







Risk assessment of maize drought disaster in southwest China using the Environmental Policy Integrated Climate model

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Abstract: The East Asian monsoon has a tremendous impact on agricultural production in China. An assessment of the risk of drought disaster in maize-producing regions is therefore important in ensuring a reduction in such disasters and an increase in food security. A risk assessment model, EPIC (Environmental Policy Integrated Climate) model, for maize drought disasters based on the Erosion Productivity Impact Calculator crop model is proposed for areas with the topographic characteristics of the mountainous karst region in southwest China. This region has one of the highest levels of environmental degradation in China. The results showed that the hazard risk level for the maize zone of southwest China is generally high. Most hazard index values were between 0.4 and 0.5, accounting for 47.32% of total study area. However, the risk level for drought loss was low. Most of the loss rate was <0.1, accounting for 96.24% of the total study area. The three high-risk areas were mainly

distributed in the parallel ridge–valley areas in the east of Sichuan Province, the West Mountain area of Guizhou Province, and the south of Yunnan Province. These results provide a scientific basis and support for the reduction of agricultural drought disasters and an increase in food security in the southwest China maize zone.

Keywords: Vulnerability; Risk assessment; Drought; EPIC model; Maize; Southwest China

Introduction

Food security is regarded as a top priority in China. Drought is a serious problem in southwestern China, where the drought risk exceeds the national average (Wang and Wang 2014). Climate change is likely to exacerbate this problem, thereby endangering food security in China (Zhou et al. 2014). The yield of maize in

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China is higher than the yield of all other crops except wheat, and the planting area and yield of maize are almost as high as in the USA, the world's largest producer of maize (Yue 2004; Jia et al. 2011). Risk assessments of the effects of drought on crops consider that the risk of drought is determined by environmental instability, hazard intensity, and vulnerability. Given the complexity of the relationship between these three parameters, previous studies have focused on the risk of drought in mountainous areas, such as southwest China and the west of Henan Province (Zhou et al. 2012; Wang et al. 2014). An increasing number of global and local initiatives have been launched to measure risk using a set of indicators and indices (Cutter 2003; Cardona 2003; Dilley 2005; Birkmann 2006; Ni 2014).

There are many models and formulas for the assessment of disaster risk. Many researchers now agree on the risk expression of the United Nations International Strategy of Disaster Reduction, where risk (R) = hazard factors (H) \times vulnerability (V) (Shi 2002; UN/ISDR 2004; World Bank and Columbia University 2005; Fedeski and Gwilliam 2007; Birkmann 2007; Wang and Zhang 2013; Yin et al. 2014). With the increase in frequency of extreme events, the management of extreme weather and climatic events (such as droughts) based on risk assessment is of increasing interest (Intergovernmental Panel on Climate Change 2013).

The Erosion Productivity Impact Calculator (EPIC) model, which was developed by the US Department of Agriculture in 1984, can be used to manage water and soil resources and to assess crop productivity. Some countries have used the EPIC model to estimate the yield of wheat, maize, sunflower, soybeans, and other crops (Chung et al. 2001; Cavero et al. 2001; Jonghan et al. 2009; Yin et al. 2014; Hyung et al. 2015). The EPIC model provided technical support for the simulation of maize growth in this study.

Numerous studies have been carried out on the effect of climatic factors (e.g. CO₂ concentration, temperature, and precipitation) on the growth and development of maize, including the effects of maturity and different varieties, planting regions, yield, and quality (Liu et al. 2001; Yang et al. 2005; Jia et al. 2010; Liu et al. 2013; Liu et al. 2014). However, there has been little research on the risks of drought disaster in typical maize-growing

regions. The maize zone of southwest China is located in the center of the karst region (Yu and Zhang 2012). A quantitative assessment of the risk of maize drought disaster in southwest China was performed based on the EPIC model. This research may provide a theoretical basis and technological support for the prevention and mitigation of drought in high-risk maize-producing areas of China.

1 Study Area

Maize is grown in China on the Northeast Plain, the North China Plain, the Sichuan Basin, the Yunnan–Guizhou Plateau and in other regions, forming a triangular distribution zone from northeast to north to southwest China. The theoretical basis for the regionalization of maize-growing in China is based on the physical characteristics of the terrain. The results of the nationwide project *Maize Planting Regionalization in China*, conducted by Tong (1992), were chosen as the basis of the regional assessment in this study.

The southwest China maize zone is the third largest maize-growing area in China. It includes Sichuan Province, Yunnan Province, most of Guizhou Province, and the west of Guangxi Zhuang Autonomous Region (Figure 1). Severe drought events occurred in this region in the summer of 2006, the autumn of 2009, and the spring of 2010 (Li et al. 2011; Li et al. 2012; Wang et al. 2014; Liu et al. 2014), causing large agricultural losses and severe shortages of drinking water.

A total 45.19 million hm² of maize is grown in this region, accounting for 18.4% of the total area of maize grown in China and 13.4% of the total production of maize in China (Liu 2002). Nearly 90% of the region's land area consists of hilly regions and plateaus; the valley and basin regions account for only 5% of the total area. Most of the land is at altitudes between 200 and 5000 m. The vertical distribution of crop planting is very obvious. The area has a temperate to subtropical moist, humid climate with abundant rainfall, rich hydrothermal resources, but poor lighting conditions. The frost-free period in this region is longer (240-330 days) than the effective growing period of maize (150-180 days). The total annual rainfall of this region is 800-1200 mm and this mainly falls between April

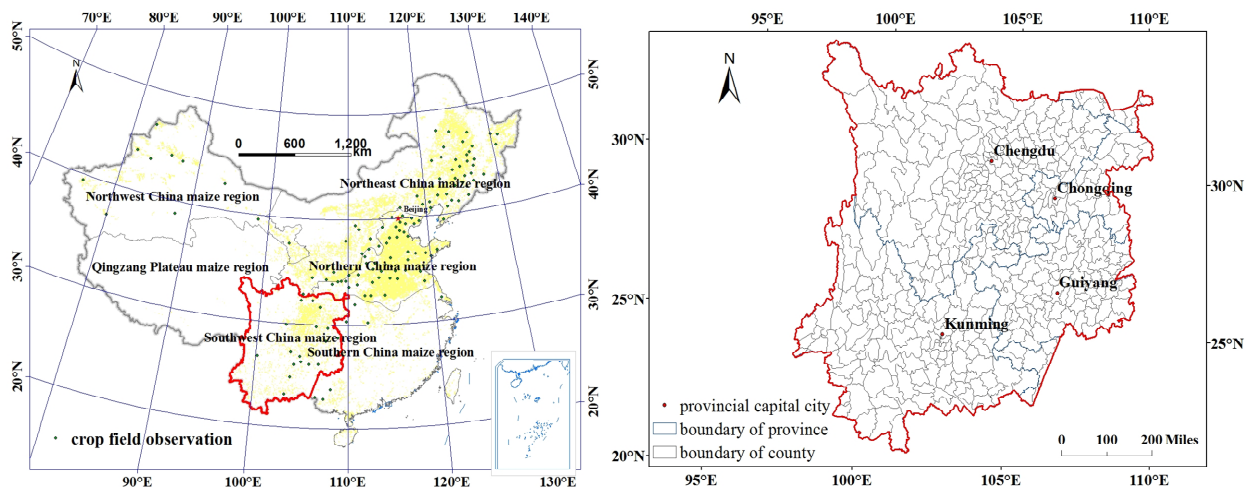


Figure 1 Location of the maize zone of southwest China.

and October, which is suitable for maize cultivation. However, there are more than 200 days per year with cloudy and dry conditions and drought frequently occurs in the spring and summer (Pan and Yang 2012; Wang and Wang 2014).

Southwest China is in the fragile karst ecological zone (Sweeting 1993; Zhang et al. 2011) and 129,600 km² of land is affected by karst rocky desertification. Southwest China's more or less contiguous karst area is one of the world's largest and has produced some spectacular landscapes. The Southwest China Karst, a UNESCO World Heritage Site since June 2007, spans the provinces of Guangxi, Guizhou, and Yunnan. It is noted for its karst features and landscapes as well as its rich biodiversity. These karst areas have an estimated, mainly rural, population of 80-100 million people (Tu 1996).

Widespread deforestation in southwest China, which began in the late 1950s, severely damaged the natural vegetation. The subsequent loss of soils reduced the water storage capacity of this zone with its abundant springs (Shapiro 1991; Huang and Cai 2007; Liu et al. 2014). Chinese scientists refer to this process as 'rocky desertification' and it is recognized as a major environmental problem in southwest China. The area affected by rocky desertification in the Southwest Karst area is increasing by almost 600 square miles per year (People's Daily Online 2005). Agriculture has been greatly affected by this loss of soil (Yu and Zhang 2012). We used the area of irrigated and dry land in the land use map to represent the distribution of maize in southwest China.

2 Material and Methods

2.1 The EPIC model

The EIPC model is used to simulate the impact of disasters on crops, crop-water relations, and the risk of drought. The major components in the EPIC model are: crop growth, yield, and competition; weather simulation; hydrological, nutrient, and carbon cycling; soil temperature and moisture; soil erosion and tillage; and plant environment control (Williams et al. 1989; Jones et al. 2005). EPIC operates on a daily time step and can be used on scales from decades to centuries (Sharpley and Williams 1990). The EPIC model is applicable to regions with homogeneous weather, soil, topography, crop rotation, and crop management. The EPIC model provides a quantitative simulation of environmental impacts on crop growth and yields. Different management options are available, including tillage operations, irrigation scheduling, and fertilizer application rates and timing.

Crop yields are calculated as a ratio of economic yield over the total actual above-ground biomass at maturity as defined by the harvest index. In addition to meteorological and soil variables, the main growth-defining factors are Potential Heat Units (PHU), the biomass – energy conversion factor, and the harvest index (Wang et al. 2005; Velde et al. 2012). Water stress (WS) is effectively controlled through the soil–water balance and supplementary irrigation (Roloff et al. 1998; Tan and Shibasaki 2003).

2.2 Materials

Table 1 lists the data used in this study; the years used were not consistent. Meteorological data from 1961 to 2005 – including daily precipitation, daily sunshine hours, daily maximum temperature, daily minimum temperature, daily relative humidity, average daily wind speed, and daily solar radiation – were collected from meteorological stations provided by the China Meteorological Administration. As a result of the lack of complete data for solar radiation needed by the EPIC model, the daily solar radiation was calculated from the daily sunshine hours and astronomical radiation (Li 1995).

The EPIC model requires a large amount of input data to describe soil attributes and textures. The spatial distribution and soil attribute data used in this study were derived from the global map of soil types (2' resolution) compiled by the United Nations Food and Agriculture Organization. The maize field observation data of all the agricultural meteorological observation stations from 1980 to 2005 were recorded, giving a total of 86 annual reports from more than 17 national agricultural meteorological observation stations.

Based on the content, scale, and accuracy of the assessments, particularly the spatial resolution of the soil data, an 8 km grid was selected as the basic unit. This data could be easily combined with MODIS remote sensing data for further analysis. The drought risk was evaluated using the mathematical models and overlay analysis in ArcGIS software and plotted as maps.

Table 1 Dataset used in this study

Dataset	Content	Data Source	Year
Meteorological observation database	Precipitation, temperature, radiation, wind speed, relative humidity, and other daily data for all meteorological stations in the maize zone of southwest China	China Meteorological Administration	1961-2005
China land use map	1:1,000,000 land use data, including paddy fields, drylands, forests, grasslands, and other major land use types	Chinese Academy of Sciences	2000
Global distribution of soil types with 2' resolution	Soil properties	Food and Agriculture Organization of the United Nations	1992
Chinese soil properties database	Soil distribution, mechanical composition, and organic carbon	Institute of Soil Science, Chinese Academy of Sciences	1996
Crop field observation database	Maize growth and development data of crop field observation stations in China	Archives of China Meteorological Administration	1980-2005
Chinese agricultural statistics database by county	Sowing area, yields and fertilizer use for maize, wheat, and rice by county in the maize zone of southwest China	China Statistical Yearbook; Chinese Academy of Sciences	1996, 2001

2.3 Risk assessment flow

2.3.1 Hazard assessment

The WS factor was simulated as a function of the supply and demand of water during the plant growth period (Williams 1995). Based on the EPIC model, WS was used as a major hazard factor and was taken into account when estimating the constraints on biomass accumulation, root growth, and yield. In the crop growth period, the daily WS can be calculated by equation 1:

$$WS_i = \frac{\sum_{l=1}^m u_{i,l}}{E_{pi}} \tag{1}$$

where WS_i is the WS factor, $u_{i,l}$ is the water utilization for soil layer l , and E_{pi} is the potential utilization of water by the plant on day i .

As the combination of the WS and the number of WS days affects the drought intensity during a crop-growing season, under scenarios with no irrigation, the intra-day WS value and number of WS days in each growing season were extracted from the daily simulation results.

The drought hazard intensity index (H) was defined as the index of maize drought hazard assessment using the equation:

$$H_{yj} = \frac{\sum_{i=1}^n (1 - WS_i) \cdot \min H}{\max H - \min H} \tag{2}$$

where H is the drought hazard intensity index during the growing season, H_{yj} is the drought hazard intensity in year y from station j , WS_i is the

intra-day water stress for day i , n is the number of days affected by WS during the growing season, and $maxH$ and $minH$ are the maximum and

minimum values of $\sum_{i=1}^n (1-WS_i)$ for all years and all simulated stations.

We used the typical maize variety Dan Yu 13 in the analysis. This variety is a mid-to late-maturing high-quality hybrid maize with a high yield and good adaptability. The growth period is 105-125 days; the plant height is 2.8 m, the ear height is 92 cm, the panicle length 20-25 cm, the 1000-grain weight is 285 g, and the kernel rate is 84% (Wu 1995). Using a pre-built basic dataset under conditions without irrigation, the maize-growing process was simulated for each 8 km grid in the study area using the EPIC model. Based on the simulation, the WS value was extracted for areas affected by WS during the maize-growing season for each year. Based on Equation 2, the H index for each 8 km grid was calculated and hazard intensity–frequency curves were produced for each assessment unit. Probability density curves and exceeding probability curves were then drawn for the maize zone of southwest China.

The return period (also known as the recurrence interval) is an estimate of the likelihood of an event recurring and is used in risk analysis. It is a statistical measurement typically based on historical data and represents the average recurrence interval over an extended period of time. The exceeding probability was converted to a range of return periods. Hazard maps were then drawn for the risk of drought once every 2, 5, 10, and 20 years.

2.3.2 Vulnerability assessment

After controlling the amount of nutrients and the aeration stress, we simulated the crop yield under two different scenarios. In scenario A1, the need for nutrients and water was fully met. In scenario A2, the need for nutrients was met, but the crop was rain-fed rather than irrigated. The yield in scenario A1 minus the yield in scenario A2 was assumed to be the reduction in yield caused by WS alone. The yield loss rate was calculated for each assessment cell. Finally, a physical vulnerability curve was obtained by fitting the function between the maize drought hazard intensity and the yield loss rate. The cumulative

value of daily WS during the maize-growing season H was selected as the assessment index for the maize drought hazard intensity.

2.3.3 Risk assessment

The drought risk assessment model in this study was based on physical vulnerability without a consideration of the drought mitigation capacity. When setting the exposure to 1 (maize-growing regions), the risk for each assessment unit was a function of the hazard intensity and the vulnerability. H was determined using the hazard intensity–probability curve, whereas V (the vulnerability) was determined by the hazard intensity–loss rate curve. The exposure (E) was assigned the value of 1 in the maize-growing regions and 0 if not in the maize-growing regions. The yield loss rate (L) under certain hazard intensities determines the value of V . The assessment index of yield loss rate was L in the A1 scenario (nutrient and water needs fully met) minus that in the A2 scenario (nutrient needs fully met, rain-fed) for each station in every year during the growing season. We defined the drought disaster risk value as the loss rate below a certain level of hazard. Maize drought loss risk maps were drawn for once in every 2, 5, 10, and 20 years.

2.4 Parameterization of the EPIC model

The genetic parameters of 82 different kinds of crops are provided in the EPIC model. These are derived from experiments in the USA and have been calibrated in other countries (Tan and Shibasaki 2003; Wriedt et al. 2009; Velde et al. 2012; Juraj et al. 2013). However, the regional physical geographical environment and crop varieties vary, so it is necessary to parameterize the EPIC model at the site scale before use.

Based on observation data in the crop fields, examples of Dan Yu 13 with better data series were selected as the representative crop variety. Taking the availability of data into consideration, data from Guiyang station in the period 1986-1991 were chosen to determine the crop parameters in the EPIC model. By repeatedly running the model, the values of the main parameters and the genetic parameters of the maize were adjusted by trial and error. Daily meteorological data, soil data, and actual field management data (plowing, sowing,

irrigation, fertilizer, pesticides, and harvesting) were entered into the EPIC model for Guiyang station. The output crop yield and actual measured crop yield were then plotted graphically (Figure 2).

In the simulation process for maize in the EPIC model, six crop parameters with a high sensitivity were used: the biomass–energy ratio, the harvest index, the maximum leaf area index, the optimum temperature for plant growth, the minimum temperature for plant growth, and the decline rate factor for the leaf area index.

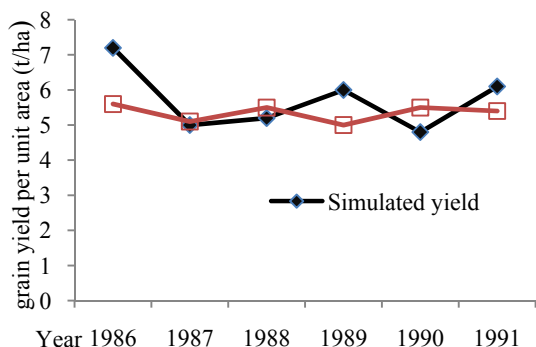


Figure 2 Comparison of simulated yield and yield observed in the field.

2.5 Validation of the EPIC model on a spatial scale

The basic principle of the spatial EPIC model is a simulation based on a grid cycle. Using the interactive data language and taking each evaluation unit (8 km grid) as a site, the decision about whether to simulate the growth process was decided by the type of land use needed by the users. If growth is not simulated, the default output value is 9999.

The results of the simulation in terms of the coefficient of determination for linear regression (R^2) were assessed by the F -test and the regression slope to give a significance level of p . Statistical yield data from the Chinese agricultural statistics database by county was used to compare the simulated yield (for data integrity in 2001) (Figure 3). The accuracy of the simulation was satisfactory ($R^2=0.8702$ and p was significant at the 0.05 level). Deviation between the simulated and statistical yield may occur as a result of data errors, data entry errors, field management data errors, and unreasonable crop parameters. If the accuracy of these data is improved, then the accuracy of the

EPIC model will also be greatly improved.

3 Results

3.1 Spatial and temporal distribution of hazard intensity

Based on the simulated information for each grid, the value of WS in the maize-growing season was extracted for each year. Based on equation 1, the hazard intensity data of each 8×8 km grid was calculated from 1961 to 2005. The average drought hazard index distribution for the southwest China maize region is given in Figure 4. The overall distribution of hazard intensity presented a mosaic structure among the counties. Most of the hazard index values were between 0.4 and 0.5 and accounted for 47.32% of total study area. The three high-value regions ($H \geq 0.4$) were mainly distributed in the parallel ridge–valley system of eastern Sichuan, the West Mountain area of Guizhou Province, and the south of Yunnan Province. These regions should be the focus of efforts to prevent and mitigate the risk of drought. The risk is not only related to the precipitation and temperature of these regions, but also to the vegetation cover, topography, and other conditions (Yu and Zhang 2012; Wang and Wang 2014).

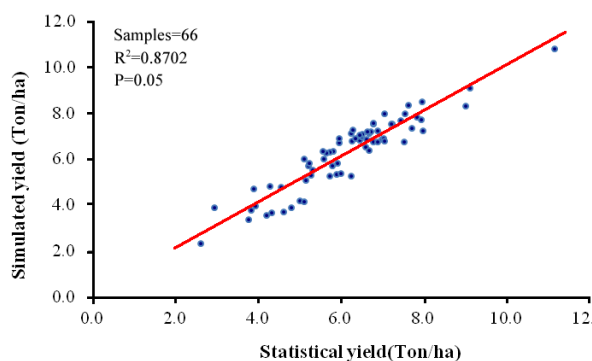


Figure 3 Verification of the EPIC model at a spatial scale.

The average value of the hazard index was between 0.3 and 0.5. The area with either a high or average risk of drought accounted for 90.35% of total study area. On a temporal scale, the hazard index varied smoothly around a value of 0.4. The inter-annual fluctuation was small with relatively low levels of instability.

3.2 Hazard risk results

The maize drought hazard index of each 8 km grid over a 40-year period was selected as the sample. An interval length of 0.005 was used for each histogram. The probability density and exceeding probability were obtained by estimating the histogram for each grid. The average annual hazard indexes of the maize regions were calculated based on the hazard index of each grid. Probability density curves (Figure 5) and exceeding probability curves (Figure 6) for the maize-growing region were then plotted. Figure 5 shows that the probability density of the drought hazard index is mainly located between 0.2 and 0.6. Figure 6 shows that the steepest curve is at 0.35. This corresponds to the maximum value of the probability density curve and the highest probability of hazard events.

By converting the exceeding probability to a certain return period, the maize hazard risk maps for drought once in every 2, 5, 10, and 20 years were drawn. Most of the maize drought hazard index averages over 40 years have at least a severe grade ($0.4 \leq H \leq 0.5$). The area of severe ($0.4 \leq H \leq 1$) grade once in 2, 5, 10, and 20 years accounted for 48.13, 57.82, 62.55, and 67.50% of the total maize area, respectively.

According to these statistics, with an increasing return period, the most severe grade ($0.5 \leq H \leq 1$) gradually increased from a 2-year return of 0.26%.

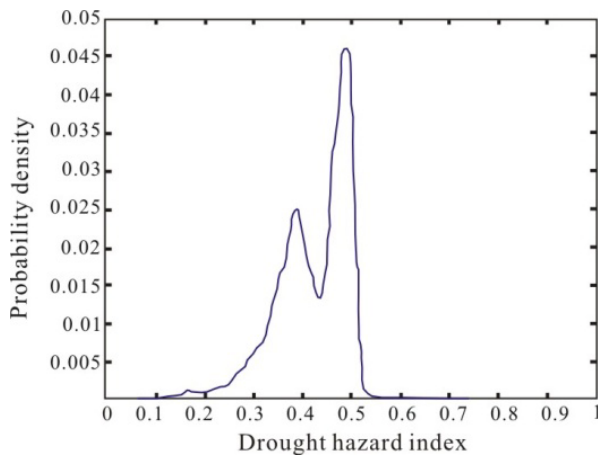


Figure 5 Probability density curve for drought hazard index.

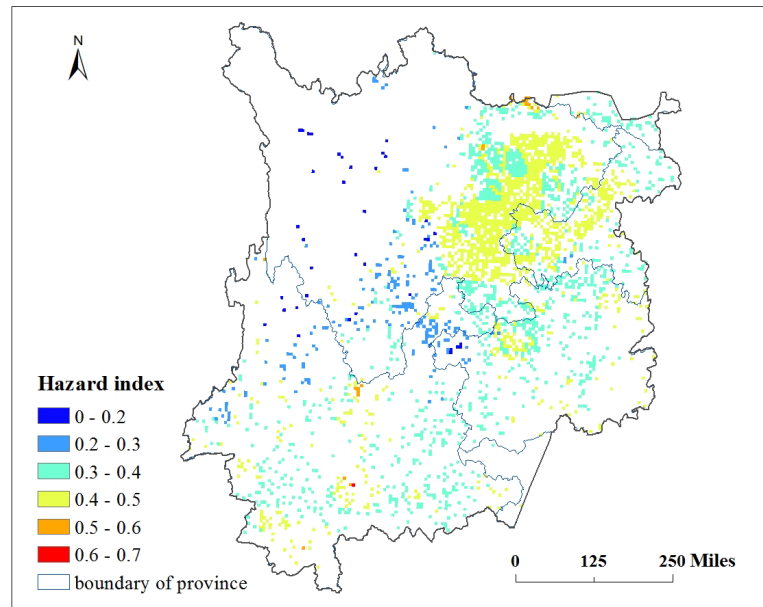


Figure 4 Average drought hazard index distribution of the southwest China maize zone.

season and maize yield loss value were calculated for each station under the two scenarios. The final vulnerability curves and corresponding functional equations were determined by a nonlinear regression model using MATLAB software (Figure 7):

$$L_s = \frac{1}{1 + 4521.02e^{(-13.03 \times H_s)}} + 0.00001 \quad (3)$$

where L_s is the yield loss rate of maize and H_s is the drought hazard intensity index. The value of R^2 for the maize zone of southwest China was 0.81 and the coefficient was significant at the 0.05 level.

3.4 Loss risk results

A series of maps showing the risk of drought disaster was drawn based on the analysis of the

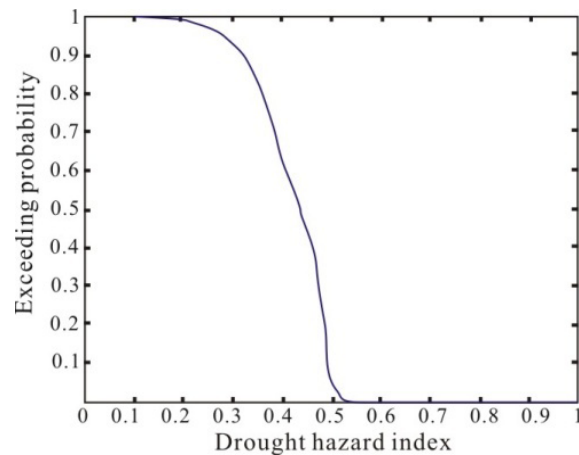


Figure 6 Exceeding probability curve for drought hazard index.

Ziyang, Neijiang, and Yanbian and the cities of Emeishan and Xichang in Sichuan Province. The least yield loss values were in the range 0-0.01, accounting for 96.24% – that is, most of the regions had a small yield loss rate. The mean yield loss rate showed an upward trend before 1981, but a decreasing trend after 1981-2005. The annual change in the yield loss rate showed a small fluctuation in the steady trend. The main loss rate was in the range 0-0.01.

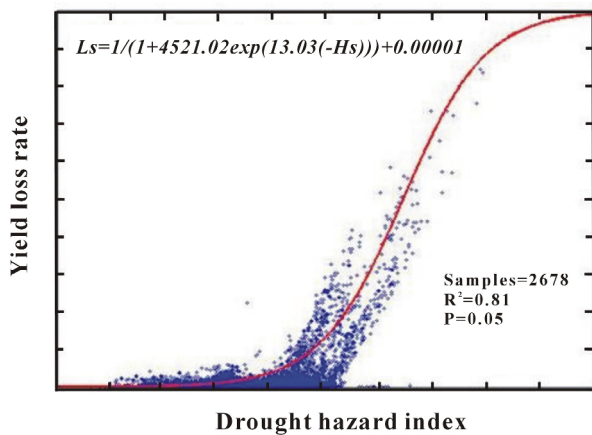


Figure 7 Physical vulnerability curve of a typical maize variety (Dan Yu 13).

In the four risk levels, the main yield loss value was in the range 0-0.05 – that is, most regions had only a small or very small yield loss rate (Figure 8). For the four risk levels of once in every 2, 5, 10, and 20 years, the area with the smallest yield loss rate (0-0.05) accounted for 54.53, 54.52, 51.72, and 48.13%, respectively. The high values were in the northeast Sichuan Basin, east of Chongqing, west of Guangxi, and north of Yunnan. The hazard risk of the southwest China maize zone was high. Most hazard index values were in the range 0.4-0.5. However, the loss risk of this region was low, mainly <0.1, and was determined by its low physical vulnerability.

4 Discussions

The drought risk assessment of the karst regions has previously focused on studies of the meteorological or hydrological factors, or other single factors or multiple indicators (Ni et al. 2009; Yao et al. 2010; Wang et al. 2011; Niu and Fan 2013; Jiang et al. 2014). The assessment of drought risk

in regions affected by rock desertification is still very weak, despite the fact that the degree of rock desertification affects the thickness of the soils in this region. The spatial variation of soil surface moisture is still unclear in the rocky environment of China's subtropical karst region and in areas with intensive land use (Zhang et al. 2011; Li et al. 2014). Drought is the major abiotic stress factor affecting the maize yield in southwest China. Levels of rock desertification in Guizhou Province in southwest China have been reported by Zhou (2001) (Table 2).

As a result of the limited amount of data available for different varieties of maize, only one variety (Dan Yu 13) was selected for this study of physical vulnerability. There was little spatial difference in the physical vulnerability of this variety of maize, so data for different maize varieties should be determined to improve our knowledge of the drought risk.

This study made a number of scenario assumptions as a result of the availability and limitations of the data. The areas of irrigated and dry land on the land use map of the maize zone of southwest China were used to represent the distribution of maize and 8 km grid cells were used as the assessment unit. A single maize variety was used and the physical vulnerability was determined based on the maize drought risk assessment. Future assessments of maize drought risk will be more accurate if the crop types, maize varieties, maize planting ratio, and capacity of disaster prevention and mitigation are further refined in the grid cells. More accurate assessments will provide better scientific guidance to determine insurance rates in the agricultural sector and to manage the risk of drought.

The definition of the risk of agricultural drought is the possibility that there will be a loss of crop yield in future time periods. This study was based on meteorological observation data for 1960-2005 and a risk assessment based on future changes in climate was not carried out. Further studies using simulated results to assess the maize drought risk are still required.

5 Conclusions

The maize zone of southwest China is located in the center of eastern Asia in one of the world's

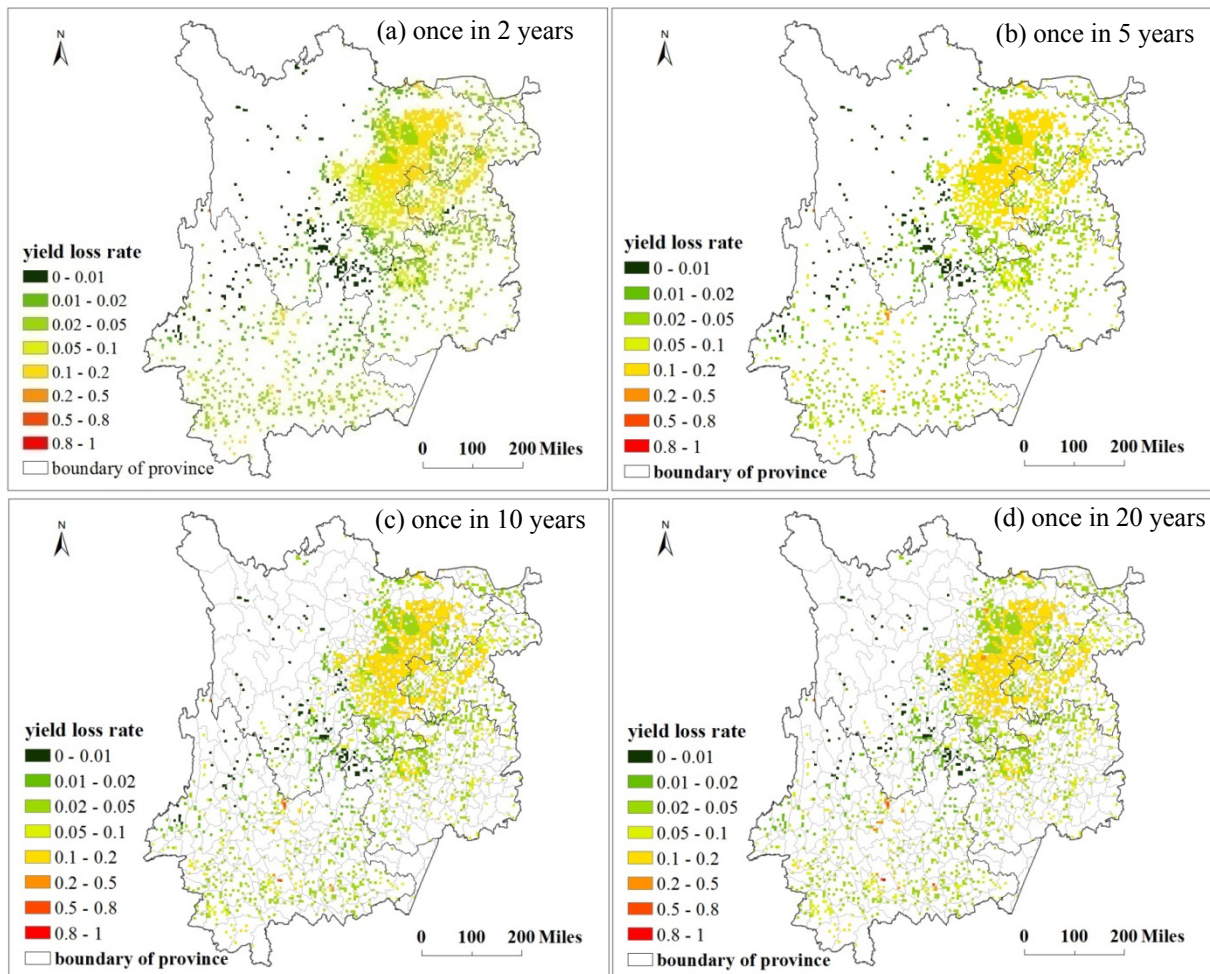


Figure 8 Drought yield loss rate of the southwest China maize region for a maize hazard risk of once in every (a) 2, (b) 5, (c) 10, and (d) 20 years.

Table 2 Division of rock desertification levels and index in Guizhou Province (Zhou 2001)

Degree of rock desertification	Division index			
	Vegetation coverage (%)	Rock exposure rate (%)	Slope (degrees)	Thickness of soil layer(cm)
Slight	35-50	>35	>15	<15
Moderate	20-35	>65	>20	<10
Severe	10-20	>85	>25	<7

three major karst regions and is a vulnerable region in terms of its eco-environment. The growth of maize in this region in the period 1960-2005 was simulated using the EPIC crop model and an assessment was made of the risk of drought disaster. Most of the hazard index values for return periods of 2, 5, 10, and 20 years were between 0.4 and 0.5. The main yield loss value was in the range 0-0.01, accounting for 96.24% of the region – that is, most of the region had a very low yield loss rate. The three high-risk areas were mainly distributed in the parallel ridge-valley system in the east of Sichuan Province, the West Mountain areas of

Guizhou Province, and the south of Yunnan Province. The risk was mainly determined by the climatic, environmental, and terrain conditions of the underlying surface.

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References

- Birkmann J (2006) Measuring Vulnerability to Natural Hazards-Towards Disaster-Resilient Societies. UNU Press, Tokyo, New York, Paris.
- Birkmann J (2007) Risk and vulnerability indicators at different scales: applicability, usefulness and policy implications. *Environmental Hazards* 7: 20-31. DOI: 10.1016/j.envhaz.2007.04.002
- Cardona OD (2003) Indicators for disaster risk management. First Expert Meeting on Disaster Risk Conceptualization and Indicator Modeling, Manizales, Columbia.
- Cavero JE, Playan N, Zapata JM (2001) Simulation of Maize Grain Yield Variability within a Surface-Irrigated Field. *Agronomy Journal* 4: 773-782. DOI: 10.2134/agronj2001.934773x
- Chung SW, Gassman PW, Huggins DR, et al. (2001) EPIC tile flow and nitrate loss predictions for three minnesota cropping systems. *Journal of Environment Quality* 30(3): 822-830. DOI: 10.2134/jeq2001.303822x
- Cutter SL (2003) The vulnerability of science and the science of vulnerability. *Annals of the Association of American Geographers* 93(1): 1-12. DOI: 10.1111/1467-8306.93101
- Dilley M (2005) Setting priorities: global patterns of disaster risk. Royal Society, London, the United Kingdom.
- Fedeski M, Gwilliam J (2007) Urban sustainability in the presence of flood and geological hazards: the development of a gis-based vulnerability and risk assessment methodology. *Landscape and Urban Planning* 83(1): 50-61. DOI: 10.1016/j.landurbplan.2007.05.012
- Huang QH, Cai YL (2007) Spatial pattern of karst rock desertification in the middle of Guizhou Province, southwestern China. *Environmental Geology* 52(7): 1325-1330. DOI: 10.1007/s00254-006-0572-y
- Hyung SC, Uwe AS, Livia R, et al. (2015) Potential effects of perfect seasonal climate forecasting on agricultural markets, welfare and land use: A case study of Spain. *Agricultural Systems* 133:177-189. DOI: 10.1016/j.agsy.2014.10.007
- IPCC (2013) Climate change: impacts, adaptation and vulnerability. Contribution of working group II to the fifth assessment report of the intergovernmental panel on climate change. Cambridge University Press, Cambridge.
- Jia HC, Wang JA, Pan DH, et al. (2011) Maize drought disaster risk assessment based on EPIC model: a case study of maize region in northern China. *Acta Geographica Sinica* 66(5):643-652. (In Chinese).
- Jia JY, Guo JP, Peng N (2010) Effects of climate change on yield of maize in northeast China. *Journal of Anhui Agricultural Sciences* 38(32): 18309-18312. (In Chinese).
- Jiang ZC, Lian YQ, Qin XQ (2014) Rocky desertification in Southwest China: Impacts, causes, and restoration. *Earth-Science Reviews* 132:1-12. (In Chinese).
- Jones RJA, Hiederer R, Rusco E, et al. (2005) Estimating organic carbon in the soils of Europe for policy support. *European Journal of Soil Science* 56(5): 655-671. DOI: 10.1111/j.1365-2389.2005.00728.x
- Jonghan K, Giovanni P, Evelyn S (2009) Using EPIC model to manage irrigated cotton and maize. *Agricultural Water Management* 96:1323-1331. DOI: 10.1016/j.agwat.2009.03.021
- Juraj B, Marijn VD, Erwin S, et al. (2013) Pan-European crop modeling with EPIC: Implementation, up-scaling and regional crop yield validation. *Agricultural Systems* 120: 61-75. DOI:10.1016/j.agsy.2013.05.008
- Li KH (1995) Climatic resources. China Meteorological Press, Beijing, China. pp 10-12. (In Chinese).
- Li QL, Fan GZ, Zhou DW, et al. (2012) Application of meteorological drought composite index in Southwest China in 2009-2010. *Journal of Chengdu University of Information Technology* 27:267-273. (In Chinese).
- Li S, Ren HD, Xue L, et al. (2014) Influence of bare rocks on surrounding soil moisture in the karst rocky desertification regions under drought conditions. *Catena* 116: 157-162. DOI: 10.1016/j.catena.2013.12.013
- Li YH, Xu HM, Liu D, et al. (2011) Features of the extremely severe drought in the east of Southwest China and anomalies of atmospheric circulation in summer 2006. *Acta Meteorologica Sinica* 25 (2): 176-177. DOI: 10.1007/s13351-011-0025-8
- Liu JD, Wang SL, Yu Q, et al. (2001) Simulation of impacts of doubled CO₂ on the climatic productivity in Huang-Huai-Hai Plain. *Journal of Natural Disasters* 10(1): 17-23. (In Chinese).
- Liu JL (2002) Maize Breeding. China Agriculture Press, Beijing, China. pp 31-33. (In Chinese).
- Liu XJ, Zhang JQ, Ma DL, et al. (2013) Dynamic risk assessment of drought disaster for maize based on integrating multi-sources data in the region of the northwest of Liaoning Province, China. *Natural Hazards* 65(3):1393-1409. DOI: 10.1007/s11069-012-0416-x
- Liu ZY, Zhang JP, Luo HX, et al. (2014) Temporal and spatial distribution of maize drought in Southwest of China based on agricultural reference index for drought. *Transactions of the Chinese Society of Agricultural Engineering* 30(2): 105-115. (In Chinese).
- Ni CJ (2014) Research on the theoretical framework of drought risk assessment. *Journal of Catastrophology* 29(3): 11-14. (In Chinese).
- Ni XB, Liu RG, Wang SJ (2009) Remote sensing of land sensitivity to drought in a karst region of southwest China. *Earth and Environment* 37(3): 221-226. (In Chinese).
- Niu SZ, Fan WG (2013). The physiological responds of cutting seedlings of ancient tea plant to drought stress and the comprehensive evaluation on their drought resistance capacity in karst region. *Acta Horticulturae Sinica* 40: 1541-1552. (In Chinese)
- Pan GT, Yang KC (2012) Facing toward challenges and corresponding strategies for maize breeding in southwestern region of China. *Acta Agronomica Sinica* 38(7): 1141-1147. (In Chinese)
- People's Daily Online. Available: http://english.peopledaily.com.cn/200504/25/eng20050425_182661.html (Accessed April 5, 2005)
- Roloff G, De JR, Zentner RP, et al. (1998) Estimating spring wheat yield variability with EPIC. *Canadian Journal of Soil Science*. 78(3): 541-549. DOI: 10.4141/S97-063
- Shapiro JR (1991) Mao's war against nature: politics and the environment in revolutionary China. Cambridge University Press, New York, the United States. pp 10-12.
- Sharpley AN, Williams JR (1990) EPIC - Erosion/Productivity Impact Calculator: 1. Model Documentation. Technical Bulletin - United States Department of Agriculture. pp 235.
- Shi PJ (2002) Theory on disaster science and disaster dynamics. *Journal of Natural Disasters* 11 (3): 1-9. (In Chinese)
- Sweeting MM (1993) Reflections on the development of Karst geomorphology in Europe and a comparison with its development in China. *Zeitschrift Fur Geomorphologie* 37:

- 127-136.
- Tan G, Shibasaki R (2003) Global estimation of crop productivity and the impacts of global warming by GIS and EPIC integration. *Ecological Modelling* 168 (3): 357-370. DOI: 10.1016/S0304-3800(03)00146-7
- Tong PY (1992) Regionalization of maize growing areas in China. China Agricultural Science and Technology Press, Beijing, China. pp 20-22. (In Chinese)
- Tu YL (1996) The analysis on reason and present situation of land rock desertification, Guizhou province. In: Li Jing, Development and Harness in Carbonate Rock Area. Guizhou People's Publishing House, Guiyang, China. pp 58-70. (In Chinese)
- UN/ISDR (United Nations International Strategy for Disaster Reduction) (2004) Living with risk: A Global Review of Disaster Reduction Initiatives. UN/ISDR, Geneva, Switzerland. pp 12-16.
- Velde V, Tubiello FN, Vrieling A, et al. (2012) Impacts of extreme weather on wheat and maize in France: evaluating regional crop simulations against observed data. *Climatic Change* 113 (3): 751-765. DOI: 10.1007/s10584-011-0368-2
- Wang D, Zhang LQ, Xue JH (2011). The study on comprehensive evaluation of seedlings drought resistance example of 6 forestation seedlings in karst mountainous region. *Chinese Agricultural Science Bulletin* 27(25): 5-12. (In Chinese)
- Wang HF, Chen XP, Cui ZL, et al. (2014) Impacts of climate change on summer maize production and adaptive selection of varieties in Xingtai County, Hebei, China. *Chinese Journal of Applied Ecology* 25(1): 155-161. (In Chinese)
- Wang K, Zhang Q (2013) A new approach to assess crop yield risk based on mixed source of data. *Scientia Agricultura Sinica*. 46 (5):1054-1060. (In Chinese)
- Wang X, He X, Williams JR, et al. (2005) Sensitivity and uncertainty analyses of crop yields and soil organic carbon simulated with EPIC. *Transactions of the ASAE* 48(3): 1041-1054. DOI: 10.13031/2013.18515
- Wang X, Wang L (2014) Evolution analysis on agricultural drought vulnerability in Karst areas in Southwestern China-an example from Guizhou province. *Guangdong Agricultural Sciences* 20: 165-169. (In Chinese)
- Williams JR (1995) The EPIC model. In: Singh VP (Ed.), *Computer Models of Watershed Hydrology*. Water Resources Publications, Highlands Ranch Colorado, USA. pp: 909-1000.
- Williams JR, Jones CA, Kiniry JR, et al. (1989) The EPIC Crop Growth Model. *Transactions of the ASAE* 32(2): 497-511. DOI: 10.13031/2013.31032
- World Bank and Columbia University (2005) Natural disaster hotspots: a global risk analysis. The World Bank Hazard Management Unit, Washington, D.C.
- Wriedt G, Velde MV, Aloe A, et al. (2009) Estimating irrigation requirements in Europe. *Journal of Hydrology* 373 (3):527-544. DOI: 10.1016/j.jhydrol.2009.05.018
- Wu JC (1995) A good maize hybrid-Dan Yu 13. *Agriculture of Beijing* 15(10): 11. (In Chinese)
- Yang X, Sun F, Lin ED, et al. (2005) Study on the sensitivity and vulnerability of maize to climate change in China. *Acta Ecologica Sinica* 24(4): 54-57. (In Chinese).
- Yao J, Xue JH, Wu QJ, et al. (2010) Drought resistance of four species of tree saplings for afforestation in karst regions. *Journal of Ecology and Rural Environment* 26(4): 318-322. (In Chinese)
- Yin YY, Zhang XM, Lin DG, et al. (2014) GEPIC-V-R model: A GIS-based tool for regional crop drought risk assessment, *Agricultural Water Management* 144: 107-119. DOI: 10.1016/j.agwat.2014.05.017
- Yu Q, Zhang HX (2012). Study on water-saving irrigation technology for maize in southwest mountain. *Journal of Anhui Agricultural Sciences* 40(35): 17048-17053. (In Chinese).
- Yue GD (2004) Cloning and analyses of genes involved in response to drought stress in maize. Doctoral degree thesis: Shandong University. (In Chinese)
- Zhang JG, Chen HS, Su YR, et al. (2011) Spatial variability of surface soil moisture in a depression area of karst region. *Clean – Soil, Air, Water* 39 (7): 619-625. DOI: 10.1002/clen.201000528
- Zhou P, Wen AB, Yan DC, et al. (2014) Changes in land use and agricultural production structure before and after the implementation of grain for green program in Western China - taking two typical counties as examples. *Journal of Mountain Science* 11(2): 526-534. DOI: 10.1007/s11629-013-2369-2
- Zhou Y, Wang JA, Yue YJ, et al. (2012) Drought risk assessment model of mountainous area based on DEM-A case study of Henan in China. In: *Association of American Geographers Annual Conference 2012*. Association of American Geographers, New York, NY.
- Zhou ZF (2001) Application of remote sensing and GIS technology for land desertification in Guizhou Karst region. *Bulletin of Soil and Water Conservation* 21(3): 52-63. (In Chinese)