Spatial-Temporal Assessment of Natural Disaster Losses Using Combined AHP-Entropy Weight Method: A Case Study of Jiangxi Province

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ABSTRACT

The Disaster Situation Index (DSI) serves as a crucial method for natural disaster loss assessment. However, the weight determination in existing assessment practices is characterized by strong subjectivity and methodological singularity, while the classification of DSI also suffers from artificial subjective arbitrariness. To resolve these two issues, this study proposes a hybrid approach integrating subjective and objective weights (AHP—Entropy Weight Method—Linear Combination Method) for indicator weight calculation, and introduces the elbow rule of spatial clustering to determine classification levels. The proposed method is validated using historical disaster data of Jiangxi Province from 2015 to 2024. Results indicate that among the past decade, 2019 witnessed the most severe disasters in Jiangxi, followed by 2020 and 2022. Spatially, extremely severe and Severe affected areas are distributed in northeastern (Shangrao) and northern (Jiujiang), southern (Ganzhou) of Jiangxi; Moderate disaster-affected areas are mainly in the southern part (Ji'an).Mild disaster-affected areas are distributed in a belt shape in the central region.Slight disaster-affected areas are mainly concentrated in the mid-western and central regions of Jiangxi Province. Consistent with the regional actual situation, the assessment results demonstrate the good practicality and effectiveness of the proposed method.

Keywords: AHP—Entropy Weight Method, Natural disaster ,disaster situation index, evaluation system

1 INTRODUCTION

In recent years, influenced by global climate change and human activities[1,2], natural disa- sters have shown trends of increased frequency, suddenness, and chained occurren-ces[3-5], re- sulting in increasingly severe losses globally. For instance, the EM-DAT recorded worldwide disaster losses amounting to US$1.25 trillion between 2001 and 2012[6]. In China, although data on affected

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populations, casualties, collapsed/damaged houses, and direct economic losses are often released by media or official sources, these figures merely reflect the disaster's impact without illustrating its specific severity or providing relevant metrics. So it is difficult to establish an intuitive perception of the losses caused by disasters for the publics. Managers also cannot immediately identify which areas are severely affected, which in turn affects disaster relief[7], material distribution and the formulation of recovery and reconstruction plans[8].

As for international scholars, they often use early warning systems, drones, remote sensing, and multi-temporal spectral analysis to assess losses from natural disasters[9-12]. However, the losses caused by disasters are often shows wide-ranging and scattered. In this case, multiple aspects are affected, such as populations, reduced crop yields, collapsed/damaged houses, and damage to infrastructure like roads and dams, as well as losses in industrial, mining, and commercial sectors[13,14]. Statistically, losses to exposed elements constitute multivariate data composed of multiple indicators. How can a single composite indicator be derived from this multivariate disaster data? Researchers in China have proposed various methods, primarily categorized into establishing classification systems for disaster losses[15,16] and developing continuous index models[17,18] Building on this, a new hierarchical comprehensive disaster situation index calculation method has been proposed in the Chinese context[19]. The disaster situation index is a widely used and mature method in China[20], based on data reported through China's "National Natural Disaster Loss Reporting System." It processes multiple indicators—such as affected population, deaths/missing persons, and affected crop areas—from four dimensions (population impact, crop loss, housing damage, and direct economic loss) through normalization. A geometric mean model is then used to calculate the disaster situation index for the multiple indicators within each dimension.

Determining indicator weights is a crucial step in using the disaster situation index for loss assessment in China. Currently, the Expert Scoring Method is predominantly used for this purpose. For example, Zheng Meixia et al. used it to determine weights for four first-level indicators (population impact, agricultural loss, housing damage, economic loss) and eight second-level indicators for Jiangxi Province, China[21]. Similarly, Yuan Yi applied this method to assign weights to eight absolute and relative indicators for natural disasters across China[22]. While numerous studies in China have combined the Analytic Hierarchy Process (AHP) and Entropy Weight Method to determine weights for multiple indicators across dimensions like risk sensitivity, vulnerability, and risk[23,24], research applying the combined AHP-Entropy Weight Method to determine weights for disaster situation indices within China remains relatively scarce. Although some Chinese scholars have used either AHP or the Entropy Weight Method individually for this purpose—e.g., Chen Xiaokang constructed a loss assessment model using AHP and verified weight rationality through consistency checks[25,26], and Zhang Fanghao et al. introduced the objective Entropy Weight Method to improve the index assessment process[27]—research integrating AHP, the Entropy Weight Method, and a linear combination method (a subjective-objective combination) to determine weights for disaster situation indicators in China is still underdeveloped.

To intuitively represent the severity of disasters in affected areas in China[28], spatial clustering is introduced. Spatial cluster analysis can objectively identify spatial heterogeneity. The K-means algorithm, a classic unsupervised machine learning method, partitions datasets into K clusters, maximizing intra-cluster similarity and inter-cluster differences, providing a basis for classifying computed disaster situation indices. Currently, within China, the classification of comprehensive disaster situation indices in loss assessment often relies on the Natural Breaks method[19,21,29].

Although this approach can perform classification, the determination of the number of classes remains somewhat subjective, and the objective quantification of the optimal number of grades still requires further research.

In summary, significant achievements have been made in the current research on the assessment of losses caused by natural disasters. However, there are still two aspects that need to be further deepened: 1) Methods for determining indicator weights are often limited, either overly subjective or objective, lacking systematic research on integrated subjective- objective approaches. 2) In terms of classifying disaster levels, there is a tendency towards artificial arbitrariness, and objective quantitative methods for classifying disaster levels are still rare.

This paper introduces an integrated subjective-objective method (AHP - Entropy Weight Method - Linear Combination) to determine the weights of indicators (Fig.1). A set of "absolute disaster index" covering four dimensions: population, agriculture, housing and economy has been constructed. Furthermore, the Elbow Method and Global Moran's I were adopted for the clustering algorithm to determine the optimal classification number and the global autocorrelation test respectively. Which serves to objectively measure the spatial differentiation of disaster losses and prevents the potential distortions arising from subjective classification. The practicality and effectiveness of this method are validated by using disaster statistics from various cities in Jiangxi Province, China over the recent decade (2015-2024).

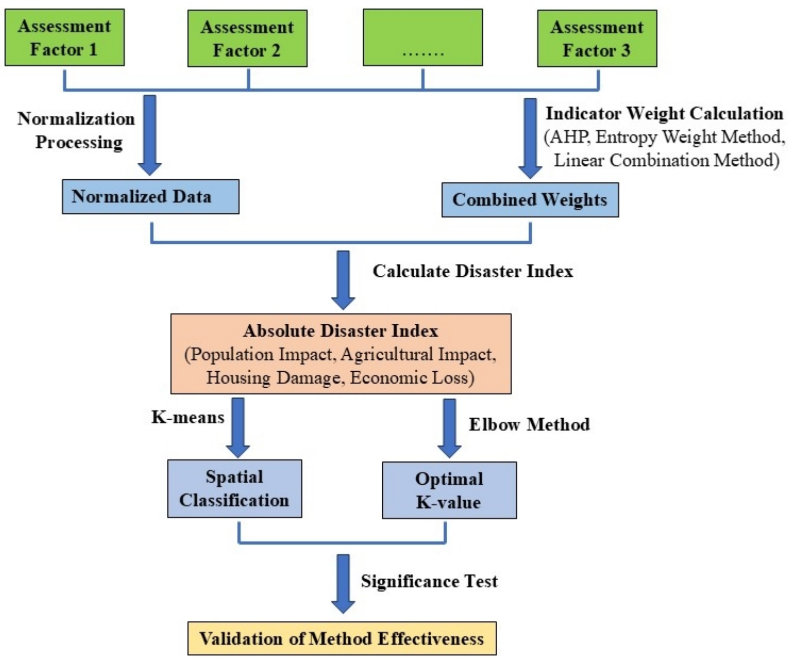


Fig.1. Technical Framework for Integrated Disaster Assessment

2 STUDY AREA AND DATA

2.1 Overview of the Study Area

Jiangxi is located on the south bank of the middle and lower reaches of the Yangtze River and has a subtropical monsoon climate (Fig.2). Due to its location in the center of the national rainstorm zone, the precipitation is abundant and unevenly distributed in time and space, mainly concentrated from April to July and in the northern and southern parts of Jiangxi Province. The terrain is long from north to south and short from east to west, surrounded by mountains on three sides, presenting a topography that is higher in the south and lower in the north.

The river system within the territory is well-developed and the river network is dense. There are over 3,700 rivers, which converge from the mountains on three sides to form five major rivers: Gan, Fu, Xin, Rao and Xiu. After flowing from south to north into Poyang Lake and then empties into the Yangtze River, when there is heavy rainfall, rivers are prone to floods beyond the warning level. Moreover, due to the flood discharge and support effect of the Yangtze River, major river basins and their tributaries such as Poyang Lake, Ganjiang River and Rao River are prone to natural disasters. Rich in water resource is a double-edged sword, both make jiangxi rich products, agricultural development rising steadily, but to a certain extent, has also led to the jiangxi became one of the serious natural disasters

Types of natural disasters in jiangxi province, mainly including drought, flood inundation and drought, etc. Meteorological disasters such as hailstorms, typhoons, low-temperature freezing and snow disasters, geological disasters such as collapses, landslides, mudslides and ground subsidence, forest fires, earthquakes and biological disasters may occur occasionally.

According to statistics from China's emergency management department, a total of 138 natural disasters occurred in Jiangxi Province in the past five years, averaging 27.6 times per year. Sixty people died or went missing due to the disaster, with direct economic losses amounting to ¥109.46 billion, accounting for 5.2‰ of the province's GDP. This seriously threatens the production and life of the people as well as the stable development of the social economy.

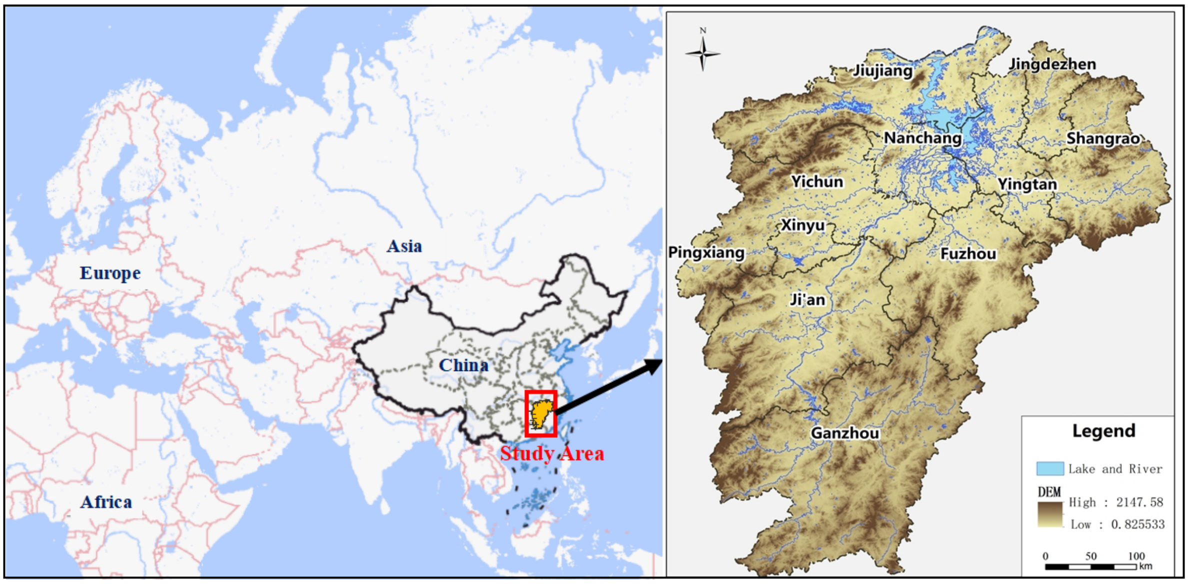


Fig.2. Topographic and Geomorphic Map of the Study Area

2.2 Data Sources

The data in this article is sourced from the statistics of the entire province from 2015 to 2024, which have been verified by the emergency management department of Jiangxi Province. The four core indicators of population, crops, housing and economic losses under the influence of natural disasters are selected as the assessment objects. These indicators are the most important and crucial ones in disaster assessment, disaster relief and the initiation of response work, which can comprehensively reflect the impact and extent of losses caused by natural disasters on the economy and society of a region[21]. The specific metrics include:

- Affected population,
- Deaths and missing persons due to disasters,
- Population relocated or in emergency shelter,

- Population in need of emergency living assistance,
- Crop area affected,
- Crop area with complete harvest failure,
- Number of collapsed houses,
- Number of damaged houses,
- Direct economic losses.

3. METHODOLOGY

3.1 Data Processing

To ensure all disaster indicators are calculated under a scientific dimensional framework, each indicator was normalized using the following formula：

$$x^* = \frac{x - x_{min}}{xmin_{max}} \tag{1}$$

where x^* represents the normalized indicator value, x is the original value of the indicator， $x_{\max}$ and $x_{\min}$ denote the maximum and minimum values of the indicator within the historical dataset, respectively. The specific maximum and minimum values used for normalizing the disaster assessment indicators in this study are provided in Table 1.

Table1 Zero Value Replacement Rules and Maximum/Minimum Values

No.	Indicator	Unit	Substitution Value for Zero Cases	Maximum Value (Year)	Minimum Value
1	Affected Population	$\times 10^4$ persons	0.01	1549.82 (2019)	0.01
2	Deaths and Missing Persons	persons	1	56 (2019)	1
3	Emergency Relocated Population	$\times 10^4$ persons	0.01	84.29 (2020)	0.01
4	Population Requiring Emergency Assistance	$\times 10^4$ persons	0.01	63.92 (2016)	0.01
5	Affected Crop Area	$\times 10^3$ hectares	0.01	1111.88 (2022)	0.01
6	Crop Area with Total Harvest Failure	$\times 10^3$ hectares	0.01	218.88 (2019)	0.01
7	Collapsed Houses	$\times 10^4$ units	0.01	1.61 (2019)	0.01

3.2 Weight Determination

3.2.1 Analytic Hierarchy Process (AHP)

A hierarchical structural model was constructed with the disaster situation index as the objective level, four primary criteria (population, agriculture, housing, and economy) at the criterion level[30], and nine specific indicators at the indicator level: affected population, deaths and missing persons, emergency relocated population, population requiring emergency assistance, affected crop area, crop area with total harvest failure, collapsed houses, damaged houses, and direct economic loss.

Using the expert scoring approach based on Saaty's 1–9 scale, pairwise comparisons were conducted among indicators at the same level to establish judgment matrices. The eigenvalue method was subsequently employed to derive the weight vectors from these matrices.

To ensure the reliability and rationality of expert judgments, consistency checks were performed using the following formula:

$$CR = \frac{\frac{(\lambda_{\max} - n)}{n-1}}{RI} \tag{2}$$

where *CR* represents the consistency ratio， $\lambda_{\max}$ denotes the largest eigenvalue of the judgment matrix,， n is the order of the matrix, and *RI* refers to the random consistency index (taken as 0.90 in this study).

A CR value less than 0.10 indicates acceptable consistency of the judgment matrix, whereas a CR value equal to or greater than 0.10 requires matrix revision and revalidation.

3.2.2 Entropy Weight Method

Consider an indicator system comprising *m* evaluation objects and *n* indicators. The primary indicator matrix can be represented as $R=\left(r_{ij}\right)_{m\times n}$. The entropy value H_i for the i-th criterion is expressed as follows[31]:

$$H_i=-\frac{1}{\ln m}\sum_{j=1}^{n} f_{ij}\ln f_{ij} \tag{3}$$

In the equation, to ensure mathematical validity, when $f_{ij}=0$ we define $f_{ij}\ln f_{ij}=0$. Simultaneously, the calculation of f_{ij} follows:

$$f_{ij}=-\frac{Z_{ij}}{\sum_{j=1}^{n} Z_{ij}} \tag{4}$$

In the formula, Z_{ij} refers to the standardized index value of the *j*-th evaluated object under the i-th criterion. The weight value expression of the *i*-th indicator is:

$$w_i^{"}=\frac{1-H_i}{\sum_{i=1}^{n}\left(1-H_i\right)} \tag{5}$$

where $0\le w_i^{"}\le 1$; H_i denotes the entropy value of the *i*-th indicator; $\sum_{i=1}^{n} H_i=1$。

3.2.3 Combined Weights

In this study, the linear combination method was adopted to obtain the combined weight values of each indicator[32]. The combined weight w_i is derived from the subjective weight $w_i^{'}$ of the analytic hierarchy process and the objective weight $w_i^{"}$ of the entropy weight method. To eliminate the interference of outliers and make the degree of difference between α and β consistent with that between $w_i^{'}$ and $w_i^{"}$. A distance function is introduced, the combined weight is expressed as: $w_i=\alpha w_i^{'}+\beta w_i^{"}$.where α and β are combination coefficients satisfying $\alpha+\beta=1$.

The expression of the distance function is summarized as follows:

$$d\left(w_i^{'},w_i^{"}\right)=\left[\frac{1}{2}\sum_{i=1}^{n}\left(w_i^{'}-w_i^{"}\right)^2\right]^{\frac{1}{2}} \tag{6}$$

The difference between the combination coefficients is denoted as: $D=\left|\alpha-\beta\right|$

Then, the system of equations is constructed as follows:

$$\begin{cases} d\left(w_i^{'},\ w_i^{"}\right)^2=\left(\alpha-\beta\right)^2 \\ \alpha+\beta=1 \end{cases} \tag{7}$$

By solving equation system （7）,we can obtained the values of α and β, These coefficients are then substituted into the combined weight formula to determine the final combined weights

($w_i = \alpha w_i^{'} + \beta w_i^{''}$).

3.3 Index Construction

The dimension index is calculated by using the weighted average method for the normalized data. The calculation formula is as follows:

Population Dimension Index:

$$I_P = P_a \bullet W_{pa} + P_d \bullet W_{pd} + P_t \bullet W_{pt} + P_r \bullet W_{pr} \tag{8}$$

Crop Dimension Index:

$$I_c = C_a \bullet W_{ca} + C_n \bullet W_{cn} \tag{9}$$

Housing Dimension Index:

$$I_H = H_r \bullet W_{hr} + H_s \bullet W_{hs} \tag{10}$$

Economic Dimension Index:

$$I_E = E \tag{11}$$

The absolute disaster Index (ADI) is calculated by using the weighted average method of the calculated dimension index. The calculation formula is as follows:

$$ADI = I_P \bullet W_P + I_C \bullet W_C + I_H \bullet W_H + I_E \bullet W_E \tag{12}$$

3.4 Disaster Severity Classification

3.4.1 Spatial Clustering

To maintain the statistical characteristics of disaster data and more accurately reflect the spatial distribution pattern of natural disaster losses, this paper adopts the K-means clustering algorithm for classification. That is, through cluster analysis, data with high similarity are classified into the same level, while data with significant differences are distributed to different levels[33,34].

To obtain a reasonable number of clusters (K value), the elbow rule is introduced. By calculating the intra-cluster sum of squares of the clustering results under different clustering values, the relationship curve between the K value and SSE is plotted. The K value corresponding to the inflection point of the curve is the optimal number of clusters.

3.4.2 Statistical Significance Testing

The Global spatial autocorrelation (Global Moran's I) is adopted to test the disaster index[35]. It can be ensured that the clusters are not randomly generated but have statistically significant characteristics[36].

The formula for calculating the Global Moran's I index is as follows:

$$I = \frac{N}{S_0} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \tag{13}$$

where:

- N is the total number of areal units,
- xi and xj are the disaster situation index values for areal units *i* and *j*, respectively,
- $\bar{x}$ is the mean value of the disaster situation index across all areal units,
- wij is the spatial weight between areal units *i* and *j*,
- S_0 is the aggregate of all spatial weights。

4 CASE ANALYSIS

4.1 Background

This study validates a new disaster assessment method that employs a combined AHP–Entropy Weight approach. The historical disaster loss data of each prefecture-level city in Jiangxi Province, China (2015–2024) are taken as examples for analysis to assess its applicability and effectivenes.

4.2 Calculation of Indicator Weights

4.2.1 Weight Determination Using AHP

The criteria are based on four first-level indicators: population, agriculture, housing, and economy. Nine secondary indicators, including the affected population, the dead and missing persons due to the disaster, the emergency relocation population, the population in need of emergency living assistance, the area affected by crops, the area of crop failure, the number of collapsed houses, the number of damaged houses and the direct economic loss, were used as the index layer. The relative importance of the first-level indicators was ranked first. As shown in Table 2:

Table2 Judgment Matrix for First-Level Indicators

First-level Indicator	Population	Agriculture	Housing	Economy
Population	1	2	3	2
Agriculture	1/2	1	3	1/2
Housing	1/3	1/3	1	1/3
Economy	1/2	2	3	1

The normalized matrix is obtained by dividing each column element of the matrix by the sum of its elements, then the weight vector and the largest eigenvalue are calculated. Consistency test was conducted according to Formula (2), and the results are shown in Table 3.

4.2.2 Weight Determination Using Entropy Weight Method

Based on the historical disaster records from 2015 to 2024, the weights for both first- and second-level indicators were calculated according to equations (3) to (5). Results are shown in Table 3.

Table 3 Calculation Results of AHP and Entropy Weight Method

First-level Indicator	AHP-derived Weight	Entropy-derived Weight	Second-level Indicator	AHP-derived Weight	Entropy-derived Weight
Population	0.30	0.213	Affected Population	0.20	0.249
			Deaths and Missing Persons	0.50	0.286
			Emergency Relocated Population	0.15	0.239
			Population Requiring Emergency Assistance	0.15	0.226
Agriculture	0.15	0.209	Affected Crop Area	0.30	0.411
			Total Crop Area Harvest Failure	0.70	0.589
Housing	0.40	0.285	Collapsed Houses	0.70	0.533
			Damaged Houses	0.30	0.467
Economy	0.15	0.293	Direct Economic Loss	1	1

4.2.3 Combined Weight Calculation Using Linear Combination Method

The combined weights for each indicator were calculated according to Equations (6) and (7). Results are shown in Table 4.

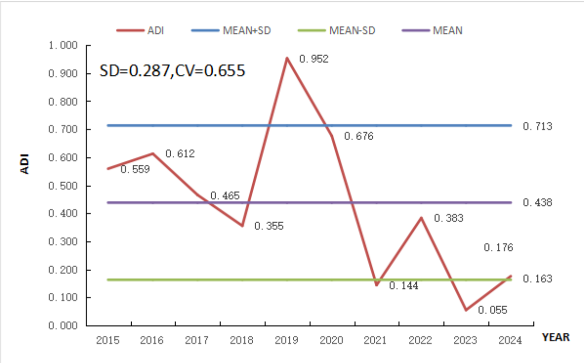
Table 4 Variable Definitions and Indicator Weights for Equations (8)-(12)

Dimension Index	Symbol	Weight Symbol	Weight Value	Normalized Indicator	Symbol	Weight Symbol	Weight Value
Population Impact	I_P	W_P	0.2632	Affected Population	P_a	W_{pa}	0.0571
				Deaths and Missing Persons	P_d	W_{pd}	0.1123
				Emergency Relocated Population	P_t	W_{pt}	0.0475
				Population Requiring Emergency Assistance	P_r	W_{pr}	0.0463
Agricultural Impact	I_C	W_C	0.1750	Affected Crop Area	C_a	W_{ca}	0.0623
				Total Crop Area Harvest Failure	C_n	W_{cn}	0.1127
Housing Damage	I_H	W_H	0.3513	Collapsed Houses	H_r	W_{hr}	0.2258
				Damaged Houses	H_S	W_{hs}	0.1255
Economic Loss	I_E	W_E	0.2105	Direct Economic Loss	E	W_{EE}	0.2105

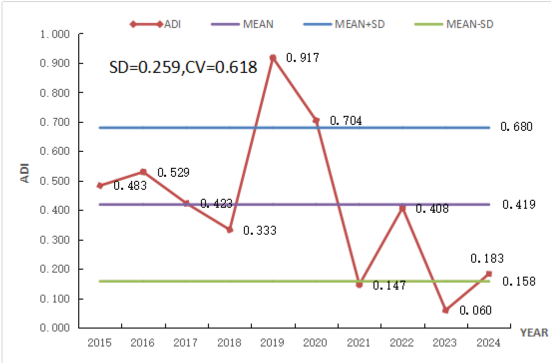
4.3 Calculation of the Disaster Situation Index

The absolute disaster situation index for each year and each city from 2015 to 2024 was calculated according to equations (8) - (12). The annual disaster situation index is shown in Figure 3. As can be seen from figure, The optimized absolute disaster loss index exhibits superior performance, which can be primarily attributed to the smaller standard deviation (SD) and coefficient of variation (CV) after optimization. This suggests that the data points cluster more tightly around the mean, representing a lower level of data dispersion. Furthermore, the optimized extreme values conform better to the overall distribution, as exemplified by the peak in 2019, which validates the rationality of the proposed calculation approach.

Also,From fig.3.(b),in the past 10 years, the top three years in terms of the severity of disasters are 2019, 2020 and 2022 in sequence.This finding is also supported by the historical distribution of disaster loss indicators. This mainly due to multiple rounds of flooding followed by a severe drought in 2019, a historically significant flood in the Poyang Lake basin in 2020, and a major drought spanning the summer, autumn, and winter of 2022.



（a）**Pre-optimization**



（b）**Post-optimization**

Fig.3. Absolute Disaster Index Trend (2015-2024)

4.4 Spatial Clustering

In order to better analyze the spatial differentiation characteristics of natural disaster loss in Jiangxi, the K-means clustering algorithm is used to classify the Absolute Disaster Indices of each city. The Elbow Method was used to determine the best K value, and the significance test was conducted to ensure the rationality and validity of the grading.From the relationship between the K-value and the Within-Cluster Sum of Squares (SSE), the plot clearly indicates shows that when $K \geqslant 5$, the decline rate of SSE is slower (the decline is less than 45%).Therefore, the optimal number of clusters was determined to be $K = 5$.

Based on Equation (13), the calculated Global Moran's I index is 0.258, with a statistical significance p-value of 0.038. Since this p-value is below the 0.05 threshold, the observed spatial clustering pattern is statistically significant.

From fig.4,The optimized absolute disaster loss index presents a more distinct grading, accompanied by reduced standard deviation and coefficient of variation（SD,0.262＜0.270，CV,0.729＜0.771）. This implies tighter data clustering and weaker fluctuation, which verifies the superior effectiveness of the optimized approach.

The city-level Absolute Disaster Index was classified into five severity levels. The first level, designated as extremely-severe disaster areas (0.80≤ ADI ≤1.00), includes the cities of Shangrao.The second level, severe disaster areas (0.60≤ ADI ≤0.80), includes the cities of Jiujiang and Ganzhou. The third level, moderate -severity disaster areas (0.40≤ ADI ≤0.60), comprises Ji'an.The four level, mild-severity disaster areas (0.20≤ ADI ≤0.40),includes Fuzhou,Yichun, and Jingdezhen. The five level,Slightly-severity disaster areas (0.00≤ ADI ≤ 0.20), includes Pingxiang, Nanchang, Yingtan, and Xinyu. The Spatial distribution of the Absolute Disaster Index classification of Jiangxi is presented in Fig.4(b).

4.5 Evaluation Conclusions

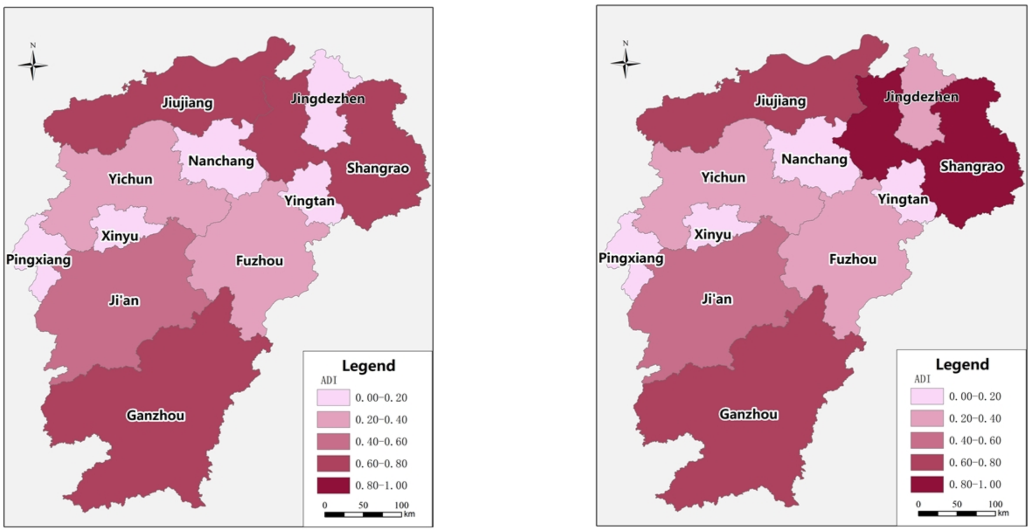
Based on the calculation results and diagrams, the following conclusions can be drawn:

(1) Temporal Distribution: Over the past decade, the losses caused by disasters were the most severe in 2019, followed by 2020, and ranked third in 2022. This can be verified in the historical distribution of disaster situation indicator. In 2019, the number of people affected by disasters, the number of people who died or went missing due to disasters, the area of crop failure and the number of collapsed houses were all the highest in the past ten years. In 2020, the number of people urgently relocated and resettled, the number of damaged houses and the direct economic losses were all the highest in the past ten years. In 2022, the area of crops affected by disasters was the largest in the past ten years.

(2) Spatial Concentration: Due to the influence of multiple factors such as rainfall, terrain and water systems, the disaster situation in some local areas is relatively severe. The losses caused were mainly concentrated in three cities: Shangrao, Jiujiang and Ganzhou. From the perspective of the Absolute Disaster Index (ADI), where all regions with an ADI exceeding 0.1 correspond to these three cities.

(3) Dimension-Specific Impacts: Strong convection in spring triggers hailstorms and heavy rainfall during the flood season induces floods and geological disasters. It has caused a large number of deaths and disappearances, with Ganzhou being the most severely affected, and the population dimension index is significantly high. Shangrao, as a major rice-growing area, has suffered significant agricultural losses and its agricultural dimension index is relatively high. Jiujiang has a developed water system and is prone to frequent flood disasters, with heavy housing collapse and economic damage, and high housing dimension index and economic dimension index.

The above findings is also consistent with the analysis of the natural disaster situation over the years published by the Office of the Jiangxi Provincial Committee for Disaster Prevention, Reduction and Relief, indicating the rationality and effectiveness of the natural disaster loss assessment method based on the AHP-entropy weight method proposed in this paper.



（a）Pre-optimization （b）Post-optimization

Fig.4. Spatial distribution of the Absolute Disaster ndex classification (Jiangxi Province)

5 CONCLUSIONS

This paper proposes to determine the weights of disaster situation indicators based on the combination of AHP-entropy weight method and linear combination method. Taking the historical disaster data of Jiangxi Province from 2015 to 2024 as an example, the effectiveness of the method was verified, and the scientificity and rationality of determining the weights of disaster indicators were achieved. Although this study verified the reliability of the results through historical disaster data, the disaster statistics themselves may have certain systematic errors, and the weights are essentially a simplified representation of complex disaster systems. In the next step, we can explore the introduction of fuzzy mathematics or weight methods considering different scenarios. At the same time, we can combine higher resolution data (such as remote sensing) for micro scale analysis and method promotion.

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