefficients was used to measure the relationship between factors and disasters, and the main influencing factors of flood and drought disasters were optimized.

3.1 *Fitting the statistical distribution of flood and drought disasters*

According to the histogram and kernel density curve, the distribution of the flood and drought disaster area proportion showed an obvious right skew. Furthermore, the skewness coefficients were 2.9987 and 2.1356, respectively, which were greater than zero, indicating the right tail length of the distribution. The normal distribution and 9 skew distribution were selected as alternative distributions. The probability density function (PDF) and

parameter estimation results of each distribution as follows(Forbes et al., 2011; McKee et al., 1993; Vicente-Serrano et al., 2010).

(1) Normal distribution

The probability density function is as follows:

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{3}$$

where $\mu = \bar{x}$, $\sigma^2 = s^2$, and $\bar{x}$ and s^2 are the sample mean value and sample variance, respectively, which are calculated from the sample data.

(2) Lognormal distribution

The probability density function is as follows:

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma x} \exp\left(-\frac{(\ln x-\mu)^2}{2\sigma^2}\right) \quad x > 0 \tag{4}$$

where $\mu = 2\ln\bar{x} - \frac{\ln(s^2+\bar{x}^2)}{2}$, $\sigma^2 = \ln(s^2+\bar{x}^2) - 2\ln\bar{x}$, and $\bar{x}$ and s^2 are the sample mean value and sample variance, respectively.

(3) Chi-squared distribution

The probability density function is as follows:

$$f(x) = \frac{1}{2^{\frac{n}{2}}\Gamma(\frac{n}{2})} \exp\left(\frac{x}{2}\right) x^{\frac{n}{2}-1} \quad x > 0 \tag{5}$$

where $n = \bar{x}$, $\bar{x}$ is the sample mean value, and $\Gamma(\cdot)$ is the gamma function.

(4) Gamma distribution

The probability density function is as follows:

$$f(x) = \beta^{\alpha} x^{\alpha-1} \frac{\exp(-\beta x)}{\Gamma(\alpha)} \quad x > 0 \tag{6}$$

where $\alpha = \bar{x}^2/s^2$, $\beta = \bar{x}/s^2$, and $\bar{x}$ and s^2 are the sample mean value and sample variance, respectively; $\Gamma(\cdot)$ is the gamma function.

(5) Beta distribution

The probability density function is as follows:

$$f(x) = \frac{x^{a-1}(1-x)^{b-1}}{\mathrm{B}(a,b)} \quad x > 0 \tag{7}$$

where $a = \frac{\bar{x}^3 - \bar{x}^2 + \bar{x}s^2}{s^2}$, $b = \frac{\bar{x} - s^2 + \bar{x}s^2 - 2\bar{x}^2 + \bar{x}^3}{s^2}$, $\bar{x}$ and s^2 are the sample mean value and sample variance, respectively, $\mathrm{B}(\cdot,\cdot)$ is the beta function.

(6) Exponential distribution

The probability density function is as follows:

$$f(x) = \lambda \exp(-\lambda x) \quad x > 0 \tag{8}$$

where $\lambda = 1/\bar{x}$, and $\bar{x}$ is the sample mean value.

(7) Power function distribution

The probability density function is as follows:

$$f(x) = cx^{c-1}\theta^{-c} \quad 0 < x < \theta, c > 0 \tag{9}$$

where $c = -\frac{s^2 \pm \sqrt{\bar{x}^2 s^2 - s^4}}{s^2}, \theta = \frac{s^2 \pm \sqrt{\bar{x}^2 s^2 - s^4} + \bar{x}^2}{\bar{x}}, and\ \bar{x}$ and s^2 are the sample mean value and sample variance, respectively.

(8) Inverse Gaussian (Wald) distribution

The probability density function is as follows:

$$f(x) = \sqrt{\frac{\lambda}{2\pi x^3}} \exp\left(\frac{-\lambda(x-\mu)^2}{2\mu^2 x}\right) \quad x > 0 \tag{10}$$

where $\mu = \bar{x}, \lambda = \frac{\bar{x}^3}{s^2}, and\ \bar{x}$ and s^2 are the sample mean value and sample variance, respectively.

(9) Pearson-III distribution

The probability density function is as follows:

$$f(x) = \frac{\beta^\alpha}{\Gamma(\alpha)}(x - a_0)^{\alpha-1} \exp\big(-\beta(1 - a_0)\big) \tag{11}$$

where $\alpha = \frac{4}{C_s^2}, \beta = \frac{2}{\bar{x}C_v C_s}, a_0 = \bar{x}\left(1 - \frac{2C_v}{C_s}\right)$, and $\bar{x}$, C_v, $and\ C_s$ are the sample mean value, coefficient of variation and skewness coefficient, respectively.

(10) Three-parameter log-logistic distribution

The probability density function is as follows:

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1}\left[1+\left(\frac{x-\gamma}{\alpha}\right)^{\beta}\right]^{-2} \tag{12}$$

where $\beta = \frac{2\omega_1-\omega_0}{6\omega_1-\omega_0-6\omega_2}$, $\alpha = \frac{(\omega_0-2\omega_1)\beta}{\Gamma(1+1/\beta)\Gamma(1-1/\beta)}$, $\gamma = \omega_0 - \alpha\Gamma(1+1/\beta)\Gamma(1-1/\beta)$, $\omega_s = \frac{1}{n}\sum_{l=1}^{n}\left(1-\frac{l-0.35}{n}\right)^s X_l'$, ω_s is the probability weight moment，and $s = 0, 1, 2$. X_l' is the result of the sample data arranged in ascending order, and $\Gamma(\cdot)$ is the gamma function.

Because most of the PDFs have no primitive function, they cannot be solved by the Newton-Leibniz formula. In this paper, the cumulative distribution function (CDF) was calculated by numerical integration.

To quantitatively select the distribution from the perspective of the statistical test, this paper uses the KS test to optimize the statistical distribution (Rosenthal, 1968; Xiao, 2017). The KS test is a non-parametric test method, which is mainly used to test whether the actual distribution is consistent with the theoretical distribution in a statistical sense. The KS test calculates the maximum vertical distance of the empirical distribution and theoretical distribution. If the distance is less than the boundary value, then the actual distribution is consistent with the theoretical distribution. The method is as follows.

Step 1: Hypothesis, $H_0: F_n(x) = F(x)$, $H_1: F_n(x) \neq F(x)$. $F_n(x)$ is the empirical distribution of the data to be fitted, and $F(x)$ is a theoretical distribution.

Step 2: Calculate the absolute value of the sample cumulative frequency (empirical distribution value) and the theoretical distribution cumulative probability (distribution function value). The largest of all absolute values is D_n, which is calculated as follows:

$$D_n = \max\{|F_n(x) - F(x)|\} \tag{13}$$

Step 3: The boundary value D_n^{α} was determined by the sample size and significance level α.

Step 4: Compare D_n and D_n^{α}. If $D_n < D_n^{\alpha}$, accept the null hypothesis, i.e., it is considered that the empirical distribution is consistent with the theoretical distribution at the significance level α.

After selecting the optimal distribution of flood and drought disasters, the CDF value of the disaster proportion is calculated. According to the CDF, the disaster risk is divided into 4 levels by equidistant classification. A large CDF value corresponds to a high level, and a high level represents a large proportion of the disaster area and a high risk.

3.2 *Analysis of influencing factors of flood and drought disaster*

Flood and drought disasters have both natural and social attributes, which are the result of the disaster-causing factors acting on the disaster-bearing body. To analyze the influencing factors of flood and drought disaster, according to the relevant references (Chen et al., 2018; Chen et al., 2019b; Qian et al., 2016; Shen et al., 2017; Simelton et al., 2009) and considering the availability of data, 35 indicators were selected as alternative indicators from natural, agricultural and socioeconomic perspectives, and the correlation coefficient between the disaster and the alternative indicators was calculated. Because there may be a linear or nonlinear relationship between disasters and factors, Pearson, Spearman and Kendall correlation coefficients were used to reflect the relationship. Furthermore, the correlation coefficient test can calculate the test p-value and analyze the significance from the perspective of the statistical test. Table 1 shows the 35 indicators, indicator units, calculation methods and reasons for selection.

Tab.1 about here

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4 Results

4.1 *Risk analysis of flood and drought disasters*

4.1.1 Fitting the statistical distribution of flood and drought disasters

According to Equation 2, the proportion of flood and drought disasters was calculated in 31 provincial administrative regions of China in 1989-2017. There were 899 sample data points in total. Because many

229 distributions cannot have a zero value, we obtained 804 drought sample points and 842 flood sample points by
230 removing the zero values in the data. The PDF $f(x)$ values of 10 distributions were obtained by estimating the
231 parameters from the sample data, and the CDF values were calculated by numerical integration. According to the
232 sample data, the empirical distribution function $F_n(x)$ was calculated, and the results of the KS test and boundary
233 value ($\alpha = 0.05$) are shown in Table 2.
234 ----------
235 Tab.2 about here
236 ----------
237 As shown in Table 2, for drought, the KS test values of the gamma distribution, beta distribution and
238 exponential distribution are all less than the boundary values, indicating that the three distributions fit the drought
239 sequence well. For floods, the KS test values of the gamma distribution, beta distribution and exponential
240 distribution are smaller than those of the other 7 distributions, but their KS test values are slightly higher than the
241 boundary value. To observe the fitting results from the figures, the histogram of flood and drought, the PDF figure
242 of the gamma, beta and exponential distributions, and the figure of the theoretical distribution and empirical
243 distribution were drawn and are shown in Figure 3.
244 ----------
245 Fig.3 about here
246 ----------
247 From Figure 3, the gamma, beta and exponential distributions fit well for flood and drought disasters.
248 Combining Table 2 and Figure 3, the best fit for drought was the gamma distribution, the best fit for flood was the
249 exponential distribution followed by the gamma distribution, and the difference between the two distributions was
250 very small. Therefore, the gamma distribution was determined as the best statistical distribution for describing the
251 flood and drought.

252 4.1.2 Temporal and spatial variation analysis of flood and drought disaster risk

253 The large proportion of disaster area corresponded to the large distribution function value; thus, the distribution
254 function value could represent the disaster risk. Figure 4 shows the change in flood and drought disaster risk in each
255 provincial administrative region, and the straight line represents the trend line.

256 ----------

257 Fig.4 about here

258 ----------

259 As shown in Figure 4, the risk of flood and drought disasters in most regions shows a downward trend, which
260 seems to be inconsistent with climate change. In recent years, the temperature has generally increased, especially in
261 the middle and high latitudes of Asia, with a trend of further warming (Grubler, 2014; WILLIAMSON, 2013). The
262 increase in temperature leads to the increase in evaporation and the uncertainty in local heavy rainfall, which further
263 increases the uncertainty of regional drought and flooding. However, temperature rise and precipitation anomalies
264 only increase the uncertainty of hazard factors, and this uncertainty is more likely to cause anomalous regional water
265 changes. Flood and drought disasters are not only affected by hazard factors but also closely related to the number
266 and value of disaster-bearing bodies exposed to the disaster environment, the sensitivity of disaster-bearing bodies
267 to hazard factors and the ability of disaster-bearing bodies to resist disasters(Fontaine and Steinemann, 2009; Luh
268 et al., 2015; Murthy et al., 2015; Pei et al., 2018). Resistance capacity refers to the ability to cope with water
269 anomalies and reduce economic and social losses, which are related to socioeconomic factors and scientific and
270 technological factors(Pei et al., 2018; Wilhite et al., 2014). In recent years, China's economy has made great progress,
271 which has led to the enhancement of the ability of disaster prevention. Although the natural factors that cause flood
272 and drought disasters show a negative trend, due to the enhancement of the ability to resist natural disasters, the
273 disaster risk shows a downward trend.

274 To analyze the spatial difference in flood and drought disaster risk, the average disaster area of each region

from 1989 to 2017 was used to express the disaster degree of the region, and then the distribution function value of the disaster was calculated. According to the probability, the risk of flood and drought disasters in each provincial administrative region of China was divided into four levels using the equidistant classification method, and the high level represents the high risk, as shown in Figure 5.

Fig.5 about here

The areas with higher drought risk were mainly distributed in Northeast and North China, while the drought risk in South and West China were relatively low. The southern region is rich in precipitation, rivers and lakes, and there are few serious drought disasters. Most of the western region is not suitable for planting crops, and the local areas that are suitable for cultivation are rich in water, meaning the risk of drought disaster is low. The areas with a high flood risk are mainly in the south, especially in Hubei, Hunan, Jiangxi and Anhui. Because of the high precipitation and abundant water resources in the south, the possibility and degree of flood disaster are higher than those in other areas. Overall, the spatial distribution of flood and drought disaster risk is consistent with the distribution characteristics of regional precipitation and water resources in China.

4.2 *Influencing factors of flood and drought disaster*

According to Equation 2, the proportion of flood and drought disasters in 31 provincial administrative regions of China from 1989 to 2017 was used as a disaster sequence, with a total of 899 values. The 35 indicators in Table 1 were used as the sequence of influencing factors. Because some data values could not be obtained, when there were missing values in some positions of the influencing factor sequence, the corresponding disaster sequence was also set as the missing value when calculating the correlation coefficient. The Pearson, Spearman and Kendall correlation coefficients of the disaster sequence and influencing factor sequence were calculated, and the P values of corresponding tests were also calculated. The mean value of the three coefficients and P value represents the

298 degree of correlation and significance, respectively, and the significance level is $\alpha = 0.05$. Figure 6 shows the
299 correlation and statistical significance between disasters and influencing factors.
300 ----------
301 Fig.6 about here
302 ----------
303 For the natural factors, the relationship between annual precipitation (X1) and flood and drought disaster was
304 the largest, and the P value was far less than 0.05, indicating that there was a statistically significant correlation
305 between disaster sequence and precipitation. Additionally, precipitation had a negative correlation with drought and
306 a positive correlation with flooding, which was also in line with the characteristics of flooding and drought.
307 Precipitation is the main source of underlying surface water resources, and the abnormal change in precipitation is
308 an important driving factor of flood and drought disasters(Fu et al., 2018; Modarres et al., 2016). Furthermore, in
309 addition to the per land groundwater supply (X7), most water-related indicators (such as X3, X4, X6, X8) are closely
310 related to drought. In contrast, except for precipitation, the other water-related indicators (X2-X9) are all weakly
311 related to flooding, and they are not significant at the level of $\alpha = 0.05$. When precipitation decreases, the
312 underlying surface water resources (including X2-X9) are the main source of irrigation and an important guarantee
313 to resist drought; thus, these values are closely related to drought. Flood is often caused by extreme precipitation,
314 and the amount of water resources in the underlying surface is mainly related to the regional topography and is not
315 the main cause of flooding.
316 For agricultural factors, there is a significant positive correlation between the per capita cultivated land value
317 (X20) and drought. A large X20 value indicates there are many disaster-bearing bodies exposed to the disaster
318 environment. When the water content changes abnormally, a large exposure results in a large proportion of the
319 disaster. Furthermore, the irrigation index (X25), the land power of agricultural machinery (X23), and the power of
320 irrigation and drainage (X24) are all negatively correlated with drought. The irrigation index is the proportion of

the area that can be irrigated in the region, while the total power reflects the ability of regional irrigation, which reflects the ability of disaster resistance, and then shows a negative correlation. For floods, the relationship between factors and floods is not strong, and most factors fail to pass the correlation test. The relationships among chemical fertilizer, reservoir capacity and flood disaster are relatively strong. Chemical fertilizer can increase grain yield, reduce grain loss and indirectly reduce the harm caused by flood disasters. The reservoir capacity reflects the regional storage capacity, which can alleviate the harm of extreme precipitation.

The proportion of agricultural population and GDP is closely related to flood and drought disasters (X30, X31). Agriculture has the most area affected by flooding and drought, and the area with a large proportion of agricultural population and GDP is sensitive to disasters. These factors have a significant negative correlation with drought, e.g., the per capita income of rural households (X32), per cultivated land rural labor (x33), Investment in water conservancy facilities (X34), and per cultivated land electricity consumed in rural areas (X35). The values of X32-X35 reflect the ability of the region to resist drought disasters, and a large value represents a strong drought resistance ability. At the same time, there is a significant negative correlation between the per capita income of farmers and floods. Farmers in high-income areas are less dependent on agriculture and have a strong ability to resist natural disasters.

In general, the mean values of the absolute correlation coefficients of drought and flood and each factor are 0.23 and 0.12, respectively, and the relationship between drought and each factor is relatively large. As a general natural disaster, drought has the characteristics of being slow and sustained, many factors affect drought, and the forms of social response are diversified. Areas with abundant rainfall are not prone to drought. Similarly, areas with abundant underlying water resources and strong drought resistance are not prone to drought. There are many factors affecting regional water resources and drought resistance capacity, which is also why drought has a strong correlation with various factors. In contrast to drought, the flood shows the characteristic of being sudden. A flood is often caused by extreme precipitation in a region, which has little to do with the water resources of the region

itself. Even in the traditional arid area, extreme precipitation may still cause flood disasters. Because of this unpredictable characteristic, the ability and method of social response to flooding is insufficient, and the relationship between flooding and various factors is relatively weak.

5 Discussion

In this paper, the flood and drought disaster risk is represented by the proportion of disaster area, and the statistical distribution of disaster is used to analyze the change trend and spatial distribution of flood and drought disaster risk in China. Furthermore, the main factors affecting flood and drought disasters are analyzed from the perspective of nature, agriculture and the social economy. The results show that the distribution of flood and drought disasters is right skewed, and the beta distribution is the best statistical distribution to use to fit the flood and drought disasters. From the perspective of temporal and spatial characteristics, the risk of floods and droughts in different regions of China shows a downward trend, mainly due to the enhancement of the ability to resist disasters. The areas with a higher drought risk are mainly distributed in Northeast and North China, and the areas with a higher flood risk are mainly distributed in the south, especially in the central and southern regions. In terms of influencing factors, precipitation is the main influencing factor of flood and drought disasters. Among agricultural and socioeconomic factors, the factors related to disaster resistance are strongly related to flood and drought disasters. Overall, the correlation between drought and various factors is stronger than that of flood, and the slowness, sustainability and diversity of methods to resist disasters are possible reasons.

Flood and drought disasters have always been a hot topic in research. The provincial-level flood and drought disaster risk analysis from the perspective of disaster area is helpful for identifying the occurrence risk of flood and drought disasters in different regions of China. The results of this study can be used as a reference for disaster classification and understanding the temporal and spatial differences in flood and drought disaster risk in China. Additionally, the study of influencing factors is helpful for identifying the coupling relationship between the factors (from nature, agriculture, economy and society) and disasters, optimizing the main influencing factors of flood and

drought disasters in China, determining the disaster-causing factors closely related to flood and drought disasters and the indexes to resist disasters, and providing a reference for exploring the formation mechanism of disasters and the ways to resist flood and drought disasters.

In previous studies, there were many methods that focused on hazard factors used to study flood and drought disasters, such as the drought index and extreme precipitation (Guo et al., 2018; Yang et al., 2018a; Yuan et al., 2019; Zuo et al., 2019). The hazard factors indicate the intensity of the water anomalies, which represent the direct cause of the disaster. However, the water anomaly does not necessarily cause the disaster, and the disaster is also related to the ability of the society to resist the disaster. Therefore, it is common to select natural and socioeconomic indicators related to disasters and use comprehensive evaluation methods to study flood and drought disaster risk (Fontaine and Steinemann, 2009; Luh et al., 2015; Murthy et al., 2015). Hazard factors or comprehensive evaluation methods mainly study disaster risks from the causes and processes of disasters, without mentioning the results of disasters (Luh et al., 2015; Murthy et al., 2015; Yang et al., 2018b; Zuo et al., 2019). In this paper, the proportion of disaster area was used to represent the disaster risk. The disaster area is the result of the disaster, which can comprehensively reflect the intensity of the disaster-causing factors and the ability of the society to cope with the disaster. The possible reasons for the large proportion of disaster areas are the high intensity of hazard factors or the weak ability to resist disasters. The regional scale of this paper included China's 31 provincial administrative regions (Taiwan Province is not included in the study area because the data could not be obtained), and the severity of flood and drought disasters were classified; thus, we obtained the change trend of flood and drought disasters in each region. Furthermore, the main factors affecting the change in flood and drought disasters were analyzed from the natural, agricultural and socioeconomic perspectives. The risk analysis of flood and drought disasters from the perspective of large-scale and proportion of disaster areas, as well as research on multi-angle influencing factors, have rarely been conducted in the past.

From 1989 to 2017, 31 provincial-level administrative regions in China were used as sample data, and the data

time scale was relatively short and the region was large, mainly because the data of longer times and smaller regions could not be obtained. A large number of sample data points can be obtained from long-term and small-scale data, which can more accurately describe the risk and influencing factors of flood and drought disasters in China. However, the disaster area is only one aspect of the flood and drought disaster results. Other results, such as the affected population, disaster losses and other factors, also reflect the results of flood and drought disaster to a certain extent, but these topics were not included in the model. Considering the flood and drought disaster risk comprehensively from the disaster area, affected population and disaster loss, the analysis results are more practical. However, due to the differences in the dimension and type of indicators, combining the three indicators organically is difficult. At present, there is no similar research on this topic, although it is a future research direction of our team.

6 Conclusion

In this paper, 31 provincial-level administrative regions in China were taken as the study area, the disaster risk was represented by the proportion of disaster area, the disaster distribution was optimized from 10 types of distribution by the KS test, the change trend of flood and drought disaster in each region was analyzed, and the disaster risk in each region was classified. Finally, 35 indicators were selected from the natural, agricultural and socioeconomic perspectives, and the relationship between disasters and indicators was analyzed to optimize the main influencing factors of flood and drought disasters. The main results were as follows.

(1) The distribution of flood and drought disasters is right skewed, and the beta distribution is the best statistical distribution that can be used to fit the flood and drought disasters.

(2) Although the abnormal degree of the hazard factor is increased due to the increase in temperature and climate change, the disaster risk of flood and drought disasters in various regions of China still shows a downward trend, mainly due to economic development and the enhancement of social resilience to disasters.

(3) The areas with a higher drought risk are mainly distributed in Northeast and North China, while the southern and western areas have a lower drought risk. The areas with a high flood risk are mainly in the south, especially in

Hubei, Hunan, Jiangxi and Anhui. This result is consistent with the distribution characteristics of precipitation and water resources in China.

(4) Precipitation is an indicator that has a strong impact on flood and drought disasters among the natural indicators, while indicators related to disaster resistance in agriculture and the social economy have a strong relationship with flood and drought disasters, such as factors reflecting regional disaster resistance and economic development level.

The research on the risk analysis and influencing factors of flood and drought disasters in the provincial administrative regions of China has a strong reference value for understanding the temporal and spatial variation law of flood and drought disasters on a large scale, the classification of regional disasters, and the identification of the coupling relationship between flood and drought disasters and related factors. Additionally, the disaster area is only one aspect that reflects the results of flood and drought disasters. The affected population and disaster loss can also be used as indicators to reflect the results of disasters. How to organically integrate disaster area, disaster population and disaster loss and other factors and establish multi-angle and comprehensive disaster risk measurement indicators is a difficult task and the next research direction.

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The authors declare that they have no conflicts of interest for this work

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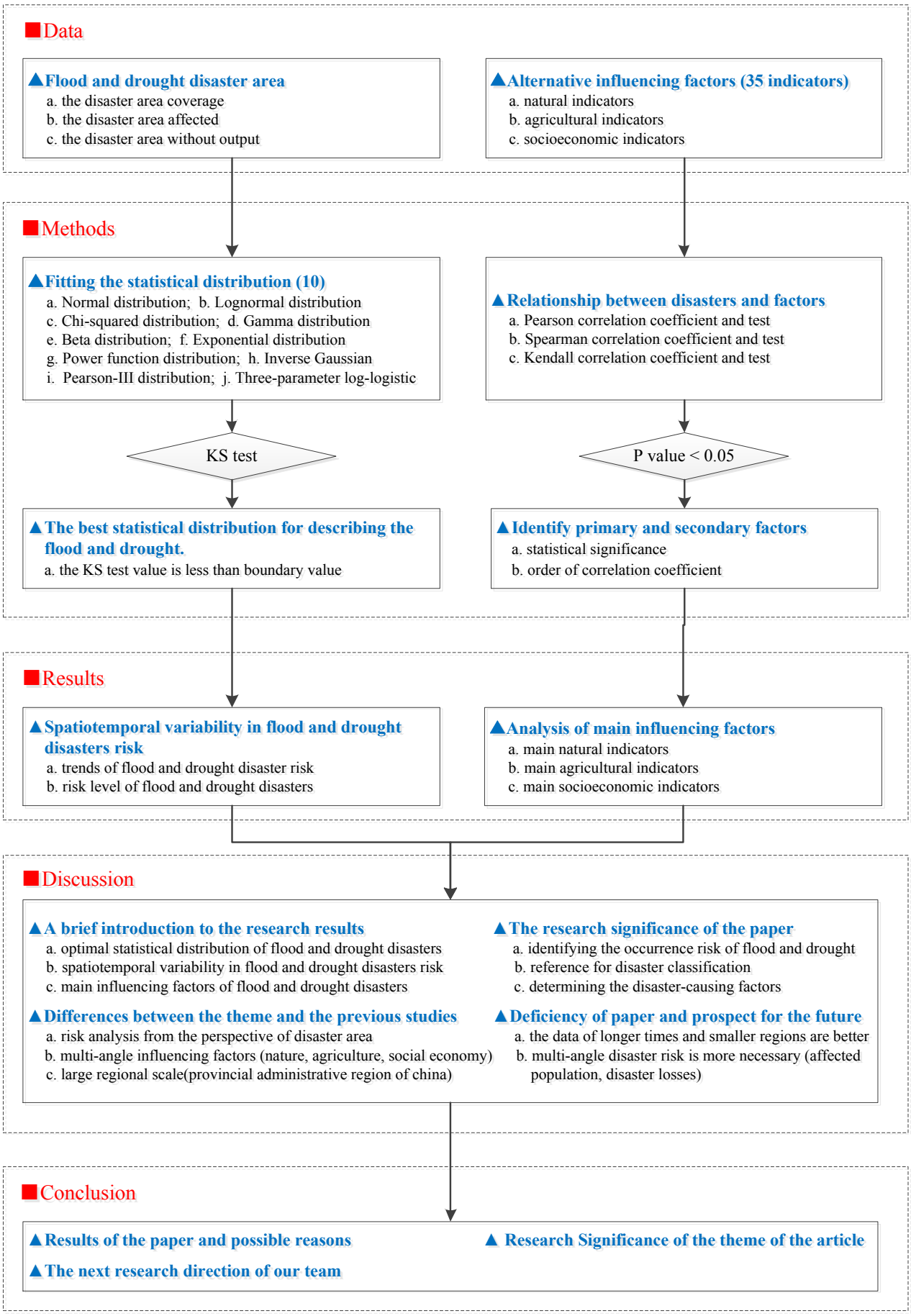


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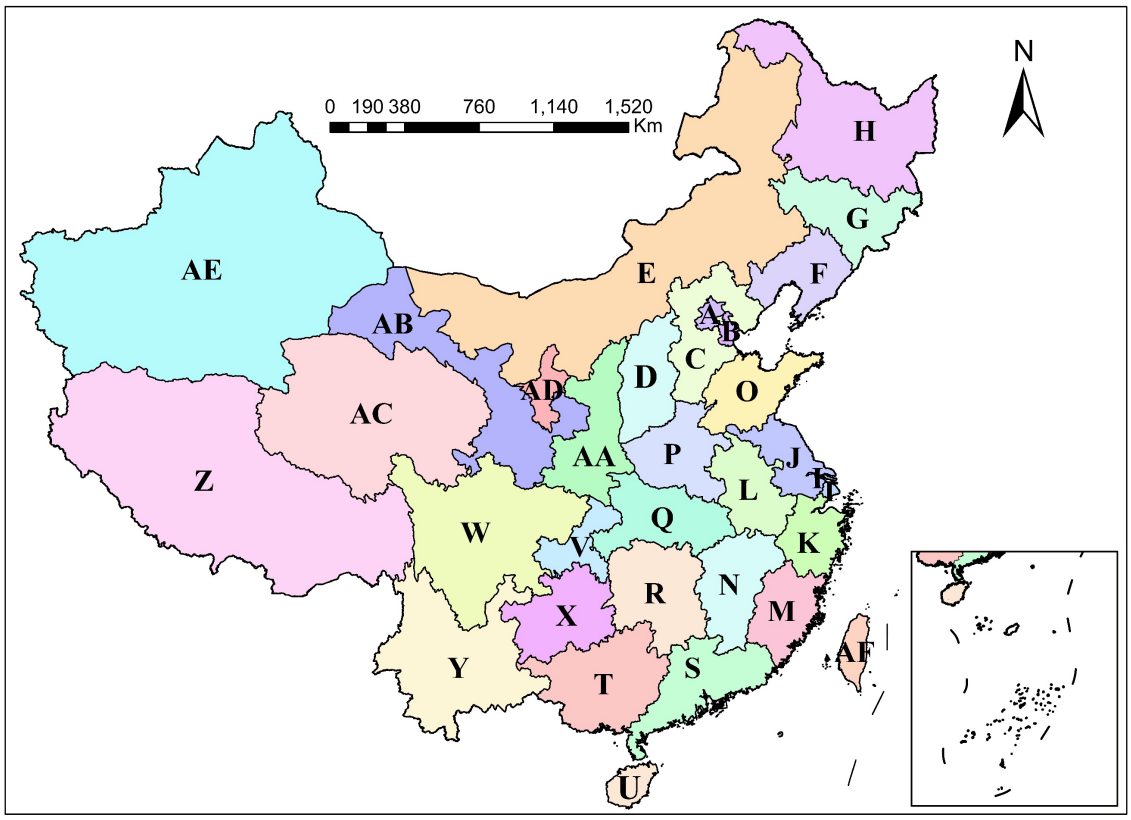


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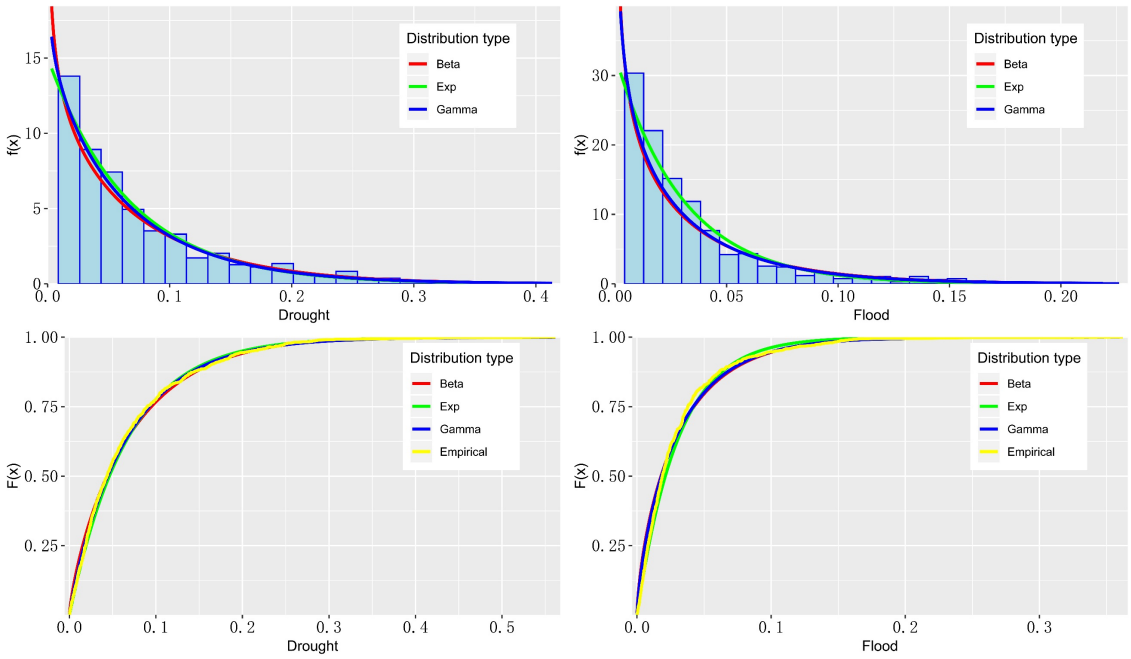


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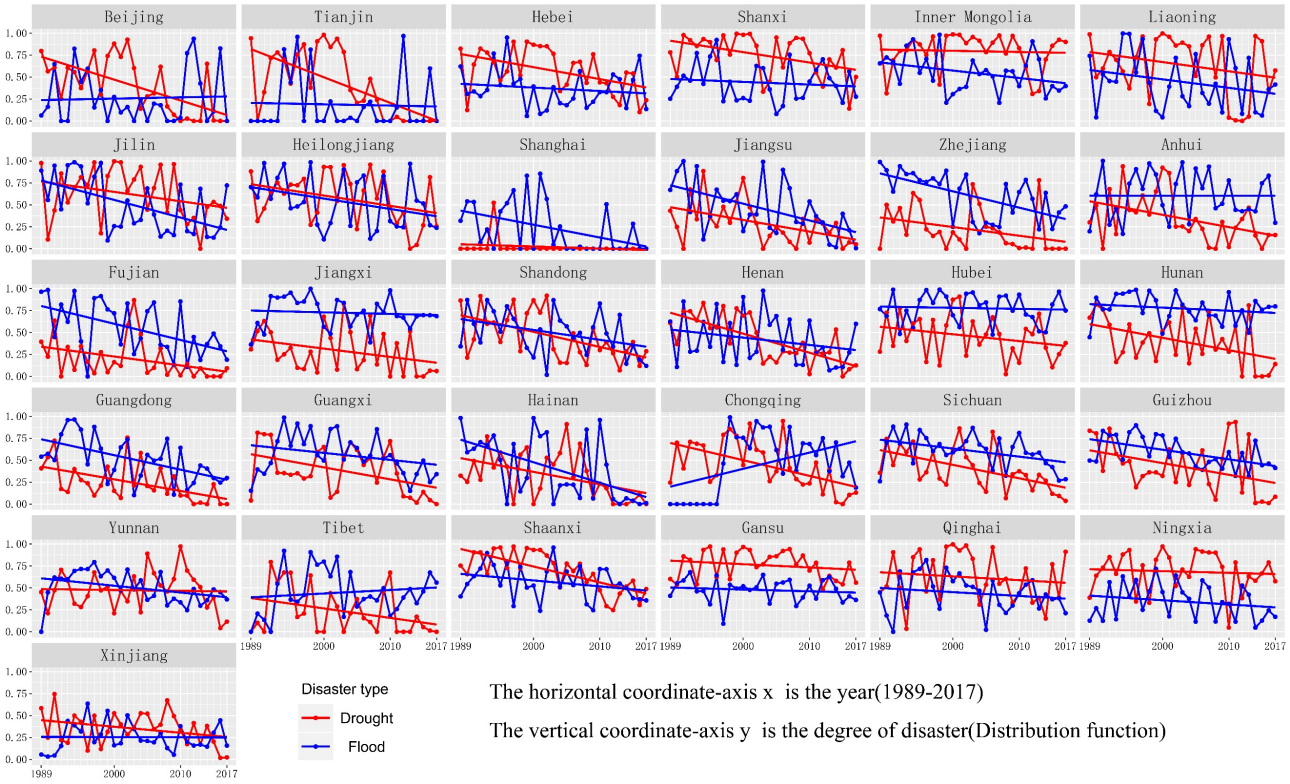


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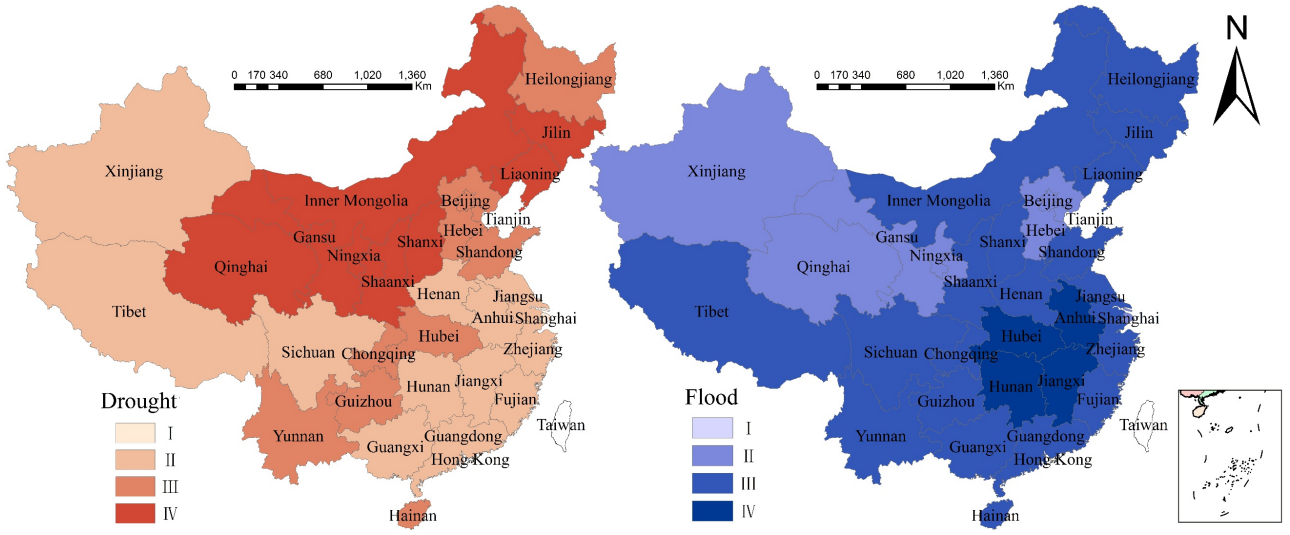


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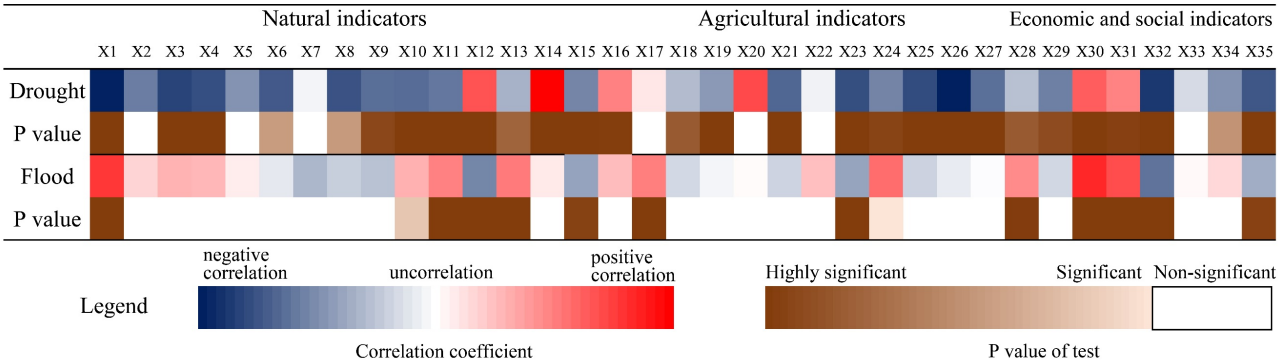


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Table 2. The results of the KS test

Table 1. The 35 indicators from nature, agriculture and the social economy

	Initial index	Unit	Computing method	Possible impact on flood and drought disaster
Natural indicators	Annual precipitation (X1); Per land water resources (X2); Per land surface water resources (X3); Per land groundwater resources (X4); Per land water supply (X5); Per land surface water supply (X6); Per land groundwater supply (X7); Per land water use (X8); Per land water use of agriculture (X9)	X1: mm; X2-X9: 10^4 m^3/ha	X1: raw data; X2-X8: water resources/area; X9: water resources/cultivated land	The surplus and deficit of water resources is the direct cause of flood and drought disasters, respectively. The shortage of water resources will cause the drought disaster. In contrast, the obvious excess of water resources will cause the flood disaster.
	Annual average temperature (X10); Annual average relative humidity (X11); Annual sunshine hours (X12)	X10: °C; X11: %;, X13: h	X10-X13: raw data	These meteorological indicators will affect the evapotranspiration of water resources, which is closely related to the formation of flood and drought disasters.
	Forest coverage rate (X13); Proportion of grassland (X14); Proportion of wetland (X15)	X14-X16: %	X14: forest area/land area; X15: grassland area/land area; X16: wetland area/land area	Forest, grassland and wetland have the functions of water conservation, soil and water conservation and climate regulation. A large proportion can reduce the possibility of flood and drought disaster.
Agricultural indicators	Cultivated land (X16); Sown area (X17); Proportion of cultivated land (X18); Proportion of sown area (X19); Per capita cultivated land (X20); Grain yield per Hectare (X21)	X16-X17: 10^3 ha; X18-X19: %; X20: ha/10 people; X21: 10 t/ha	X16-X17: raw data; X18-X19: area/land area; X20: cultivated land/population; X21: grain yield / sown area	The indicators such as area and yield mainly reflect the exposure of the disaster-bearing body from the perspective of agriculture. When the water resources change abnormally, the large area or high yield area has a large loss, and the large exposure tends to result in a high risk.
	Irrigation area (X22); Per cultivated land power of agricultural machinery (X23); Per cultivated land power of irrigation and drainage (X24); Irrigation index (X25); Per cultivated land chemical fertilizers (X26); Per cultivated land capacity of reservoirs (X27)	X22: 10^3 ha; X23-X24:10 kw/ha; X25: %; X26:10 t/ha; X27: 10^4 m^3/ha	X22: raw data; X23-X24: power/cultivated land; X25: irrigation area/cultivated land; X26: chemical fertilizers/cultivated land; X27: capacity of reservoirs/cultivated land	These indicators reflect the ability to resist floods and droughts from the perspective of agricultural infrastructure. Large values represent strong disaster resistance and low adverse effects.
Socioeconomic indicators	Population (X28); Population density (X29); Proportion of agricultural population (X30); Proportion of agricultural GDP (X31)	X28:10^4 people; X29: people/ha; X30-X31: %	X28-X29: raw data; X30: rural population/population; X31: agricultural GDP/GDP	These indicators reflect the sensitivity of the disaster-bearing body from the perspective of the social economy, and the highly sensitive areas are prone to the impact of flood and drought disasters.
	Per capita income of rural households (X32); Per cultivated land rural labor (X33); Investment in water conservancy facilities (X34); Per cultivated land electricity consumed in rural areas (X35)	X32: yuan; X33: 10 people/ha; X34: 10^8 yuan; X35: 10^5 kwh/ha	X32: raw data; X33: labor/cultivated land; X34: raw data; X35: electricity/cultivated land	These indicators reflect the disaster resistance ability from the perspective of the social economy. Large values represent strong disaster resistance ability. When water resources change abnormally, large disaster resistance ability can reduce the impact of disasters.

Table 2. The results of the KS test

Type	KS test results of 10 distributions					Boundary value
Drought	Normal	Lognormal	Chi-squared	Gamma	Beta	0.04796
	0.328	0.111	0.601	0.025	0.047	
	Exponential	Power function	Inverse Gaussian	Pearson-III	Log-logistic	
	0.031	0.163	0.115	0.628	0.128	
Flood	Normal	Lognormal	Chi-squared	Gamma	Beta	0.04687
	0.37	0.088	0.701	0.073	0.085	
	Exponential	Power function	Inverse Gaussian	Pearson-III	Log-logistic	
	0.053	0.219	0.087	0.66	0.096	

Figures

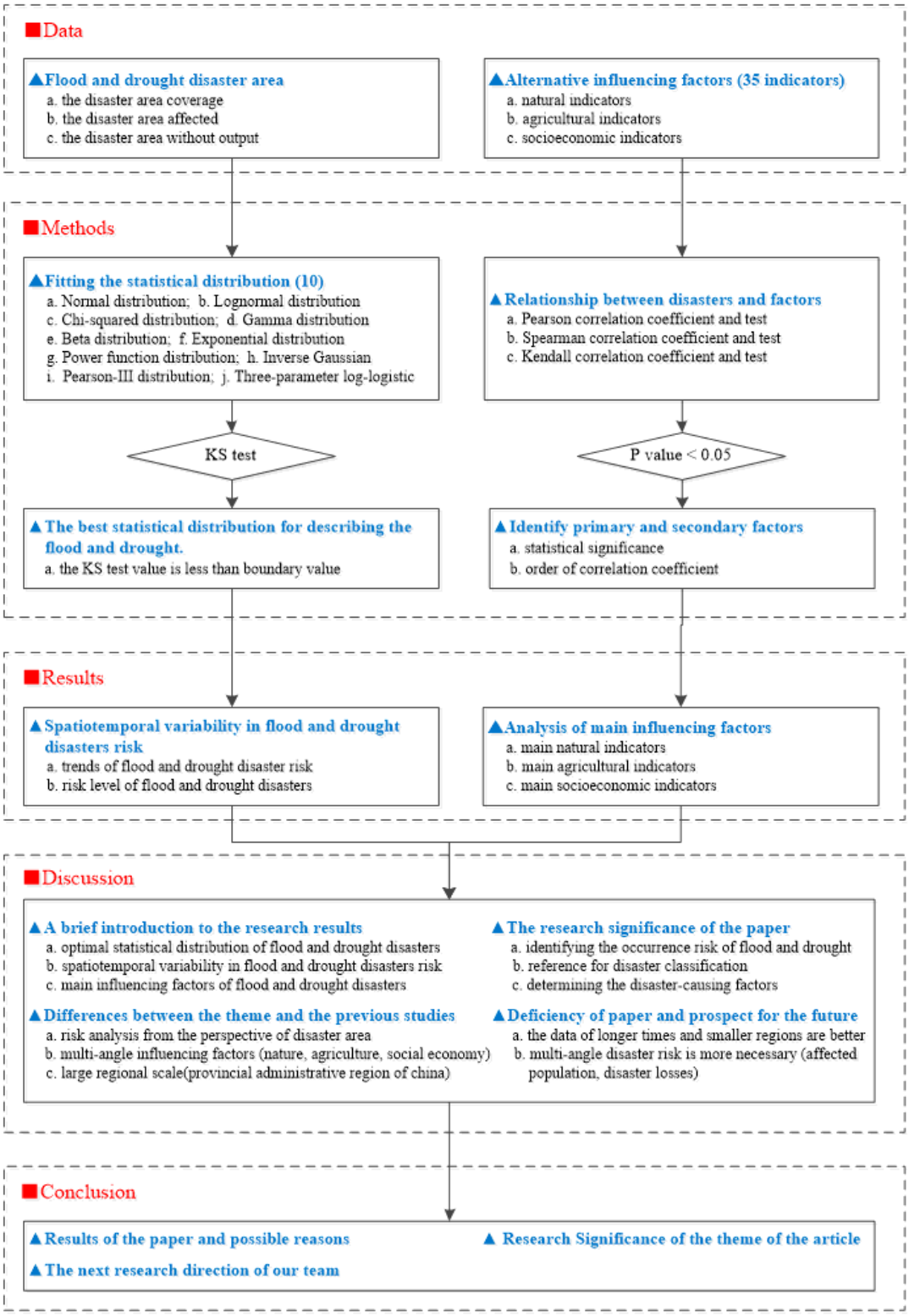


Figure 1

The framework of paper

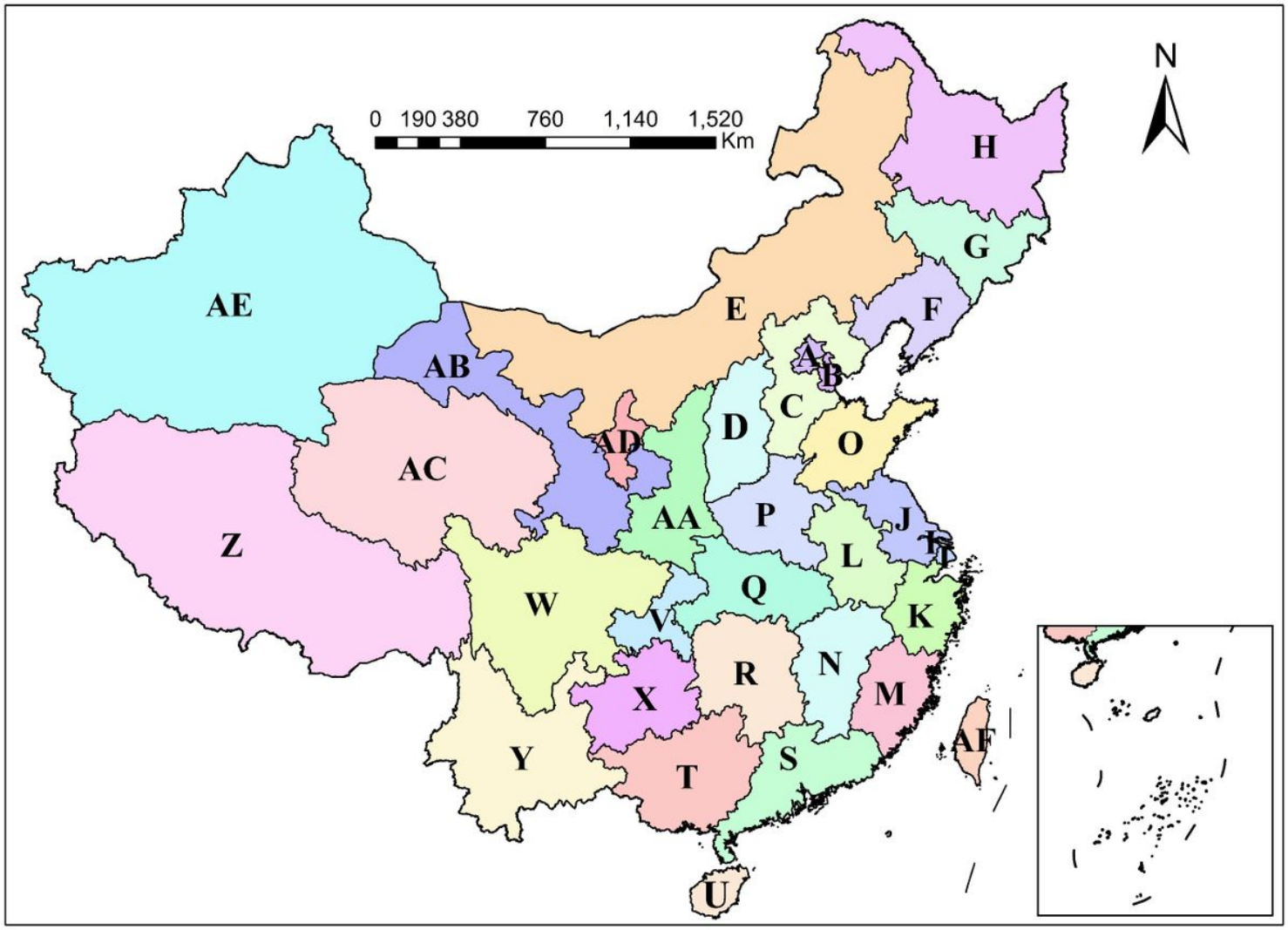


Figure 2

Provincial administrative regions of China. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

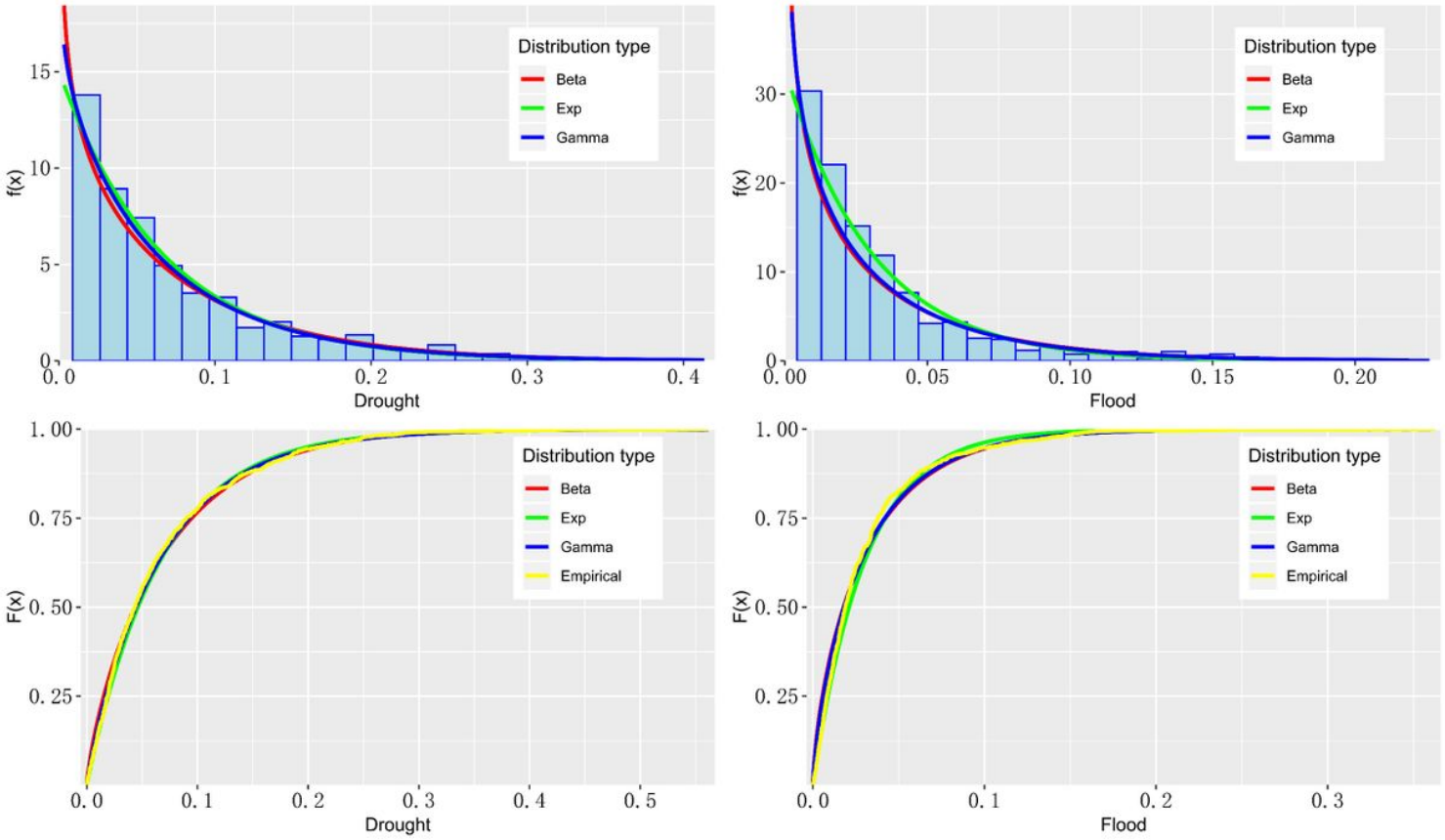


Figure 3

Distribution fitting of flood and drought disasters.

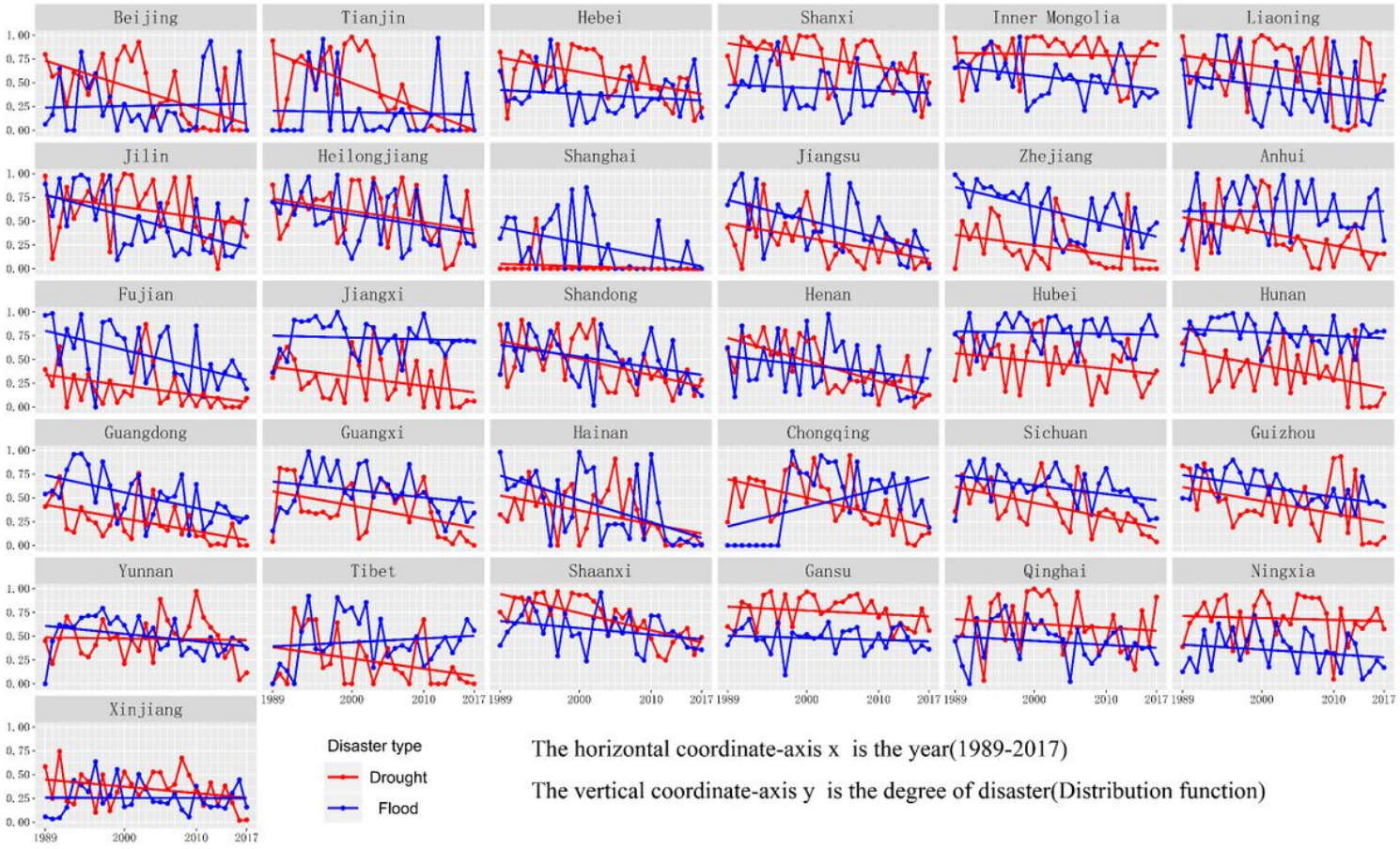


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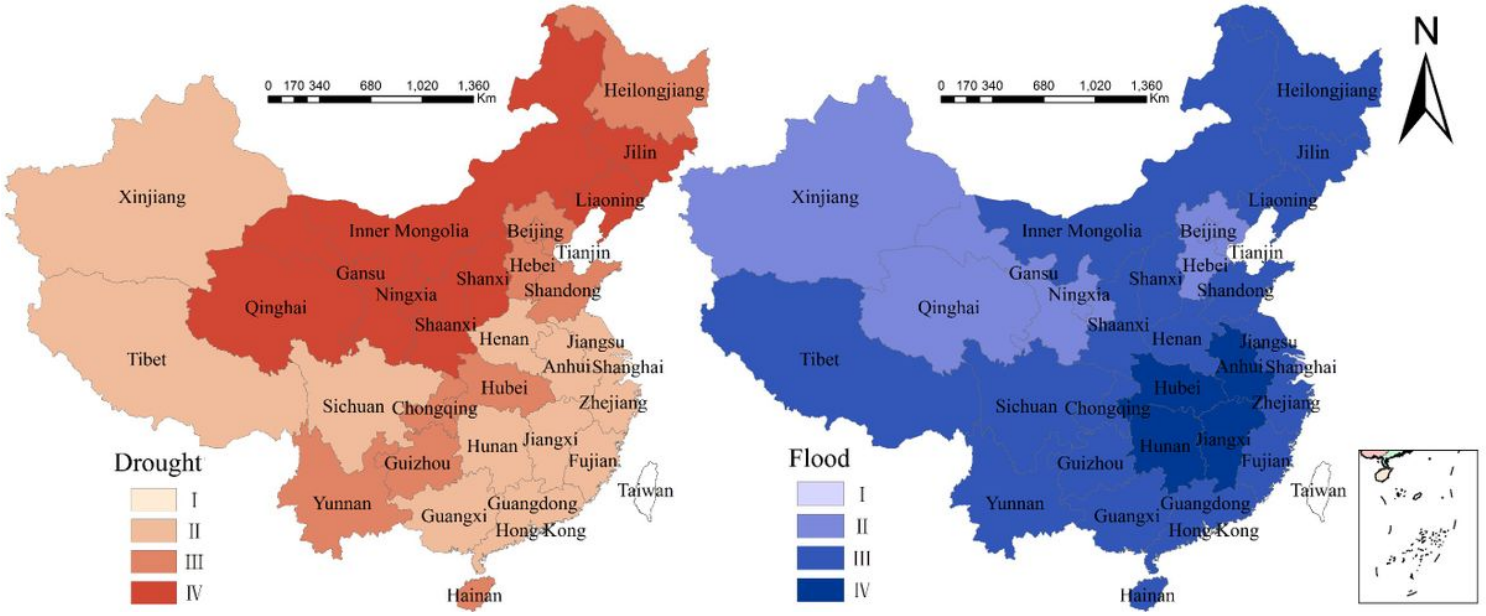


Figure 5

Risk level of flood and drought disasters. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research

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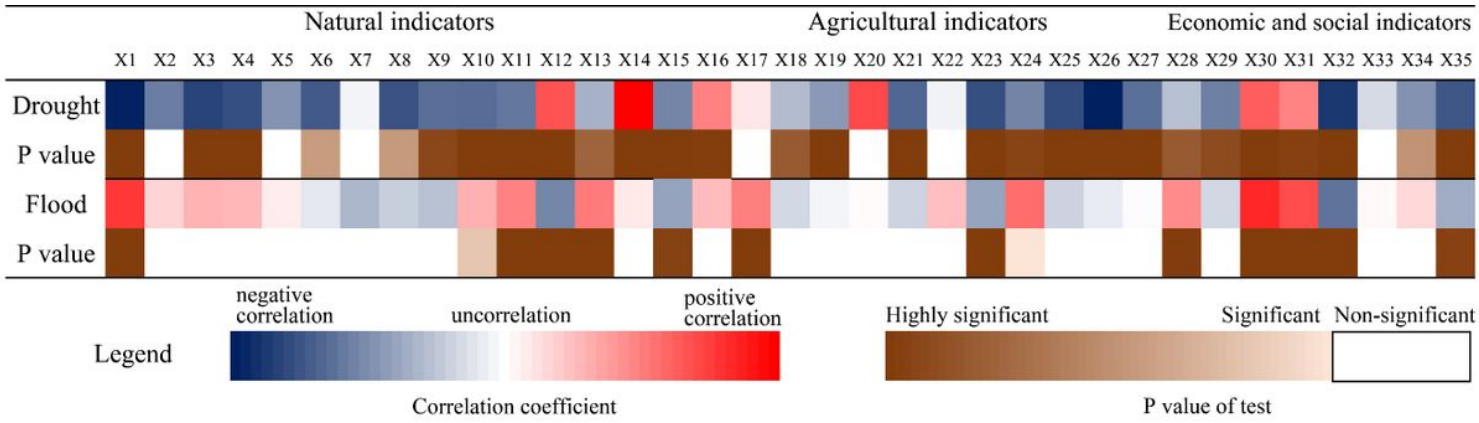


Figure 6

Correlation and significance between disasters and influencing indicators (X1-X35 are shown in Table 1).