

Dynamic risk assessment of drought disaster: a case study of Jiangxi Province, China

Ping Ai, Binbin Chen, Dingbo Yuan, Min Hong and Hongwei Liu

ABSTRACT

The dynamic risk assessment of drought is crucial in the transition from the crisis management model to the risk management model, which can reveal the evolution mechanism of drought disasters. Due to a lack of data and research perspectives, most current studies are still based on static risk assessment. This study proposes a conceptual model for the dynamic risk assessment of droughts based on the probability of their occurrence and potential impacts. The developed dynamic risk index considers the hazard, exposure, vulnerability, and capacity for drought mitigation. The analytic hierarchy process (AHP) method was used to determine the weight coefficient of each indicator in the model. The novelty of the proposed model lies in the integration of four elements of drought disasters with spatiotemporal characteristics. Jiangxi Province, which is frequently affected by drought, was selected as the study area to validate the proposed model. Experimental results demonstrate that the proposed model rapidly reflects the degree of drought disaster risk caused by drought events and the influencing factors at monthly and annual scales. Moreover, the datasets based on the influencing factors of drought disasters in different regions have a good commonality in the proposed model.

Key words | capacity for drought mitigation, drought disaster, dynamic risk assessment, exposure, hazard, vulnerability

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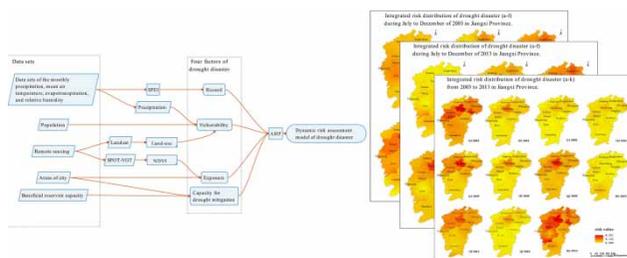
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HIGHLIGHTS

- A dynamic risk assessment model with spatiotemporal characteristics was established.
- Four factors based on temporal and spatial changes were incorporated in this model.
- The innovative method was provided for the risk management of drought disaster.
- Monthly and annual time scales were selected for the validation of the model.

GRAPHICAL ABSTRACT



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INTRODUCTION

Drought is probably the most complex and severe natural disaster, which affects more people than any other type of natural hazard (Wilhite 2000). Globally, it has the widest range of influence, the longest duration of prevalence, and causes huge economic loss (Sheffield *et al.* 2014).

The risk of drought disasters is their possible impact on social, economic, and natural environmental systems (Zhang 2004). Owing broadly to a lack of data and varying research perspectives, most of the drought disaster risk research does not involve the essential characteristics of the risk of loss caused by drought disaster and only focuses on drought risk. Researchers use the theory of risk formation based on natural disasters for drought risk assessment. A common tool for drought risk assessment is to estimate the drought indices using observable meteorological and hydrological data, which can be used as an individual index or as a combination of other indices. A variety of drought indices have been proposed, such as the Palmer drought severity index (PDSI) (Vasiliades *et al.* 2011), the standardized precipitation index (SPI) (Raziei *et al.* 2013), the standardized precipitation evapotranspiration index (SPEI) (Hernandez & Uddameri 2014), the soil moisture deficit index (SMDI) (Narasimhan & Srinivasan 2005), and the normalized difference vegetation index (NDVI) (Choudhury *et al.* 1987). Integrated analysis of the frequency, recurrence period, exposure, and vulnerability are the variables that are used to characterize the risk posed by droughts (Birkmann 2007). Commonly used exposure and vulnerability indicators include land use (Martin *et al.* 2016), socioeconomic indicators (Dabanli 2018), geographic information (Belal *et al.* 2012), and crop growth (Zhang 2004). However, the severity of the risks identified through these drought indices is based on a stationary Markov stochastic process. In other words, the future development of drought disaster risk is only related to the historical drought risk situation, where the corresponding probability does not change because of the translation of time, and hence, only a static risk is assessed. Thus, the results obtained are limited to the probability distribution of the risk of drought disasters for a specific period.

The principle of the dynamic assessment of risk due to droughts considers spatiotemporal change as the key constraint. The results of the assessment process and risk characterization change with time and space, reflecting the impact of the drought disaster risk for different periods with changes in the indicators. Certain studies have attempted to establish a dynamic vulnerability assessment model for drought disasters by fitting the vulnerability curves between the drought indices and the drought disaster loss rates in different periods, achieving the transition from the static risk assessment (Zhang *et al.* 2019), to a certain extent. Risk assessment usually considers loss factors, drought indices, and the nature of drought disasters; however, these cannot accurately reflect all the characteristics of the risks caused by drought disasters, as they are complex. Studies dynamically assessing the risk of drought disasters by considering all four factors (i.e., hazard, exposure, vulnerability, and capacity for drought mitigation) of drought disasters are rare. Therefore, with increased data availability and improved computation techniques, a dynamic risk assessment of drought disasters based on the spatiotemporal change in hazards, exposure, vulnerability, and capacity for drought mitigation is essential.

Research on the dynamic assessment of natural disaster risks has not progressed as desired owing to the negligence of time-dependent changes in risks, resulting in non-technical conceptual studies (Huang 2015). In 1988, the Office of Science and Technology Information of the U.S. Department of Energy developed the Plant Risk Status Information Management System (PRISIM) to ensure the safety of nuclear power plants in Arkansas. Inspectors can rapidly obtain monitoring information and use it to update the results of the risk analysis to achieve a dynamic assessment of risks. Jain & Davidson (2007) systematically studied the dynamic changes in hurricane risks and proposed that these risks change over time owing to changes in the number, type, location, vulnerability, and value of buildings. Lopez-Nicolas *et al.* (2017) proposed a risk assessment framework for economic loss based on agricultural droughts, which integrated a random time series model for predicting runoff and water storage, a statistical regression

model based on water balance, and a crop value assessment based on irrigation water and crop prices. This model dynamically assesses the risk of drought disasters through the price fluctuations caused by water shortages. Zhang *et al.* (2015) analyzed the relationship between water shortage and drought risk in three stages (before, during, and after the drought disaster) and showed that the contributions of the hazard factors to the risk varied at the different stages.

The current trend in drought disaster research is the transformation from drought crisis management to drought risk management (Wilhite 2016). Dynamic monitoring and assessment of drought disasters at different scales is the most vital component of drought risk management. A dynamic risk assessment of drought disaster can reveal their spatiotemporal evolution mechanisms and provide essential inputs for the scientific formulation of disaster reduction plans. The main purpose of this study is to propose a conceptual model for the dynamic risk assessment of drought disasters through the construction of a mathematical model based on the interactions between the factors of drought at different times. To achieve this, the analytic hierarchy process (AHP) (Saaty 1987) method that uses weight coefficients of the hazard, exposure, vulnerability, and capacity for drought mitigation indicators was developed. This model was applied to the study area to dynamically analyze the integrated risk of drought disaster.

MATERIALS AND METHODS

Study area

The study area, Jiangxi Province (Figure 1), is located in southeastern China (from 113°34'36" E to 118°28'58" E and from 24°29'14" N to 30°04'41" N). It spans about 620 km from north to south and is 490 km wide from east to west. The total land area of the province is 166,948 km², accounting for 1.74% of the total land area of China. It is located near the Tropic of Cancer and belongs to a subtropical warm and humid monsoon climate. It is warm and rainy in spring and hot and humid in summer. The annual average temperature ranges from 16.3 to 19.5 °C, increasing from north to south, and the province experiences 240–307 days of a frost-free period per annum.

The average annual temperature of northeast Jiangxi, the northwestern mountainous region of Jiangxi, and the Poyang Lake Plain is 16.3–17.5 °C. The average annual temperature of Gannan Basin is 19.0–19.5 °C, and the extreme maximum temperature is above 40 °C at one of the hottest areas in the middle reaches of the Yangtze River. The daily average temperature is stable over 10 °C for a duration of 240–270 days, and the active accumulated temperature is 5,000–6,000 °C within this period. The average annual precipitation in Jiangxi Province is about 1,600 mm. During the year, precipitation is distributed as follows: the wet period accounts for about 46% of the whole year, mainly concentrated in April, May, and June; the dry period accounts for 21%, mainly concentrated in January, September, October, November, and December; and the intermediate period accounts for about 33%, mainly concentrated in February, March, July, and August.

Data sources

According to the change characteristics of each of the four factors for drought disaster, the change in drought disaster risks over time and space is mainly affected by the status of each factor and their interrelationships. The four influencing factors for the dynamic risk assessment of drought disasters include hazard, exposure, vulnerability, and capacity for drought mitigation. The hazard is expressed by the degree of deviation of the meteorological and hydrological factors for various types of drought-induced events from normal values. The data pertaining to rainfall, evapotranspiration, and temperature from 12 meteorological stations influencing the formation of drought events in the study area during 2000–2013 were used. Land-use information pertaining to the study area was extracted from Landsat thematic mapper (TM) images with a spatial resolution of 30 m. The ratios of the areas of each land-use type were derived for each city within Jiangxi Province and used as the exposure factor. Vulnerability to a disaster (by society, environment, etc.) is a measure of the inability to resist or respond to a hazard (Cutter & Finch 2008). The vegetation health coefficient was calculated using the NDVI derived from SPOT VEGETATION 10-day synthesis (VGT S10) instruments to obtain the sensitivity of the disaster-bearing component. The agricultural population and its

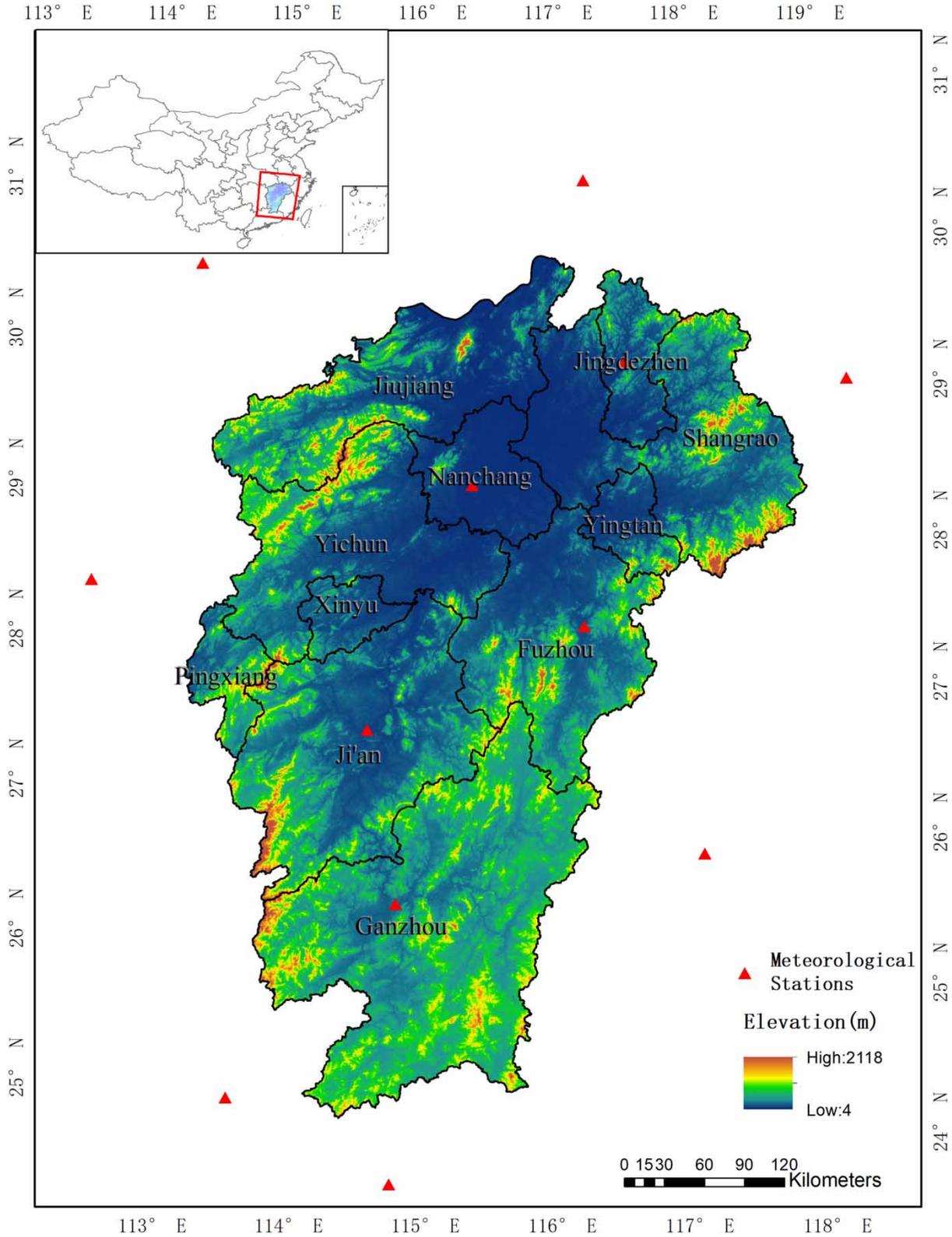


Figure 1 | Extent of the study area and the location of meteorological stations in Jiangxi Province.

region-wise ratios represent the scale of the annual disaster-tolerant component. The capacity for drought mitigation was calculated using capacities of the beneficial reservoirs and the regions serviced by them. Table 1 provides detailed information on the data used in this study for the dynamic risk assessment of drought disasters in Jiangxi Province.

Methodology

Conceptual model for the dynamic risk assessment of drought disasters

Drought disaster risk has both natural and social attributes (Martin et al. 2016). The objective of a dynamic risk assessment of drought disasters is to construct a dynamic model that can represent the non-linear changes in the risks over time and space. The model presented here not only determines the form of representation of drought disaster risks but also expresses the method of dynamic risk analysis. Scholars who study the theory of disaster systems believe that disasters are the result of interactions between hazards and the potential impact of disasters (Smith 2004). Therefore, the concept of risk in the context of drought disasters is defined as follows:

$$\text{Risk} = P(\text{Disasters}) \times \text{Effect} \quad (1)$$

where $P(\text{Disasters})$ is the probability of the occurrence of drought disasters, and Effect is the potential impact of drought disasters.

The dynamic risk assessment of drought disaster with four influencing factors is a more comprehensive consideration in current drought disaster assessment research. Drought disasters are controlled by the hazard, vulnerability, exposure, and capacity indices for drought mitigation (Zhang & Okada 2006), whereas they are not based on random sequences, and hence, the probability of occurrence cannot be estimated by their distribution function. From the perspective of natural meteorological factors, drought disasters are mainly caused by abnormal changes in factors such as rainfall and evaporation. The probability of occurrence of rainfall and evaporation displays certain randomness. To distinguish the risk of drought disasters at different times, the conceptual model presented in formula (1) was expanded by multiplying the probability index of drought disaster hazard factors by the potential impact indicators at different times (Figure 2). Accordingly, the integrated risk (R_t) of a drought disaster at time t can be expressed as follows:

$$\begin{aligned} R_t &= P(\text{Disasters})_t \times \text{Effect}_t \\ &= H_t \times (keE_t + kvV_t - kaA_t) \end{aligned} \quad (2)$$

where R_t is the integrated risk of the drought disaster at time t , $P(\text{Disasters})_t$ is the probability of the drought disaster at time t , and Effect_t is the potential impact of the corresponding drought disaster at time t . The potential impact of drought disasters is a result of the combined effects of prevalent disaster environmental factors, disaster-bearing factors,

Table 1 | Sources of data for the dynamic risk assessment of drought disaster in Jiangxi Province

| Types | Index name | Source |
|---------------------------------|--|--|
| Hazard | Datasets of the monthly precipitation, mean air temperature, evapotranspiration, and relative humidity from 2000 to 2013 from 12 meteorological stations | National Meteorological Information Center (http://www.cma.gov.cn) |
| Exposure | Land-use types and proportions of land-use types | Landsat TM image |
| Vulnerability | Population, rainfall, and SPOT-VGT NDVI | The Environmental and Ecological Science Data Center for West China (http://westdc.westgis.ac.cn) Flemish Institute for Technological Research (http://www.vgt.vito.be/) Statistical Bulletin of National Economic and Social Development for Jiangxi Province |
| Capacity for drought mitigation | Beneficial reservoir capacity | Jiangxi Water Resources Bulletin Atlas of the Jiangxi Reservoir Distribution |

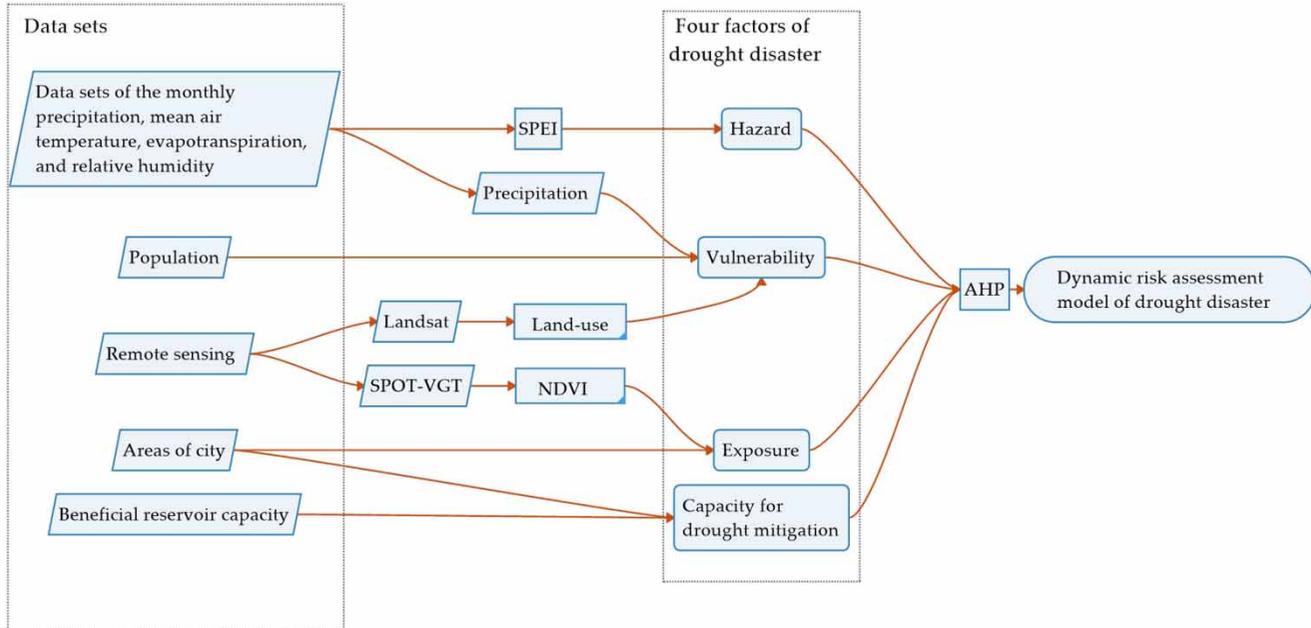


Figure 2 | Representation of the methodological framework used in this study.

and disaster reduction capacity. Here, H_t , E_t , V_t , and A_t are the hazard, exposure, vulnerability, and capacity for drought mitigation, respectively, at time t ; and ke , kv , and ka are the weight coefficients of the corresponding indicators.

Hazard assessment of drought disasters

The hazard of drought disaster is the natural variation factor and abnormal degree of drought disaster, which includes the dynamic change of drought disaster in time, space, and intensity. Based on the characteristics of the drought disaster, the hazard of the drought disaster can be identified and analyzed. The SPEI has the characteristics of multiple timescales, which can represent various types of droughts and better reflect the variations in drought characteristics. The SPEI was utilized as the drought event identification index, and a drought event was identified when SPEI was less than -1 . The risk of the drought disaster hazard is expressed by the absolute value of the difference between the probabilities of SPEI of the drought event and that of SPEI being -1 , as follows:

$$h_x = |p_x - p_{-1}| \quad (3)$$

where h_x is the hazard risk when SPEI is x , p_x is the probability when SPEI is x , and p_{-1} is the probability when SPEI is -1 (Zhang *et al.* 2009).

There are two types of non-drought moments during a drought event: (1) the time when the SPEI value is greater than -1 occurs in the middle of the drought event and (2) the time when the SPEI is greater than -1 occurs at the beginning and end of the drought event. When the SPEI value is greater than -1 , $p_x - p_{-1}$ is greater than zero. Months with an SPEI greater than -1 occur at different times during the drought event, and the associated risks differ. In such situations, h_x cannot be calculated using formula (3). For the first case, the risk index for a particular month is calculated by adding the average hazard risk value of the month (when the SPEI value of the preceding and following months was less than -1) and the $p_x - p_{-1}$ value of the month. In the second case, $p_x - p_{-1}$ is the risk index.

Exposure assessment of drought disasters

Exposure to drought disasters is a measure of the degree of contact between various objects affected by the drought. In China, statistics on losses caused by drought disasters are

available for different administrative divisions. Based on the area of each city or region and the area of each land-use type present within each city or region, the exposure ratios for each land-use type within each city or region were computed (Chen *et al.* 2016). Moreover, this land-use information, reflecting various types of surface features, is spatiotemporal. Usually, when the timescale considered is small, many types of features do not change significantly, and when it is large, the changes are ignored. The main land-use type in the study area is natural vegetation, and its growing period extends far more than 1 year. Furthermore, in this study, the annual scale was selected as the unit of time for the extraction of land-use information. Therefore, the drought disaster exposure index based on the surface-cover type in a certain year is as follows:

$$E(mn)_t = \frac{a(mn)_t}{a(m)_t} \quad (4)$$

where $E(mn)_t$ is the drought disaster exposure index of the m th city or region and n th feature at time t ; $a(mn)_t$ is the area of the m th city or region and n th feature at time t .

Vulnerability assessment of drought disaster

Vulnerability to a disaster is common (Blaikie *et al.* 1994) and is the result of the range of social, economic, and natural environment systems under the influence of hazards, which can be characterized as the disaster factors' sensitive responses and self-recovery capabilities (Zhang *et al.* 2011). Vulnerability is not only confined to the sensitivity of the affected component to a drought disaster but also to the size of the affected component. When the scale of the disaster-bearing component is larger, the risk of disaster attack is higher (Birkmann *et al.* 2013). Therefore, the vulnerability to drought disasters includes the sensitivity to the water shortage faced by the receiver or end-user (such as vegetation, people, and their activities: agriculture and industry) and the scale of the end-user. Vegetation health is closely related to water resources, which is why we used it as the sensitive indicator. There are many indicators of vegetation health, such as vegetation condition index (VCI) and vegetation health index (VHI) (Bento *et al.* 2018). Longer series or more types of data are required to calculate these indicators.

The NDVI can effectively monitor vegetation health and natural environment at multiple scales and can be easily obtained from VGT S10. Therefore, the vegetation health coefficient was obtained from the NDVI averaged over the years for each month. In addition, human beings are the main participants in ecosystems and are affected by natural disasters. Therefore, population was simplified as a measure of the size of the end-user (Simelton *et al.* 2009). The annual demographic data published by the government provide the ratio of the non-agricultural to the agricultural population. Thus, the vulnerability index V_{ij} of the affected component in year i and month j was obtained as follows:

$$V_{ij} = F_i N_j, \quad 1 \leq j \leq 12 \quad (5)$$

where V_{ij} is the vulnerability index of year i and month j , F_i is the ratio of the non-agricultural to the agricultural population in year i , and N_j is the dimensionless vegetation health coefficient in the j th month of the year.

The dimensionless vegetation health coefficient N_j was obtained from the normalization of the monthly average NDVI values.

$$N_j = \frac{\text{NDVI}_j}{\sum_{j=1}^{12} \text{NDVI}_j}, \quad 1 \leq j \leq 12 \quad (6)$$

where NDVI_j is the multi-year monthly average NDVI value for the j th month.

Disaster reduction capacity assessment

Disaster reduction capacity is the ability to resist and recover from drought disasters in risk areas, and the reservoir is an important engineering measure to deal with the losses caused by drought disasters. While considering the storage and water supply capacity of the reservoirs, the upstream and downstream relationships of the relevant reservoirs and the data on water supply and water transfer were found to be lacking. Therefore, the disaster reduction process of the reservoirs was simplified. It was assumed that the reservoirs provide water supply to their respective captive cities or regions only, and hence, the reservoir storage capacity at a certain time was divided by the

city/region area to derive the disaster reduction capacity of the city/region (Equation (7)) (Ehsani et al. 2017).

$$a_{m,t} = \frac{\sum_{i=1}^n (c_i)_{m,t}}{s_m}, \quad 1 \leq m \leq 11 \tag{7}$$

where $a_{m,t}$ is the disaster reduction capacity of the m th city/region at time t , $(c_i)_{m,t}$ is the reservoir storage capacity of the i th reservoir in the m th city/region at time t , s_m is the total area of the m th city/region, and n is the number of all the reservoirs in the m th city/region.

Disaster reduction capacity varies for different cities/regions, and these can be ranked by a difference of 1 between them. The normalized disaster reduction capacity index of each city/region was obtained as follows:

$$A_{m,t} = \frac{a_{m,t}}{\sum_{m=1}^{11} a_{m,t}} \tag{8}$$

where $A_{m,t}$ is the disaster reduction capacity index of the m th city at time t and $a_{m,t}$ is the disaster reduction capacity of the m th city at time t . There were 11 cities in the study area.

RESULTS

Determination of index weight of the model

The risk assessment based on the four factors of disaster theory is in a primary stage, and there are still significant differences and uncertainties in the judgment of the importance of each factor by different experts. AHP and fuzzy analytical hierarchy process (FAHP) (Chang 1996) are commonly used methods to determine the weight coefficients of each index in the model. The AHP method makes use of the characteristics of behavioral science to quantify the empirical judgment of decision-makers. When the factor structure is complex and there is a lack of necessary data, this method is more practical. FAHP is a highly complex process compared with AHP. Therefore, in this study, AHP was adopted to calculate the weight coefficient of each factor. In the selection of the scale, compared with the original one-to-nine scale, the four-factor scale makes

it easier to judge the importance of each index, and the consistency check process is omitted. This method is simple, fast, and the accuracy conforms to the calculation requirements. Through this method, the four-factor scale of drought disasters was constructed by approximately replacing the results of direct expert investigations.

Table 2 indicates that vulnerability is the most important factor, followed by the hazard exposure and mitigation capacity factors. The main feature of a drought disaster is the loss of the hazard-bearing component. The hierarchy achieved here forms the core of distinguishing between a drought disaster and drought. The interplay of the four factors listed in Table 2 reflects the characteristics of drought disasters.

The achieved weights for the four factors through the AHP method were redistributed according to the relationship between the feature layer and each of the indicator layers, with the final calculation of the weight coefficients of the indicators in the model (Table 3).

Based on the dynamic risk assessment model and the weight coefficients of the various indicators in Table 3, the calculation formula for the dynamic risk assessment of drought disasters in the model is:

$$R_t = h_t \times (0.024e_{1t} + 0.050e_{2t} + 0.039e_{3t} + 0.044e_{4t} + 0.700v_t - 0.143a_t) \tag{9}$$

where R_t is the integrated risk of a drought disaster at time t ; h_t is the risk index of hazard factors at time t ; e_t is the risk of exposure at time t , including forest, wetland, dryland (i.e., arable land, grassland, and others), and artificial surfaces; v_t is the risk of vulnerability at time t ; and a_t is the capacity for drought mitigation at time t .

Table 2 | Four-factor scale for drought disaster

| Factor | Vulnerability | Hazard | Exposure | Mitigation capacity |
|---------------------|---------------|--------|----------|---------------------|
| Vulnerability | 1 | 2 | 4 | 6 |
| Hazard | 1/2 | 1 | 2 | 2 |
| Exposure | 1/4 | 1/2 | 1 | 1 |
| Mitigation capacity | 1/6 | 1/2 | 1 | 1 |

Table 3 | Weight coefficients for the dynamic risk assessment model for drought disaster

| Target layer | Sub-target layer | Feature layer | Indicator layer | Weight coefficients |
|--|--------------------------------|---|---|---------------------|
| Risk of drought disaster Risk = $P(\text{Disaster}) \times \text{Effect}$ | $P(\text{Disaster})$ Effect | Hazard (1.000) Exposure (0.157) | Hazard (h) | 1.000 |
| | | | Forest area ratio (e_1) | 0.024 |
| | | Vulnerability (0.700) Mitigation capacity (0.143) | Wetland area ratio (e_2) | 0.050 |
| | | | Dryland area ratio (e_3) | 0.039 |
| | | | Artificial surface area ratio (e_4) | 0.044 |
| | | | Vulnerability (v) | 0.700 |
| | | | Mitigation capacity (a) | 0.143 |

Case study

Jiangxi is a major agricultural province and an important grain production area in China. However, due to the impact of climate change in recent years, drought disasters have occurred frequently. Depending on the information on the duration, intensity, and area of influence of drought disasters recorded in the ‘China Meteorological disaster Yearbook’, ‘China disaster Chronicle,’ and ‘Jiangxi Yearbook’. In the summer of 2003, Jiangxi Province suffered sustained high temperature and drought, and the drought continued into winter. The total rainfall for the three seasons of summer, autumn, and winter in Jiangxi Province in 2003 was the lowest since the records began in 1959. In June, drought disaster occurred in central Jiangxi Province; in July, drought disaster occurred in Shangrao, Jingdezhen; severe drought disaster occurred in Nanchang from August to October, and the disaster aggravated in the south-central area of Jiangxi Province from October to November. In 2013, the average temperature in Jiangxi Province was the second-highest in history, and the amount of summer precipitation was 37% less than during the same period in normal years. In July, drought disasters occurred in the central and southern parts of Jiangxi Province; in August, drought disasters spread to the north; and from August to October, drought disasters occurred throughout the province, while severe drought disasters occurred in Nanchang. The high temperatures and severe droughts in 2003 and 2013 had a widespread, long duration, and resulted in severe disasters, which were rare in recorded history. Thus, we selected 2003 and 2013 as typical years for the dynamic risk assessment of Jiangxi Province.

The SPEI was utilized as the drought identification index. As the study area is located in the subtropical monsoon climate region, the water cycle is rapid, such that the monthly scale is more sensitive, which can reflect the development trend of drought events (Duan 2013). Simultaneously, the monthly dynamic risk assessment can conform to the requirements of disaster risk management for the early warning of drought disasters and achieve the purpose of effectively mitigating the impact of drought disasters (Grasso & Singh 2011). Therefore, the monthly scale was selected for drought event identification and drought disaster risk analysis. Finally, the annual scale was selected to analyze the total dynamic change process in drought disaster risk from 2003 to 2013.

Dynamic risk assessment of the drought disaster in 2003

The risk presented by drought disaster events, calculated based on the SPEI probability of each meteorological station, was used to obtain the spatial distribution of the risk using the inverse distance weighted (IDW) spatial interpolation method (Figure 3). The study area was dominated by a summer drought in 2003, which occurred in the central and northeast regions of the study area in June and July. This drought spread throughout the entire province between August and September, and gradually eased from north to south from October to November.

The disaster reduction capacity of each city/region before the occurrence of the drought was calculated based on the cumulative rainfall of the cities/regions in the study area 3 months before the drought. It was assumed

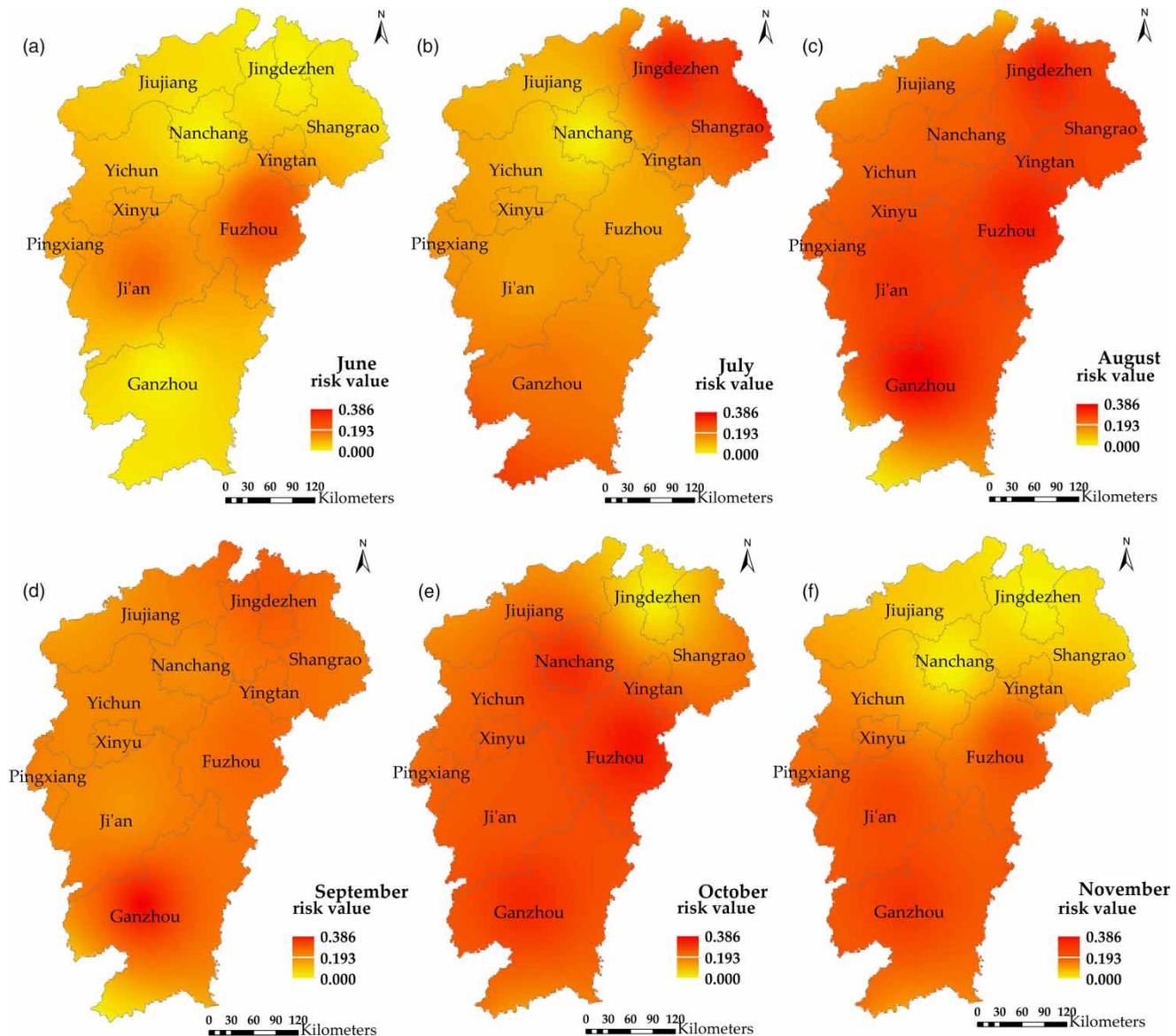


Figure 3 | Risk distribution of drought event (a–f) during June–November of 2003 in Jiangxi Province.

that each reservoir only has a 4-month drought resistance capacity, and the disaster reduction capacity was considered the same for the months in between. Finally, the integrated risk for each city/region was calculated. As shown in Figures 3 and 4, the drought phenomenon first appeared in the central area of the study area in June. Since agriculture is mainly distributed in the central region of Jiangxi Province, the scope and intensity of the integrated drought disaster risk are higher than the risk of drought events. At the same time, Nanchang had the

largest population, and its inhabitants were more vulnerable. Therefore, the overall risk for Nanchang was higher than that of the surrounding Jiujiang and Shangrao areas. The drought occurred throughout the province in July, and Nanchang was affected by the drought, and the integrated risk continued to increase. At this time, the reservoirs in Ji'an, Ganzhou, and Fuzhou began to supply water, and the integrated risk of the three places was reduced. In August and September, droughts occurred in all cities in the study area. Owing to the lack of disaster

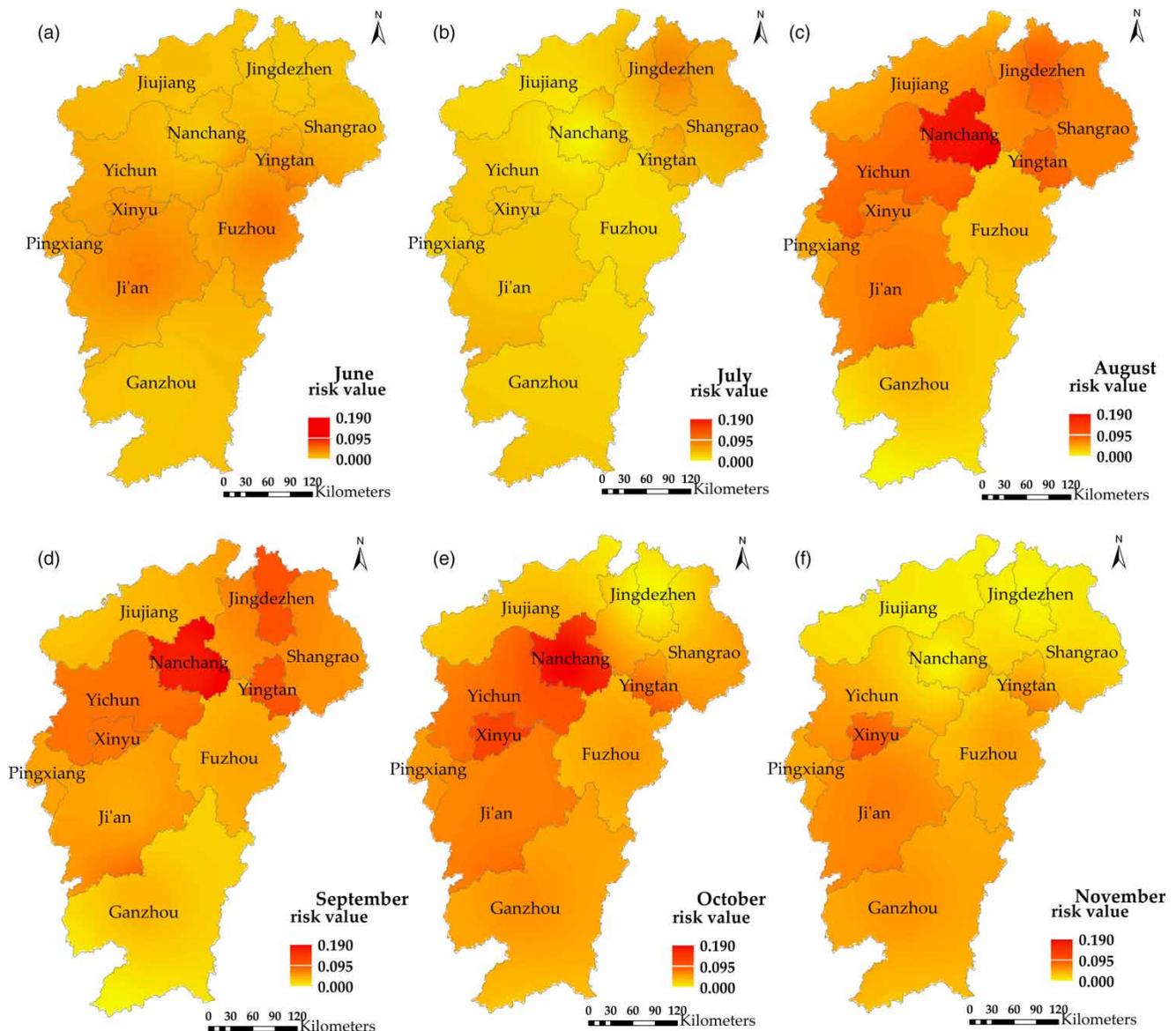


Figure 4 | Integrated risk distribution of drought disaster (a–f) during June–November of 2003 in Jiangxi Province.

reduction capabilities of the reservoirs in Nanchang, its integrated risk was highest among all cities. With the easing of the drought conditions in the northern part of the study area in October and November, the integrated risk of drought disasters in Nanchang was reduced. However, the exposure of Xinyu City (mainly drylands and paddy fields) was higher than that of the surrounding cities such that when the drought continued in the central region, its integrated risk was significantly higher than that of the other areas.

Dynamic risk assessment of the drought disaster in 2013

Similarly, analyses were performed for 2013. Figure 5 shows that the study area suffered a summer drought in 2013. In July, the drought mainly occurred in the southern Ganzhou region, and it gradually spread from the south to the north-east. In October, in the majority of the areas, its intensity was at a maximum, as evidenced by the risk values. By December, the drought showed a decreasing trend from the north, and the south got relieved. The northern regions

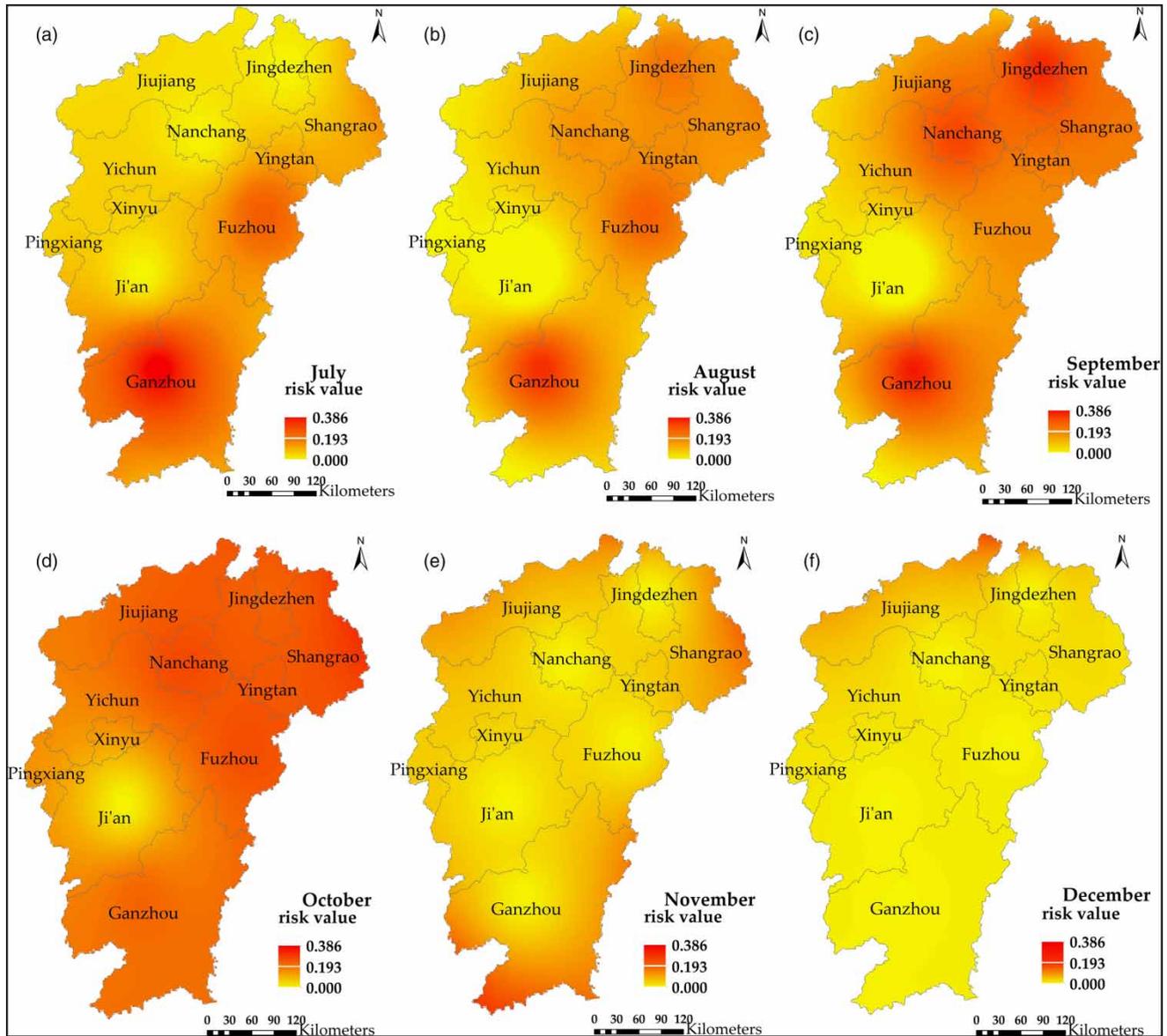


Figure 5 | Risk distribution of drought event (a–f) during July–December of 2013 in Jiangxi Province.

of Yichun, Jiujiang, Nanchang, Shangrao, and Jingdezhen had minimum risk levels. Ji'an did not experience drought, with a risk value of zero.

As shown in Figures 5 and 6, the drought in July mainly occurred in the southern region, but the central region, with concentrated agriculture, had maximum exposure and vulnerability, resulting in a higher integrated risk in the central and southern regions than in the other regions. The capacity of the reservoirs for each city in August was investigated to compare the impact of disaster reduction

capacity computed based on the dynamic risk assessment model for 2013. Nanchang, as the provincial capital, has accelerated its urbanization in recent years. The impervious surface of the city has increased significantly, and the exposure mainly affected by vegetation coverage showed a decreasing trend. However, the vulnerability affected by population and vegetation health has increased rapidly, coupled with the weak disaster reduction capacity of the reservoirs in Nanchang. Therefore, the risk for Nanchang was the highest among all cities/regions. Ji'an

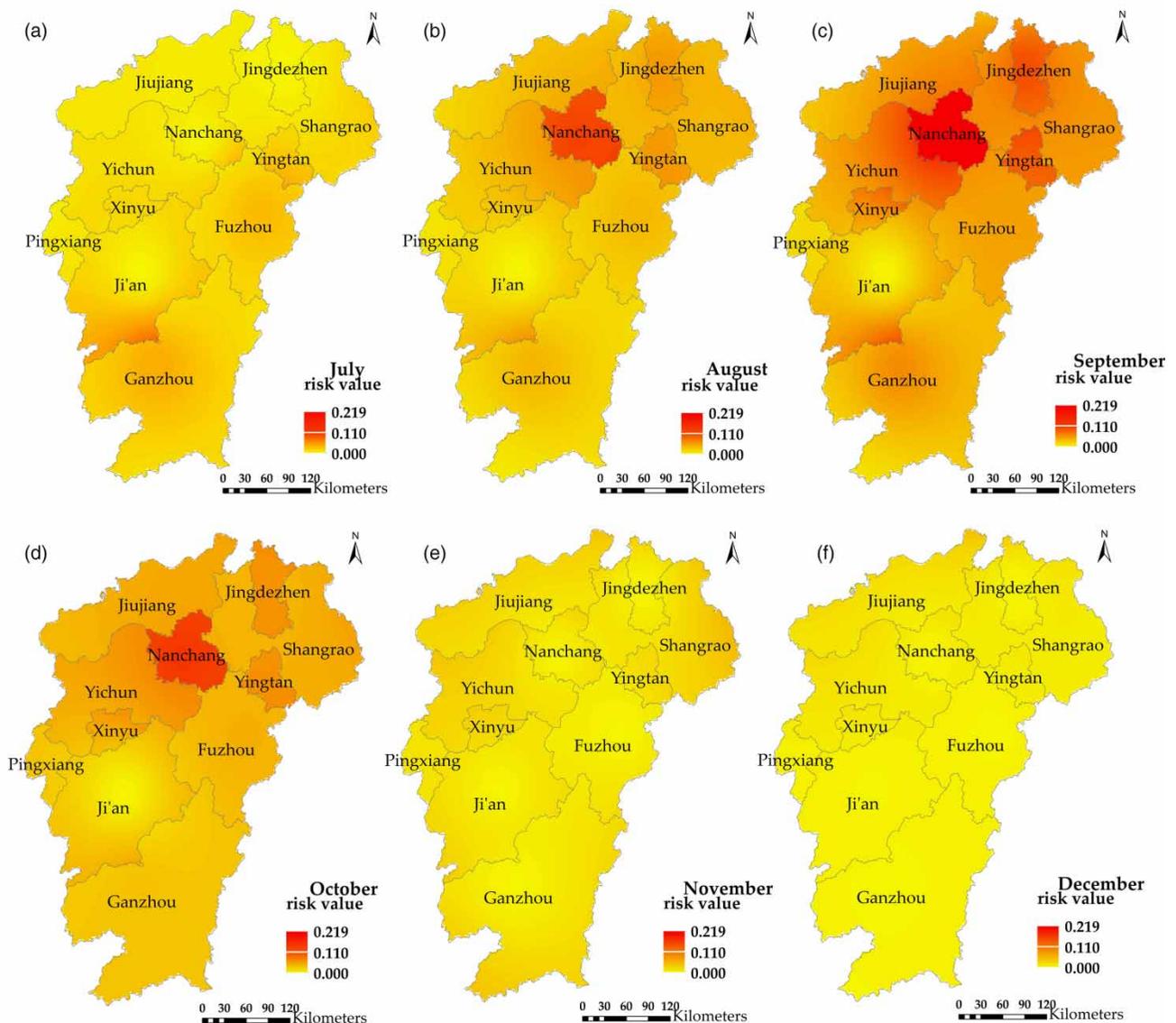


Figure 6 | Integrated risk distribution of drought disaster (a–f) during July–December of 2013 in Jiangxi Province.

meteorological station did not show drought event, and hence, Ji'an reservoir was not considered in the analysis. The magnitude of the integrated drought risk for each city/region in the study area was closely related to the risk of hazards and the vulnerability of the affected component: the higher the risk of hazards, the greater the vulnerability, and the greater the magnitude of the integrated risk. It is important to develop both engineering and non-engineering measures of drought mitigation scientifically and economically, for the development of the country. Finally, in terms of the spatial patterns, the integrated drought disaster risk

intensity in the northern region was higher than that in the southern region, which, hence, requires more attention. The results of dynamic drought disaster risk assessment accord with the actual situation.

Dynamic risk assessment of the drought disaster from 2003 to 2013

For a typical year, the monthly scale was used to characterize the changes in drought and the drought disaster risk during the year. In this section, the annual scale data were

adopted by the model's various impact factors to thoroughly analyze the dynamic changes of drought disaster risk in Jiangxi Province from 2003 to 2013 (Figure 7). During these years, the integrated risk of drought disasters in 2003 and 2013 was the highest. The province was affected by drought disasters, and the areas of severe drought were mainly distributed in the north-central part of Jiangxi. The

integrated risk of drought disasters in 2007, 2009, and 2011 was relatively serious, mainly distributed in the northern region, and the degree of risk decreased from north to south. In other years, the drought disaster risk intensity was relatively small. Due to the high population density and advanced crop production in the central and northern regions, the impact of drought disasters was particularly

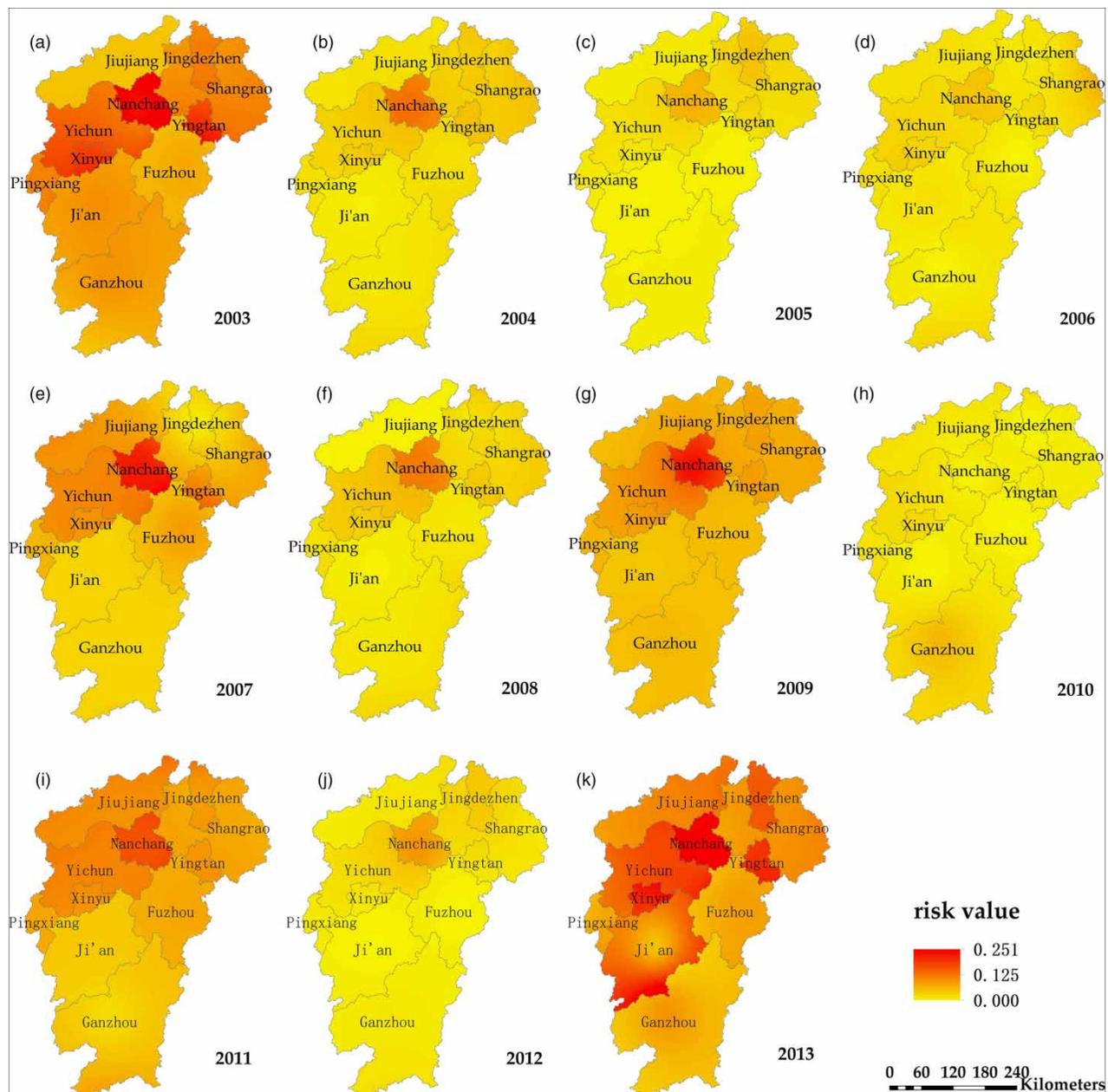


Figure 7 | Integrated risk distribution of drought disasters (a-k) from 2003 to 2013 in Jiangxi Province.

evident. Coupled with the weak disaster reduction capacity, Nanchang City, which had the largest population and the most developed economy, has always had the highest risk of drought disasters in the years with more serious drought disasters.

DISCUSSION

Static assessments of drought disaster risk do not address issues pertaining to disaster risk zoning, recurrence period, and the changes in the disaster risk over time. The risk of drought disasters is not static; it changes with time (Wilhite et al. 2014). The development of drought risk assessments should be a dynamic process that changes continuously with time. Based on the research on the dynamic assessment of natural disaster risks, this study proposed a dynamic assessment model of drought disasters based on the four factors of drought disasters over time.

The experimental results show that, compared with the drought risk at a monthly scale calculated based on the SPEI probability of each meteorological station, the results of the dynamic risk assessment model were more consistent with the actual situation recorded in the yearbook. The integrated drought disaster risk showed an increasing, followed by a decreasing trend during the drought disaster process, which reflects the cumulative change processes with respect to the risk. At an annual scale, the drought disaster risk was greatly affected by drought, but dynamic changes in factors such as vegetation coverage, artificial impervious surface, population, and disaster reduction capability would also directly affect the distribution and intensity of the drought disaster risk. The experimental results were consistent with the yearbook records. This study, therefore, indicates that the risk of drought disasters changes dynamically with spatiotemporal changes because the influencing factors of hazards, vulnerability, exposure, and the capacity for drought mitigation are also changing dynamically. The dynamic risk assessment model for drought disasters and the risk indicators proposed were validated in this study. Therefore, the results of this research provide an innovative method for the risk management of drought disasters.

In summary, compared with previous drought disaster assessment models, the improvements yielded by this

model are as follows: (1) Dynamic integration of the impact factors of drought disasters into the model. This includes the SPEI of the study area, land use, and NDVI obtained from remote sensing analysis, surface rainfall, population, and reservoir volume. Due to the limitation of the data acquisition capacity, the time scales of the factors are different. However, they were able to reflect the dynamic changes in various factors affecting drought disasters at monthly and annual scales. (2) The results of the drought disaster risk calculated by the model are dynamic. The model calculation results are at a monthly or annual scale, which can reflect the dynamic change process of the drought disaster risk within the specified time.

Although the monthly and annual scales of the model were selected to identify drought events and assess the drought disaster risk in the study area, it is limited by the existing observation and data collection conditions. In future studies, by integrating the influencing factors collected at a smaller time scale or live data, such as real-time monitoring of rainfall, evapotranspiration, soil water content, reservoir scheduling information, or night light remote sensing data, at a unified scale, we will be able to receive more timely dynamic information on drought disaster risks to provide decision support for drought disaster risk managers. Meanwhile, the selection of drought disaster indicators remains in an exploratory stage. For example, in the evaluation of the vulnerability indicators, only two influencing factors, namely the ecological vulnerability coefficient and the ratio of non-agricultural to agricultural population, were selected. However, the vulnerability response caused by drought is in all aspects of human social activities, and it is difficult to quantify the vulnerability to drought disasters through only two factors. The lack of other indicators is due to insufficient research on socioeconomic attributes, and it is difficult to collect data on the corresponding time scale. In addition, the model should be verified in more study areas with different climatic conditions to improve the common applicability of the model.

CONCLUSIONS

Based on a conceptual model of the dynamic risk assessment of drought disaster, the sub-indices of hazard,

exposure, vulnerability, and capacity for drought mitigation for a certain period and their interrelationships between time and space were analyzed. A mathematical model for the dynamic risk assessment of drought disasters was developed. Monthly and annual time scales were selected for the validation of the developed model.

The results show that when compared with traditional static assessment methods, the dynamic disaster risk assessment model proposed in this study can accurately reflect the distribution and magnitude of the drought disaster risk at a specified time. Furthermore, the model reflected the dynamic change characteristics in drought disaster risk with time.

AUTHOR CONTRIBUTIONS

Conceptualization, P. A.; methodology, B. C.; software, B. C.; validation, D. Y.; formal analysis, M. H.; resources, D. Y.; data curation, D. Y.; writing – original draft preparation, B. C.; writing – review and editing, P. A.; visualization, B. C.; supervision, P. A.; project administration, D. Y.; and funding acquisition, P. A., M. H., and H. L.

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CONFLICTS OF INTEREST

No conflict of interest exists in the submission of this manuscript, and the manuscript is approved by all authors for publication.

DATA AVAILABILITY STATEMENT

All relevant data are available from an online repository or repositories.

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