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Research Article

Risk Assessment of Maize Drought in China Based on Physical Vulnerability

Fang Chen,[1,2,3] Huicong Jia,[1,4] and Donghua Pan[5]

[1]*Key Laboratory of Digital Earth Science, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Beijing 100094, China*
[2]*University of Chinese Academy of Sciences, Beijing 100049, China*
[3]*Hainan Key Laboratory of Earth Observation, Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences, Sanya 572029, China*
[4]*Department of Geography and Center for Environmental Sciences and Engineering, University of Connecticut, Storrs, CT 06269, USA*
[5]*National Disaster Reduction Center of China, Ministry of Civil Affairs of the People's Republic of China, Beijing 100124, China*

Correspondence should be addressed to Huicong Jia; jiahc@radi.ac.cn

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Applying disaster system theory and with reference to the mechanisms that underlie agricultural drought risk, in this study, crop yield loss levels were determined on the basis of hazards and environmental and hazard-affected entities (crops). Thus, by applying agricultural drought risk assessment methodologies, the spatiotemporal distribution of maize drought risk was assessed at the national scale. The results of this analysis revealed that the overall maize drought risk decreases gradually along a northwest-to-southeast transect within maize planting areas, a function of the climatic change from arid to humid, and that the highest yield loss levels are located at values between 0.35 and 0.45. This translates to drought risks of once in every 10 and 20 years within 47.17% and 43.31% of the total maize-producing areas of China, respectively. Irrespective of the risk level, however, the highest maize yield loss rates are seen in northwestern China. The outcomes of this study provide the scientific basis for the future prevention and mitigation of agricultural droughts as well as the rationalization of related insurance.

1. Introduction

In disasters, risk is defined as the probability of loss and depends on three factors: hazards, vulnerability, and exposure. This means that if the magnitude of any one of these factors changes, the risk will correspondingly increase or decrease [1–3]. An increasing number of global and local initiatives have been launched to measure the risk with a set of indicators [4, 5]. There are many models and formulas of disaster risk assessment. All the definitions described the risk only from one or more aspects. Currently, more researchers agree on the risk expression of the United Nations ISDR (International Strategy of Disaster Reduction) [6, 7]. With the increase in frequency of extreme events, the management of extreme climate events based on risk assessment becomes an academic research hot spot [8]. Since the 1970s, some countries, including the United States, Japan, and the United Kingdom, have routinely carried out flood, earthquake, landslide, and debris flow disaster risk analyses and assessments. The results of these studies provide critical data that can be used to determine who is responsible for disaster mitigation and the implementation of relief efforts [9–15]. Disaster risk assessment and management in China has been the focus of considerable research attention since the country's participation in the International Decade for Natural Disaster Reduction. The results of studies carried out to date have both enriched the overall scope of natural disaster research and played a role in disaster management [16–23]. In general, however, natural disaster risk assessment tends to be integrated from the perspective of disaster

systems, applying both single and multiple indexes to the evaluation of disaster risk mechanisms.

Previous drought research mainly focused on the drought index [24, 25], drought disaster loss [26–28], drought monitoring [29, 30], and drought forecasting [31, 32], and so on. With the advancing of drought research, more attention should be paid to the overall structure of the drought disaster system. Based on the study of the process of drought disaster system dynamics, the future likelihood of drought disaster and the possibility of losses were more concerned [33, 34]. Risk of drought has become the hot issue. Taking crop as the hazard-affected bodies, the emphasis of drought risk research has been changed mechanisms of crop growth from a statistical aspect. Vulnerability curves have provided new ideas with it. The majority of research is on loss risk assessment through quantitative simulation of the relationship between a specific drought index and crop biomass [35–37].

China has a typical monsoon climate and is also an agricultural country with the largest population in the world. The instability of the monsoon climate in China has led to frequent drought-related disasters. Drought is the major constraining factor on maize growth and development, one of the three main national grain crops. Thus, taking maize as the target for this research, an agricultural drought risk assessment was performed by assessing physical crop vulnerabilities. Overall, many scholars have carried out a lot of research on the climatic factors on the growth and development of maize, variety maturity, suitable area, yield, and quality [38–40]. Based on a formation mechanism of drought risk, there is a lack of research on maize drought risk assessment from a systematic view on a national scale. Studies on the factors that cause agricultural drought disasters have therefore focused mainly on the development of indicators and on the impact of hazard-inducing factors [41–44]. The standardized precipitation index (SPI) is one indicator that is often applied to characterize drought, as it can be used to quantify precipitation deficits over different timescales (e.g., one month, three months, six months, 12 months, 24 months, and 48 months) [45]. The objective of this study is two-fold: (1) to simulate a physical vulnerability curve of typical maize by fitting the function between the maize drought hazard index and the yield loss rate and (2) to analyse the spatial and temporal distribution of the maize drought hazard risk and loss risk in China. The results of this study align with the requirements for sustainable agricultural development in China and provide an important baseline for early warning and drought risk reduction. This study therefore makes a contribution to the safeguarding of national food security.

2. Materials and Methods

2.1. Meteorological Data. Meteorological data in this study were collected from 752 meteorological stations, with data provided by the China Meteorological Administration, including daily precipitation, daily relative humidity, daily sunshine hours, and average daily wind speed during 1961–2015.

2.2. Crop Observational Data. Crop observational data were extracted from the annual reports of national agricultural meteorological observation stations stored in the archives of the China Meteorological Administration. The information in these reports includes basic crop information; crop growth periods; yield components, factors, and information; and field management processes and meteorological conditions during the growth period.

2.3. Data on Hazard-Affected Bodies. Exposure to drought-inducing hazards is a prerequisite if crops are affected by these disasters. Therefore, if a body is not exposed to an environment containing a particular hazard, an agricultural drought will not occur and the risk remains zero. The main data sources used in this study are presented in Table 1. The flow of data calculation is shown in Figure 1.

2.4. Methods. SPI values for maize crop growth periods are used as the drought hazard index. This index of SPI has been commonly utilized for characterizing droughts [46], mainly because it is spatially invariant and is therefore a reliable indicator for comparing one location with another. Thus, following reference [45], drought intensity was classified into four categories: "normal," "moderately dry," "severely dry," and "extremely dry." Values of the SPI were calculated in this study by fitting a gamma probability distribution to interpolated rainfall fields; thus, the corresponding cumulative rainfall probabilities were then transformed to a standardized normal distribution using a mean of zero and a variance of one, with monthly and three-monthly time periods considered sufficient to preserve intra-annual variability. The results of the three-month SPI analysis are presented for simplicity. Maize crop growth period SPI values for the period between April and September from 1961 to 2015 were calculated in this study. The IDW (inverse distance weighted) method was applied to interpolate meteorological station data into spatial data.

Hazard-inducing factors were assessed in this study in two ways. (1) Probability risk based on the fixed drought hazard index. (2) Drought hazard index based on fixed exceeding probability. The drought hazard index probability was initially calculated, including the probability density and the probability that the hazard-inducing factor index was exceeded. The risk was then calculated using a fixed probability that the factor index was exceeded as well as the fixed drought hazard index. The fixed drought hazard index is used to calculate the probability of drought under different hazard index levels, including four levels of drought hazard index according to the data histogram: SPI less than −0.15, SPI less than −0.30, SPI less than −0.40, and SPI less than −0.45. The fixed exceeding probability is to calculate drought hazard indexes at once in 2, 5, 10, and 20 years.

Artificial neural networks (ANNs), which emulate the parallel distributed processing of the human nervous system, have proven to be very successful in dealing with complicated problems. Due to their powerful capability and functionality, ANNs provide an alternative approach for many assessment problems that are difficult to solve by

Table 1: Database of drought hazard-affected bodies.

Data	Information content	Sources	Year(s)
Land use data	National 1 : 1 million land use vector map	Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences	2010
Crop yield data	Corn production in each county	Statistical Yearbook of Chinese Cities and Counties	Between 1996 and 2015
Crop yield data	Corn acreage in each county	Statistical Yearbook of Chinese Cities and Counties	Between 1996 and 2015
Crop regionalization	Regionalization of maize planting	Chinese National Atlas of Agriculture	2003
Crop phenological periods	Crop phenological periods	Chinese National Atlas of Agriculture	2003

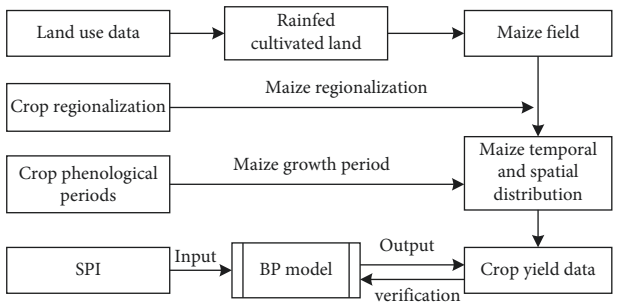

Figure 1: Flow chart for data calculation.

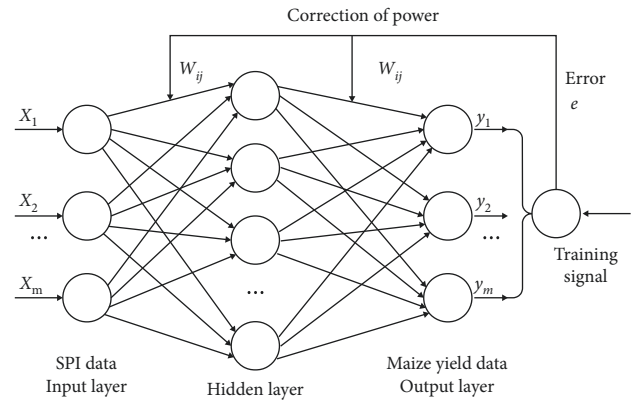

Figure 2: Application of BP-ANN model in the vulnerability curve simulation.

conventional approaches [47]. The backpropagation (BP) neural network is currently the most widely used ANN [48, 49]. It has been used increasingly in geographical and ecological sciences because of its ability to model both linear and nonlinear systems without the need to make any assumptions. Generally, the BP neural network used in the aforementioned studies was reported to yield significantly better results than conventional methods. Therefore, it was chosen for this article to provide a technical support for risk assessment.

The difference between the actual and theoretical yields was then used as the loss in drought yield reduction, given the actual drought hazard index at each meteorological station, and the BP-ANN model was applied to simulate a drought vulnerability curve using the software MATLAB. A nonlinear statistical model was then used to fit a regression between the drought hazard index and yield loss rate data, and a vulnerability curve and corresponding equation for the common maize variety Danyu 13 were then generated (Figure 2). The crop species Danyu 13 is mid-late-maturing hybrid maize with the characteristics of high yield, high quality, and wide adaptability [50].

Without considering the drought mitigation capacity, while setting exposure to 1 (maize-growing regions), the risk of each assessment cell was a function of hazard index and vulnerability. Formula P (Loss) $= f(H, E, V)$ is a theoretic equation. H is indicated through the hazard index-probability curve. V is indicated through the hazard index-loss rate curve. E (exposure) is assigned to 1 if it is in maize-growing regions, setting E to 0 if not. The loss rate (*Loss*) under certain hazard index delegates the value of V. Drought disaster risk is the loss rate under a certain level of hazard. Finally, the loss risk maps of maize drought risk in China were drawn.

3. Results and Analysis

3.1. Hazard Risk Assessment

3.1.1. Probability Risk Based on the Fixed Drought Hazard Index. Based on the SPI database of maize growth periods and fixed degrees of drought hazard index, drought probabilities were calculated via excess probability for each 1 km grid unit in the form of a series of risk maps.

The results of this study showed that, in general, given different levels of drought hazard index, the northwestern, northeastern, and northern Chinese maize regions exhibit the highest values of hazard risk across the national planting areas (Figure 3). In addition, as the drought hazard increases, the risk probability gradually decreases; thus, the highest probability risk values (0.63) can be seen in the northwestern, northeastern, and northern Chinese maize regions associated with an SPI growth period value of less than −0.15. The data also revealed that the highest recorded risk probability was 0.60, which is associated with a drought hazard index level of less than −0.15 within the growth period, whereas the highest risk probabilities were 0.50 and 0.45, respectively, given drought hazard index levels of less than −0.40 and less than −0.45 within the growth period.

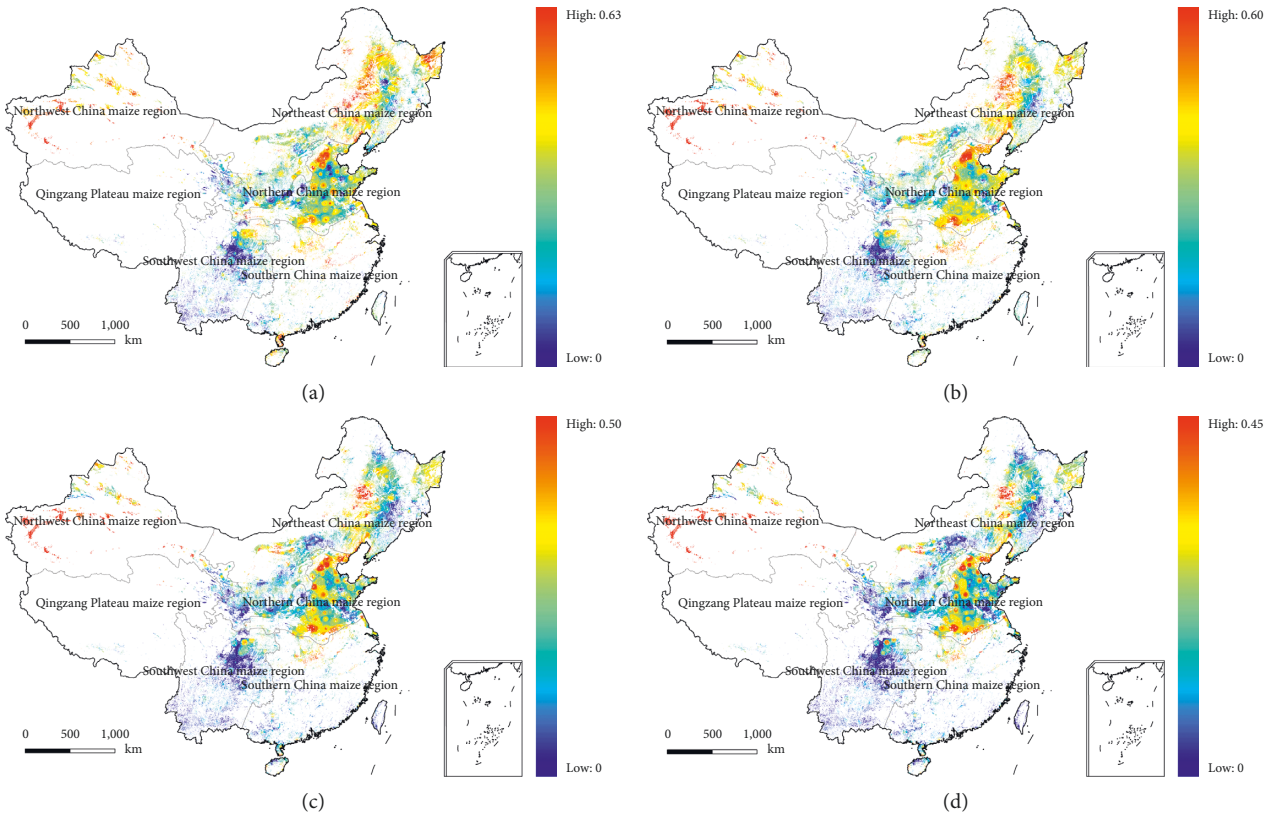

Figure 3: Maps showing probability risks, given different maize drought hazard indexes across China. (a) SPI less than −0.15, (b) SPI less than −0.30, (c) SPI less than −0.40, and (d) SPI less than −0.45.

3.1.2. Drought Hazard Index Based on Fixed Exceeding Probability. Based on the SPI database of maize growth periods and fixed degrees of exceeding probabilities, four maps of maize drought hazard risk were calculated at different risk levels (Figure 4). These results show that 91.52% of the maize-planting areas in China fall within the light drought hazard index range between 0.1 and 0.2 and correspond with a risk level of once in every two years. In contrast, the drought hazard index range for once in every five year risk falls between 0.3 and 0.4 and encompasses 52.98% of the total Chinese maize-planting area, whereas the drought hazard indexes for once in every ten year events are between 0.3 and 0.4 and 0.4 and 0.5, accounting for 45.71% and 37.37% of the total cultivated area, respectively. Similarly, the drought hazard index for once in every 20 year events ranges between 0.5 and 0.6 and encompasses 48.73% of the national cultivated area. These data show that, irrespective of the risk level, the drought hazard index is the largest in the northwestern maize region of China because of a more severe level of drought hazard; most of the drought hazard index values for this region were 0.5 or higher, followed successively by the northern and northeastern maize regions of China.

3.2. Results of Vulnerability Curves. As discussed above, a drought vulnerability curve was simulated in this study by applying the BP-ANN model in the software MATLAB. A nonlinear regression model was then used to simulate a drought vulnerability curve and the corresponding regression equation, as follows:

$$L_s = \frac{0.5564}{1 + 25.58 \times e^{10.16\times(-H_s)}}. \quad (1)$$

In this expression, L_s represents the yield loss value of Danyu 13, whereas H_s denotes the corresponding drought hazard index.

The physical vulnerability curve generated in this study conforms to a logistic distribution (Figure 5); thus, linearity in this relationship comprises a growth curve that increases from 0 to 1 while the maximum loss rate value is about 0.6. This relationship is also highly consistent because it has an R^2 (coefficient of determination) value of 0.81.

3.3. The Risk of Loss. Using the drought-induced hazard index and the physical vulnerability curve for maize, a series of risk of loss maps for different hazard levels (for a maize hazard risk of once in every 2, 5, 10, and 20 years) across China were generated (Figures 6–9). The comparisons show that the risk of maize yield losses across China tends to decrease along a northwest-to-southeast transect, which results from a switch in climate between arid and humid regions. The results show that 75.30% of Chinese maize-growing areas have yield loss rates between 0.05 and 0.1, consistent with a once in every two years level of risk,

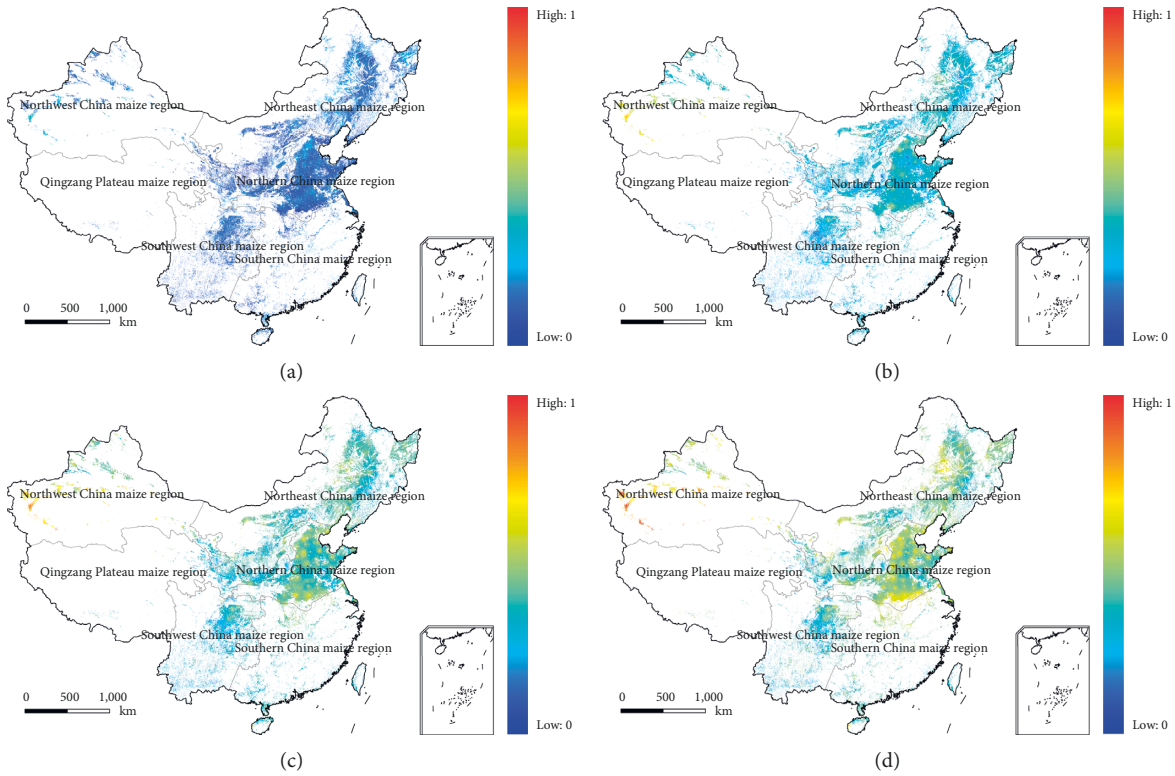

Figure 4: Maps showing drought hazard indexes for China at different timescales. (a) Once in two years, (b) once in five years, (c) once in ten years, and (d) once in 20 years.

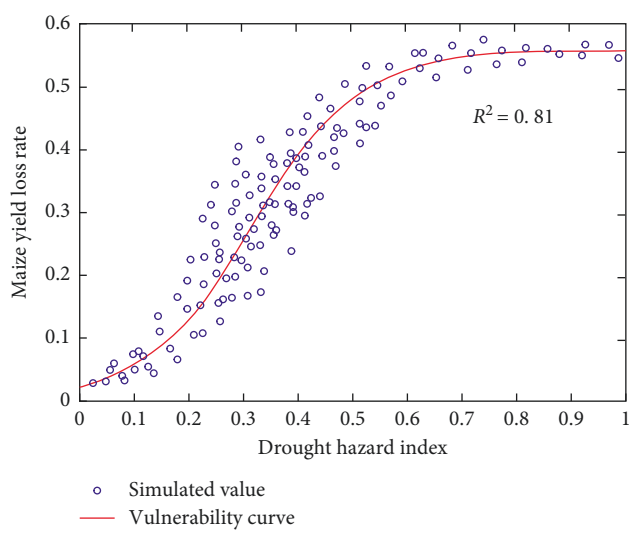

Figure 5: Calculated physical vulnerability curve for the common maize variety Danyu 13.

whereas the risk level once in every five years corresponds with a higher yield loss risk rate of between 0.25 and 0.35, accounting for 46.22% of the total area. In contrast, the once in 10 and 20 years risk levels tend to encompass yield loss rates between 0.35 and 0.45, accounting for 47.17% and 43.31% of the total maize-planting areas across China, respectively. These comparisons also show that, irrespective of the level of risk, the highest yield loss rates occur in the northwestern maize region of China.

4. Conclusions and Discussions

The vulnerability of agricultural hazard-affected bodies is determined by the unique physical characteristics of crops. However, by determining the relationship between drought hazard index and disaster loss percentage, a vulnerability curve for a particular hazard-affected body can be generated. A hazard, vulnerability curve, risk evaluation system for the assessment of drought risk based

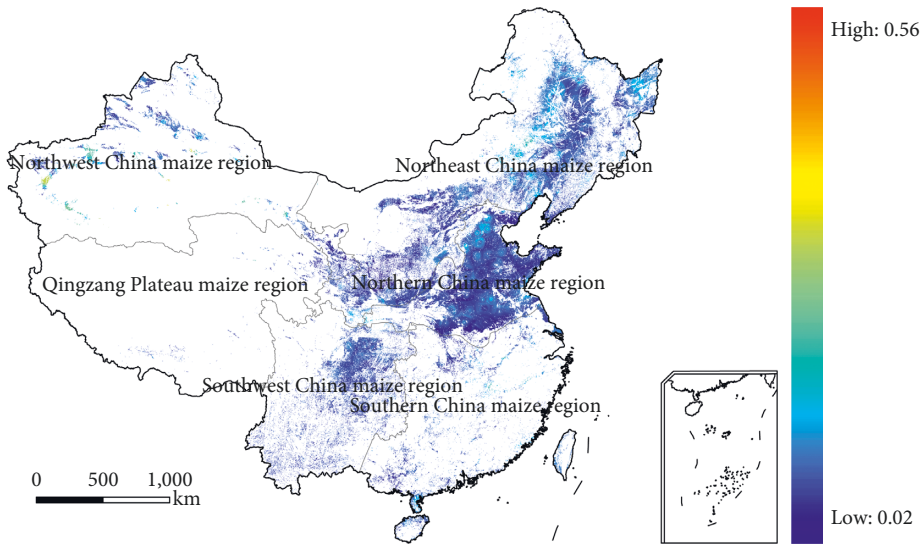

Figure 6: Map showing areas of China where the drought yield loss rate is such that a risk of hazard to maize is likely to occur once in every two years.

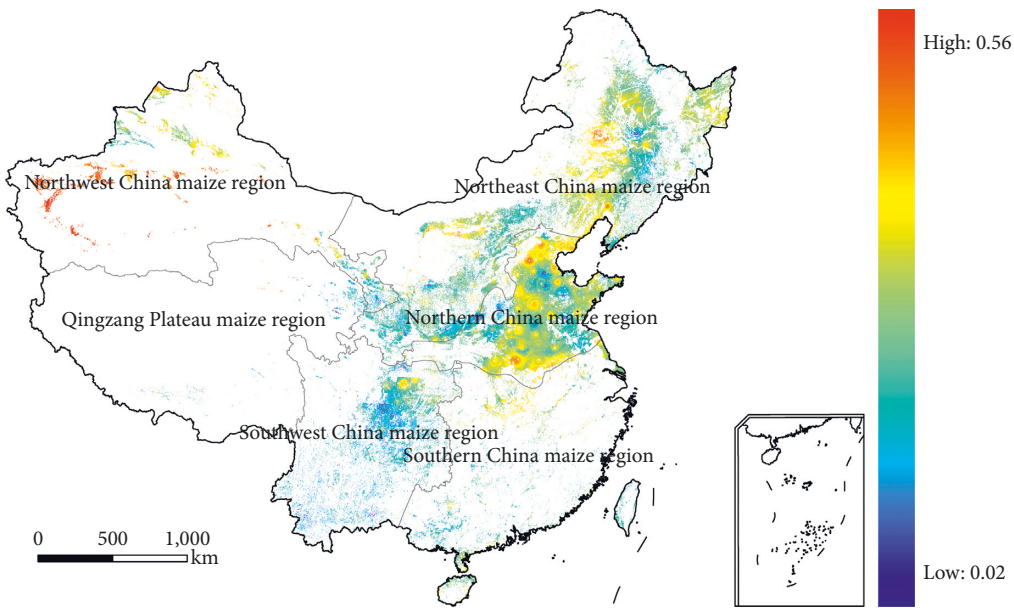

Figure 7: Map showing areas of China where the drought yield loss rate is such that a risk of hazard to maize is likely to occur once in every five years.

on physical vulnerability is therefore proposed as a result of this study.

Applying the drought risk assessment method, in this study, the spatiotemporal distribution of maize drought risk was evaluated quantitatively across China for the first time. The results of this analysis revealed that the risk of maize yield losses in China decreases along a northwest-to-southeast transect, which is caused by the climatic transition from arid to humid. Most yield loss rates at the 10-year-risk and 20-year-risk levels fall between 0.35 and 0.45 and account for 47.17% and 43.31% of the total Chinese maize-planting areas, respectively. The highest rate of yield loss at all four risk levels occurs in the northwestern Chinese maize region. It is not only related to the climate zone in which the maize areas are located but also to the regional differences in land surface conditions. While in arid and semiarid regions, the dependence on irrigation of maize planting and growth in these areas was most obvious.

Because of data limitations, a number of assumptions were necessary in this study with regard to the spatial distribution and varieties of maize crops and the homogeneity of units used for evaluation. In future analyses, it will be necessary to refine the crop types and varieties as well as planting ratios and to incorporate both disaster prevention and mitigation measures as evaluation units. The current study is based on meteorological observation data of

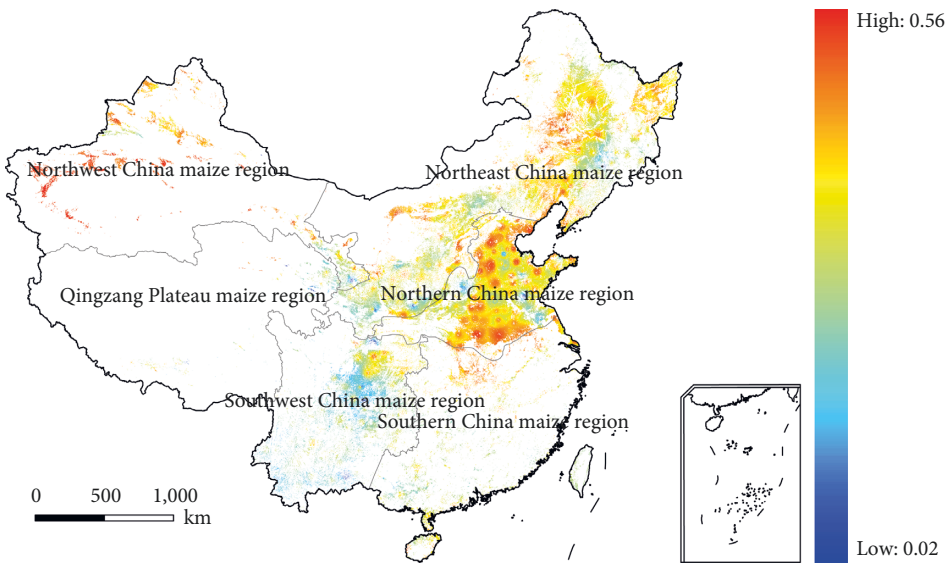

Figure 8: Map showing areas of China where the drought yield loss rate is such that a risk of hazard to maize is likely to occur once in every ten years.

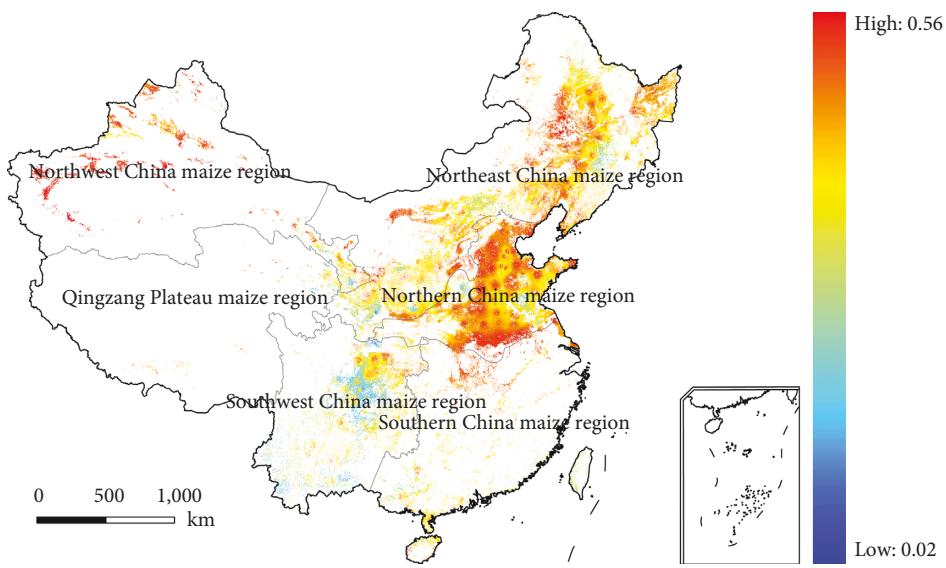

Figure 9: Map showing areas of China where the drought yield loss rate is such that a risk of hazard to maize is likely to occur once in every 20 years.

1960–2015, and a risk assessment under future climate change still need further study. These analytical improvements are likely to lead to more accurate risk assessments and will provide an enhanced scientific reference for the rational planning and utilization of Chinese agricultural land, the prevention and mitigation of drought, and the rationalization of an insurance system for the planting industry that incorporates a predetermined regional premium rate.

Data Availability

The land use data used to support the findings of this study were supplied by the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, under license and so cannot be made freely available. Requests for access to these data should be made to the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, xxgk@igsnrr.ac.cn. The crop yield data, crop regionalization, and crop phenological period's data used to support the findings of this study are available from the corresponding author jiahc@radi.ac.cn upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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