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 proportion of the disaster area represents the degree of the disaster. The statistical distribution of the proportions was optimized from 10 alternative distributions based on a 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 gamma 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.

Keywords 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 5 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 (Shao and Kam 2020; Yan et al. 2014). 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 differences between this paper and previous studies are as follows. First, the proportions of floods and the drought disaster area are combined as an index to measure disaster risk; then, the distribution of disaster risk is fitted, and the disaster levels are divided. The proportion of the disaster area is the result of various factors acting on a bearing body, which can directly reflect the degree of influence for a given disaster. Second, because flood and drought disasters are highly related to nature and society, from the perspectives of nature, agriculture and socioeconomics, the main factors that influence disasters are selected based on correlation analysis. Next, with China’s provincial administrative regions as the research area, the statistical distribution of flood and drought disaster risk is fitted. Finally, 35 indicators are selected from natural, agricultural and socioeconomic perspectives. The relationship between the disaster area ratio and different indicators is analyzed to determine the main factors that influence flood and drought disasters.

The framework of this paper is shown in Fig. 1.

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, Hong Kong and Macao SAR are not included in the study area because the necessary 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, municipalities and autonomous regions) of China are shown in Fig. 2.

2.1 Flood and drought disaster areas

China’s meteorological disaster yearbook defines disaster area coverage, disaster areas that are affected and disaster areas without output according to the proportion of crop yield reduction caused by disasters. Among them, the disaster area coverage was reduced by more than 10% as a result of disasters, the disaster areas affected were reduced by more than 30%, and the disaster areas without output were reduced by more than 80%. The area of 100% reduction as a result of disasters was estimated from three types of disaster areas (Xiao et al. 2017).
Fig. 1 The framework of the paper
where $i=1, 2$ represent drought and flood, respectively, $j=1, 2, \ldots, 31$ represent the 31 provincial administrative regions. DA is the disaster area with 100% yield reduction, DA1 is the disaster area coverage; DA2 is the disaster area affected; and DA3 is the disaster area without output. Because of the difference in sowing area in different provinces of China, the disaster areas were not comparable. Therefore, the proportion of disaster area was used as the sample data to fit the distribution of flood and drought disasters. The calculation method is as follows.

$$DA_{ij} = DA_{3ij} \times 0.9 + \left( DA_{2ij} - DA_{3ij} \right) \times 0.55 + \left( DA_{1ij} - DA_{2ij} \right) \times 0.2$$  \hspace{1cm} (1)$$

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

$$PDA_{ij} = \frac{DA_{ij}}{SA_j}$$  \hspace{1cm} (2)$$

where PDA is the proportion of disaster area, and SA is the total sown area. The definition of disaster area type and disaster data are from China’s civil affairs statistical yearbook and China’s meteorological disasters yearbook. PDA is used as a random variable to fit the observed statistical distribution, and missing values were removed when fitting the distribution.

## 2.2 Influencing factor data

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. In the method, the correlation coefficients between factors and $PDA$ are calculated. If data for a factor or $PDA$ are missing, the corresponding values are removed in pairs.

## 3 Methods

The research of this paper is divided into two parts. In the first part, according to the sample data obtained from Eq. 2, the distributions of flood and drought are fitted. 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. Therefore, 9 common skewed distributions and the normal distribution 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 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:

   $$f(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{(x - \mu)^2}{2\sigma^2}\right)$$  \hspace{1cm} (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:
| Table 1  | The 35 indicators from nature, agriculture and the social economy |
|---------|---------------------------------------------------------------|
| Alternative indicators | Unit | Computing method | Possible impact on flood and drought disasters |
| Natural indicators | Annual precipitation (X1); Per area water resources (X2); Per area surface water resources (X3); Per area groundwater resources (X4); Per area water supply (X5); Per area groundwater supply (X7); Per area water use (X8); Per area water use for agriculture (X9) | X1: mm; X2–X9: $10^4 \text{ m}^3/\text{ha}$ | X1: raw data; X2–X8: water resources/area; X9: water resources/cultivated land area | A surplus or deficit of water resources is a direct cause of flood and drought disasters, respectively. A shortage of water resources will cause a drought disaster. In contrast, excessive water resources will cause a 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 | Forests, grasslands and wetlands provide water conservation, soil and water conservation and climate regulation functions. A large proportion of these land use types can reduce the possibility of flood and drought disasters occurring |
| 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: $10^3 \text{ ha}$; 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 |
| Alternative indicators                                                                 | Unit                                                                 | Computing method                                                                 | Possible impact on flood and drought disasters                                                                 |
|---------------------------------------------------------------------------------------|----------------------------------------------------------------------|----------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------|
| 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: 10³ ha; X23–X24: 10 kwh/ha; X25: %; X26: 10 t/ha; X27: 10⁴ m³/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: 10⁴ 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: 10⁸ yuan; X35: 10⁵ 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. |
where \( \mu = 2 \ln \bar{x} - \frac{\ln(s^2 + \bar{x}^2)}{2} \), \( \sigma^2 = \ln \left( s^2 + \bar{x}^2 \right) - 2 \ln \bar{x} \), 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:

\[
f(x) = \frac{1}{2^n \Gamma \left( \frac{n}{2} \right)} x^{n-1} \exp \left( -\frac{x^2}{2} \right) x > 0
\]

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:

\[
f(x) = \beta^\alpha x^{\alpha-1} \frac{\exp(-\beta x)}{\Gamma(\alpha)} \quad x > 0
\]

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:

\[
f(x) = \frac{x^{a-1}(1-x)^{b-1}}{B(a, b)} \quad x > 0
\]

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

6. Exponential distribution

The probability density function is as follows:

\[
f(x) = \lambda \exp(-\lambda x) \quad x > 0
\]

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

7. Power function distribution

The probability density function is as follows:

\[
f(x) = cx^{c-1} \quad 0 < x < \theta, c > 0
\]
where \( c = \pm \frac{\sqrt{x^2 - s^2}}{\sqrt{x^2}}, \theta = \frac{\sqrt{x^2 - s^2 + s^2}}{\bar{x}}, \) 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:

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

where \( \mu = \bar{x}, \lambda = \frac{s^3}{\bar{x}^2}, \) 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:

\[
f(x) = \frac{\beta^a}{\Gamma(\alpha)} (x - a_0)^{a-1} \exp\left(-\beta\left(1 - a_0\right)\right)
\]

where \( \alpha = \frac{4}{c_s^2}, \beta = \frac{2}{2c_sC_s}, a_0 = \bar{x}\left(1 - \frac{2C_s}{c_s}\right) \) and \( \bar{x}, C_s \) 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:

\[
f(x) = \frac{\beta^a}{\Gamma(\alpha)} \left(1 + \left(\frac{x - \gamma}{a}\right)^{\beta}\right)^{-1}
\]

where \( \beta = \frac{2\omega_1 - \omega_3}{\omega_3 - \omega_1}, \alpha = \frac{\omega_2 - \omega_3}{\omega_1 - \omega_2}, \gamma = a_0 - a(1 + 1/\beta)\Gamma(1 - 1/\beta)\omega_3 = \frac{1}{n} \sum_{i=1}^{n} \left(1 - \frac{i-0.35}{n}\right)^s X'_i, \omega_s \) is the probability weight moment, and \( s = 0, 1, 2, X'_i \) 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 nonparametric 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.

\[H_0 : F_n(x) = F(x), H_1 : F_n(x) \neq F(x)\]

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:

$$D_n = \max \{|F_n(x) - F(x)|\}.$$  \hspace{1cm} (13)

Step 3 The boundary value $D^n_\alpha$ was determined by the sample size and significance level $\alpha$.

Step 4 Compare $D_n$ and $D^n_\alpha$. 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 $\alpha$.

After selecting the optimal distribution of flood and drought disasters, the CDF value of the disaster proportion is calculated. In this paper, the proportion of the disaster area is used as a random variable to fit the observed statistical distribution. A CDF was used. A large CDF value is equivalent to a high proportion of the disaster area, reflecting a severe disaster and high disaster risk. According to the CDF, the disaster risk is divided into 4 levels by equidistant classification (Farhangfar et al. 2015; Murthy et al. 2015). 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, 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. There may be a linear or nonlinear relationship between disasters and factors; the Pearson correlation coefficient can measure linear relationships, and the Spearman and Kendall correlation coefficients based on rank can measure nonlinear relationships. Therefore, the three correlation coefficients are used to determine the relationships between disasters and factors. Furthermore, the correlation coefficient test can calculate the test $p$ value and analyze the significance from the perspective of the statistical test. If $P < 0.05$, there is a significant correlation between factors and disasters, and a small $P$ value or large correlation coefficient reflects a strong correlation. Table 1 shows the 35 indicators, indicator units, calculation methods and reasons for selection.
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 Eq. 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 distributions cannot have a zero value, we obtained 804 drought sample points and 842 flood sample points by removing the zero values in the data. The PDF $f(x)$ values of 10 distributions were obtained by estimating the parameters from the sample data, and the CDF values were calculated by numerical integration. According to the sample data, the empirical distribution function $F_n(x)$ was calculated, and the results of the KS test and boundary value ($\alpha = 0.05$) are shown in Table 2.

As shown in Table 2, for drought, the KS test values of the gamma distribution, beta distribution and exponential distribution are all less than the boundary values, indicating that the three distributions fit the drought sequence well. For floods, the KS test values of the gamma distribution, beta distribution and exponential distribution are smaller than those of the other 7 distributions, but their KS test values are slightly higher than the boundary value. To observe the fitting results from the figures, the histogram of flood and drought, the PDF figure of the gamma, beta and exponential distributions, and the figure of the theoretical distribution and empirical distribution were drawn and are shown in Fig. 3.

From Fig. 3, the gamma, beta and exponential distributions fit well for flood and drought disasters. Combining Table 2 and Fig. 3, the best fit for drought was the gamma distribution, the best fit for flood was the exponential distribution followed by the gamma distribution, and the difference between the two distributions was very small. Therefore, the gamma distribution was determined as the best statistical distribution for describing the flood and drought.

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

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

As shown in Fig. 4, the risk of flood and drought disasters in most regions shows a downward trend, which seems to be inconsistent with climate change. In recent years, the temperature has generally increased, especially in the middle and high latitudes of Asia, with a trend of further warming (Grubler 2014; Williamson 2013). The increase in temperature leads to the increase in evaporation and the uncertainty in local heavy rainfall, which further increases the uncertainty of regional drought and flooding. However, temperature rise and precipitation anomalies only increase the uncertainty of hazard factors, and this uncertainty is more likely to cause anomalous regional water changes. A disaster involves a disaster-causing factor acting on a disaster-bearing body, eventually transforming into a flood or drought disaster. Flood and drought disasters are not only affected by hazard factors but also closely related to the number and value of disaster-bearing bodies exposed to the disaster environment, the sensitivity of disaster-bearing bodies to hazard factors and the ability of disaster-bearing bodies to resist disasters (Fontaine and Steinemann 2009;
Luh et al. 2015; Murthy et al. 2015; Pei et al. 2018). Resistance capacity refers to the ability to cope with water anomalies and reduce economic and social losses, which are related to socioeconomic factors and scientific and technological factors (Pei et al. 2018; Wilhite et al. 2014). In recent years, China’s economy has made great progress, which has led to the enhancement of the ability of disaster prevention (Xu et al. 2021). Although the natural factors that cause flood and drought disasters show a negative trend, due to the enhancement of the ability to resist natural disasters, the disaster risk shows a downward trend.

To analyze the spatial difference in flood and drought disaster risk, the average disaster area proportion in 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 CDF, the risk of flood and drought disasters in each provincial administrative region of China was divided into four levels using the equidistant classification method (Farhangfar et al. 2015; Murthy et al. 2015), and the high level represents the high risk, as shown in Fig. 5.

The areas with higher drought risk were mainly distributed in Northeast and North China, while the drought risk in South and West China was relatively low. The southern region is rich in precipitation, rivers and lakes, and there are few serious drought disasters. Taking precipitation as an example, the average precipitation in Inner Mongolia, Gansu, Ningxia and Qinghai was only approximately 330 mm in 2017, and the precipitation in southern regions, such as Hunan, Jiangxi, Fujian and Guangdong, reached more than 1800 mm. Additionally, the southern region has a relatively developed economy and a strong ability to resist drought disasters. Due to the climate and topography, most of the western regions, such as Xinjiang and Tibet, are not suitable for planting crops. The proportion of the cultivated land area in Tibet and Xinjiang is only 0.36% and 3.16%, respectively. 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. Taking Hunan and Hubei as examples, in 2017, the disaster area coverage in Hunan Province was 990 (10^3 ha), the disaster area affected was 493.7 (10^3 ha), and the disaster area without an output was 119.3 (10^3 ha). The disaster area coverage in Hubei Province was 692.7 (10^3 ha), the disaster area affected was 398 (10^3 ha), and the disaster area without an output was 160.4 (10^3 ha). Overall, the spatial distribution of flood and drought disaster risk is consistent with the distribution characteristics of regional precipitation and water resources in China. Precipitation is closely related to the formation of flood

| Type | KS test results of 10 distributions | Boundary value |
|------|-----------------------------------|----------------|
| Drought | Normal | 0.328 | Lognormal | 0.111 | Chi-squared | 0.601 | Gamma | 0.025 | Beta | 0.047 |
| | Exponential | 0.031 | Power function | 0.163 | Inverse Gaussian | 0.115 | Pearson-III | 0.628 | Log-logistic | 0.128 |
| Flood | Normal | 0.37 | Lognormal | 0.088 | Chi-squared | 0.701 | Gamma | 0.073 | Beta | 0.085 |
| | Exponential | 0.053 | Power function | 0.219 | Inverse Gaussian | 0.087 | Pearson-III | 0.66 | Log-logistic | 0.096 |
and drought disasters (Fig. 6). In terms of the corresponding trend, economic development enhanced the ability to resist disasters and further affected the division of disaster risk.
4.2 Influencing factors of flood and drought disaster

According to Eq. 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 degree of correlation and significance, respectively, and the significance level is $\alpha = 0.05$. Fig. 6 shows the correlation and statistical significance between disasters and influencing factors.

The horizontal axis in Fig. 6 includes 35 candidate indicators, and the vertical axis represents the correlation coefficient and statistical significance of drought and flood events with different indicators. In the first and third lines of the vertical axis, dark colors represent large correlation coefficients, and different colors represent positive or negative correlations. In the second and fourth lines, dark colors represent highly significant relations ($P < 0.05$), and white denotes a nonsignificant relationship ($P \geq 0.05$).

For the natural factors, the relationship between annual precipitation (X1) and flood and drought disaster was the largest, and the $P$ value was far less than 0.05, indicating that there was a statistically significant correlation between disaster sequence and precipitation. Additionally, precipitation had a negative correlation with drought and a positive correlation with flooding, which was also in line with the characteristics of flooding and drought. Precipitation is the main source of underlying surface water resources, and the abnormal change in precipitation is an important driving factor of flood and drought disasters (Fu et al. 2018; Modarres et al. 2016). Furthermore, in addition to the per land groundwater supply (X7), most water-related indicators (such as X3, X4, X6, X8) are closely related to drought. In contrast, except for precipitation, the other water-related indicators (X2–X9) are all weakly related to flooding, and they are not significant at the level of $\alpha = 0.05$. When precipitation decreases, the underlying surface water resources (including X2–X9) are the main source of irrigation and an important guarantee to resist drought; thus, these values are closely related to drought. Flood is often caused by extreme precipitation (Zhang and...
Chen 2019), and the amount of water resources in the underlying surface is mainly related to the regional topography and is not the main cause of flooding.

For agricultural factors, there is a significant positive correlation between the per capita cultivated land value (X20) and drought. A large X20 value indicates there are many disaster-bearing bodies exposed to the disaster environment. When the water content changes abnormally, a large exposure results in a large proportion of the disaster. Furthermore, the irrigation index (X25), the land power of agricultural machinery (X23), and the power of 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 (Pei et al. 2018), 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. X33 mainly reflects the rural labor resources, which provide human security and aid in disaster resistance. X32, X34 and X35 reflect the regional economic capacity and infrastructure. High income and water conservancy facilities are related to strong disaster resistance (Wu et al. 2013). 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 (Wu et al. 2013).

In general, the mean values of the absolute correlation coefficients between droughts and floods and each factor are 0.23 and 0.12, respectively. For significant factors \( P < 0.05 \), the mean values of \( P \) value were 0.00076 and 0.00116, respectively. Therefore, the relationship between drought and each factor is relatively notable. As a general natural disaster, drought has the characteristics of being slow and sustained, many factors affect drought, and the

![Fig. 6 Correlation and significance between disasters and influencing indicators (X1–X35 are shown in Table 1)](image_url)
forms of social response are diversified. For example, the areas with abundant precipitation or water resources are not prone to drought. Moreover, economically developed areas have a strong ability to resist drought. Even if water availability is limited, the impact of disasters will be reduced due to appropriate antidisaster measures in these areas, thus reducing the affected area. 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 (Chen et al. 2019a). Because of this unpredictable characteristic, the ability and method of social response to flooding are 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 gamma 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 popular research topic. As a direct result of flood and drought disasters, the proportion of the disaster area can effectively reflect the degree of a regional disaster and the regional disaster risk. Provincial-scale flood and drought disaster risk analyses are helpful for identifying the flood and drought disaster risks in different regions of China, dividing flood and drought disaster levels and understanding the temporal and spatial differences in flood and drought disaster risks in China; these tasks provide an important basis for identifying the flood and drought disaster degrees in different regions. Additionally, flood and drought disasters are not only related to natural factors, such as disaster-causing factors, but also to agricultural and socioeconomic factors and regional disaster resistance. Determining the factors that influence drought and flood events from the perspectives of nature, agriculture and socioeconomics is helpful for identifying the coupling relationships between factors and disasters, identifying the main factors that influence flood and drought disasters in China and providing a reference for exploring the formation mechanism of disasters and mitigating 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.
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). The difference between this paper and previous studies is that the proportion of the disaster area is used to express the risk of flood and drought disasters in this paper. The proportion of the disaster area reflects the results of flood and drought disasters, comprehensively encompasses the intensity of disaster-causing factors and the ability of an area to resist disasters and is an excellent indicator of the degree of a disaster. Moreover, flood and drought disasters involve disaster factors acting on a disaster-bearing body, a process which has both natural and social attributes. Finally, this paper focuses on the provincial administrative regions in China as the research areas, fits the statistical distributions of the proportions of flood and drought disaster areas and divides the disaster risk levels of different regions. Moreover, 35 alternative indexes were selected from natural, agricultural and socioeconomic perspectives, and the main factors that influence flood and drought disasters were selected by using the relevant analysis methods.

From 1989 to 2017, 31 provincial-level administrative regions in China were used as sample data; the data time scale was relatively short, and the region was large, mainly because data over longer periods and for 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

Research on the risk of flood and drought disasters and the corresponding influential factors in the provincial administrative regions of China provides an important reference for understanding the temporal and spatial variations in flood and drought disasters at a large scale. Additionally, this approach can aid in regional disaster classification and the identification of the coupling relationships between flood and drought disasters and related factors. Compared with previous studies, (1) this paper uses the proportions of flood and drought disaster areas to express the disaster risk, fits the statistical distributions of flood and drought disaster risks and divides the disaster grades of different regions. (2) Flood and drought disasters have both natural and social attributes. From natural, agricultural and
socioeconomic perspectives, 35 indicators were selected. The relationships between disasters and factors were analyzed, and the main factors that influence flood and drought disasters in China were selected.

In this paper, 31 provincial administrative regions in China were selected as the research area, and the statistical distributions of flood and drought disaster risks at the provincial level in China were fitted. The main factors that influence flood and drought disasters were analyzed from different perspectives. The conclusions are as follows: (1) the distribution of flood and drought disasters is right-skewed, and the gamma distribution is the best statistical distribution to fit the flood and drought disasters. (2) The areas with a high drought risk are mainly distributed in Northeast and North China, while the southern and western areas have a comparatively low drought risk. The areas with a high flood risk are mainly in the south, especially in Hubei, Hunan, Jiangxi and Anhui. (3) Precipitation, among the natural indicators, is an indicator that has a strong impact on flood and drought disasters, and agricultural and socioeconomic indicators related to disaster resistance have a strong relationship with flood and drought disasters; these factors reflect regional disaster resistance and the economic development level.

It is an interesting concept to represent the disaster risk based on the disaster distribution because such results are a direct reflection of disasters that have occurred. However, the disaster area does not fully reflect 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. Determining how to organically integrate the disaster area, disaster population, disaster loss and other factors and establish multiperspective and comprehensive disaster risk measurement indicators is a difficult task and future research direction.

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Declarations

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

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