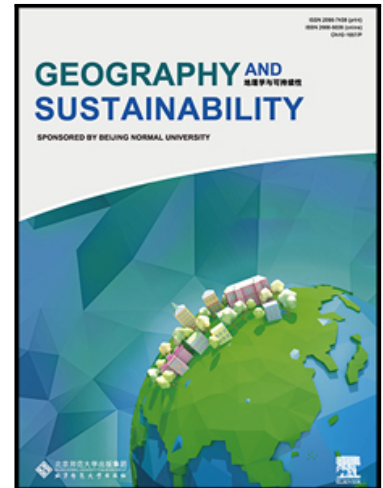


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## Drought risk assessment in China: evaluation framework and influencing factors

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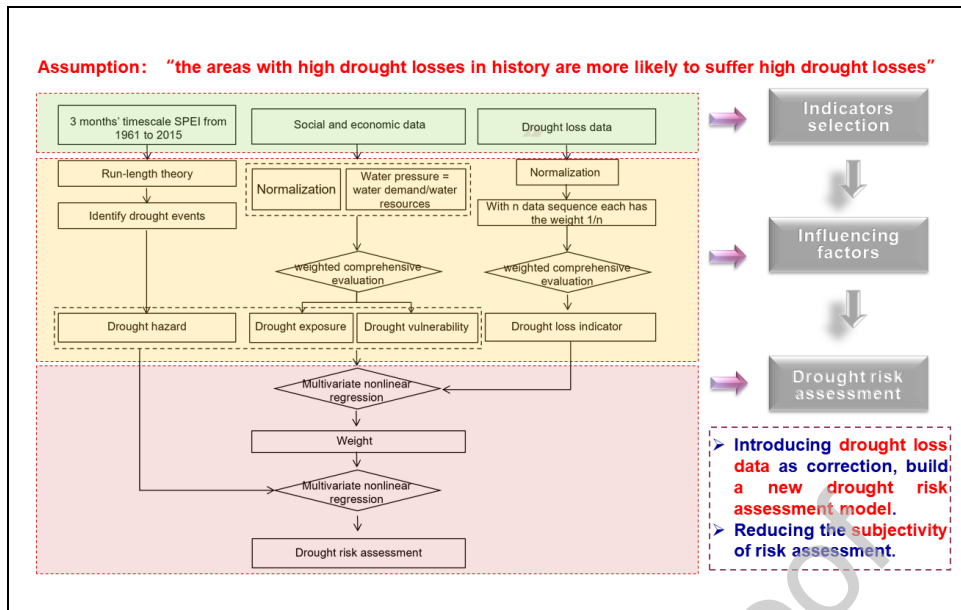
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**Abstract:** Global warming and rapid economic development have led to increased levels of disaster risk in China. Previous attempts at assessing drought risk were highly subjective in terms of assessment methods and selection of the assessment indicators and which resulted in appreciable uncertainty in the results of these risk assessments. Based on the assumption that areas with historically high drought losses are more likely to suffer future high drought losses, we develop a new drought risk assessment model that includes historical drought loss data. With this model, we map the regional differentiation of Chinese drought risk. Regions with high (extreme high) drought risk account for 4.3 percent of China's area. Five significant high-risk

areas have been identified: Northeast China, North China, the east part of Northwest China, the east part of Southwest China and a small part in west of Northwest China. Areas with high and extreme high drought risk are dominant in the Heilongjiang Province, accounting for 32% of the total area, followed by the Ningxia Hui Autonomous Region, with 26% of total area. The contribution of each influencing factor has been quantified, which indicates that high-exposure and high-vulnerability account for the high-risk of drought. We recommend that measures like strengthening the protection of cultivated land and reducing dependence on the primary industry should be taken to mitigate to drought-induced losses.

**Keywords:** Drought risks; Drought risk evaluation framework; Drought hazard; Drought exposure; Drought vulnerability

**Graphical abstract**



## 1. Introduction

Drought is a recurring phenomenon caused by persistent precipitation deficits (Zargar et al., 2011; Zhang et al., 2018), that may lead to water scarcity. Thus water demand for agricultural and urban uses, human consumption and ecosystems, cannot be satisfied which poses a challenge for water resource management (Liu et al., 2017a; Liu et al., 2017b; Sadeghi and Hazbavi, 2017; Zhang et al., 2018; Yu et al., 2018, 2019). Furthermore, global warming tends to accelerate the hydrologic cycle (Allen and Ingram 2002; Zhang et al., 2019), which increases occurrences of extreme weather (Li et al. 2015; Gu et al, 2019). Thus, enhancing human mitigation to droughts is of critical importance. Scientific evaluation of this risk is the first mitigation step along with developing a more drought-resilient society (e.g. Carrão et al., 2016).

Disaster risk includes: the occurrence of natural disasters; the population and assets

exposed to the hazard, their vulnerability to damage; and associated monetary losses (Wang et al., 2018; UNISDR, 2015; IPCC, 2014). The IPCC (2018) concurs and defines disaster risk as the probability that a community or society will experience disruptive changes causing loss of human life and property due to hazardous natural events during a specific period. Thus, drought risk can be defined as the potential impact of droughts on the environment, social development and human welfare which is the result of complex interactions between exposure and vulnerability to natural hazards (IPCC, 2014).

The international response to drought disasters tends to focus on post-disaster management (Carrao et al., 2016). However, this isn't working as the world still suffers from the impact of droughts (NCDC, 2019; EEA, 2010). Drought has become one of China's costliest natural hazards causing economic losses of up to 289 billion yuan between 2012 to 2016 amounting to 15.6 percent of the total direct economic losses from all meteorological disasters (China Meteorological Administration, 2017). Generally, massive losses by droughts result in calls for drought risk assessment analysis (Wilhite et al., 2014). However, the identification of high drought risk areas in China has not attracted much attention.

Some disaster risk assessment research has emerged in recent years (Xu et al., 2011; Han et al., 2016; Jia et al., 2016; Ahmadalipour et al., 2019). For example, Zeng et al. (2019) assessed the agricultural drought risk in southwest China based on drought hazard and vulnerability. Han et al. (2016) assessed the spatial distribution characteristics of a drought risk index in southwestern China based on the vulnerability of the environment, sensitivity and exposure factors. Most of the drought

risk assessments in China have focused on specific provinces and regions, thus there isn't a national approach which makes disaster risk assessments difficult to verify (Hagenlocher et al., 2019).

Constructing a rational risk assessment framework has become an important issue. The most commonly used drought risk assessment model involves using an analytic hierarchy process (AHP) to construct a comprehensive risk assessment index. Unfortunately this process tends to be subjective and affects the validity of the assessment results. This paper describes our improvements to the assessment model. First, we make the assumption that "areas that historically suffered great losses are more likely to suffer losses in the future". Then we introduce historic drought losses to correct the drought risk assessment process. Finally, we create a new drought risk assessment model using multiple nonlinear regression techniques. The model evaluates the risk of drought across China and identifies areas of high drought risk thus providing the scientific and technological basis for drought risk management and comprehensive disaster prevention and mitigation.

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## 2. Material and methods

### 2.1. Material

#### 2.1.1. Meteorological data

Meteorological data are sourced from the Global SPEI (Standardized Precipitation Evapotranspiration Index) dataset (<https://digital.csic.es/>), i.e. SPEI base v2.5 which provides reliable information on global drought conditions (Begueria et al., 2010). The dataset covers the period from 1901 to 2015 with spatial resolution of  $0.5^{\circ} \times 0.5^{\circ}$ . The SPEI time scale used in this study is three months (e.g. Vicente-Serrano et al.,

2011).

### 2.1.2. Social and economic data

The NASA Center for Social and Economic Data and Application (SEDAC) (<https://sedac.ciesin.columbia.edu/>) provides global grid population data, global agricultural area distribution data in 2000, global pasture area distribution data in 2000 and reservoir data. These datasets were used as the source for the socio-economic data in this study. The spatial resolution of the world raster population dataset is  $2.5\text{min} \times 2.5\text{min}$ , including population for 2000, 2005, 2010, 2015 and 2020 (projected). The spatial resolution of the agricultural and pastoral distribution dataset is  $5\text{min} \times 5\text{min}$ . The grid values represent the proportion of cropland area and pasture area to total area in 2000. The reservoir data set includes reservoirs with a water storage capacity of more than 0.1 cubic kilometers in 2011. The primary industry GDP, total water resources and total water demand in various cities (excluding Hong Kong SAR, Macao SAR, and Taiwan region) were obtained from the 2015 statistical yearbooks of the provinces and municipalities. Gross domestic product (GDP) and land-use data were obtained from the Resource and Environment Data Cloud Platform (<http://www.resdc.cn/>). GDP was obtained from the 2015 China GDP data with spatial resolution of  $1\text{km} \times 1\text{km}$ . The land use data was sourced from the remote sensing monitoring dataset of land use status in 2015 that included six types of cultivated land, forest land, grassland, waters, residential land and unused land as well as 25 secondary types. The spatial resolution of this dataset is  $1\text{km} \times 1\text{km}$ .

### 2.1.3. Drought loss data

Drought loss data used in this study includes direct and indirect losses caused by natural disasters. The China Meteorological Disaster Statistical Yearbook (CMA, 2018) documented the losses from drought including: droughts with duration of more than 20 days; drought-affected crop areas of 100,000 hectares or greater; and droughts that reduced production and domestic water for 100,000 or more people. The CMA records include direct economic losses, drought-affected population and drought-affected crop areas. This study analyzed disaster data between 2011-2012 and 2014-2016. Data from 2013 were not used due to missing data.

## 2.2. Integrated evaluation framework for drought risk assessment

Drought risk (*Risk*) includes three components: Hazard (*Haz*), Hazard Exposure (*Expo*) and Vulnerability (*Vul*) (Ahmadalipour et al., 2019):

$$Risk = Haz \times Expo \times Vul \quad (1)$$

According to the drought risk definition, we believe that the drought risk should be able to reflect the actual situation as far as possible, therefore, we make assumptions that "the areas with high historical drought losses are more likely to suffer high future drought losses". Thus we attach drought loss data to the disaster risk assessment framework and put forward a new risk assessment framework based on multivariate nonlinear regression method as shown in Figure. 1.

### 2.3. Calculation of the drought influencing factors

#### 2.3.1. Drought Hazard Calculation

Compared with other drought monitoring indicators the SPEI index comprehensively considers the influence of precipitation, temperature and evapotranspiration, and has multi-time-scale characteristics. As the SPEI index has been widely used in drought research (Yu et al., 2014), our drought hazard factor has been calculated using this indicator based on the run-theory. According to this theory (Spinoni et al., 2014), drought occurs when the SPEI index is smaller than the drought threshold typically set to -1. The time period from a drought event beginning to the end of a is defined DT. The cumulative water shortage during the drought is defined as the drought intensity (DI) -- the severity of the drought. In this study, the drought hazard factor was computed as the cumulative drought intensity from 1901 to 2015:

$$\text{Drought hazard: } dh = \sum_{i=1}^n DI_i \quad (2)$$

Where  $i$  denotes the drought frequency

#### 2.3.2. Drought Exposure Calculation

The drought exposure factor is the number of different types of physical entities that are exposed to droughts. The selection of the drought exposure indicators and drought vulnerability indicators follow three rules: accessibility, reasonability and fitting the definition of drought influencing factors. The selected indicators are shown in Table 1. The selection of indicators for exposure are based on Carrao et al. (2016) and include three types of entities: population, cropland and pasture. Because crop

growth is highly sensitive to climate change and moisture, it is most vulnerable to drought. The impact of drought on pasture reflects the impact of drought on the ecological environment. In addition, humans are also one of the important drought disaster victims.

Because each indicator had a different unit they were normalized using the extreme normalization method. When the indicator had a positive effect on the influencing factors, we used positive normalization, otherwise we used negative normalization:

$$\text{Positive normalization: } x = (x^0 - \min(x_{\text{sequence}})) / (\max(x_{\text{sequence}}) - \min(x_{\text{sequence}})) \quad (3)$$

$$\text{Negative normalization: } x = 1 - (x^0 - \min(x_{\text{sequence}})) / (\max(x_{\text{sequence}}) - \min(x_{\text{sequence}})) \quad (4)$$

where:

$x$  dimension eliminated indicators

$x^0$  original indicator

Then, the drought exposure indicators should be combined together:

$$\text{Drought exposure: } de = \sum_{i=1}^n \alpha_i \times I_{e,i} \quad (5)$$

where:

$de$  denote the exposure factor

$\alpha_i$  denote the weights of the  $i_{th}$  indicator

$I_{e,i}$  denote the  $i_{th}$  exposure indicator

### 2.3.3. Drought Vulnerability Calculation

Drought vulnerability is the tendency to be affected by droughts or the ability to recover from the droughts. The vulnerability indicators are again based on Ahmadalipour et al. (2019) as shown in Table 1. Droughts are usual develop slowly and economically developed areas are better able to mitigate the adverse effects of droughts than poorer areas. Regions with a high proportion of primary industries are more easily affected by droughts. In this study, the water pressure indicator is defined as the ratio of the total water demand to the total water resources (Carrao et al., 2016). When the water pressure is  $> 1$ , regional water demand exceeds the regional water resources, thus regional water security is threatened. Crop types and farming activities also affect the drought vulnerability. For our analysis, we subdivided farmlands into paddy fields, irrigated fields and rain-fed fields. Rain-fed agriculture depends on the availability of precipitation and are more susceptible to droughts, thus the number of reservoirs represents a region's ability to mitigate drought. Regulating regional water resources can help to mitigate the effects of drought as shown in Table 1. These indicators need to be normalized and combined:

$$\text{Drought vulnerability: } dv = \sum_{j=1}^m \beta_j \times I_{v,j} \quad (6)$$

where:

$dv$  respectively denote the drought vulnerability factor

$\beta_j$  denote the weights

$I_{v,j}$  denote the  $j_{th}$  vulnerability indicator

#### 2.3.4. Drought Loss Calculation

The drought loss indicator combines three dimensions: direct economic loss by droughts, the drought-affected population and drought-affected crop area. After normalization, they should be combined:

$$\text{Drought loss: } loss_k = (I_{le,k} + I_{lp,k} + I_{lc,k})/3 \quad (7)$$

where:

$I_{le,k}$  direct economic loss by droughts in the  $k$ th province

$I_{lp,k}$  is the drought-affected population in the  $k$ th province

$I_{lc,k}$ , is the drought-affected crop area in the  $k$ th province

$loss_k$  is the drought disaster indicator of the  $k$ th province

#### 2.4. Drought risk assessment model

The development of the drought risk assessment model includes two steps: 1) Making sure the drought loss data should be in the same spatial scale as that of the drought indicator values; 2) Getting weights of indicators based on multivariate non-linear model ;3) Using the weights and indicators to calculate the drought risk.

The specific calculation steps are as follows:

$$\text{The weights: } loss \sim \lambda \times dh \times de \times dv \quad (8)$$

$$\text{Drought risk: } R = \lambda \times dh \times de \times dv \quad (9)$$

where:

$dh$ , is the drought hazard

$de$ , is the drought exposure

$dv$  is the drought vulnerability

$\lambda$  is the weight of drought hazard factor

### 3. Results

#### 3.1. Drought hazard

Based on the frequency and intensity of regional meteorological drought, the spatial distribution of the drought hazard is mapped in Figure. 2. Regions with the high (extreme high) ( $Haz > 0.651$ ) hazard are found mainly in northwest and southwest China, accounting for about 35.7 percent of the study region. While the northeast, east, central and south China are dominated by low or extremely low hazard ( $Haz < 0.525$ ), accounting for 53.5% of the study region. Based on SPEI, we find that droughts occur with high intensity and long durations in high-hazard areas. During the drought period the average drought intensity is -1.5 to -1.9 with the average drought duration being five months to one year. In low-hazard areas the drought intensity during the drought period is between -1.1 and -1.5, which means lower drought intensity and the average drought duration of less than four months. In terms of drought frequency, it is about once a year in low-hazard areas, while less than once every 1.5 years in high-hazard areas. Droughts in northwestern China are characterized by high intensities and long durations.

#### 3.2. Drought exposure

Drought exposure in this study refers to pasture area shown in Figure 3a, cropland area shown in Figure 3b, population shown in Figure 3c and the drought risk shown in Figure 3d. Regions that are sparsely populated were excluded from our analysis (Güneralp et al., 2015; Chen et al., 2018). We found that regions with high (extremely high) drought exposure ( $\text{Expo} > 0.478$ ) accounted for 13.8 percent of the total study area, and were located in northeastern, eastern, and central China. These regions are flat and fertile, and are major food producing regions. Specifically, the nine major commodity grains are all located in high (extreme high) drought exposure areas ( $\text{Expo} > 0.478$ ), including Sanjiang Plain and Songnen Plain in the northeast; Jianghuai Plain and Taihu Plain in the east; Poyang Lake on the central Plain; the Dongting Lake Plain, Jiangnan Plain; Chengdu Plain in the southwest and the Pearl River Delta. Thus this cropland is the most important with respect to drought exposure.

In order to explore the contribution of indicators to exposure, a correlation between them has been calculated (Guo et al., 2016; Kim-Anh and Liou, 2019). The result shows that cropland indicator accounts most for drought exposure, and the correlation between them is up to 0.99, while the correlation coefficients between pasture indicator, population indicator and drought exposure are -0.024 and 0.22, respectively, which means that they both have corrective effect to exposure index because the contribution of them is relatively small. The pasture indicator has a negative correlation being close to 0, which is most likely due to the fact that drought loss data has only minimally considered the impact of drought on the ecological

environment.

### 3.3. Drought vulnerability

Based on the results of existing research (Kim et al., 2019; Chen et al., 2013; Naumann et al., 2014), we selected five indicators to calculate the drought vulnerability: gross domestic product (GDP) shown in Figure. 4a, the percentage of the primary industry GDP shown in Figure 4b, irrigated land as a percentage of total cropland shown in Figure. 4c, water pressure shown in Figure. 4d, and spatial distribution of water reservoirs shown in Figure. 4e. The drought vulnerability is built based on aforementioned indicators as shown in Figure. 4f. Due to data limitations, provincial data will be used where county level data is missing. In order to show differences between levels, the natural breakpoint method is used. Figure. 4f shows that the drought vulnerability in the northeast is the highest ( $Vul > 0.584$ ), with high levels of vulnerability in the northeast, northwest and southwest ( $Vul > 0.373$ ). These regions have revenues and are more dependent on the primary industry. The indicator that has the greatest contribution to the drought vulnerability is primary industry GDP, whose correlation reaches 0.988. GDP, the proportion of the irrigated area under cultivation, and the number of reservoirs were negatively correlated to the drought vulnerability. This suggests that developed areas equipped with irrigation and better infrastructure have lower vulnerability levels which greatly enhance resilience and mitigate drought risk.

### 3.4. Drought risk

Based on our drought risk assessment model, the correlation coefficient ( $r$ ) between drought risk and drought loss indicator is 0.59. Based on Eq. (1), calculations were done on hazard, exposure and vulnerability and the spatial pattern of drought risk as shown in Figure. 5. High and extreme high drought risk ( $Risk > 0.796$ ) can be found mainly in the northeast and northwest and these regions are also dominated by high levels of vulnerability and exposure. In terms of hazards, there are large differences between regions. The drought frequency in the northeast is higher, while the drought intensity is higher in the northwest. On the whole, the regions with high (extreme high) drought risk account for 4.3 percent of China's land area. Regions with extreme high drought risk areas ( $Risk > 1.49$ ) account for 0.9 percent of China's land area. Regions with medium drought risk ( $1.49 > Risk > 0.796$ ) are widely distributed and located mainly in the north, accounting for 10.8 percent of China's land area.

For each administrative unit, additional analysis was done for areas of regions with different drought risks (except Hong Kong SAR, Macao SAR and Taiwan region) as shown in Figure. 6. Sixty-one percent of China's land area is dominated by extreme low drought risk, and 15 percent by medium and high drought risk. Among the administrative regions, Shandong Province has the smallest area with extreme low risk. The areas with high and extreme high risk is low in Shandong Province. Most of (96 percent) Shandong Province is dominated by medium and low drought risk. However, the largest proportion of medium, high and extreme high drought risk area is in Henan Province account for about 67 percent of total area. Henan and Shandong

Provinces are regarded as more susceptible to drought because they have a high frequency of mild and moderate drought, and have high levels of agricultural production. Economic development in these two provinces is dominated by manufacturing industry instead of the primary industry and water reservoirs are prevalent which helps to manage water resources. Taking all factors into consideration, the drought risk of these two provinces is high. From the perspective of high and extreme high drought risk, the province with the largest proportion of land in these categories (32 percent) is Heilongjiang Province, followed by Ningxia Hui Autonomous Region at 26 percent of total area. However the situation in these two provinces are different. Heilongjiang Province is a humid and semi-humid region, but the precipitation is unevenly distributed throughout the year with springtime being the most susceptible to drought (Fu et al., 2018). It has a high drought risk because it is a major agricultural production area. Drought in the Ningxia Hui Autonomous Region, is due to uneven spatial distribution of water resources, primarily in the southern part of the region. Although the Yellow River passes through this province, water supply is limited and drought are severe (Yang et al., 2015). Drought mitigation efforts are particularly important for these two regions. The Gansu Province is subject to a high proportion of regions with extremely high drought risk concentrated mainly in the Longnan area. Unfavorable precipitation levels coupled with high exposure and high vulnerability make this region extremely vulnerable to drought.

#### **4. Discussion**

Because drought risk can be geographically diverse, the spatial impact of the influencing factors should be considered as an important part of any drought policy. In this study, the attribution method (Wu et al., 2015) is used to combine risk, exposure and vulnerability according to RGB to obtain the composition of the factors for each region. According to the median value of the three factors, eight regions can be divided (hazard = 0.562, exposure = 0.614, vulnerability = 0.620), and appropriate mitigation measures to drought can be achieved as shown in Figure. 7. Low hazard-low exposure-low vulnerability regions are dominated by extremely low drought risk, thus no additional drought disaster reduction measures are needed. In general, for regions with high drought risk ( $H_{\text{high}}$ ), water shortage is an important issue. It needs to strengthen water resources infrastructure construction in accordance with actual conditions in the region. For example, the implementation of trans-basin water transfer projects have helped to alleviate droughts in parts of the northwest where water resources are limited. In addition, the risk of drought can be mitigated to through the rainwater harvesting. In agricultural production, water use efficiency can be improved by promoting agricultural water-saving technologies, improving the construction of agricultural and pastoral water infrastructure and developing water-saving irrigation. Regions with high exposure ( $E_{\text{high}}$ ) are heavily populated with high percentages of cropland, including the Heilongjiang, Shandong and Henan provinces. These regions have historically suffered severe losses from drought and need significant drought mitigation attention.

Mitigation to drought impact can be done by: 1) reducing the exposure of the

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entities by controlling cropland areas and implementing the policies to reclaim forests and pastures from cropland (Pei et al., 2017); and 2) strengthening the protection of cropland and reducing vulnerability by selecting water-efficient and drought-resistant crop varieties, adjustments to planting structure, strengthening drought resistance of agricultural and pastoral land and promotion of agricultural insurance (Xing et al., 2017).

For regions with high vulnerability ( $V_{\text{high}}$ ), corresponding measures can be taken by adjusting industrial structure, reducing dependence on agriculture, promoting diversification of non-agricultural economy and economic development and promoting the use of agricultural and livestock products. It is also important to increase the added value of agricultural and livestock products, and promote industrial transformation (Pei et al., 2017). Finally, it is necessary to enhance water conservancy facilities such as reservoirs to ensure timely irrigation of agriculture.

## 5. Conclusions

Based on the hazard, exposure and vulnerability, a new drought risk assessment model has been developed by integrating drought loss. Using the model drought risk in China is mapped. The five most significant drought risk areas in China are: Northeast, North, East Northwest, East Southwest and a small part of the West Northwest. From the perspective of influencing factors, high-risk areas in China developed due to high-exposure and vulnerability, indicating that the social and economic growth may lead to higher drought losses.

It is recommended that high-drought risk areas should consider the following measures to reduce the risk of drought: strengthen the protection of cultivated land; strengthen the construction of farmland infrastructure; adjust the industrial structure and reduce dependence on a single industry. This model has provided a new way of assessing drought risk which should improve drought impact decision making.

#### **Declaration of Competing Interest**

The authors have no conflicts of interest to declare.

#### **Acknowledgments**

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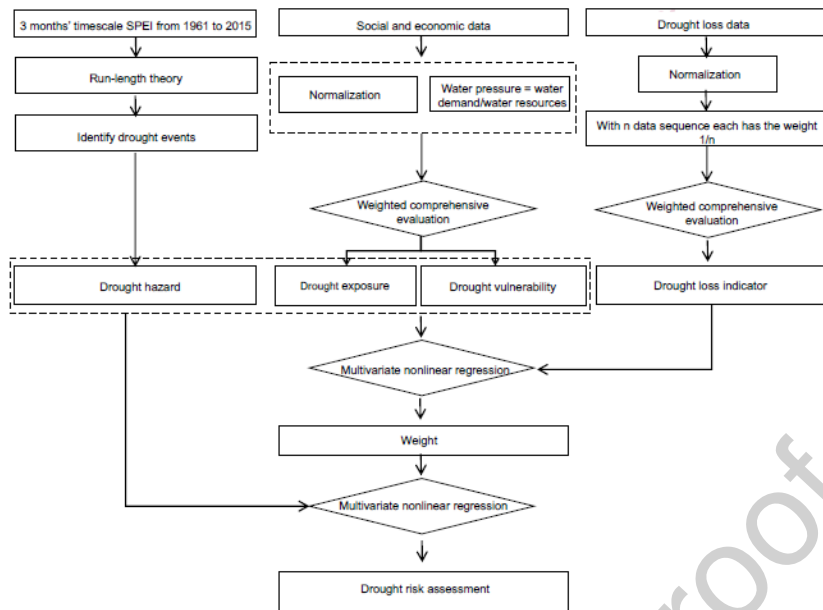
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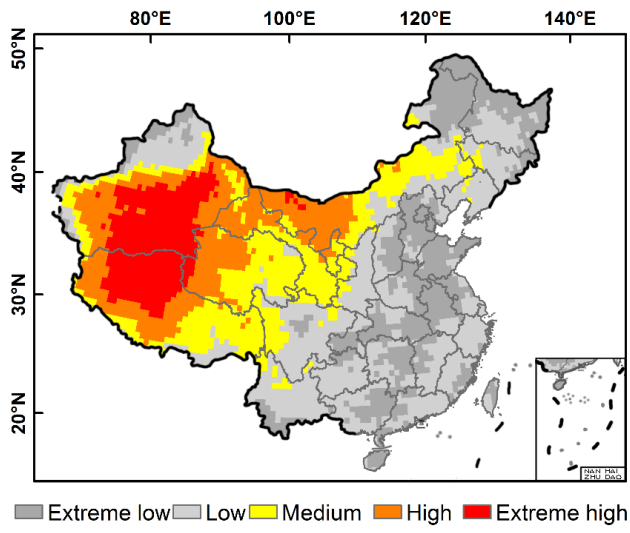
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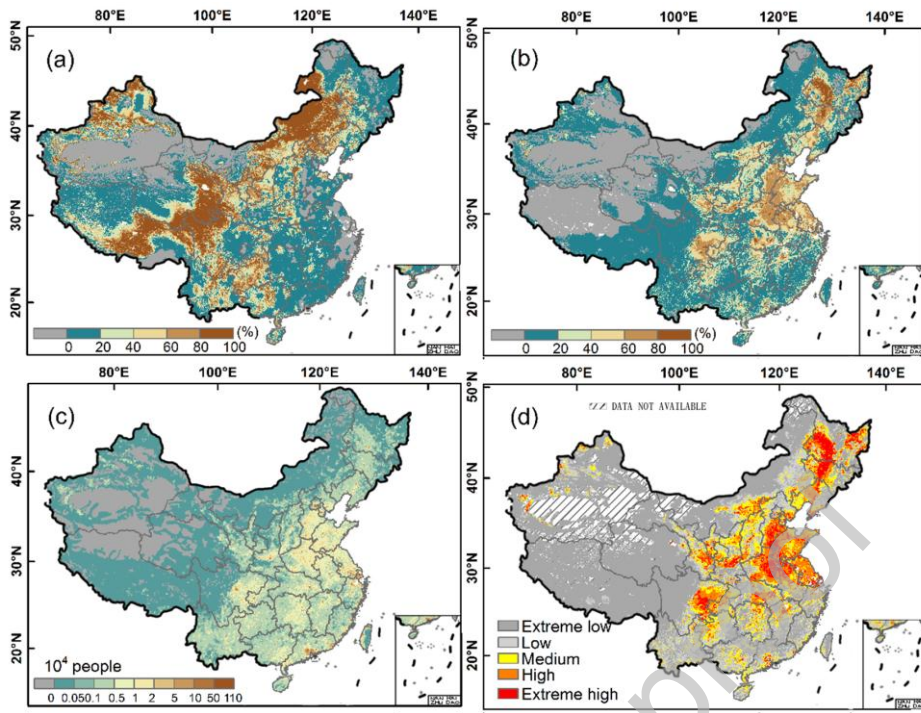
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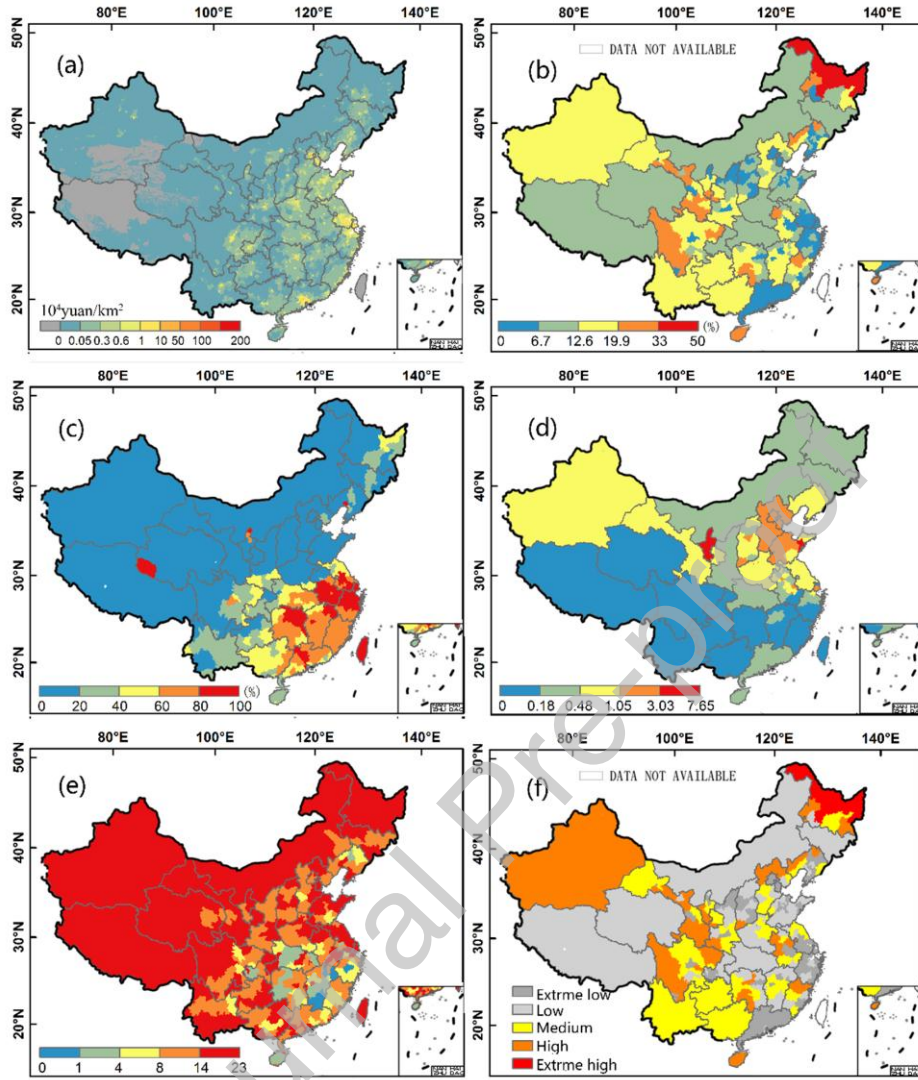
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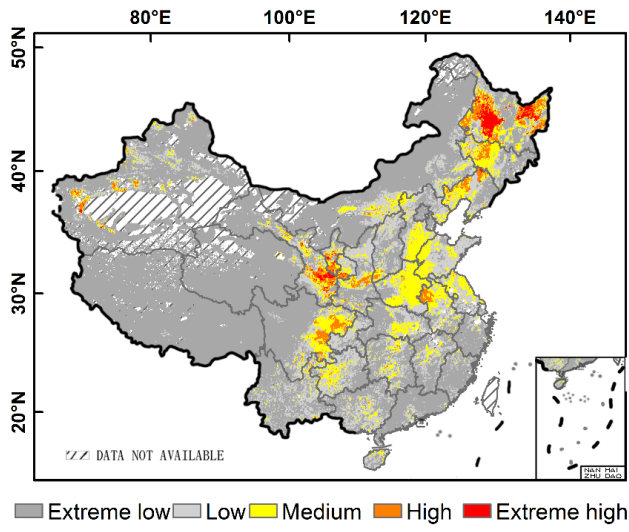




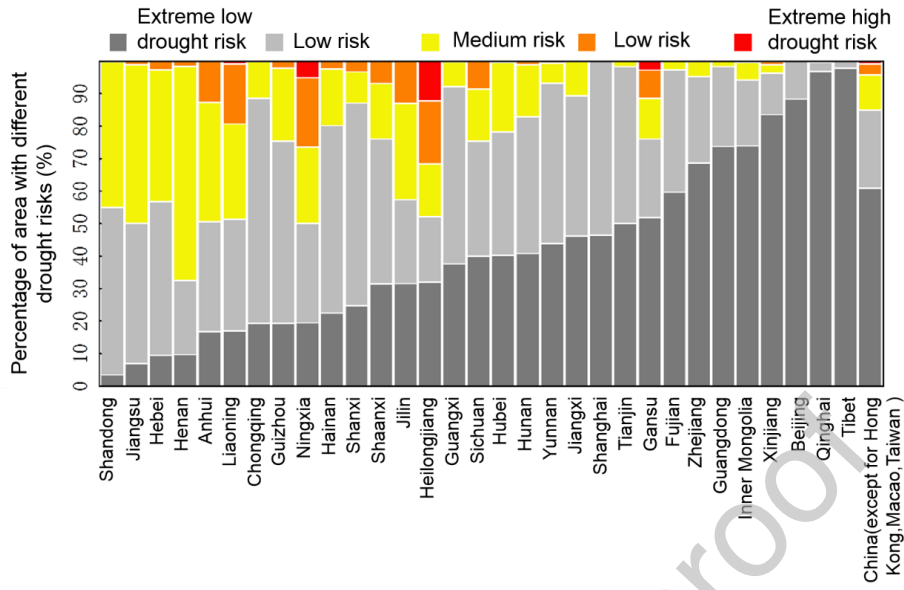
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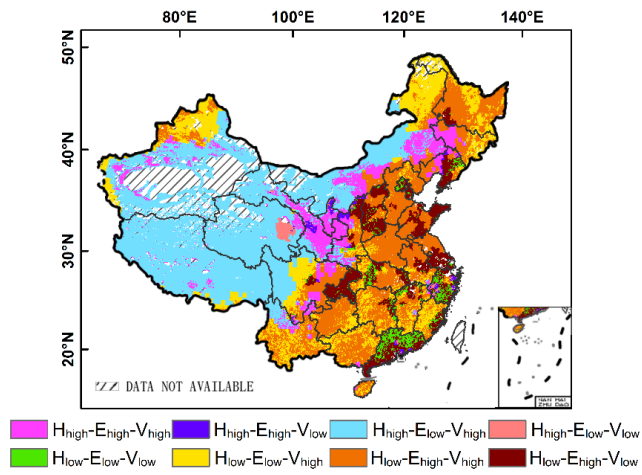






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## Graphical Abstract

**Assumption:** "the areas with high drought losses in history are more likely to suffer high drought losses"

