Disaster Risk Index Assessment Considering Subjective and Objective Weights and Emergency Communication Technologies

Xiang Li *

Department of Electronic and Information Engineering, Beijing Jiaotong University, Beijing, China, 100091

* Corresponding Author Email: 21721013@bjtu.edu.cn

Abstract. To assist Emergency Communication companies in making decisions, it is necessary to assess the potential risks of natural disasters in a region and the possible losses to people and property. Therefore, a disaster - risk index assessment model is established. Firstly, this model evaluates the disaster risks of a region from four aspects: natural disasters, economic development level, environmental stability, and national aid. Secondly, for this model, the methods of index standardization and weight determination are described in detail, and a combination of subjective and objective methods is used to determine the weights of the indicators. Finally, to verify the effectiveness of the model, the data of 40 countries are input into the model, and the Disaster Risk Index (DRI) of each country is calculated by the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS).

Keywords: Disaster Risk Index, Natural Disaster Factors, Ecological Stability Indicator, State Assistance in Disasters, Indicator Normalization Method.

1. Introduction

Extreme weather events are becoming a crisis for property owners and Emergency Communication companies. In recent years, the frequency of extreme weather and natural disasters has been increasing, making it necessary for Emergency Communication companies and real - estate companies to consider natural disasters as an important factor in their business development.

In recent years, research on disaster risk assessment at home and abroad has received extensive attention, especially on how to combine Geographic Information System (GIS), remote-sensing technology, and disaster warning systems to improve the accuracy of assessment. In China, many studies focus on using GIS and remote - sensing technology to analyze the spatial distribution and frequency of natural disasters and explore the relationship between disaster risks and socio - economic conditions [1]. In addition, some studies quantify disaster risks through methods such as fuzzy comprehensive evaluation [2] and Bayesian networks [3], and evaluate the disaster vulnerability and response capabilities of different regions [4]. Internationally, significant progress has been made in disaster risk assessment models. Many models not only consider the frequency and intensity of natural disasters but also incorporate factors such as social vulnerability, economic development, and environmental stability [5]. The disaster risk index released by the United Nations Development Programme [6] has been widely used to assess the disaster risk status of countries and regions, especially in the assessment of disaster vulnerability in the socio-economic context. However, existing studies generally fail to fully integrate key factors such as national aid and lack the combination of subjective and objective methods in weight determination. Therefore, this study determines the weights of each indicator by combining subjective and objective methods, further integrates factors such as national aid, and proposes a more comprehensive Disaster Risk Index Assessment Model (DRIAM) to make up for the deficiencies in comprehensiveness and scientificity of existing studies.

The development of the DRIAM model involved the selection of four primary indicators and several secondary indicators to comprehensively assess the potential impact of disasters on communication systems. These indicators encompass multiple dimensions, including the frequency of natural disasters, regional economic development levels, ecological stability, and the capacity for national and social assistance. Through a comprehensive weight analysis of these indicators, the accuracy of disaster risk assessment was optimized, providing reliable data support for decision-making in emergency communication companies.

This study details the construction process of the DRIAM model, discusses the selection of indicators and their corresponding weight distribution methods, and validates the model's effectiveness and accuracy through specific case studies. The objective of this research is to provide emergency communication companies with a scientific and systematic tool for disaster risk assessment, thereby aiding in more precise judgments and deployments in disaster management and emergency response.

2. Disaster risk

In order to help Emergency Communication companies assess the potential risk of natural disasters in an area and the property damage it may cause, we have developed a Disaster Risk Index Assessment Model (DRIAM). Then, we take the regional Disaster Risk Index (DRI) into the profit analysis of Emergency Communication, and establish an Emergency Communication Profit Model (IPM), which can analyze the Emergency Communication returns under different disaster risk indices to help Emergency Communication companies make decisions.

2.1. Establish Disaster Risk Index Assessment Model

2.1.1. Discussion of the Superior and Inferior Indicators

The potential natural disaster risk of a country or region and its possible property loss are related to a variety of factors [7]. In order to comprehensively assess the disaster risk of a country, we establish a DRIAM, in which we consider 4 superior indicators and 14 inferior indicators [8]. We are going to discuss about them in detail.

(1) Natural Disaster

One of the most important factors to consider in assessing a country's or region's disaster risk profile is the number of natural disasters and the amount of property damage each causes. Although the occurrence of many natural disasters is accidental, but the frequent occurrence of natural disasters in the area will have a greater potential for natural disasters [9]. Therefore, we choose four inferior indicators to assess the local natural disaster situation, which are: Disaster deaths toll (N1), Total number of disaster-affected people (N2), Total economic losses caused by disasters (N3), Number of natural disasters (N4). In the case of N3, particular attention is given to the economic losses resulting from the disruption of communication systems after a disaster. Furthermore, in N4, the model emphasizes the impact of the frequency of disasters on the communication network's load-bearing capacity. Frequent disasters may exacerbate the vulnerability of communication networks, leading to a heightened risk of system failure.

(2) Economic Development Level

The level of economic development of a region is related to the property losses caused by natural disasters. When an area has a higher level of economic development and a dense population, the potential losses caused by natural disasters will be greater. In order to measure the impact of economic development level on disaster risk index, we selected four inferior indicators, which are: Per capita GDP (D1), Per capita disposable income (D2), Urbanization rate (D3), Per capita industrial output (D4). In D3, the level of urbanization directly impacts the density of communication networks in urban areas as well as their emergency recovery capabilities during a disaster. Additionally, it assesses the coverage of communication infrastructure and its disaster resistance capacity. Well-developed communication infrastructure contributes significantly to enhancing the recovery capability of communication systems following a disaster.

(3) Ecological Stability

The occurrence of natural disasters is also related to the stability of the local ecological environment. The better the ecological environment of a region, the less likely natural disasters will occur. On the contrary, if the ecological environment of a region is unstable and the climate changes more, then the possibility of natural disasters is greater [10]. In order to measure the impact of ecological stability on disaster risk index, we selected three inferior indicators, which are:

Vegetation Coverage (E1): A higher level of vegetation coverage helps reduce soil erosion and the occurrence of natural disasters, thereby indirectly improving the stability of communication infrastructure.

Annual Precipitation (E2): Changes in precipitation levels may affect the interference resistance of communication lines, particularly in mountainous and remote regions.

Biodiversity Index (E3): The diversity of the ecological environment influences the likelihood of disaster occurrences and also affects the disaster resilience of the areas where communication infrastructure is located.

State Assistance

When natural disasters occur, the timely assistance of the state and society will greatly reduce casualties and property losses. Emergency Communication companies should also take this factor into account when making decisions. When the country and society are willing to invest more human and material resources and financial resources to disaster relief, the loss of some natural disasters can be reduced to the minimum. In order to measure the impact of state assistance on disaster risk index, we selected three inferior indicators, which are: State relief funds (S1), Number of relief personnel (S2), Social assistance funds (S3).

In Figure 1, Figure shows the framework of the DRIAM.

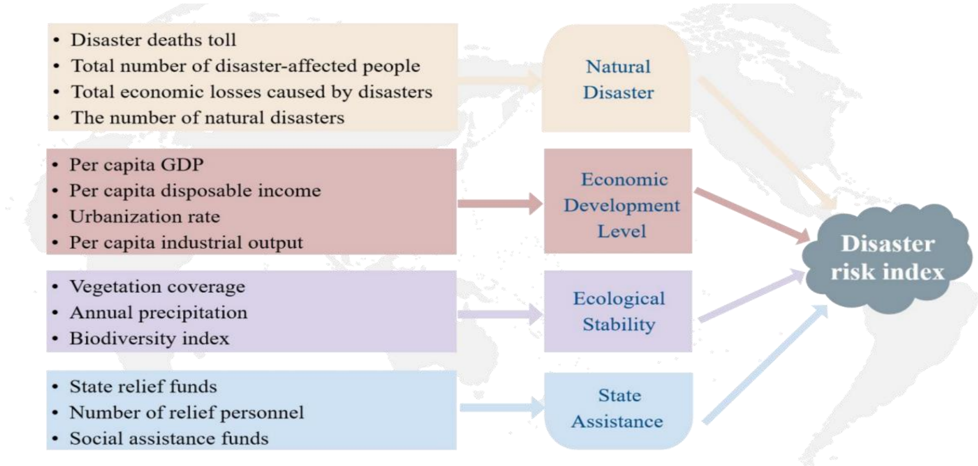

Figure 1. Framework of DRIAM.

Next, we will normalize the data of the indicator. After that, the weights of each superior and inferior indicator will be determined using combination weighting method.

2.1.2. Normalization Inferior Indicators

Inferior indicators need to be transformed into a [0, 1] range for consistency. In addition to this, it's necessary to convert these indicators into benefit-type ones, meaning that higher values should represent better outcomes. To achieve this, we apply various normalization techniques based on the unique characteristics of each indicator. These methods include the logistic function, maximum normalization, moderate normalization, minimum normalization, and fuzzy mathematics' subordinate function. Below, we describe how each method is applied.

(1) Logistic function

This normalization technique is suitable for indicators that do not have a defined upper bound. The normalization follows these principles: as the original value approaches zero, the normalized value should approach zero; conversely, as the original value tends toward infinity, the normalized value should approach one. Additionally, there should be a steep increase in the normalized values when the original values are near zero. To fulfill these requirements, the logistic function is selected as the normalization method.

$$y = \frac{1}{1+e^{-b(x-x_0)}} \tag{1}$$

Where y is the normalized indicator; z is the original indicator; z is the minimum standard of the indicator; b is a parameter to controlz the climbing speed of the normalization function. The value of b will be determined in the solution of model.

(2) Maximum normalization method

This method is used to normalize the benefit-type indicators, like enrolment rate of higher education. The greater the indicator is, the better the situation is. The way to normalize the indicators is:

$$x' = \frac{x}{x_{max}} \tag{2}$$

Where x_{max} is the maximum of the indicator?

(3) Moderate normalization method

This approach bears resemblance to the maximum normalization method. It is specifically applied to the normalization of cost - type indicators. The process of normalizing these indicators is as follows:

$$x' = \frac{|x-x_{op}|}{\max\{|x_{\max}-x_{op}|,|x_{\min}-x_{op}|\}} \tag{3}$$

Where x_{op} is the option value of the indicator?

(4) Subordinate function

This approach serves the purpose of normalizing discrete indicators. These indicators are capable of being categorized into multiple intervals, each associated with a distinct discrete grade. Drawing upon the principles of fuzzy mathematics, we determine the mapping between the value set and the evaluation set as follows:

$$\{Awful, Bad, Normal, Excellent\} = \{1,2,3,4,5\} \tag{4}$$

The partial large Cauchy distribution is determined as:

$$f(x) = \begin{cases} \frac{1}{1+\frac{a}{(x-b)^2}}, 1 \le x < 3 \\ c\ln x + d, 3 \le x \le 5 \end{cases} \tag{5}$$

Here, the parameters of the partial large Cauchy distribution membership function can be determined as:

$$\begin{cases} a = 1.09, b = 0.852 \\ c = 0.375, d = 0.370 \end{cases} \tag{6}$$

By applying these normalization techniques, every single inferior indicator can be effectively normalized. The data that has been normalized then constitutes a Y matrix. At this point, we will not elaborate on the specific methods for each individual inferior indicator.

2.1.3. Determination of the Weights for Indicators

Various methods exist for determining the weights of indicators. To improve the accuracy of our model, we adopt a combination weighting approach to calculate the weights of all indicators. This approach integrates the Analytic Hierarchy Process (AHP), a subjective weighting method, with the Entropy Weight Method (EWM) and the Coefficient of Variation Method (CVM), which are objective weighting methods.

The AHP method, while effective in capturing expert judgment, is inherently subjective and may be influenced by the decision maker's personal biases, making it susceptible to variation. On the other hand, the EWM and CVM methods, though objective, can be highly sensitive to data fluctuations, which may result in errors. Therefore, by combining these methods, the proposed combination weighting approach aims to mitigate potential errors and enhance the precision of the weight determination process.

(1) Analytic Hierarchy Process

First, establish a hierarchical structure model, which is presented in Figure 1.

Next, construct all the judgment matrices within both the superior indicator layer and the inferior indicator layer.

$$\mathrm{A} = \left(\mathrm{a_{ij}}\right)_{\mathrm{n\times n}} \tag{7}$$

In this context, A represents the judgment matrix. The element $\mathrm{a_{ij}}$ denotes the relative importance of z_i with respect tox_j, and n is the number of inferior indicators in each group. Due to space constraints, the judgment matrix will not be presented here.

Subsequently, the weights of each layer are calculated, and a consistency check is carried out. The relevant results are presented as follows.

(2) Entropy Weight Method

Once the normalization process is completed, we obtain the matrix Y. Subsequently, we employ the Entropy Weight Method (EWM) to compute the weights of the inferior indicators, as described in reference [11].

The first step is to calculate the probability matrix $\mathrm{P_{ij}}$. Based on the concepts of self - information and entropy in information theory, we can determine the information entropy Ei for each inferior evaluation indicator. The formula for this calculation is:

$$E_i = -\ln(n)^{-1} \sum_{j=1}^{n} P_{ij} \ln\left(P_{ij}\right) \tag{8}$$

After obtaining the information entropy, we further calculate the weight of each previously defined inferior evaluation indicator using the following

$$w_i = \frac{1-E_i}{k-\sum_i E_i} \quad i = 1,2,\cdots,k \tag{9}$$

(3) Coefficient of Variation Method

In addition, we utilize the Coefficient of Variation Method (CVM) to assign weights to the five superior indicators. Here is a brief introduction to the application of the Coefficient of Variation Method.

The Coefficient of Variation Method makes use of the information from various indicators and determines the weight of each superior indicator by calculating a value. This approach is considered objective as it aims to provide weights based on the inherent characteristics of the data.

Due to the influence of different dimensions, it is challenging to directly compare the superior indicators. Therefore, we use the coefficient of variation of each superior indicator to measure the degree of difference among them. The formula for each indicator can be expressed as:

$$V_i = \frac{\theta_i}{\overline{z_i}} \quad \mathrm{i} = 1,2,3,4,5 \tag{10}$$

(4) Combination weight

We denote the weight calculated by the Analytic Hierarchy Process asW_{i1} . The weights of the inferior indicators calculated by the EWM and the weights of the superior indicators calculated by the Coefficient of Variation Method are denoted asW_{i2}.

The combined weight formula is as follows:

$$W_i = \frac{V_i}{\sum_{i=1}^{n} V_i} \quad i = 1,2,3,4,5 \tag{11}$$

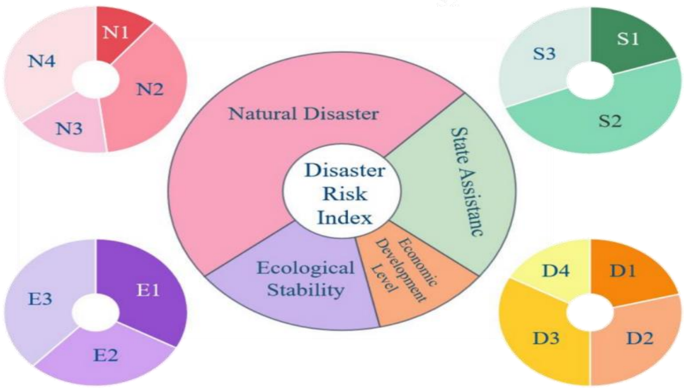

Figure 2. Indicators weights.

2.1.4. Presentation of Disaster Risk Index Assessment Model

We chose 40 countries from different continents and with diverse development statuses as the research subjects to calculate their Disaster Risk Index (DRI).

The TOPSIS comprehensive evaluation method is employed to assess the DRI of these 40 countries. A higher DRI value for a country implies a greater likelihood of experiencing a natural disaster and a higher potential for property damage. We gathered data from these 40 countries and conducted the relevant calculations as described in reference [12].

From the above - mentioned calculations, we obtain a standardized Y matrix, and now we determine the optimal scheme and the worst scheme for each indicator:

The optimal scenario $Y+$ is defined as:

$$Y^+ = (\max\{y_{11}, y_{21}, \cdots, y_{n1}\}, \max\{y_{12}, y_{22}, \cdots, y_{n2}\}, \cdots \max\{y_{1m}, y_{2m}, \cdots, y_{nm}\}) \\ = (Y_1^+, Y_2^+, \cdots, Y_m^+) \tag{13}$$

The worst scenario Y^- is composed of the minimum value of each column element in the Y matrix:

$$Y^- = (\min\{y_{11}, y_{21}, \cdots, y_{n1}\}, \min\{y_{21}, y_{22}, \cdots, y_{n2}\}, \cdots, \min\{y_{1m}, y_{2m}, \cdots, y_{mm}\}) \tag{14}$$

Calculate the proximity of each indicator to the optimal scheme and the worst scheme:

$$D_i^+ = \sqrt{\sum_{j=1}^m w_j \left(Y_j^+ - y_{ij}\right)^2}, |D_i^- = \sqrt{\sum_{j=1}^m w_j \left(Z_j^- - z_{ij}\right)^2} \tag{15}$$

Calculate the closeness of each indicator to the optimal scheme:

$$DRI_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{16}$$

3. Result analysis

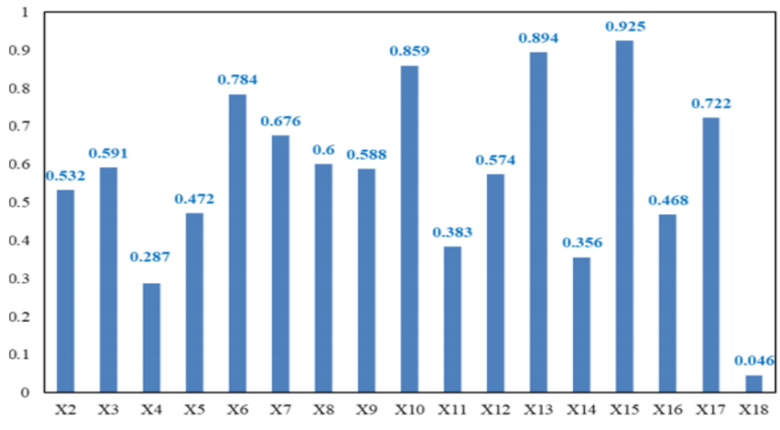

Figure 3. Typical national risk index.

As shown in Figure 3, the disaster risk index of some typical countries is presented.

By inputting data from 40 countries across different continents with varying levels of development into the DRIAM model and using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to calculate the Disaster Risk Index (DRI), the effectiveness and accuracy of the model were thoroughly validated. The calculated disaster risk indices were divided into four levels, which were visually represented in blue (low risk), green (lower risk), yellow (higher risk), and red (high risk). The natural disaster risk levels of the 40 countries are clearly displayed in Figure 4. This color-coding method significantly improves the efficiency of information delivery, allowing decision-makers to quickly grasp the disaster risk profile of each country and then develop more targeted emergency response strategies.

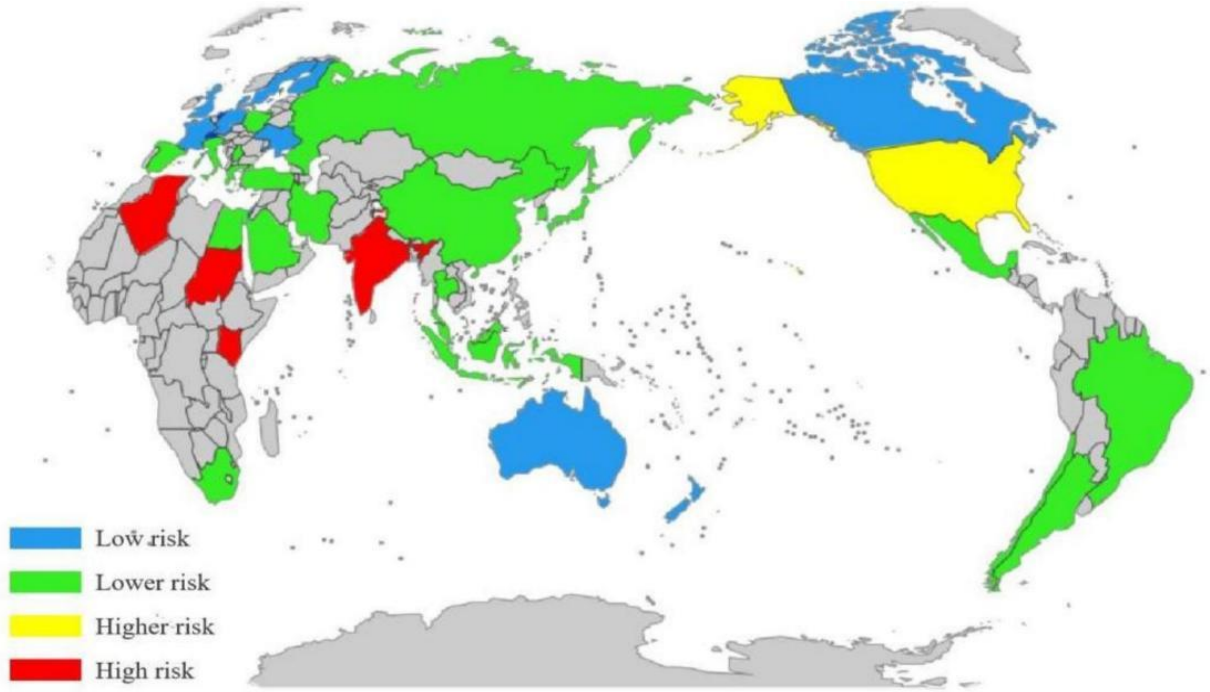

Figure 4. Disaster Risk Levels of 40 Countries.

From the result analysis, there is a significant difference in the disaster risk levels of the 40 countries. To further validate the effectiveness of the model, we conducted a detailed analysis of the indicator data for countries at different risk levels.

In high-risk countries, taking Japan as an example, it is located on the Pacific Ring of Fire, where earthquakes, tsunamis, and other natural disasters frequently occur. From the indicator data, the number of disaster-related deaths (N1) and total economic losses caused by disasters (N3) are at relatively high levels in the statistics. Additionally, due to its developed economy and dense population, the economic development level indicators also increase its potential disaster losses. India and the Philippines are similarly affected by frequent tropical storms, floods, and other disasters, along with high population density and specific economic structures, which together contribute to their high-risk levels in the model evaluation. This aligns closely with the actual situation.

On the other hand, low-risk countries like Canada and Iceland show contrasting characteristics. Canada is vast, with a relatively sparse population, and the frequency of natural disasters is relatively low, resulting in lower values in the natural disaster dimension indicators. Although Iceland experiences frequent geological activities, its advanced disaster warning and response systems, along with outstanding performance in national assistance indicators, effectively reduce the losses caused by disasters, which led to its classification as a low-risk country in the model evaluation.

Further statistical tests were performed to calculate the correlation coefficient between the model's evaluation results and actual disaster occurrences. The results showed a strong positive correlation between the two, fully demonstrating that the DRIAM model can accurately distinguish countries of different risk levels based on multiple factors such as historical disaster records, geographical environment, climate conditions, and national assistance. The model exhibits high differentiation and accuracy in disaster risk assessment, providing solid data support and scientific decision-making guidance for Emergency Communication companies in setting reasonable Emergency Communication rates, government departments in planning disaster prevention and mitigation strategies, and relevant institutions in formulating disaster risk management measures.

In the future, as the global demand for disaster risk assessments continues to grow, this model is expected to be applied and promoted in a broader range of fields, such as Emergency Communication actuarial science, urban planning, and emergency management.

4. Recommendations for Emergency Communication System Construction in High-Risk Areas

Establishing an efficient emergency communication system is crucial in disaster-prone regions. Emergency communication in high-risk areas faces numerous challenges, including vulnerable infrastructure, lack of backup communication channels, insufficient system capacity, and suboptimal human-machine interaction. To address these challenges, this paper proposes four core strategies for the design of emergency communication systems: system robustness, redundancy, adaptability, and availability.

4.1. System Robustness

First and foremost, enhancing system robustness is fundamental to improving disaster response efficiency. Infrastructure in high-risk areas is often damaged during disasters, leading to communication disruptions. Therefore, it is essential to incorporate physical hardening technologies, modular designs, and rapid recovery technologies to enhance the system’s resilience. For example, strengthening the physical structure of communication facilities and improving the recovery capabilities of communication systems can ensure rapid restoration of normal functions during a disaster.

4.2. Redundancy

Redundancy is key to ensuring the continuous operation of the communication system. Multi-channel communication ensures that backup systems can quickly take over when the primary channels fail. The deployment of alternative systems such as satellite phones, radio networks, and mobile communication towers helps maintain communication during disasters. Additionally, ensuring that the power supply to communication facilities is not disrupted by the disaster, through the use of backup power systems, is an integral part of redundancy.

4.3. Adaptability

Adaptability refers to the system’s ability to respond to sudden and dynamic disaster conditions. As disaster environments change rapidly, the communication system must be flexible enough to adjust to evolving demands. For instance, cloud computing platforms can offer on-demand scaling services, while modular designs allow for quick resource adjustments based on the scale of the disaster. A system with high adaptability can improve communication efficiency and ensure timely and effective emergency responses.

4.4. Availability

Lastly, availability emphasizes the user-friendliness of the system. During a disaster, the system should be easy to operate and cater to the needs of diverse user groups, including the elderly, disabled individuals, and those with limited technical skills. Moreover, providing simple interfaces and adequate training ensures that all stakeholders can quickly and effectively use emergency communication tools in critical situations, thereby enhancing the overall effectiveness of the system.

5. Conclusions

This study constructs the DRIAM model based on emergency communication and telecommunications engineering knowledge, integrating 14 secondary indicators across four dimensions: natural disasters, economic development, environmental stability, and national assistance. The model not only encompasses core factors influencing disaster risk but also considers emergency communication infrastructure, information transmission efficiency, and post-disaster recovery capabilities, with a particular emphasis on the role of national assistance and communication support. This enables the model to accurately reflect differences in emergency communication capabilities across countries, providing a comprehensive perspective for disaster response decision-making.

5.1. Scientific Weight Determination Method

The weight determination method combines Analytic Hierarchy Process (AHP), Entropy Weight Method (EWM), and Coefficient of Variation Method (CVM), integrating subjective and objective approaches. This combination avoids bias from a single method and ensures a scientifically reasonable weight distribution for the model, accurately reflecting the critical role of emergency communication systems in disaster management. For instance, weight allocation in areas like information transmission speed, network coverage, and communication equipment reliability provides effective support for assessing communication factors in disaster risk.

5.2. Model Effectiveness and Practical Value

By applying data from 40 countries and using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), the model accurately differentiates countries' disaster emergency communication capabilities and overall disaster risk management levels. The model demonstrates high discriminatory power in practical applications, offering valuable decision-making support for Emergency Communication companies, government agencies, and telecom operators, especially in planning post-disaster communication recovery and optimizing emergency communication networks. As disaster frequency increases and emergency communication demands evolve, this model will enhance global disaster emergency communication response capabilities.

5.3. Implications for Future Research

This study provides a new framework and methodology for disaster risk assessment in the field of emergency communication. Future research can expand upon this model by incorporating cutting-edge technologies in telecommunications, such as 5G, satellite communication, and IoT, for more precise spatiotemporal analysis. Additionally, exploring the integration of climate change impacts on disaster risk and the sustainability of communication infrastructure will help develop disaster emergency communication systems better suited to future needs. These efforts will strengthen communication resilience and emergency response capabilities in the face of natural disasters worldwide.

References

[1] Li, Q., Zhang, M., & Wang, L. Fuzzy comprehensive evaluation method for disaster risk in China. Natural Hazards, 2017,85(2), 121-136

[2] UNDP (United Nations Development Programme). Human Development Report 2016: Human Development for Everyone. UNDP, 2016.

[3] Aldunce, P., Beilin, R., & Mertens, F. The evolving approach to disaster risk management: From integrated risk management to holistic approaches. Disasters, 2016, 40(3), 563-586.

[4] Yue, Y. J., Wang, J. A., Zou, X. Y., & Shi, P. Risk assessment of aeolian sand disaster on cities in sandy areas of Northern China based on RS, GIS, and models. Journal of Natural Disasters, 2008.

[5] Lu, Y., Zhai, G., & Zhou, S. An integrated Bayesian networks and Geographic Information System (BNs-GIS) approach for flood disaster risk assessment: A case study of Yinchuan, China. Ecological Indicators, 2024.

[6] Ma, G., Zhang, J., Jiang, W., Liu, J., & Li, Z. GIS-based risk assessment model for flood disaster in China. In Proceedings of the 18th International Conference on Geoinformatics, 2010.

[7] UNISDR.Sendai *Framework for Disaster Risk Reduction 2015-2030*. United Nations Office for Disaster Risk Reduction.

[8] Dalal S, Bassu D. Deep Analytics for Workplace Risk and Disaster Management [J].Ibm Journal of Research and Development, 2019, PP(99):1-1.

[9] Tang A P, Wen A H. Earthquake Disaster Managemf Zhengzhou, China. Natural Hazards and Risk, Tayloent and Emergency Communication [J]. Progress in Earth science, 2004(S1):8.

[10] Xin J, Huang C. Fire risk analysis of residential buildings based on scenario clusters and its application in fire risk management[J].Fire Safety Journal, 2013, 62(pt.A):72-78.

[11] Peng J. Modeling natural disaster risk management: Integrating the roles of Emergency Communication and retrofit and multiple stakeholder perspectives. [D].University of Delaware. 2013.

[12] King R O. Tsunamis and earthquakes: is federal disaster Emergency Communication in our future? [J].Congressional Research Service, Library of Congress, 2015.