Research on Amazon Forest Fire Based on Cellular Automata Simulation

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Abstract—**Wildfire, especially uncontrolled flammable vegetation hazard in rural or wilderness areas, seriously affected human life and safety, prediction methods has been researched widely in recent decades. According to Amazon forest fire situation, an advanced system hierarchical clustering model is established in this paper, and the diffusion simulations of Amazon forest fire is implemented by using the cellular automata model, which constructed with the previous model. Then, the diffusion speed and diffusion range of different brightness parameters are analyzed. Furthermore, combined with the three-dimensional effect of fire and smoke simulated by particle system, the entropy weight TOPSIS model is constructed to the optimized ranking of wildfire risk index with its longitude and latitude, and obtain the relationship diagram of latitude, longitude and wildfire risk index after extracting data. The feasibility and rationality of the proposed method is verified by simulation results.**

Keywords-advanced system hierarchical clustering model; cellular automata; entropy weight TOPSIS; outlier analysis; particle system simulation

I. INTRODUCTION

Extreme events occur for wildfire from time to time, although the burning area of only 3-5% of wildfires exceeds 100 hectares[1]. However, the burning area of the top 1% of wildfires accounts for 80-96%. Nowadays, communities around the world are currently at risk of massive, severe wildfires that directly threaten people and bring life-threatening impacts on air quality, water availability and quality, as well as soil integrity. After the devastating wildfire season in the United States in 2000, a new term "megafire" was coined. The impact or severity of wildfires on society has reached a new level. In fact, in Western states, the frequency of wildfires has been increasing. Statistical analysis of a wide range of areas shows the relationship between the acres burned and its intuitively favorable conditions for fire occurrence. These views lead to the general attribution of large-scale fires[2]. More speculatively, individual fires are attributed to climate change and fuel accumulation. The understanding and prediction of large-scale wildfire events in the world is a developing interdisciplinary research field, which develops rapidly with the development and application of computational models. Recent two-way coupled computational fluid dynamics models, including weather forecasting models and modules, are equipped with algorithms representing fire spread and heat release, simulating the interactions of the fire atmosphere across three orders of magnitude.(The data used in this article comes from this website:http://mcm.tzmcm.cn/).

At present, fire diffusion prediction is used mostly in indoor, ships, high-rise buildings and other scenes, but rarely in natural scenes. The main causes lie in that many factors in the natural environment lead to a complex and nonlinear change process of fire diffusion. Yang Jun et al simulated land-use change through the cellular automata model, and the experimental results were accurate[3]. Therefore, cellular automata are suitable for complex system simulation. According to these, this paper proposes a method to study forest fire diffusion in Amazon based on cellular automata simulation. This method avoids the subjectivity of data, that is, no objective functions and tests are needed. Also, it can well describe the comprehensive influence intensity of multiple indexes

II. ESTABLISH THE HIERARCHICAL CLUSTERING MODEL OF ADVANCED SYSTEM

According to the elbow method, we can roughly estimate the optimal number of clusters through graphs.

Supposing that n samples in total were divided into K classes ($k \le n-1$, that is, there is at least a class with two elements), C_k was used to define the k-th class ($k=1,...,K$), and u_k was used to refer to its center of gravity. The degree of distortion is known for each class of the class is equal to the sum of squares of the distance from the center of gravity and its position of internal members, then the distortion of the k-th class is as follows:

$$\sum_{i\in C_k} \left|x_i - u_k\right|^2 \tag{1}$$

The total distortion degree (polymerization coefficient) of all classes was defined as:

$$J = \sum_{k=1}^{K} \sum_{i\in C_k} | x_i - u_k |^2 \tag{2}$$

Supposing the horizontal coordinate as the number of clustering classes K, the vertical coordinate as the polymerization coefficient J, then the polymerization coefficient line graph was made and shown in Fig. 1:

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As shown in Fig. 1, a significant change occurs at K=6, and the number of clustering classes was determined as 3.

After determining the number of clustering classes, the new class sequentially combined by two classes with short distance constantly iterates, and the final classification result was shown in the ice chart:

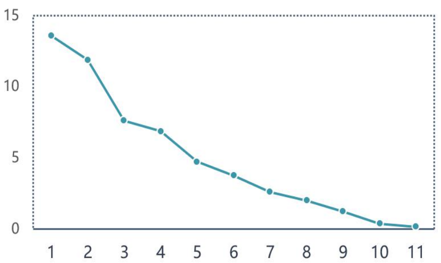

Figure 1. Polymerization coefficient line graph

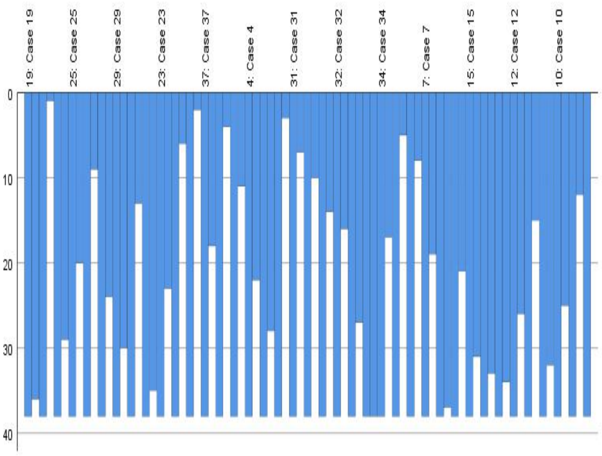

Figure 2. Ice chart

Therefore, the data extraction section can be substantially clustered into 4 groups, that is, four sets of variables. The four sets of variables were substituted into the correlation coefficient equation:

$$r_s = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \tag{3}$$

Since there may be an over-fitting phenomenon in the calculation process, so the cross-test was conducted.

TABLE I. CROSS-TEST RESULTS TABLE

CV Accuracy Scores	0.987	0.965	0.943	0.935	0.998	0.924	0.976	0.934	0.937	0.978
CV Accuracy	0.95	+/-	0.035							

As shown in Table 1, the cross-test accuracy of this model fluctuates between 0.950.035, indicating that the model test results are good.

III. FIRE POINTS DISTRIBUTION

A confidence interval of more than 80% was chosen and points planning with distance less than 1km within 24 hours were proposed as follows.

$$\begin{cases} T_{20} \ge 315 \\ 20 + T_S \le T_{20} \le 70 + T_S \\ T_{20} - T_{31} \ge 18 \end{cases} \tag{4}$$

T_{20} and T_{31} were used as the brightness of channels 20 and 31; TS was used for the ground temperature with the unit of K.

IV. PARTICLE SYSTEM SIMULATION

The three-dimensional effect of fire and smoke was simulated using a particle system.As a professional three-dimensional simulation platform, Unity3D itself provides a rich library of vegetation and particle systems, which provided the conditions for the simulation of flame and smoke. Steps of realizing the visual three-dimensional effect of fire and smoke using Unity 3D were shown as follows:

A. Establish templates of fire and smoke particles with a given particle life cycle, size, color and transparent Alpha channel value.

B. Set up the location of the fire and smoke particles and initialize the emission rate and the number of particles through simulating the regional digital terrain information.

C. Control the generation and die of particles using life cycle according to the forest fire spread speed and accordingly update the apparent characteristics and attributes to realize the visual three-dimensional dynamic movement of fire and smoke.

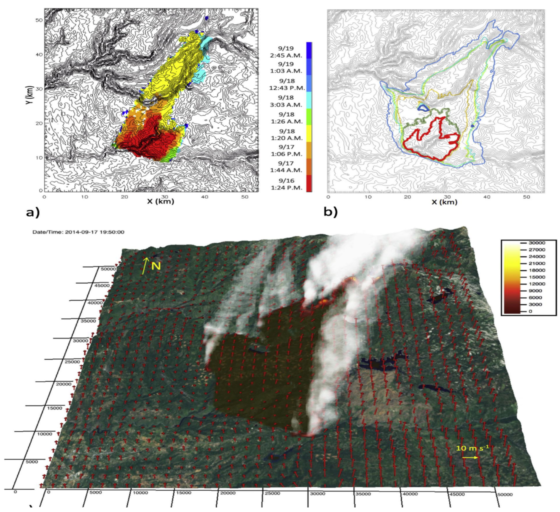

Figure 3. Visual three-dimensional dynamics of fir and smoke based on particle system.

From Fig. 5, it can be seen that the relationship between these two parameters and wildfire index is not only valid, but positive and negative, in which two indexes are used to construct the cell space.

V. CELLULAR AUTOMATA & ENTROPY TOPSIS MODEL

MATLAB was used to demonstrate Amazon forest fires and analyze them spatially.The cellular automata model of forest fire has three states: vacancy, burning trees and trees. Then the state of a cell at the next moment is determined by its state at that moment and the states of four surrounding neighbors according to certain rules, and the rules are set as follows:

- If four neighbors of a tree cellular are burning, then the state of the cellular at the next moment is still burning.
- A burning cellular becomes the number of vacancies (n) at the next moment.
- All tree cellular start burning with a low probability (to simulate the fire P caused by lightning).
- All vacant cellular become trees with a low probability (to simulate the growth of new trees).
- Fire brightness (T) detected by Brightness Satellite

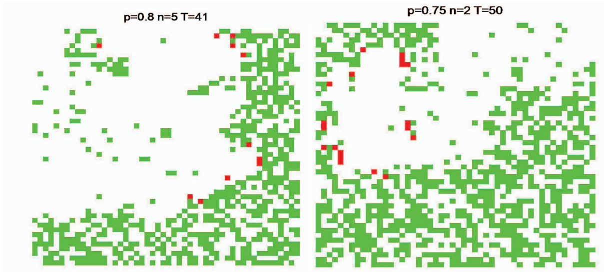

Figure 4. Distribution diagram of the wildfire risk index

The higher the probability of lightning splitting trees is and the more the surrounding vacancies are, the more intense the fire hazard will be and the higher the wildfire risk index will be.

The advanced simulation effect diagram after adding wind speed and brightness is shown as follows:

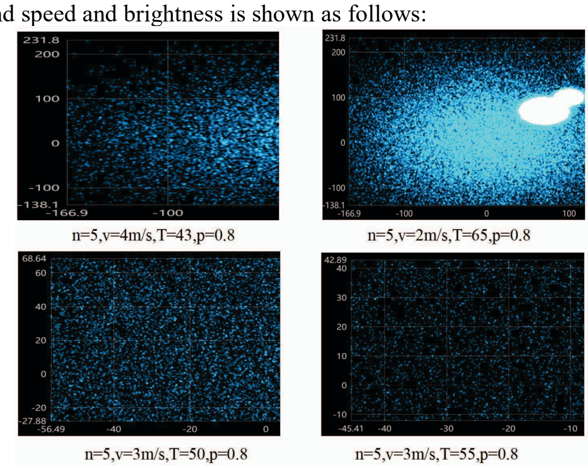

Figure 5. Advanced simulation effect diagram after adding wind speed and brightness

Through cleaning the six sets of simulation charts, the spatial changes of fire diffusion. The stronger the brightness and wind detected by satellite are, the higher the wildfire risk index and the faster the spatial diffusion of fire will be; The more intensive the fire points are, the weaker the brightness and the spatial diffusion, and the lower the wildfire risk index will be.

Then, the entropy weight TOPSIS model was constructed to sort the wildfire risk index in different latitude and longitude spaces according to the simulation results. After standardizing the data, the TOPSIS method was used to construct positive and negative ideal solutions; and then according to multiple attributes, comprehensive evaluation values are given to regions to divide regional weights.

A. Construct the scheme set, attribute set and decision matrix[6].

Supposing the scheme set as $S=\{S_1,S_2,...,S_m\}$, the attribute set as $P=\{P_1,P_2,...,P_n\}$, the attribute set including benefit attribute, that is, the bigger the attribute value is, the better the index will be, and cost attribute, that is, the smaller the attribute value is, the better the index will be; as well as the multi-attribute decision-making matrix $X=(x_{ij})_{m\times n}$, of which x_{ij} is the index value of the *j*-th attribute of the *i* scheme, $i=1,2,...m,\ j=1,2,...,n.$

B. Solve the standardization decision-making matrix.

The method of vector planning was used to design the standardization decision-making matrix $Y=(y_{ij})_{m\times n}$, among them:

$$y_{ij}=\frac{x_{ij}}{\sqrt{\sum_{i=1}^{m}x_{ij}^2}},i=1,2,...,m,\ j=1,2,...,n \tag{7}$$

C. Determine the factor weight.

The characteristic proportion of the index is:

$$f_{ij}=\frac{y_{ij}}{\sum_{j=1}^{n}y_{ij}} \tag{8}$$

The information entropy is:

$$H_i=-\frac{1}{\ln n}\sum_{j=1}^{n}f_{ij}\ln f_{ij} \tag{9}$$

Among them *ln0=0.*

The entropy weight method can be effectively used to cover the evaluation of variation degree and objectively reflect its importance. The entropy is calculated as follows:

$$w_i=\frac{1-H_i}{m-\sum_{i=1}^{m}H_i} \tag{10}$$

The weight is calculated as:

TABLE II. INDEX WEIGHT

latitude	longitude	brightness	confidence	bright_t31
0.21	0.123	0.121	0.1181	0.1748

After constructing weighting matrices $Z=(z_{ij})_{m\times n}$, the weight vector of various factors was given by the entropy weight method $w=[w_1,w_2,...,w_n]^T$, then

$$z_{ij}=y_{ij}\cdot w_i, i=1,2,...,m, j=1,2,...,n \tag{11}$$

D. Determine the positive ideal solutionand negative ideal solution.

Supposing $A^+=(z_1^+,z_2^+,...,z_n^+), A^-=(z_1^-,z_2^-,...,z_n^-)$, among them

$$z_j^+=\begin{cases}\max\limits_{1\le i\le m} z_{ij}, j\in j^+\\ \min\limits_{1\le i\le m} z_{ij}, j\in j^-\end{cases}, z_j^-=\begin{cases}\min\limits_{1\le i\le m} z_{ij}, j\in j^+\\ \max\limits_{1\le i\le m} z_{ij}, j\in j^-\end{cases} \tag{12}$$

Results and scores are shown as follows:

E. Calculate the distance from various schemes to ideal solutions.

Distance between the scheme S_i to the positive ideal solution A^+.

$$T_i^+, T_i^+=\sqrt{\sum_{j=1}^{n}(z_{ij}-z_j^+)^2}, i=1,2,...,m \tag{13}$$

Distance between the scheme S_i to the positive ideal solution A^-.

$$T_i^-, T_i^-=\sqrt{\sum_{j=1}^{n}(z_{ij}-z_j^-)^2}, i=1,2,...,m \tag{14}$$

F. Calculate all ranking index values of each scheme.

The comprehensive evaluation index is:

$$C_i=\frac{T_i^-}{T_i^+ + T_i^-}, i=1,2,...,m \tag{15}$$

Results and scores are as follows:

latitude	longitud	the risk ofwild fire
-12.311	-48.151	0.003386365
-12.073	-48.735	0.001993221
-12.14	-55.078	0.002064897
-10.723	-49.527	0.002372153
-11.264	-53.951	0.004263493
-6.705	-45.571	0.006053936
-6.323	-53.409	0.006065392
-6.325	-53.421	0.003587771
-6.707	-45.585	0.006054172
-6.116	-52.585	0.005147443

Figure 6. Quantitative map of longitude and latitude

All extracted visual data of longitude, latitude and risk were shown in the following relationship diagram of latitude, longitude and wildfire risk index of the Amazon forest fires:

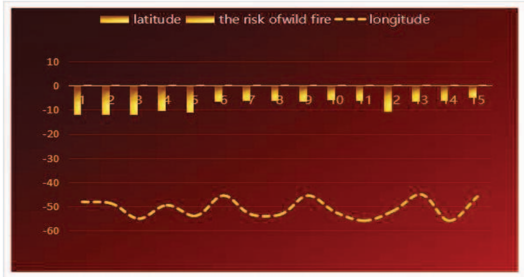

Figure 7. Relationship diagram of latitude, longitude and wildfire risk index

VI. CONCLUSIONS

Based on the advanced system hierarchical clustering model, this paper constructs the cellular automata model, and obtains the diffusion simulation results of the Amazon forest fire. Also, the diffusion speed and range of different brightness parameters are analyzed. Then, combined with the three-dimensional effect of fire and smoke simulated by particle system, the entropy weight TOPSIS model is constructed to the optimized ranking of wildfire risk index and longitude and latitude and obtain the relationship diagram of latitude, longitude and wildfire risk index after extracting data.

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