Fractional Linear Regression Equation in Agricultural Disaster Assessment Model Based on Geographic Information System Analysis Technology

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Abstract

This article combines geographic information system (GIS) technology and database technology to analyse agricultural, natural disasters. The article uses a fractional linear regression equation to define the comprehensive intensity grading standard of the disaster-causing factors of torrential rain. At the same time, we use GIS to superimpose the agricultural vulnerability index into the storm disaster risk zoning to obtain the degree of agricultural impact under different levels of risk. At the end of the thesis, the model is applied to actual case analysis to verify the effectiveness of the algorithm model.

Keywords: Heavy rain, hazard factors, geographic information system, disaster risk, fractional linear regression equation, quantitative evaluation

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1 Introduction

Global warming has led to an increase in the frequency of burdensome precipitation events in most regions. The torrential rains and floods caused by weighty rainfall have caused significant economic losses to the country.
and people. In addition, heavy rains and floods have directly harmed agricultural production and output and caused huge losses.

Foreign scholars have done a lot of research on the methods of storm disaster risk assessment. They believe that the formation of disasters results from the comprehensive effects of the carrier’s vulnerability, hazards and exposure [1]. The risk assessment method proposed by scholars has certain practicability. Domestic research on torrential rain disasters mainly focuses on disaster-causing indicators, risk assessment models and zoning methods. Many studies use the frequency of heavy rain disasters as disaster indicators for risk assessment. This method can only describe the number of disasters singly and cannot efficiently assess the degree of risk of disasters. The disaster indicators of torrential rains must consider the type of area, intensity, and duration of occurrence to have pertinence and practical guiding significance. Disaster risk assessment is a complicated process, and most researches focus on establishing rainstorm risk assessment models. Some scholars obtained the evaluation model of Weifang City’s agricultural economic loss rate based on the disaster loss rate index and the comprehensive disaster evaluation index combined with geographic information system (GIS) technology. Some scholars have combined the catastrophe assessment method to assess the risk of rainstorm disasters in the Songhua River mainstream. Some others comprehensively consider disaster-causing factors, disaster-bearing bodies and disaster prevention capabilities to build a model to assess the risk of heavy rain disasters in Fujian Province. Still others established an evaluation model for hazard factors, hazard-pregnant environment, risk exposure factors, and disaster loss coefficients. We selected two cases of heavy rain in Beijing for evaluation, and the effect was significant. The predecessor’s research results laid the foundation for the theoretical research and business application of storm disaster risk assessment technology. However, the rainstorm disaster risk assessment has prominent regional characteristics. According to local conditions, selecting risk assessment factors and conducting quantitative grading assessments can increase the practicability of storm disaster risk and impact assessment.

Because of this, this study comprehensively considered the type of rainfall area, the intensity, and duration of the rainfall and determined the disaster-causing index of the rainstorm disaster. We combined the environmental vulnerability factors such as terrain elevation, elevation standard deviation, river network density, etc., into the cause of storm disaster to establish a storm disaster risk assessment model. We carried out grading assessments of rainstorm disasters [2]. For the agriculture most severely affected by rainstorms, we also applied GIS technology to superimpose data such as agricultural population, economic density, and agricultural planting area into the risk assessment to obtain the spatial distribution characteristics of the impact of rainstorms on agriculture in the province. In the end, the paper studied the “‘7.19’ heavy rain event in Hebei Province in 2017 as an example, application and test aimed at a more accurate assessment of the risk of heavy rain disaster and agricultural impact. This article provides a timely and efficient scientific basis for disaster relief decision-making and post-disaster reconstruction.

2 Materials and methods

2.1 General information

The rainfall data comes from 975 stations in Hebei Province. Topographic data is provided by the National Basic Geographic Information Center (NGCC). The water system data adopts the 1:50,000 perennial river data provided by the Basic Geographic Information Center. Primary data (economy, population, an agricultural area, etc.) come from the Hebei Provincial Bureau of Statistics.
2.2 Research methods

2.2.1 Comprehensive Index of Rainfall Intensity

The disaster index of rainstorm disaster considers the type, intensity and duration of rainfall area. According to the temporal and spatial distribution of rainfall in China and the vulnerability of the environment for rainstorm disasters, we divide China into four types of rainstorm-sensitive areas, and Hebei Province belongs to the third type [3]. On this basis, we comprehensively consider the rainfall intensity and duration to calculate a comprehensive rainfall intensity index:

\[ RSI = I \times T \] (1)

In the formula, RSI is the comprehensive index of rainfall intensity. \( I \) is the rainfall intensity index. \( T \) is the rain duration index. The evaluation standard of rainfall intensity index and rainfall duration index refers to literature (see Tables 1 and 2).

| Table 1 Evaluation standard of daily precipitation intensity index |
|---------------------------------------------------------------|
| **Daily Precipitation Intensity Index** | **24 h rainfall/mm** |
| 1 | ≥ 80.0 |
| 2 | 60.0–79.9 |
| 3 | 40.0–59.9 |
| 4 | 20.0–39.9 |

| Table 2 Rainfall duration index assignment standard |
|--------------------------------------------------|
| **Rain duration index** | **Number of consecutive rainy days/d** |
| 1 | ≥ 6 |
| 2 | 4 ≤ T < 6 |
| 3 | 2 ≤ T < 4 |
| 4 | <2 |

We use formula (1) to calculate the comprehensive index of rainfall intensity. See Table 3 for grading standards.

| Table 3 Grading Standard of Comprehensive Rainfall Intensity Index |
|---------------------------------------------------------------|
| **Grading standards** | **Rain intensity index** |
| Super strong | 1 ≤ RSI ≤ 4 |
| Strong | 4 < RSI ≤ 8 |
| Stronger | 8 < RSI ≤ 12 |
| Medium | 12 < RSI ≤ 16 |

2.2.2 Heavy rain disaster sensitivity index

In the case of disasters of the same intensity, the higher the sensitivity, the heavier the damage caused by meteorological disasters, and the greater the risk of disasters [4]. From the analysis of the causes of rainstorm disasters, it is found that the sensitivity index mainly considers terrain elevation, elevation standard deviation, and river network density closely related to rainstorm disasters.

1. Topographic factors. Topographic factors include elevation and elevation standard deviation. Among them, the standard deviation of elevation represents the degree of change of topography. For example,
surface runoff always gathers in low-lying land. Therefore, the lower the elevation and the smaller the elevation standard deviation, the higher the risk of heavy rain disasters [5]. According to the literature research results and the actual situation of Hebei Province, the grading standard of the terrain elevation and the standard deviation of the elevation is determined in Table 4.

| Terrain elevation/m | Elevation standard deviation/m |
|---------------------|-------------------------------|
| ≤ 100              | 0.9                           |
| 100–300            | 0.8                           |
| 300–700            | 0.7                           |
| ≥ 700              | 0.6                           |

2. River network density. The denser the river network and the closer to the river, the greater the risk of heavy rain disasters. Short-term heavy rainfall can easily cause river water to overflow and inundate surrounding land and farmland [6]. Therefore, the river network density is an essential disaster-generating environment for the formation of torrential rain disasters. In this study, the river network density is based on the river data provided by the Geographic Information Center, which is calculated in GIS.

The environmental sensitivity of rainstorm disasters is a careful consideration of terrain factors and river network density. We standardise the terrain factor and river network density separately and use the weighted summation method to obtain the sensitivity index. According to the importance of each factor to the rainstorm disaster and the expert’s scoring results, the weight coefficients are respectively 0.6 (topographic factor) and 0.4 (river network density):

\[
V_H = D \times 0.6 + H \times 0.4
\]

In the formula, \(V_H\) is the sensitive index of rainstorm disasters. \(D\) is the terrain factor, and the grading assignment is obtained from Table 4. \(H\) is the river network density, calculated in GIS.

2.2.3 Heavy rain disaster risk assessment model

The storm disaster risk comprehensively considers both the hazard factors and the hazard-pregnant environment. If the disaster-causing factors of heavy rain are dangerous, and the disaster-pregnant environment is not conducive to the occurrence of heavy rain disasters. If the hazard factor is less dangerous, the risk of a rainstorm disaster is higher than simply considering the hazard factor. This will also cause severe rainstorms [7]. Therefore, we use the weighted quadrature method to form the rainstorm disaster risk index of the hazard factors and the sensitivity of the hazard environment. The calculation is as follows:

\[
F = RSI \omega_1 \times V_H \omega_2
\]

In the formula: \(F\) is the rainstorm disaster risk index. \(RSI\) is the rainfall intensity comprehensive index. Its calculation method is shown in formula (1). \(V_H\) is the sensitivity index, and the calculation method is shown in formula (2). \(\omega_1\) and \(\omega_2\) are weight coefficients determined by experts. To eliminate the difference in dimension and magnitude of each factor, we normalised the factors involved in the calculation. The calculated results have been tested and repeatedly adjusted. Finally, five levels of heavy rain disasters are determined: extremely high-risk area, high-risk area, high-risk area, medium risk area and low-risk area.

2.2.4 Agricultural impact assessment of heavy rain disaster

Based on the rainstorm disaster risk assessment, we have graded and assessed the severity of agricultural impacts across the province. Under the same level of rainstorm disaster risk level, the denser the agricultural population, the higher the agricultural production value, and the larger the agricultural planting area, the more...
severe the damage to the agriculture by the rainstorm disaster \[8\]. In summary, we obtained three vulnerability indicators according to Hebei Provincial Statistics Bureau: agricultural economic density (agricultural GDP/agricultural area), agricultural population density (agricultural population/land area), and the proportion of crop sown (crop sown area/land area). After normalising each factor, we calculate the agricultural vulnerability index using a weighted sum method. Based on the importance of each factor to the rainstorm disaster and the expert scoring demonstration, the paper determines the weighting coefficients to be 0.2 (agricultural economic density), 0.4 (crop sowing proportion), and 0.4 (agricultural population density). The calculation formula is as follows:

\[
VS = G \times 0.2 + D \times 0.4 + R \times 0.4
\]  

Where \(VS\) is the agricultural vulnerability index, \(g\) is the density of the agricultural economy, \(D\) is the planting proportion of crops, \(R\) is the agricultural population density. After calculating the agricultural vulnerability index, we normalise it and superimpose the agricultural vulnerability index based on the rainstorm disaster risk zoning to obtain the rainstorm disaster agricultural impact zoning.

2.3 Fractional linear regression equation

2.3.1 Criteria for the selection of independent variables

According to empirical analysis, we assume that there is \(m\) independent variables that affect the response variable \(y\), which is recorded as \(x_1, x_2, x_3, \cdots, x_m\). For any subset \(\{x_i_1, x_i_2, x_i_3, \cdots, x_i_p\}, 1 \leq p \leq m\) of the independent variable set \(\{x_1, x_2, x_3, \cdots, x_m\}\). How to evaluate the effect of the regression equation established by this subset and the dependent variable? It is true that the residual sum of squares \(S_E\) reflects how well the linear regression equation fits the actual data. But according to the principle of least squares estimation, when we construct the regression equation, every time we increase the value of the independent variable \(S\), the residual sum of squares corresponding to \(p\) independent variables decreases. And \(S_E\) decreases at a faster rate, so MSE shows a downward trend. When the number of independent variables \(p\) reaches a specific number, the decrease speed of \(S_E\) slows down, which is slower than the change of \(n - p - 1\), which leads to an upward trend of MSE. Thus, changing the criterion is consistent with maximising the adjustment coefficient of determination \(R^2 = 1 - \frac{S_E/n - p - 1}{S_T/n - 1}\).

Criterion 1: The mean square error is the smallest.

The mean square error \(MSE = \frac{S_E}{n - p - 1}\) is the average of \(S_E\) and its degrees of freedom \(n - p - 1\). When there are fewer independent variables, as the number of independent variables \(p\) increases, \(n - p - 1\) gradually decreases. And \(S_E\) decreases at a faster rate, so MSE shows a downward trend. When the number of independent variables \(p\) reaches a specific number, the decrease speed of \(S_E\) slows down, which is slower than the change of \(n - p - 1\), which leads to an upward trend of MSE. Thus, changing the criterion is consistent with maximising the adjustment coefficient of determination \(R^2 = 1 - \frac{S_E/n - p - 1}{S_T/n - 1}\).

Criterion 2: The \(C_p\) statistic is minimised.

Maslow proposed this criterion from the perspective of prediction in 1964.

\[
C_p = \frac{(n - m - 1)S_E^{(p)}}{S_E^{(m)}} + 2p - n
\]

Where \(S_E^{(m)}\) is \(m\) independent variables. \(x_1, x_2, x_3, \cdots, x_m\) corresponds to the residual sum of squares. \(S_E^{(p)}\) is the residual sum of squares corresponding to \(p\) independent variables \(\{x_i_1, x_i_2, x_i_3, \cdots, x_i_p\}\).

Criterion 3: AIC Criterion.

Japanese statistician Akaike Hiroji proposed in 1974 based on the principle of maximum likelihood estimation:

\[
AIC = n \ln(S_E) + 2p
\]
2.3.2 Choosing the optimal regression equation

We set the independent variable that affects the variable $y$ as $x_1, x_2, x_3, \ldots, x_m$. Any subset of the independent variable set $\{x_1, x_2, x_3, \ldots, x_m\}$ (containing at least 1 independent variable) and $y$ establish a regression equation. We can find an optimal regression equation by comparing it according to the criteria introduced above. Since there are $m$ independent variables, there are a total of $C_m^p (1 \leq p \leq m)$ equations with the number of independent variables $p$. To find the optimal regression equation, the number of regression equations we need to compare is:

$$C_m^1 + C_m^2 + C_m^3 + \cdots + C_m^m = 2^m - 1$$

(7)

2.3.3 Stepwise regression

Step 1: We establish $m$ one-variable regression equations with $m$ independent variables $x_1, x_2, x_3, \ldots, x_m$ and $y$ respectively, and calculate the F-test statistic value of the regression coefficients corresponding to each independent variable, denoted as $F_1^1 + F_2^1 + F_3^1, \ldots, F_m^1$. We set $F_i^1 = \max\{F_1^1 + F_2^1 + F_3^1, \ldots, F_m^1\}$. For a predetermined significance level $\alpha$, the critical value $F_\alpha(1, n-2)$ is known. If $F_i^1 \geq F_\alpha(1, n-2)$, then introduce its corresponding variable $F_i^1$ into the regression equation. Otherwise, end variable selection.

Step 2: We establish $m-1$ binary linear regression equations with the selected independent variable subset $\{x_{i_1}\}$ and the remaining independent variable $x_j (1 \leq j \leq m, j \neq i_1)$, respectively with the dependent variable $y$. Calculate the $F_j^2 \geq F_\alpha(1, n-3)$ statistic value $F_j^2 (j = 1, 2, \ldots, j \neq i_1)$ in the same way. We set $F_j^2 = \max\{F_1^2 + F_2^2 + F_3^2, \ldots, F_m^2\}$. If $F_j^2 \geq F_\alpha(1, n-3)$, then introduce the corresponding variable $x_j^2$ into the regression equation. At this time, the selected independent variable subset is $\{x_{i_1}, x_j^2\}$. Otherwise, the variable selection ends.

Step 3: We repeat the selected independent variable subset $\{x_{i_1}, x_j^2\}$ following Step 2 until there are no variables introduced into the equation. In this way, a subset of the independent variables selected according to the forward method is obtained.

3 Example application and inspection

From 08:00 on July 18 to 08:00 on July 21, 2017, Hebei Province experienced the most extensive rainstorm to heavy rain in the past 5 years from the southwest to the northeast. Precipitation started in Handan on the morning of July 18 and ended in Chengde in the early hours of the 21st. The heavy rainfall stage was mainly concentrated on July 19. This torrential rain is called the ‘7.19’ torrential rain event [10]. This article uses this as an example to evaluate and test the disaster risk and agricultural impact of heavy rains.

3.1 The actual rainfall and the division of the comprehensive index of rainfall intensity

Based on rainfall data, we analysed the spatial distribution of the “7.19” rainfall process in Hebei Province in 2017 (Figure 1). Accumulative rainfall exceeds 50mm in most parts of the province, including Shijiazhang and Baoding, southwestern Xingtai and Handan, northern Zhangjiakou, Chengde, most of Hengshui, most of Langfang. The accumulated rainfall is more significant than 100mm. The cumulative rainfall in parts of Qinhuangdao and Cangzhou, and parts of Tangshan exceeded 250 mm.

According to the intensity grading standard of the disaster-causing factors of heavy rain (Table 3), we get the spatial distribution pattern of the comprehensive intensity of heavy rain (Figure 2). The distribution map of the comprehensive intensity level of heavy rain is consistent with the existing distribution law of rainfall (Figure 1). During this heavy rain, the total rainfall intensity in most parts of the province was medium and above [11]. Among them, Handan, Xingtai, Shijiazhuang, Baoding, Langfang, Cangzhou and Hengshui are solid. On the other hand, the rainfall in most parts of Zhangjiakou, Chengde and Qinhuangdao is relatively low and has not yet reached the torrential rain level.
3.2 Rainstorm disaster risk assessment

We combined the above comprehensive index of rainstorm intensity with the environmental data (including elevation, the standard deviation of elevation, and river network density) of the disaster-causing environment in various places in Liaoning. According to formula (3), the disaster risk index of this rainfall process was calculated and analysed. We determined the distribution of five risk areas of the "7.19" rainstorm disaster, as shown in Figure 3. Most areas of Liaoning have higher and higher risk areas [12]. Among them, Tangshan, Shijiazhuang, Baoding, most of Cangzhou, Handan, and most of Langfang have extremely high rainstorm risk levels. On the other hand, for places such as the northeast of Zhangjiakou and Chengde, the eastern part of
Qinhuangdao, and some areas of Hengshui, where the comprehensive intensity of heavy rain is powerful. The risk level is lowered because of the low vulnerability of local environmental factors, topography, river density, and other factors that are not conducive to heavy rain disasters.

Fig. 3 Risk assessment of heavy rain disaster in Hebei Province from 08:00 on July 18 to 08:00 on July 21, 2017

3.3 Assessment of the agricultural impact of heavy rain disasters

The agricultural impact assessment of rainstorm disasters is based on the careful consideration of agricultural vulnerability factors based on the risk of rainstorm disasters, including statistical data such as agricultural

Fig. 4 Agricultural impact assessment of heavy rain disaster in Hebei Province from 08:00 on July 18 to 08:00 on July 21, 2017
population density, agricultural economic density, crop planting proportion, and land use in various regions. We superimposed the vulnerability factor into the storm disaster risk zoning and calculated the impact of the "7.19" storm disaster on agriculture in different regions (Figure 4). It can be seen from the figure that most of Shijiazhuang, the western part of Tangshan, part of Baoding, most of Handan, part of Cangzhou, and part of Langfang are agricultural affected areas above the level of heavy rain disasters. This indicates that agriculture in the areas mentioned above has been severely affected. As for the severe rain disaster risk intensity in Baoding and the Shijiazhuang area, the agricultural impact intensity is reduced to medium because the agricultural population density in the areas mentioned above is smaller than in other areas. In addition, the proportion of agricultural planting is relatively small [13]. Therefore, in the same rainstorm risk level, the agricultural losses that may be caused are relatively small.

3.4 Inspection of evaluation results

This article analyses rainfall intensity, rainstorm disaster risk assessment, and agricultural impact assessment distribution rules and characteristics for the "7.19" rainstorm event in Hebei Province. The research results are consistent with the actual situation of the rainstorm disaster. According to the statistics and analysis of the Hebei Meteorological Bureau, the "7.19" rainstorm is the process from the most extensive rainstorm to the extreme rainstorm in the past four years. The whole area of Handan and Shijiazhuang City experienced extreme rainstorms. Heavy rains occurred in Baoding, the eastern part of Xingtai, Hengshui, Cangzhou, Shijiazhuang southern Langfang. Figure 2 can better reflect the hazards of rainstorm disasters, and the areas with higher rainfall comprehensive intensity levels are consistent with the rainstorm facts [14]. The heavy rainfall caused waterlogging in farmland in the disaster-stricken cities, and the direct economic loss caused by the heavy rain disaster was 663 million Yuan. Among them, the direct economic loss of agriculture is 320 million Yuan. The direct economic loss of industrial transportation is 225 million Yuan, and the direct economic loss of water conservancy projects is 118 million Yuan. Xingtai, Hengshui, Cangzhou, Shijiazhuang, and other places have experienced torrential rains to varying degrees. Among them, with the most significant rainfall, Baoding was the hardest-hit area, with a total of 217,100 people affected. The high-value areas of heavy rain disaster risk assessment (Figure 3) and agricultural impact assessment (Figure 4) are more consistent with the actual disaster situation.

4 Conclusion

Based on GIS and fractional linear regression equations, this paper establishes a rainstorm disaster risk assessment model. It obtains the degree of agricultural disasters in different regions by superimposing agricultural vulnerability indicators. We used the "7.21" heavy rain event in Hebei Province in 2016 to conduct a case analysis. The assessment results obtained were consistent with the actual situation of the heavy rain disaster. In addition to the formation of rainstorms, disasters are closely related to rainfall conditions. Factors such as topographical factors, river network density, soil and soil quality, vegetation conditions, drainage status, and river siltation are also important.

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