Front. Earth Sci.
https://doi.org/10.1007/s11707-024-1135-9

RESEARCH ARTICLE

Quantitative study of rice, wheat, and maize insurance premium rates based on disaster loss data

Yaoyao WU[1], Qianxun WANG[1], Jialiang LI[2,3], Hanqi LIAO[1], Guizhen GUO (✉)[1]

1 National Disaster Reduction Center of China (NDRCC), Ministry of Emergency Management, Beijing 100124, China
2 TAIAN Agricultural Insurance Research Institute, Beijing 100032, China
3 China Pacific Property Insurance Co., Ltd, Shanghai 200120, China

Abstract China is one of the countries with the most diverse natural disasters in the world, and the rapidly increasing demand for disaster risk protection for rice, wheat, and maize underscores the necessity of developing robust agricultural insurance to ensure food security. Based on county level disaster loss data for floods, droughts, and typhoons and planting area data for rice, wheat, and maize from 2015 to 2021, in this paper, a quantitative model for insurance premium rates is established and the insurance premium rates for rice, wheat, and maize in each county of China are determined. The main conclusions are as follows. 1) In rice producing regions, there are 118 counties with high rates, mainly concentrated in the eastern and south-western part of Hubei, central-northern part of Hunan, north-western part of Guizhou, and northern part of Jiangsu. Examples of areas with relatively high rates include the Zengdu District, Dawu County, and Jiangxia District in Hubei, with rates of 0.200, 0.198, and 0.196, respectively. 2) There are 54 counties with high rates in wheat producing regions, mainly concentrated in the central and north-western regions, including Suixian County and Laifeng County in Hubei and the Langya District in Anhui, with rates of 0.448, 0.412, and 0.428, respectively. 3) The counties with high rates for maize producing regions are mainly concentrated in the eastern part of Inner Mongolia, central and northern part of Shanxi, and southern part of Liaoning. Lintao County and the Pingchuan District in Gansu and Lanling County in Shandong having rates of 0.200, 0.190, and 0.197, respectively. The results reveal the occurrence of regional differences in agricultural insurance rates for rice, wheat, and maize in China, further enhancing the accuracy of insurance rates and providing a reference for the implementation of differentiated rates across regions nationwide. Our method has significance for further improving the framework and model of crop disaster risk management and disaster reduction work.

Keywords agricultural insurance, rice, maize, wheat, premium rate determination, regional differences, disaster risk

Received August 9, 2024; accepted October 21, 2024

E-mail: guoguizhen2008@126.com

1 Introduction

China is one of the countries with the most diverse natural disasters in the world, with frequent droughts, floods, typhoons, and other disasters, which have a significant impact on agricultural production, particularly on staple crops such as rice, wheat, and maize. Agricultural insurance, as a vital safeguard against natural disaster risks in agricultural production, has received considerable attention from the Chinese government (Zhou, 2012; Tuo, 2023). In 2017, the Ministry of Agriculture and Rural Affairs conducted trials of disaster insurance for rice, wheat, and maize in major grain producing counties in China. By the end of 2023, the coverage rate of agricultural insurance for the three staple crops (rice, wheat, and maize) had surpassed 70% nationwide. The effective compensation role of agricultural insurance in mitigating disaster losses has been realized (Huang et al., 2020). With the rapid development of insurance services for these three staple crops, conducting scientifically grounded research on premium rate determination for the sake of enhancing the precision, efficiency, and fairness of agricultural insurance plays a critical role in fostering sustainable agricultural development.

The determination of insurance premium rates primarily entails calculating the expected crop yield loss by delineating the distribution pattern of regional crop yields per unit area. Currently, two predominant methodologies—parametric and non-parametric approaches—for estimating crop yield distributions have been proposed (Turvey and Zhao, 1999; Zhang and Wang, 2021). Early research focused on parametric methods, and scholars have employed various parametric distribution models such as the normal, beta, gamma, weibull, logistic, and hyperbolic secant distribution, (Nelson and Preckel, 1989; Chen and Miranda, 2004; Ozaki et al., 2008). The normal curve for determining crop insurance premium rates was used as early as 1958 (Botts and Boles, 1958). Some scholars have adopted a symmetric data perspective and have employed odd log-normal logistic, beta, SN, and skew-t distributions to forecast soybean production in Brazil, thus laying the groundwork for rate determination (Duarte et al., 2018). One study focused on drought resistant maize varieties utilized a hierarchical Bayesian multivariate spatial model to forecast yields, laying the foundation for index insurance rate calculations (Awondo et al., 2020). Additionally, a novel method based on multi-dimensional weighted distributions for premium determination was established. Taking Manitoba, Canada, as an example, in this method, auxiliary factors that may reflect systemic risks, such as economic and market conditions, weather, and soil, were utilized to reweight historical loss experiences, thereby improving agricultural insurance pricing (Zhu et al., 2019). Many scholars have also employed Johnson family distributions, copula models, and adaptive parameter estimation methods to predict crop yield losses and determine insurance premium rates (Lu et al., 2008; Goodwin and Hungerford, 2015; Shen et al., 2018).

Non-parametric estimation methods offer flexibility by not imposing restrictions on the distributional form of the sample. This allows for more adaptable assumptions regarding the form of the function and the distribution, making them less susceptible to observational errors. Consequently, these methods have garnered increased attention and emphasis in recent years. Scholars have extensively employed non-parametric estimation methods to fit crop yield distributions (Goodwin and Ker, 1998; Yu, 2013). Some scholars utilized non-parametric estimation methods to evaluate insurance premium rates concerning crop yield distributions; however, they found that the efficacy of kernel density estimation is limited by the restricted sample size (Truvey and Zhao, 1999). A methodological framework incorporating non-parametric kernel density has been used to estimate regional crop yield insurance premium rates. This approach was then applied to estimate maize production risk losses and determine pure insurance premium rates in Hebei Province (Wang et al., 2007). Some scholars enhanced the precision of crop yield data using an empirical Bayes nonparametric kernel density estimator, thereby facilitating the calculation of insurance premium rates (Ker et al., 2000 and Goodwin, 2000). Research based on farm yield data for wheat and maize in Shandong Province has been conducted to estimate bivariate yield distributions using non-parametric methods (Zheng et al., 2014). Studies on drought risk assessment in Xizang Zizhiqu have employed non-parametric methods to determine county level barley insurance premium rates. Additionally, these studies also refined crop insurance premium rates using an enhanced Grey Model (1, 1) model (Shi et al., 2023). Scholars have also combined various types of data and developed methods such as kernel density estimation, non-parametric Bayesian model estimation, and non-parametric Bayesian model averaging to predict crop yield losses and to determine insurance premium rates (Racine and Ker, 2006; Liu and Ker, 2020; Ramsey, 2020).

In summary, academic extensive research has been conducted on agricultural insurance premium rates, but several issues persist, for example, the scarcity of data, particularly the acquisition of information on disaster losses and insured entities. Moreover, the combined impact of multiple natural disasters on crops has rarely been considered, and the specialization and refinement of agricultural insurance product rates remain inadequate. As such, employing a uniform rate across broad regions cannot accurately capture the non-uniform distribution of agricultural risks in different areas within a province. Consequently, enhancing the credibility of premium rates for the three staple crops emerges as a crucial avenue for future research (Rejesus et al., 2015; Woodard and Verteramo-Chiu, 2017; Tang et al., 2021). Accordingly, in this study, we integrated various disasters, utilizing county level disaster loss data from the National Disaster Reduction Center of China (NDRCC) for 2015 to 2021, including data for major natural disasters such as floods, droughts, and typhoons. Additionally, we incorporated data on the planting areas of the three staple crops. The collected authoritative, complete, detailed, and long-term county-level data were used to address the data scarcity. We determined agricultural insurance premium rates for each county to provide insights for enhancing the precision of premium rates for the three staple crops. Ultimately, our results contribute to the assurance of high quality and sustainable development of agricultural insurance.

2 Materials and methods

2.1 Basic data

The data utilized in this study included historical disaster loss data, data on the planting areas of three staple crops (rice, wheat, and maize) and crop growing periods, and administrative division data. The historical disaster loss data, mainly county level crop loss data detailing affected and failure areas due to floods, droughts, and typhoons, extended from 2015 to 2021. The crop planting area data consisted of 20 m resolution raster data for rice, wheat, and maize from 2016 to 2021 nationwide. The data for the crop growing periods entailed chronological data points for the growth stages of rice, wheat, and maize. Further details of the data are presented in Table 1.

2.2 Research methods

2.2.1 Research ideas and framework

In this study, we established a three-dimensional *X*-*Y*-*Z* matching analysis method system (the time-space-disaster loss matching method), which is described in Section 2.3.2. Based on theoretical foundations such as insurance theory and geo-information map theory, as well as data including spatiotemporal agricultural crop distribution, disaster losses, geographic information, and policy literature, we conducted a county level study of the agricultural disaster trends and premium rates. The specific technical route is outlined in Fig. 1.

2.2.2 Three-dimensional temporal (*X*) - spatial (*Y*) - disaster loss (*Z*) matching analysis method for crops

Given that the statistical data from the NDRCC do not distinguish specific crop loss, or take rice, wheat, and maize as the primary crop varieties, in this study, we developed a three-dimensional time (*X*) - space (*Y*) - disaster loss (*Z*) matching analysis method. The method integrates crop growth cycle and spatial distribution characteristics with disaster occurrences. Specifically, consulting crop phenology to define planting and harvesting periods, thereby establishing the temporal dimension (*X*-axis, Table 2). Furthermore, the method requires sorting the planting areas of the three crops across provinces nationwide to determine their spatial distribution (*Y*-axis, Fig. 2). Incorporating the temporal and spatial dimensions and aligning with the reported time and space of disaster occurrences, we applied the proportional planting areas of rice, wheat, and maize within the same province to categorize their corresponding disaster losses.

This categorization, termed disaster loss matching in this paper (referred to as the *Z*-axis), entails disaggregating the crop disaster loss data into losses specifically associated with rice, wheat, and maize. Taking Anhui as an example, first, regarding the aspect of spatial matching, rice, wheat, and maize were determined to be the main cultivated crops. Second, by matching the growth period of the three crops, assuming that the disaster occurred in November, rice and maize harvesting had basically completed at this time, and wheat was the major crop affected by the disaster. Therefore, the disaster data were classified as wheat disaster data.

2.2.3 Crop insurance premium rate determination

In the insurance industry, agricultural insurance premiums are commonly composed of four main elements: the pure premium rate, security rate, administrative cost rate, and profit rate (Tuo and Li, 2005).

The pure premium rate is established upon the foundation of the long-term average loss rate, which embodies the insurance premium aligned with the insurer's indemnification for regular losses. The occurrence of accidents is regular from the perspective of the whole society. Although it is accidental for the individual, according to the law of large numbers, the disaster loss will be generally stable at a certain level, and this relatively stable loss is the normal loss of the society, constituting the main part of the insurance rate.

The security rate, conceived to fortify the insurer's financial robustness, theoretically stems from extraordinary losses and corresponds to the portion of the insurance premiums intended to compensate the insurer for such exceptional losses. The stability and regularity of loss can only be reflected in terms of a long time and large space. In reality, many factors cause the loss to deviate from the average loss, so the insurance premium determined using the pure rate is not sufficient to compensate for the actual loss. Thus, it is necessary to add the security rate to ensure safety. The safety rate is theoretically related to the size of the mean square error of the loss rate. In practical applications, it is commonly determined as a proportion of the pure premium rate, which is expressed as follows: Security Rate = Security Coefficient × Pure Premium Rate.

Table 1 Basic data

Name	Content	Source	Size
Administrative division	Administrative division map of China	Map World	--
Historical disaster data	Flood, typhoon, and drought disaster data for counties from 2015 to 2021	National Disaster Reduction Center of China	2453
Remote sensing image of rice	The main planting area of rice in China from 2016 to 2021	National Ecosystem Sciences Data Center	17.28 GB
Remote sensing image of wheat	The main planting area of wheat in China from 2016 to 2021		1.12 GB
Remote sensing image of maize	The main planting area of maize in China from 2016 to 2021		1.89 GB
Time period for planting and harvesting	Planting and harvesting time for rice, wheat, and maize	Key agricultural product market information platform	—

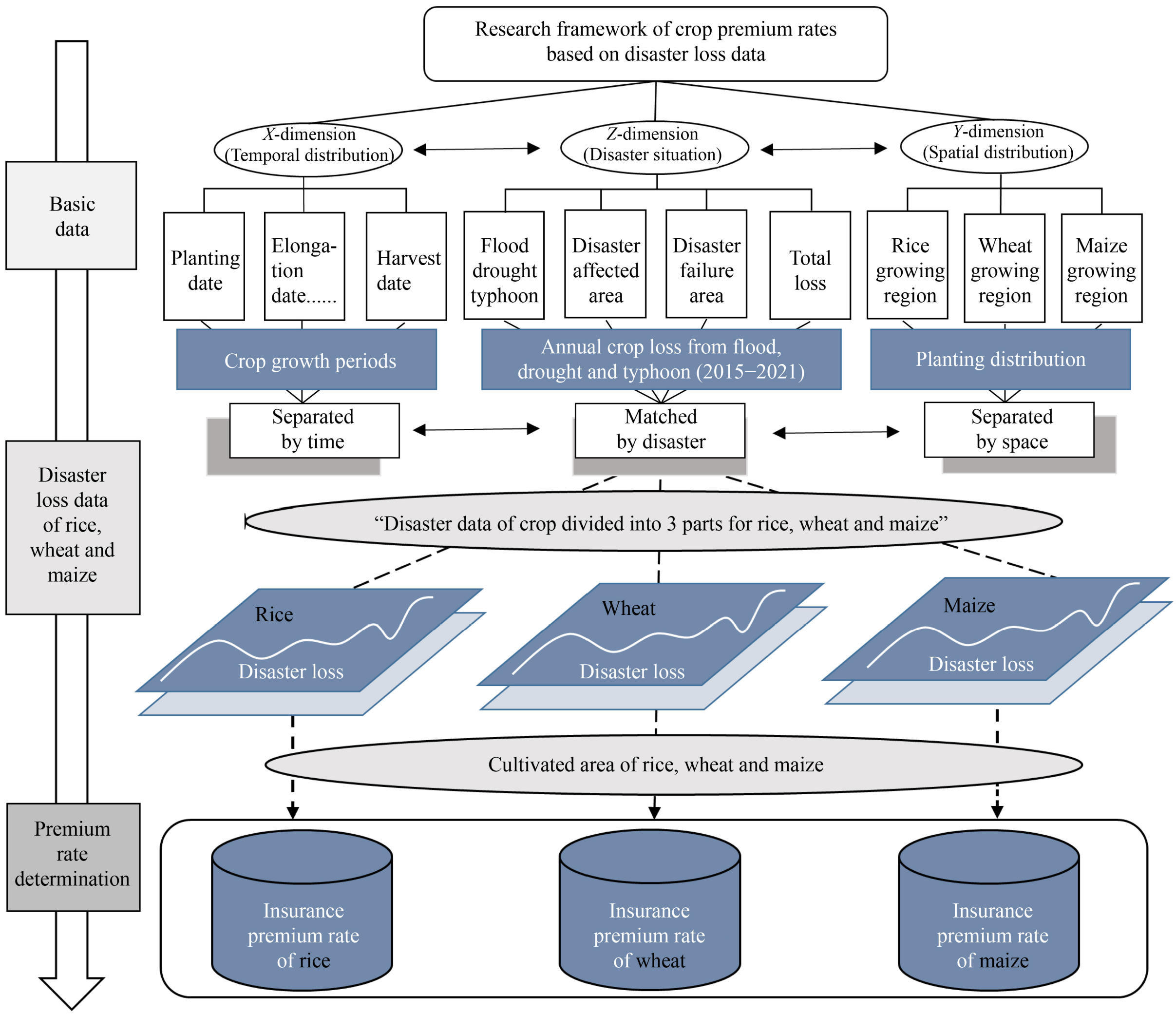

Fig. 1 Research framework of crop premium rates based on disaster loss data.

The administrative cost rate is grounded in the various operating expenses incurred by the insurer in conducting insurance operations (including loss prevention, survey, loss assessment, and claims). The premiums determined by this factor are allocated toward covering the insurer's operational costs. In practical application, it is typically determined as a proportion of the pure premium rate and is defined as follows: Administrative Cost Rate = Administrative Cost Rate Coefficient × Pure Premium Rate. The coefficient is generally determined according to the ratio of the average administrative cost to all expense in previous years.

The profit rate refers to the proportion reserved in advance to ensure a balanced budget and slight surplus in agricultural insurance operations. This ratio is commonly determined by insurers based on comprehensive assessment, typically as a certain percentage of the pure premium rate. Adhering to these foundational principles, the calculation formulas for agricultural insurance premiums used in this study are as follows:

$$AI = GI + SI + BI + PI, \tag{1}$$

$$SI = GI \times a, \tag{2}$$

$$BI = GI \times b, \tag{3}$$

$$PI = GI \times c, \tag{4}$$

where AI is the insurance premium rate, GI is the pure premium rate, SI is the security rate, with the safety coefficient as the coefficient. BI is the administrative cost rate with b as the coefficient. PI is the profit rate with c as the coefficient. Based on empirical data, we set the values of a, b, and c to 15%, 20%, and 5%, respectively.

From Eqs. (1)–(4), it is evident that the core of calculating agricultural insurance premium rates lies in determining the pure premium rate (i.e., the loss rate). In this study, we computed the pure premium rates for the three staple crops by calculating the average loss rate over multiple years (Eq. (5)). In Eq. (5), Sa_i is the affected area of a certain crop in year i, Sf_i is the area of crop failure for that crop in year i, St_i is the planting area of that crop in year i, P is the yield per unit area of the crop in that year,

Table 2 Growth periods of the three major crops in each province

Province	Growth periods of three major crop					
	Rice		Wheat		Maize	
	Sowing	Harvest	Sowing	Harvest	Sowing	Harvest
Sichuan	Apr.1st	Sept. 30th	Sept. 1st	May 30th	Apr. 1st	Sept. 30th
Anhui	Apr. 1st	Aug. 30th	Sept. 1st	May 30th	Mar. 20th	Sept. 30th
Hubei	Apr. 1st	Aug. 30th	Sept. 1st	May 30th	——	——
Jiangsu	Apr. 1st	Aug. 30th	Sept. 1st	May 30th	——	——
Heilongjiang	May 1st	Sept. 30th	——	——	Apr. 10th	Oct. 30th
Jilin	May 1st	Sept. 30th	——	——	Apr. 10th	Oct. 30th
Yunnna	Apr. 1st	Sept. 30th	——	——	Apr. 1st	Sept. 30th
Hunan	Apr. 1st	Aug. 30th	——	——	——	——
Jiangxi	Apr. 1st	Aug. 30th	——	——	——	——
Chongqing	Apr. 1st	Sept. 30th	——	——	——	——
Guizhou	Apr. 1st	Sept. 30th	——	——	——	——
Zhejiang	Apr. 1st	Aug. 30th	——	——	——	——
Guangdong	Mar.1st	Oct. 30th	——	——	——	——
Guangxi	Mar. 1st	Oct. 30th	——	——	——	——
Henan	——	——	Sept. 1st	May 30th	Apr. 1st	Sept. 30th
Shandong	——	——	Sept. 1st	June 10th	Apr. 1st	Sept. 30th
Hebei	——	——	Sept. 1st	June 20th	Apr. 1st	Sept. 30th
Xinjiang	——	——	Sept. 1st	July 30th	Apr. 10th	Oct. 30th
Shannxi	——	——	Sept. 1st	June 20th	Apr. 10th	Oct. 30th
Gansu	——	——	Sept. 1st	July 30th	Apr. 10th	Oct. 30th
Inner Mongolia	——	——	——	——	May 1st	Oct. 30th
Liaoning	——	——	——	——	Apr. 10th	Oct. 30th
Shanxi	——	——	——	——	Apr. 10th	Oct. 30th

and n is the total number of years considered for analysis (ranging from 2015 to 2021, $n = 7$ in this study):

$$GI = \frac{1}{n}\sum_{i=1}^{n}\frac{30\% \times Sa_i \times p + 100\% \times Sf_i \times p}{St_i \times p}. \quad (5)$$

It should be noted that, in this study, GI was calculated according to the ratio of the lost production to the total production, that is, in the calculation of the lost production, the affected area and the failure area of the crop were calculated to be 30% output loss and 100% output loss, respectively, that is, $30\% \times p \times Sa_i$ + $100\% \times p \times Sf_i$, and in the calculation of the total production, $St_i \times p$.

Additionally, the planting area, interpreted from remote sensing data at the county level, was adjusted according to the ratio of the national statistical area data to the area data interpreted from the remote sensing images. For years with missing data on the planting areas, adjustments were made based on the corresponding ratios from the statistical data for the adjacent years.

3 Results

3.1 Natural disaster trend analysis and insurance premium determination for rice

The counties with high average disaster affected areas of rice were mainly concentrated in the Yangtze River and Huaihe River basins (region A is used in the following paragraph), the Yangtze River and Hanjiang River basins (region B), Dongting Lake and Poyang Lake (region C), Songhua River Basin (region D), and the Leizhou Peninsula (region E). The affected areas were divided into five grades: extremely high (> 15 × 10^3 hm^2), high (10 × 10^3 – 15 × 10^3 hm^2), medium (6 × 10^3 – 10 × 10^3 hm^2), low (3 × 10^3 – 6 × 10^3 hm^2), and extremely low (< 3 × 10^3 hm^2). Among them, 61, 67, 104, 212, and 984 counties were extremely high grade, high grade, medium grade, low grade, and extremely low grade, respectively (Fig. 3).

There were 15 extremely high grade affected counties in region A, of which the top three were Feng County,

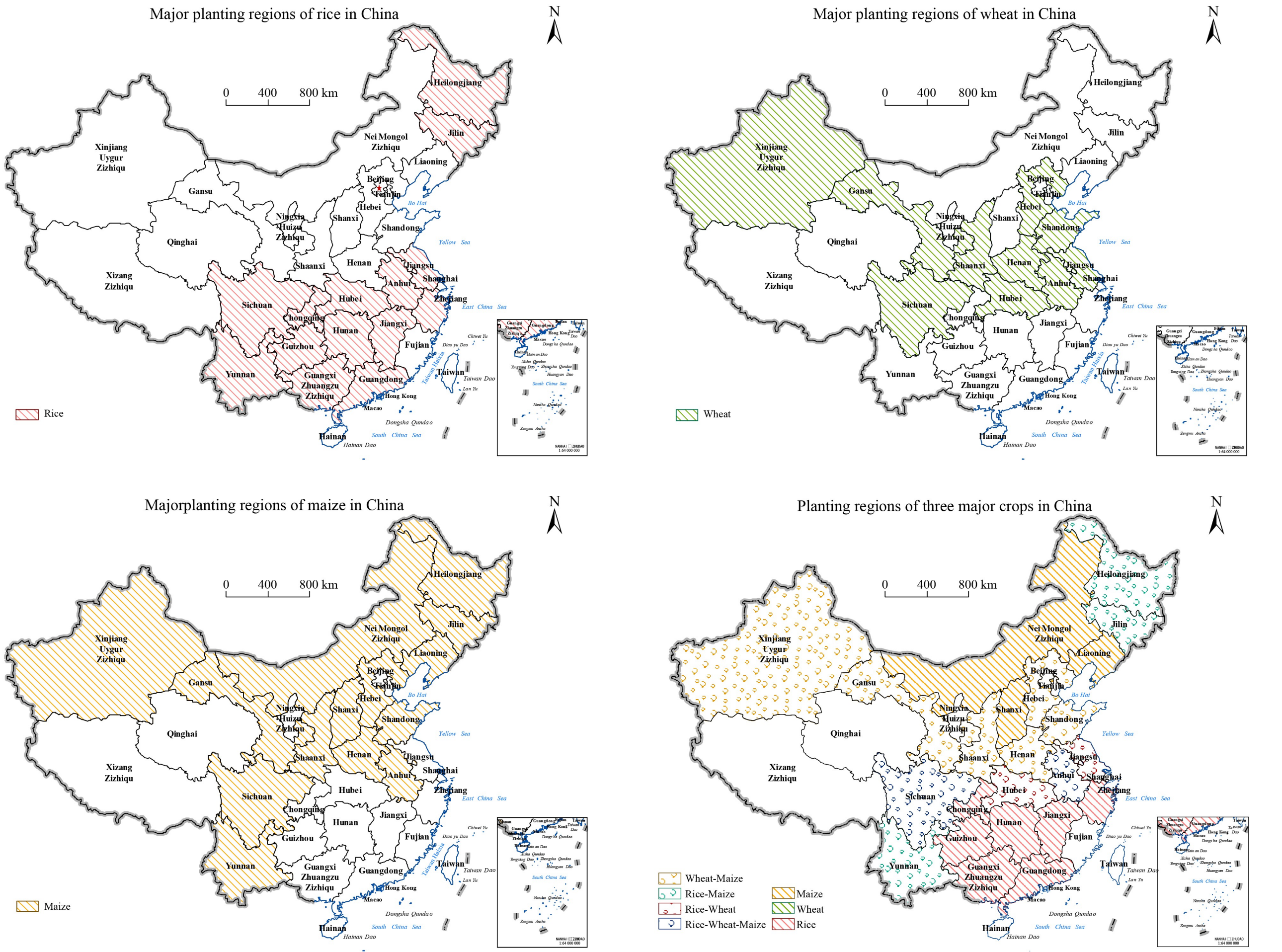

Fig. 2 Growing areas of the three major crops in China.

Suixi County, and Pei County, with affected areas of 91.8 × 10^3 hm^2, 40.1 × 10^3 hm^2, and 37.8 × 10^3 hm^2, respectively. There were 22 extremely high grade affected counties in region B, and the top three were Jianli County, Sui County, and Xiantao City, with affected areas of 43.2 × 10^3 hm^2, 42.6 × 10^3 hm^2, and 42.3 × 10^3 hm^2, respectively. There were seven extremely high grade affected counties in region C, and the top three were Leiyang City, Yuanjiang City, Xiangtan County, with affected areas of 149.6 × 10^3 hm^2, 21.4 × 10^3 hm^2, and 18.6 × 10^3 hm^2. In region D, there were seven extremely high grade affected counties, and the top three were Yilan County, Fuyuan City, and Wuchang City, with affected areas of 24.9 × 10^3 hm^2, 21.3 × 10^3 hm^2, and 18.6 × 10^3 hm^2, respectively. There were seven extremely high grade affected counties in region E, and the top three were Lianjiang City, Leizhou City, and Xuwen County, with affected areas of 43.5 × 10^3 hm^2, 43.2 × 10^3 hm^2, and 27.0 × 10^3 hm^2, respectively (Fig. 3). The spatial distribution of the average disaster failure area of rice was similar to that of the affected area, but differences were also observed. The counties with high average failure areas were primarily concentrated in regions A, B, and C (Fig. 4).

The regions with high pure premium rates for agricultural insurance against natural disasters affecting rice crops were primarily concentrated in eastern and south-western Hubei, central and northern Hunan, north-western Guizhou, northern Jiangsu, coastal and north-western Zhejiang, coastal Guangdong, north-western and southern Yunnan, and southern Heilongjiang. The pure premium rates were divided into extremely high (> 0.15), high (0.08–0.15), medium (0.06–0.08), low (0.02–0.06), and extremely low (< 0.02). The pure premium rate classification of wheat and maize are the same in the following paragraph. Specifically, there were 23 extremely high rate and 24 high rate counties in Hubei, accounting for 51.1% of the total number of counties in the province, which was the largest proportion in all of the provinces. There were six and 10 counties with the first two levels in Hunan, accounting for 13.3% of the total number of counties in this province. There were five and four counties with the first two levels in Guizhou, accounting for 12.2% of the total number of counties in this province. There were 12 and 13 counties with the first two levels in Yunnan, accounting for 19.5% of the total number of counties in this province. In Zhejiang, there were 23 and 10 counties with the first two levels,

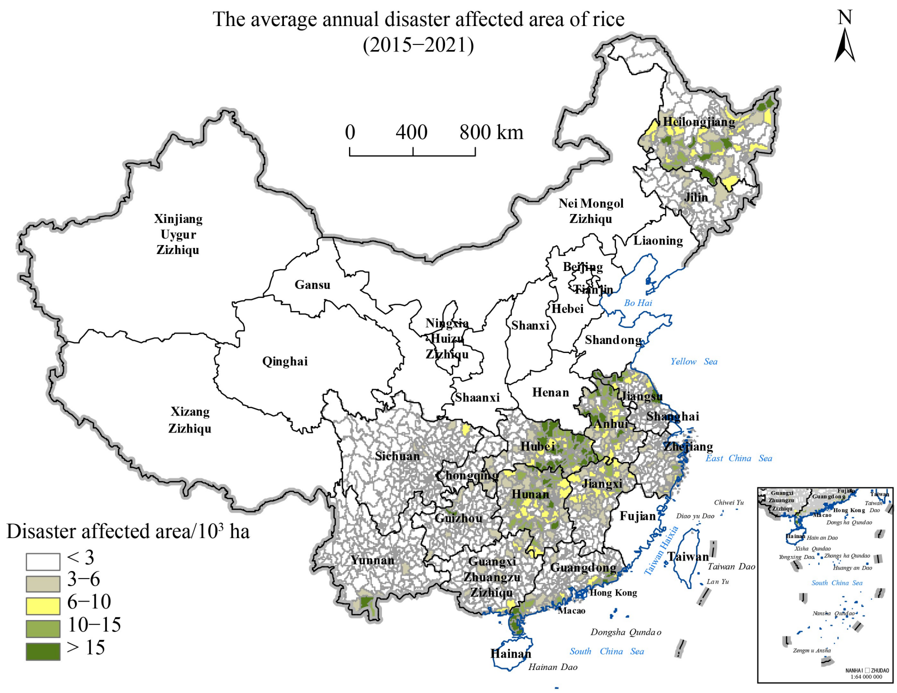

Fig. 3 Average disaster affected area of rice during 2015–2021.

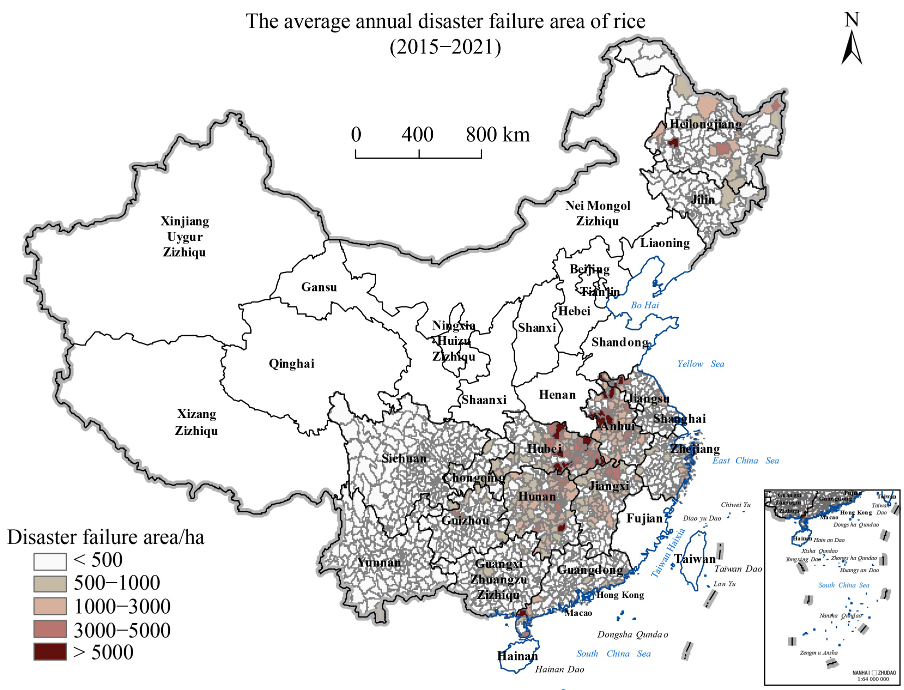

Fig. 4 Average disaster failure area of rice during 2015–2021.

accounting for 38.8% of the total number of counties in this province. In Guangdong, there were 10 and 16 counties with the first two levels, accounting for 25.5% of the total number of counties in this province. In Jiangsu, there were six and four counties with the first two levels, accounting for 15.6% of the total number of counties in this province. In Heilongjiang, there were 20 and 11 counties with the first two levels, accounting for 29.2% of the total number of counties in this province (Fig. 5).

The integrated premium rate and pure premium rate for rice were linearly correlated, and their spatial distribution patterns were similar. The integrated premium rates were divided into five grades: extremely high rate (> 0.20), high rate (0.11–0.20), medium rate (0.08–0.11), low rate (0.03–0.08), and extremely low rate (< 0.03). The integrated premium rate classification of wheat and maize

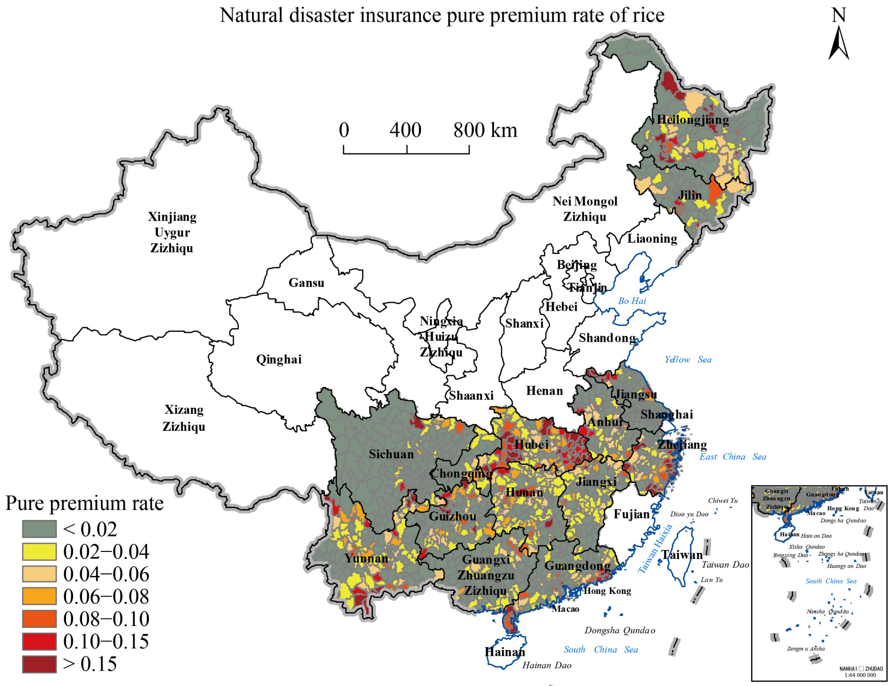

Fig. 5 Natural disaster insurance pure premium rate for rice.

are the same in the following paragraph. Specifically, there were 23 extremely high rate and 26 high rate counties in Hubei, and the top three high rate counties were the Zengdu District, Dawu County, and Jiangxia District, with rates of 0.200, 0.198, and 0.196, respectively. There were 6 extremely high and 11 high rate counties in Hunan, and the top three high rate counties were Anhua County, Yuetang District, and Sangzhi County, with rates of 0.172, 0.167, and 0.147, respectively. There were five extremely high rate counties in Guizhou, and the top three extremely high rate counties were Jinsha County, Huagang District, and Daozhen Autonomous County, with rates of 0.470, 0.304, and 0.270, respectively. In Yunnan, there were 12 extremely high and 14 high rate counties, and the top three counties with high rates were Weixi Autonomous County, Suijiang County, and Hekou Autonomous County, with rates of 0.195, 0.180, and 0.180, respectively. There were 24 extremely high and nine high rate counties in Zhejang, and the top three counties with high rates were the Beilun District, Kecheng District, and Pingyang County, with rates of 0.188, 0.173, and 0.170, respectively. There were 10 extremely high and 16 high rate counties in Guangdong, and the top three high rate counties were the Pengjiang District, Jiexi County, and Nanao County, with rates of 0.188, 0.180, and 0.176, respectively. There were six extremely high rate and four high rate counties in Jiangsu, and the top three high rate counties were Xinyi City, Tinghu District, and Jiawang District, with rates of 0.189, 0.182, and 0.131, respectively. In Heilongjiang, there were 20 extremely high rate and 11 high rate counties, and the top three counties with high rates were Sifangtai District, Bin County, and Daowai District, with rates of 0.195, 0.191, and 0.183, respectively (Fig. 6).

3.2 Natural disaster trend analysis and insurance premium determination for wheat

The counties with high average disaster affected areas of wheat were mainly concentrated in south-west Henan (region A1 in the following paragraph), central and northern Hubei (region B1), central and western Anhui (region C1), and south-east Shandong (region D1). The affected areas were divided into five grades: extremely high (> 10×10^3 hm^2), high (5×10^3 – 10×10^3 hm^2), medium (3×10^3 – 5×10^3 hm^2), low (1×10^3 – 3×10^3 hm^2), and extremely low (< 1×10^3 hm^2). Among them, there were 26 extremely high grade counties, 49 high level grade counties, 40 medium grade counties, 122 low grade counties, and 761 extremely low grade counties (Fig. 7).

There were three extremely high grade affected counties in Region A1, namely, Dengzhou City, Ruzhou City, and Sheqi County, with affected areas of 16.6×10^3 hm^2, 13.5×10^3 hm^2, and 11.6×10^3 hm^2, respectively. There were two extremely high grade affected counties in region B1, namely, Suixian and Tianmen, with affected areas of 20.1×10^3 hm^2 and 10.8×10^3 hm^2, respectively. There were six extremely high grade counties in region C1, and the top three were Taihe County, Qianshan City, and Shou County, with affected areas of 27.1×10^3 hm^2, 22.2×10^3 hm^2, and 15.4×10^3 hm^2, respectively. There were a total of 14 extremely high grade counties in Shandong, and the top three were the Zhanhua District,

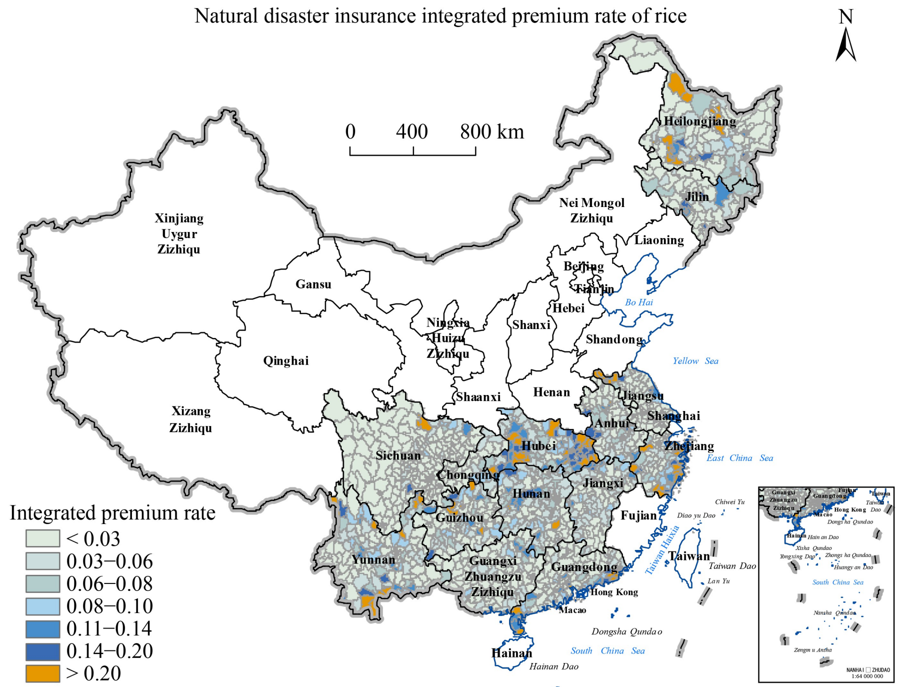

Fig. 6 Natural disaster insurance integrated premium rate for rice.

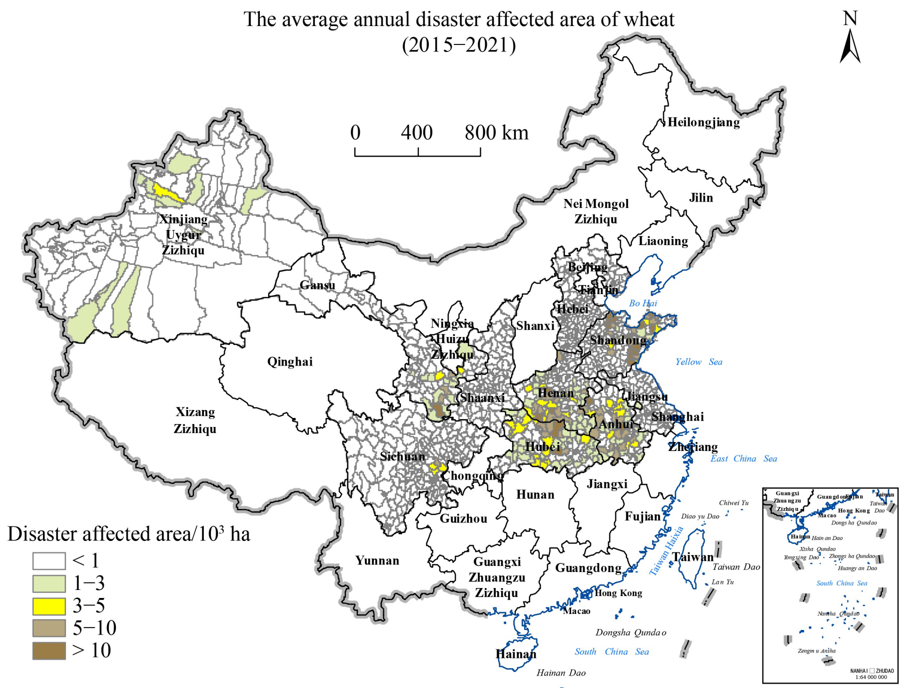

Fig. 7 Average disaster affected area of wheat during 2015–2021.

Zhucheng City, and Ju County, with affected areas of 29.9×10^3 hm^2, 18.0×10^3 hm^2, and 14.9×10^3 hm^2, respectively (Fig. 7). The spatial distribution of the average disaster failure area of wheat was similar to that of the affected area, but there were some small differences in the Xinjiang Uygur Zizhiqu (Fig. 8).

The regions with high pure premium rates for wheat were mainly concentrated in the central areas (Hubei and Anhui) and certain part of the north-west (Gansu and Xinjiang). Specifically, there were 18 extremely high rate and 22 high rate counties in Hubei, accounting for 41.7% of the total number of counties in this province, which was the largest proportion among all of the provinces. There were 12 extremely high rate and 13 high rate counties in Anhui, accounting for 28.1% of the total number of counties in this province. There were three

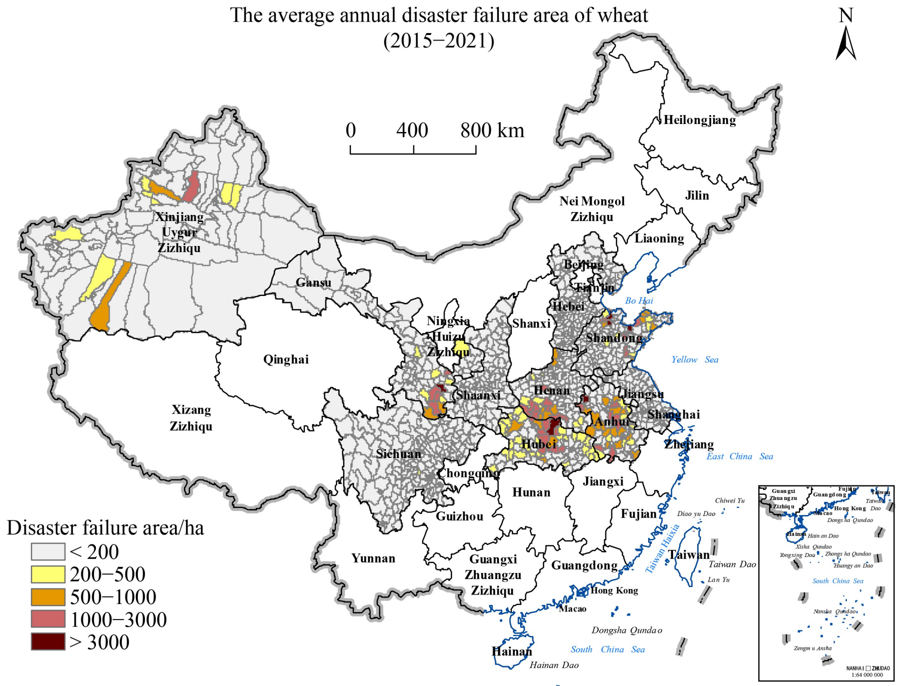

Fig. 8 Average disaster failure area of wheat during 2015–2021.

extremely high rate and eight high rate counties in Gansu, accounting for 13.9% of the total number of counties in this province. In Xinjiang, there were six extremely high rate and four high rate counties, accounting for 15.4% of the total number of counties in this province (Fig. 9).

The integrated premium rate for wheat was linearly correlated with the pure premium rate, and they had similar spatial distributions. There were 54 extremely high rate counties, 54 high rate counties, 28 medium rate counties, 81 low rate counties, and 781 extremely low rate counties. Specifically, there were 19 extremely high rate and 21 high rate counties in Hubei, and the top three extremely high rate counties were Suixian, Laifeng County, and Zhushan County, with rates of 0.448, 0.412, and 0.338, respectively. There were 14 extremely high rate and 13 high rate counties in Anhui, and the top three

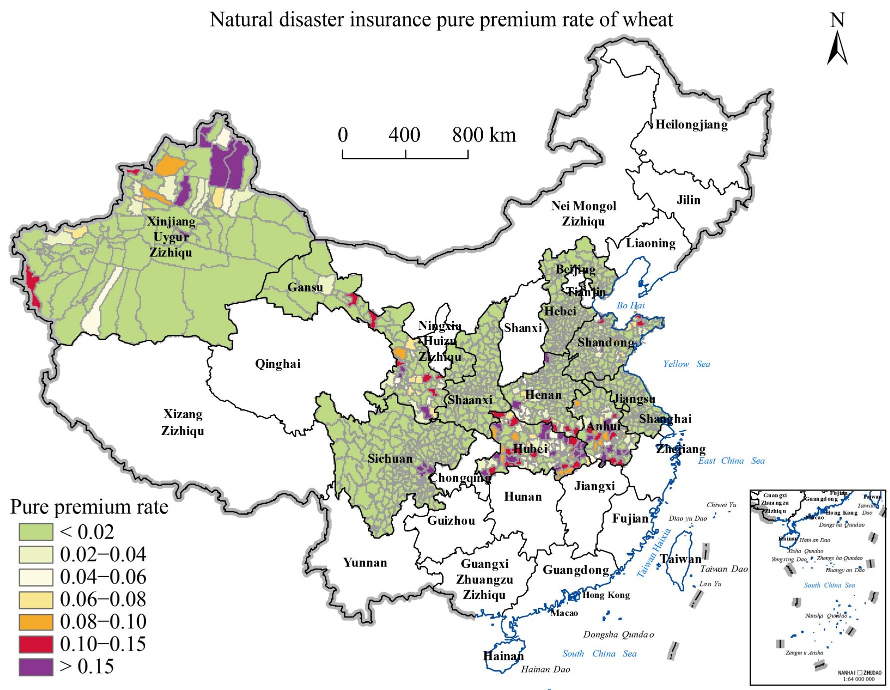

Fig. 9 Natural disaster insurance pure premium rate for wheat.

extremely high rate counties were the Langya District, Chaohu City, and Huizhou District, with rates of 0.428, 0.403, and 0.387, respectively. There were four high rate counties in Gansu, namely, Hezheng County, Dongxiang Autonomous County, Wudu District, and Gaotai County, with rates of 0.255, 0.248, 0.240, and 0.205, respectively. There were six extremely high rate counties in Xinjiang, and the top three were Habahe County, Yanqi Autonomous County, and Fuhai County, with rates of 0.457, 0.443, and 0.427, respectively (Fig. 10).

3.3 Natural disaster trend analysis and insurance premium determination for maize

The counties with high average disaster affected areas of maize were mainly concentrated in Nei Mongol, northeast China (Heilongjiang, Jilin, and Liaoning), Shandong, Shanxi, Anhui, and Gansu. The affected areas were divided into five grades: extremely high (> 15 × 10^3 hm^2), high (10 × 10^3–15 × 10^3 hm^2), medium (6 × 10^3–10 × 10^3 hm^2), low (3 × 10^3–6 × 10^3 hm^2), and extremely low (< 3 × 10^3 hm^2), of which 170 counties were extremely high grade, 106 counties were high grade, 144 counties were medium grade, 221 and 695 counties were low and extremely low grades (Fig. 11).

There were 54 extremely high grade affected counties in Inner Mongolia, and the top three were Erguna city, Horqinyouyiqian Banner, and Naiman Banner, with affected areas of 216 × 10^3 hm^2, 125 × 10^3 hm^2, and 116 × 10^3 hm^2, respectively. In northeast China, there were 39 extremely high grade affected counties, and the top three were Linghai City, Yilan County, and Yi County, with areas of 54 × 10^3 hm^2, 41 × 10^3 hm^2, and 36 × 10^3 hm^2, respectively. There were 21 extremely high grade affected counties in Shandong, and the top three were Lijin County, Shouguang City, and Guangrao County, with areas of 49 × 10^3 hm^2, 40 × 10^3 hm^2, and 40 × 10^3 hm^2, respectively. There were 17 extremely high grade affected counties in Shanxi, and the top three were the Shuocheng District, Linxian County, and Tunliu District, with areas of 41 × 10^3 hm^2, 40 × 10^3 hm^2, and 38 × 10^3 hm^2, respectively. There were seven extremely high grade affected counties in Anhui, and the top three were Lujiang County, Shou County, and Suixi County, with areas of 30 × 10^3 hm^2, 20 × 10^3 hm^2, and 19 × 10^3 hm^2, respectively. A total of 14 counties in Gansu were extremely high grade, and the top three were Huining County, Tongwei County, and Minle County, with affected areas of 40 × 10^3 hm^2, 39 × 10^3 hm^2, and 39 × 10^3 hm^2, respectively (Fig. 11). The spatial distribution of the average disaster failure area of rice was similar to that of the affected area, but there were some differences, which were chiefly concentrated in Nei Mongol, northeast China, and Anhui Province (Fig. 12).

The regions with high pure premium rates for maize were mainly concentrated in eastern and north-western Inner Mongolia, central and northern Shanxi, southern Liaoning, northern and eastern Shandong, northern and south-eastern Gansu, central and south-eastern Anhui, and southern Henan. Specifically, there were 34 extremely high rate and 13 high rate counties in Inner Mongolia, accounting for 66.2% of the total number of counties in this province. There were 32 and 27 counties with the first two grades in Shanxi, accounting for 60.2%

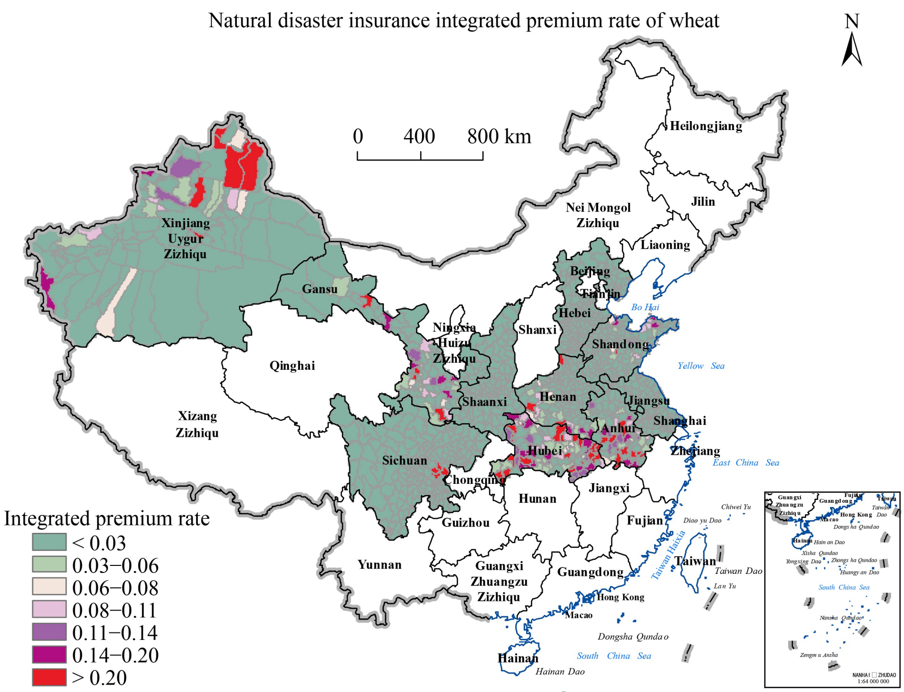

Fig. 10 Natural disaster insurance integrated premium rate for wheat.

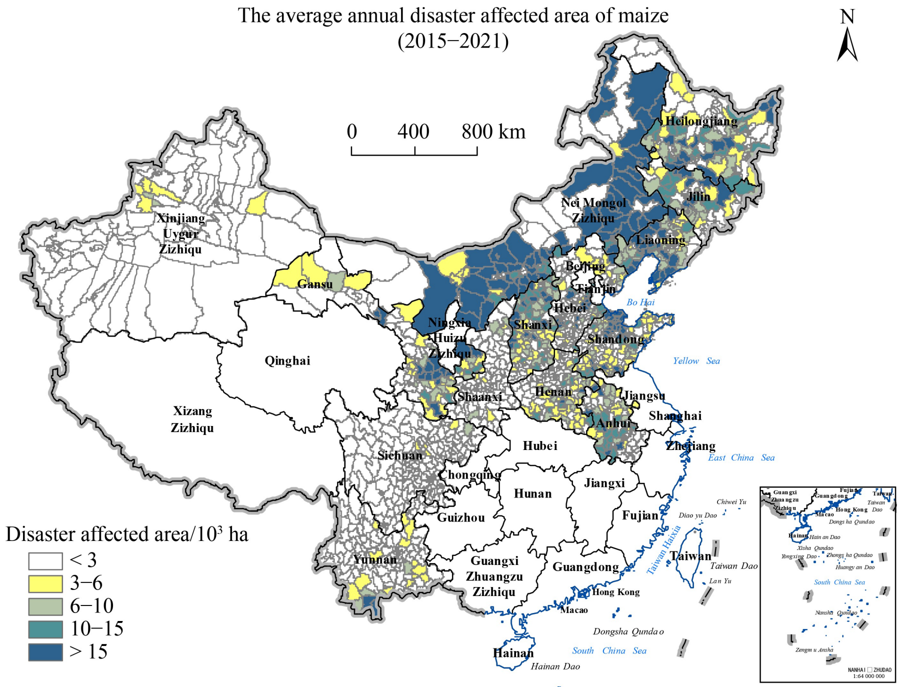

Fig. 11 Average disaster affected area of maize during 2015–2021.

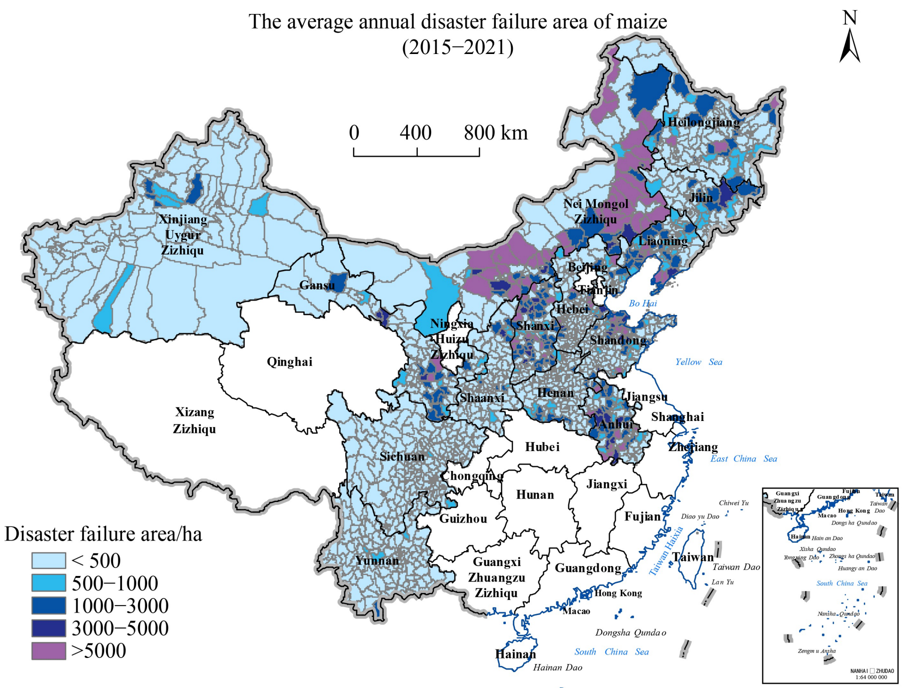

Fig. 12 Average disaster failure area of maize during 2015–2021.

of the total number of counties in this Province. In Liaoning, there were 12 and 17 counties with the first two levels, accounting for 34.1% of the total number of counties in this province. There were 17 and 11 counties with the first two grades in Shandong, accounting for 22.2% of the total number of counties in this province. In Gansu, Anhui, and Henan, there were 19 and 17 counties, 22 and six counties, and 14 and six counties with the first two levels, accounting for 51.4%, 49.1%, and 14.1% of the total number of counties in these provinces (Fig. 13).

The spatial distribution of the integrated premium rate for maize was similar to that of the pure premium rate, and they were linearly correlated. Specifically, there were 38 and 10 counties with the first two levels in Nei Mongol, and the top three high rate counties were the Shiguai District, Tuquan County, and Wuyuan County, with rates of 0.189, 0.186, and 0.186, respectively. In Shanxi, there were 34 and 26 counties with the first two levels, and the top three high rate counties were Zhangzi County, Quwo County and Xiangfen County, with rates of 0.184, 0.182, and 0.174, respectively. In Liaoning, there were 12 and 17 counties with the first two levels, and the top three high rate counties were Xiuyan Autonomous County, Shuangta District, and Qingyuan Autonomous County, with rates of 0.193, 0.181, and 0.180, respectively. There were 17 and 11 counties with the first two levels in Shandong, and the top three high rate counties were Lanling County, Longkou City and Zhoucun District, with rates of 0.197, 0.191, and 0.169, respectively. In Gansu, Anhui, and Henan, there were 20 and 16 counties, 22 and six counties, and 14 and six counties with the first two levels, and the top three high rate counties were Lintao County, Pingchuan District, and Kangxian County; the Lieshan District, Fengyang County, and Sanshan District; and the Pingqiao District, Linzhou City, and Old City in these provinces, with rates of 0.200, 0.190, and 0.186; 0.196, 0.169, and 0.156; and 0.173, 0.150, and 0.130, respectively (Fig. 14).

4 Discussion

4.1 Comparative analysis of agricultural insurance premium rate

In this study, we selected three provinces across China, namely, Jiangxi, Henan, and Liaoning, where agricultural insurance has advanced relatively quickly. A comparative analysis was conducted between the current insurance premium rates for the three staple crops in these regions and the findings of this study. The goal was to provide insights for optimizing insurance schemes in each area by comprehensively considering natural disaster factors. For specific county-level premium rates, please contact the author.

At present, the rate for rice in the high risk areas is 5% in Jiangxi, and 4% in the other areas. The high risk areas are Poyang County, Yugan County, Wannian County, Yongxiu County, Duchang County, Hukou County, Ruichang City, Pengze County, Jinxian County, Nanchang County, and Xinjian District. The rates in Henan are 4.4% for rice, 4.6% for maize, and various rates for wheat, namely, 4% in the high risk areas, 3.8% in the medium risk areas, and 3.6% in the low risk areas. Luoyang, Sanmenxia, Luohe, and Zhumadian are high risk areas; Zhengzhou, Kaifeng, Pingdingshan, Xinxiang, Xuchang, Nanyang, Shangqiu, Xinyang, Zhoukou, and Jiyuan are medium risk areas; and Anyang, Hebi, Jiaozuo, and Puyang are low risk areas. Liaoning's rates are 4.1% for rice, 4.2% for wheat, and 6.1% for maize[1)]. It can be seen from the comparison of these counties that many of the counties in these provinces still have a uniform rate (Tables 3–5), but the reality is that the counties are affected differently by natural disasters due to their various geographic, environmental, and societal

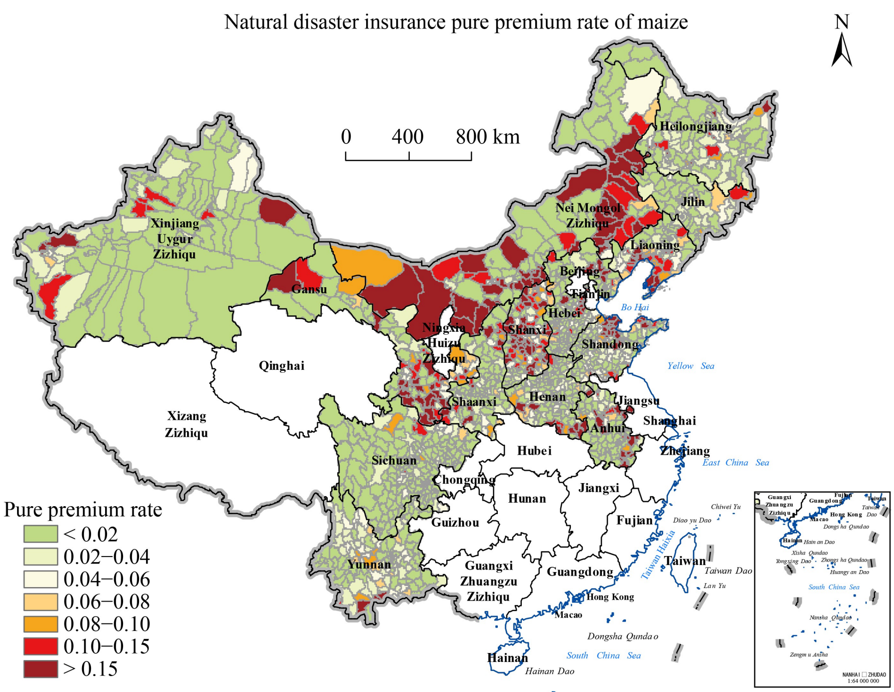

Fig. 13 Natural disaster insurance pure premium rate for maize.

1) Source: Measures for the Management of Agricultural Insurance Premium Subsidies in Jiangxi Province (2022), Implementation Plan for the full cost Insurance of Three major food crops in Henan Province (2021), and Implementation Rules for the Management of Agricultural Insurance Premium Subsidies in Liaoning Province (2022).

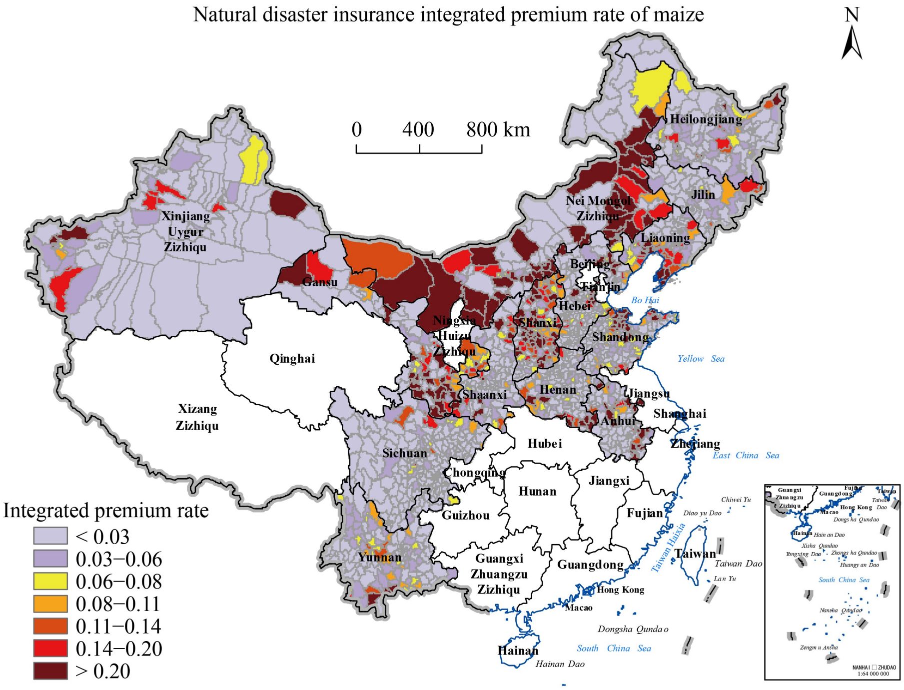

Fig. 14 Natural disaster insurance integrated premium rate for maize.

Table 3 Comparison of the integrated premium rate for rice and the current rate (typical county)

Province	County	Result of this study (A)	Current rate (B)	A–B
	Hukou	13.84%		8.84%
	Ruichang	11.08%		6.08%
Jiangxi	Duchang	9.39%	5.00%	4.39%
	Pengze	8.43%		3.43%
	Yongxiu	4.35%		–0.65%

Table 4 Comparison of the integrated premium rate for wheat and the current rate (typical city)

Province	County	Result of this study (A)	Current rate (B)	A–B
	Anyang	6.80%	3.60%	3.20%
	Nanyang	6.77%	3.80%	2.97%
Henan	Pingdingshan	6.55%	3.80%	2.75%
	Jiaozuo	4.42%	3.60%	0.82%
	Luoyang	3.14%	4.00%	–0.86%

Table 5 Comparison of the integrated premium rate for maize and the current rate (typical city)

Province	County	Result of this study (A)	Current rate (B)	A–B
	Huludao	9.76%		3.66%
	Fushun	9.41%		3.31%
Liaoning	Liaoyang	7.90%	6.1%	1.80%
	Yingkou	6.02%		–0.08%
	Benxi	3.06%		–3.04%

conditions. The results of this study provide a reference for research on the current rates at the county level.

Notably, few studies have considered the disaster losses caused by multiple disasters when determining the crop insurance premium rate, and many studies have calculated the expected loss of the crop yield from the distribution model of the unit crop yield, so the accuracy of the results is limited due to insufficient data and a low credibility. In the future, based on this study and previous research, more types of disaster losses and natural disaster risk regionalization should be considered for improving the accuracy of the premium rate determination (Wu et al., 2023).

4.2 Further improvement and refinement of the data

The present study has some limitations. Improving and refining the data are an important direction in future research, and more technical support is needed. Further work can be carried out in the following aspects. 1) In terms of disaster loss data, it is still difficult to obtain loss data for different crop types at the county level. The crop disaster data from the NDRCC have not been classified and counted according to the crop types, and the accuracy of the matching method used in this study can also be improved. In addition, detailed insurance business data are still lacking. Further research should focus on expediting the planning of agricultural insurance data strategies. This encompasses amalgamating insurance business statistics, farmer demographics, and government departments' agricultural data. Making more detailed categorical statistics and establishing a big data platform for agricultural insurance are indispensable tasks. 2) In terms of remote sensing data, in this study, constrained by the precision of the satellite image interpretation, the interpreted planting areas of the staple crops have bias compared to the actual areas. Therefore, it is necessary to accelerate the integration and application of new technologies such as satellite remote sensing, unmanned aerial vehicles (UAVs), geographic information systems, and the Beidou positioning system into crop insurance research, thereby further refining the precision of crop insurance rate determination (Zhang, 2020).

4.3 Exploring agricultural index insurance products for the three staple crops

Agricultural index insurance products have advantages over traditional agricultural products in terms of mitigating adverse selection and moral hazards. Crop disasters require integrated risk analysis that considers various factors such as disaster factors, crop vulnerability, planting area environment, and disaster mitigation capabilities in crop growth regions. Several studies have employed models such as the Grach, Egarch, and Copula models to simulate weather index distributions (Erhardt and Engler, 2018). Some weather index insurance products based on factors such as the cumulative rainfall and accumulated temperature have been designed (Conradt et al., 2015). Additionally, some scholars have considered the meteorological hazard intensity and topographic index among eight risk variables in index products for maize damage (Niu and Chen, 2016). However, index insurance faces challenges in risk pricing, including inadequate empirical data, intricate interdependencies among different risks, and pervasive basis risk (Zhang and Meng, 2020). In future studies, it is advisable to advance research on integrated risk index insurance products tailored for the three staple crops analyzed in our study. This entails developing multifaceted disaster risk index models that incorporate various hazards, factors, and processes, which is essential for mitigating vulnerabilities in food security and fostering sustainable growth of agricultural insurance.

4.4 Further exploration of crop catastrophe insurance under extreme weather conditions

In recent years, under the background of global climate change, the frequency and severity of extreme weather events have increased, escalating both the uncertainties and systemic risks associated with agricultural production. For instance, in 2019, northeastern China experienced severe drought, impacting 102 counties in three provinces. Similarly, in 2020, significant flooding occurred in the Yangtze River Basin and the Huaihe River Basin. In 2021, regions such as Henan and Shanxi provinces experienced heavy rainfall, leading to substantial crop yield losses and resulting in insurance payouts exceeding several billion dollars of compensation by local insurance firms. Research indicates that future extreme droughts and extremely high temperatures will significantly reduce grain yields. By 2030, it is estimated that the grain production in north-eastern China will decrease by 13.8 million tons, representing a reduction of approximately 12%. There is an urgent need to advance research on crop insurance under extreme weather conditions (Gu and Song, 2023). Further work can include conducting thorough analyses of catastrophic risks to elucidate the principal factors driving crop catastrophes across various regions; undertaking risk assessments to examine the likelihood of catastrophic events and quantifying the losses; and devising agricultural catastrophic insurance products to establish mechanisms for risk diversification within the agricultural insurance sector, thereby mitigating disaster losses through risk transfer and risk sharing strategies, bolstering agricultural production resilience, and safeguarding national food security.

5 Conclusions

In this study, based on county level disaster data, we established a 3-D matching temporal (X) - spatial (Y) - disaster loss (Z) analysis method. The aim of this study was to explore the extent of disaster losses in the primary rice, wheat, and maize producing regions nationwide and to delineate regional disparities in agricultural premium insurance rates. Through this approach, the precision of agricultural insurance rates was significantly enhanced, providing valuable insights for the implementation of regional differential rates across China. Our method demonstrated significance for further improvement of the framework and model of crop disaster risk management and disaster prevention and reduction work.

In the rice producing regions, the average area affected by natural disasters (floods, droughts, and typhoons) was particularly pronounced in the counties concentrated within the Yangtze-Huaihe River Basin, Yangtze-Hanjiang River Basin, the plain in Hubei and Hunan, the Songhua River Basin, and the Leizhou Peninsula. Regarding the determination of integrated agricultural insurance rates, the areas with high rates were primarily concentrated in the eastern and southwestern part of Hubei Province, central and northern part of Hunan Province, northwestern part of Guizhou Province, northern part of Jiangsu Province, coastal and northwestern part of Zhejiang Province, coastal areas in Guangdong Province, northwestern and southern part of Yunnan Province, and southern part of Heilongjiang Province. Notably, the areas with high premium rates in the traditional typical rice growing counties included the Zengdou District, Dawu County, and Jiangxia District in

Hubei Province and the Sifangtai District and Bin County in Heilongjiang Province, where the integrated premium rates reached 0.200, 0.198, 0.196, 0.195, and 0.191, respectively.

In the wheat production regions, the areas with high average disaster affected areas were mainly concentrated in the south-western part of Henan Province, central and northern regions of Hubei Province, central and western areas of Anhui Province, and southeastern part of Shandong Province. Regarding the determination of the integrated agricultural insurance premium rates for natural disasters, the regions with high rates were predominantly located in central and northwestern China. Counties such as Sui County and Laifeng County in Hubei Province, the Langya District in Anhui Province, and Habahe County and Yanqi Hui Autonomous County in the Xinjiang Uygur Zizhiqu had rates as high as 0.448, 0.412, 0.428, 0.457, and 0.443, respectively.

In terms of the maize producing regions, the areas with high average disaster affected areas were predominantly concentrated in northeastern China, Nei Mongol Zizhiqu, Shandong Province, Shanxi Province, Anhui Province, and Gansu Province. Regarding the determination of the integrated agricultural insurance premium rates in the context of natural disasters, the counties with high rates were mainly concentrated in the eastern Nei Mongol Zizhiqu, central and northern part of Shanxi Province, southern part of Liaoning Province, northern and eastern part of Shandong Province, northern and southeastern part of Gansu Province, central and southeastern part of Anhui Province, and southern part of Henan Province. Among these regions, Gansu Province, Nei Mongol Zizhiqu, Shanxi Province, Shandong Province, and Anhui Province contained a large number of counties with high rates. In particular, counties such as Lintao County and the Pingchuan District in Gansu Province, Lanling County and Longkou City in Shandong Province, and the Shiguai District in Nei Mongol Zizhiqu had high rates, reaching 0.200, 0.190, 0.197, 0.191, and 0.189, respectively.

Acknowledgments This work was supported by the Science and Technology Project of Shanghai TAIAN Agricultural Insurance Research Institute.

Competing interests The authors declare that they have no competinginterests.

References

Awondo S N, Kostandini G, Setimela P, Erenstein O (2020). Multi‐site bundling of drought tolerant maize varieties and index insurance. J Agric Econ, 71(1): 239–259

Botts R R, Boles J N (1958). Use of normal curve theory in crop insurance ratemaking. J Farm Econ, 40(3): 733–740

Chen S L, Miranda M J (2004). Modeling Multivariate Crop Yield Densities With Frequent Extreme Events. In: 2004 Annual meeting, August 1–4, Denver, CO. American Agricultural Economics Association (New Name 2008: Agricultural and Applied Economics Association)

Conradt S, Finger R, Spörri M (2015). Flexible weather index-based insurance design. Clim Risk Manage, 10: 106–117

Duarte G V, Braga A, Miquelluti D L, Ozaki V A (2018). Modeling of soybean yield using symmetric, asymmetric and bimodal distributions: implications for crop insurance. J Appl Stat, 45(11): 1920–1937

Erhardt R, Engler D (2018). An extension of spatial dependence models for estimating short-term temperature portfolio risk. N Am Actuar J, 22(3): 473–490

Goodwin B K, Hungerford A (2015). Copula‐based models of systemic risk in US agriculture: implications for crop insurance and reinsurance contracts. Am J Agric Econ, 97(3): 879–896

Goodwin B K, Ker A P (1998). Nonparametric estimation of crop yield distributions: implications for rating group‐risk crop insurance contracts. Am J Agric Econ, 80(1): 139–153

Gu Y, Song J G (2023). Promoting the high-quality development of agricultural insurance and escorting the construction of an agricultural power in the new era: Taian Agricultural Insurance Research Institute Achievement (Volume one). Beijing: China Agriculture Press

Huang Z Y, Zuo A, Sun J M, Guo Y Z (2020). Potato farmers' preference for agricultural insurance in China: an investigation using the choice experimental method. J Integr Agric, 19(4): 1137–1148

Ker A P, Goodwin B K (2000). Nonparametric estimation of crop insurance rates revisited. Am J Agric Econ, 82(2): 463–478

Liu Y, Ker A P (2020). Rating crop insurance contracts with nonparametric bayesian model averaging. J Agric Resour Econ, 45(2): 244–264

Lu Y, Ramirez O A, Rejesus R M, Knight T O, Sherrick B J (2008). Empirically evaluating the flexibility of the Johnson family of distributions: a crop insurance application. Agric Resour Econ Rev, 37(1): 79–91

Nelson C H, Preckel P V (1989). The conditional beta distribution as a stochastic production function. Am J Agric Econ, 71(2): 370–378

Niu H, Chen S W (2016). Study on determining the premium rate of maize yield based on risk zoning: a case study of 17 cities in Shandong Province. Insurance Studies, (1): 65–75 (in Chinese)

Ozaki V A, Goodwin B K, Shirota R (2008). Parametric and nonparametric statistical modelling of crop yield: implications for pricing crop insurance contracts. Appl Econ, 40(9): 1151–1164

Racine J, Ker A (2006). Rating crop insurance policies with efficient nonparametric estimators that admit mixed data types. J Agric Resour Econ, 31(1): 27–39

Ramsey A F (2020). Probability distributions of crop yields: a Bayesian spatial quantile regression approach. Am J Agric Econ, 102(1): 220–239

Rejesus R M, Coble K H, Miller M F, Boyles R, Goodwin B K, Knight T O (2015). Accounting for weather probabilities in crop insurance rating. J Agric Resour Econ, 40(2): 306–324

Shen Z, Odening M, Okhrin O (2018). Adaptive local parametric estimation of crop yields: implications for crop insurance rate making. Eur Rev Agric Econ, 45(2): 173–203

Shi J Q, Gan C L, Guo Y N, Du J, Zhou K S (2023). Determination and prediction of Tibetan barley insurance rate based on drought risk. Chin J Agrometeor, 44(11): 1043–1056 (in Chinese)

Tang Y, Cai H, Liu R (2021). Farmers' demand for informal risk management strategy and weather index insurance: evidence from China. Int J Disaster Risk Sci, 12(2): 281–297

Tuo G Z (2023). The policy context of the development of agricultural insurance in China – Based on the study of the guiding opinions in the central "No. 1 Document" in the past 20 years. Insurance Theory & Practice, (03): 1–13 (in Chinese)

Tuo G Z, Li J (2005), Agricultural Insurance. Beijing: Renmin University Press

Turvey C G, Zhao J (1999). Parametric and non-parametric crop yield distributions and their effects on all risk crop insurance premiums. University of Guelph, Department of Food, Agricultural and Resource Economics, Working Papers

Wang L H, Yang H, Tian Z H, Yan Z Y (2007). Study on determining regional yield insurance premium rate of maize by non-parametric kernel density method. J Chin Agric U, 12(1): 90–94 (in Chinese)

Woodard J D, Verteramo‐Chiu L J (2017). Efficiency impacts of utilizing soil data in the pricing of the federal crop insurance program. Am J Agric Econ, 99(3): 757–772

Wu Y Y, Liao H Q, Fang L, Guo G Z (2023). Quantitative study on agricultural premium rate and its distribution in China. Land (Basel), 12(1): 263–276

Yu Y (2013). Feasibility of regional differential rate determination for crop yield insurance: empirical study based on nonparametric kernel density estimation. J Statistics Inform, 28(10): 75–80 (in Chinese)

Zhang Q, Wang K (2021). The uncertainty of agricultural yield risk assessment and agricultural insurance pricing: literature review and wayforward. Scient Agric Sin, 54(22): 4778–4786 (in Chinese)

Zhang X D (2020). Remote sensing technology and insurance applications: applications and challenges. Financial Theory Practice, (02): 104–109 (in Chinese)

Zhang Y Y, Meng S W (2020). Research progress and improvement strategy of agricultural index insurance pricing model. J Statistics Inform, 35(01): 30–39 (in Chinese)

Zheng Q, Wang H H, Shi Q H (2014). Estimating bivariate yield distributions and crop insurance premiums using nonparametric methods. Appl Econ, 46(18): 2108–2118

Zhou Y L (2012). Agricultural insurance achievement, question and future development in China. Insurance Studies, (05): 3–9 (in Chinese)

Zhu W, Tan K S, Porth L (2019). Agricultural insurance ratemaking: development of a new premium principle. N Am Actuar J, 23(4): 512–534