IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received March 3, 2020, accepted March 13, 2020, date of publication March 17, 2020, date of current version March 27, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2981368

Volcanic Ash Cloud Diffusion From Remote Sensing Image Using LSTM-CA Method

LAN LIU AND XIAN-KUN SUN
School of Electronic and Electrical Engineering, Shanghai University of Engineering Science, Shanghai 201620, China

Corresponding author: Lan Liu (liulan@sues.edu.cn)

This work was supported by the Shanghai Foundation for Development of Science and Technology, China, under Grant 19142201600.

ABSTRACT Monitoring of volcanic ash cloud is conducive to the disaster prevention and mitigation and public safety. To tackle of large amount and various types of data and continuous changes of volcanic ash cloud monitoring, in this paper, a new long short term memory (LSTM) and cellular automaton (CA) (i.e., LSTM-CA) collaborative computing method for volcanic ash cloud diffusion is proposed via neural networks. Based on diffusion characteristics of volcanic ash cloud, a CA model of volcanic ash cloud in the three-dimensional spaces was first constructed. And then the constantly changing sequential characteristics of volcanic ash cloud was learned by LSTM neural network and further treated as the evolution rule of the CA diffusion model of volcanic ash cloud in three-dimensional space. Next, simulation experiments and analysis were conducted in terms of wind direction, wind speed, step size and the number of cell. Finally, the proposed LSTM-CA collaborative computing method was tested and verified in the actual Etna ash cloud diffusion case. The experimental results show that: (1) in the two-dimensional space, the proposed LSTM-CA method can obtain a good initial simulation effect of volcanic ash cloud diffusion, and the total accuracy of volcanic ash cloud identification reached 96.1%; (2) in the three-dimensional space, the proposed LSTM-CA method can exact simulate the horizontal and vertical diffusion trends of volcanic ash cloud; (3) the proposed LSTM-CA method can significantly reduce the modeling complexity of volcanic ash cloud and improve the calculation efficiency of spatiotemporal data. It seems to provide a new idea to identify and simulate the volcanic ash cloud in complex environments.

INDEX TERMS Neural networks, collaborative computing, volcanic ash cloud diffusion, remote sensing data, simulation.

I. INTRODUCTION

Global volcanic eruption not only occurred almost synchronously with seismic activity, but also concentrated on the major volcanic belts formed on the edge of the plate [1]. The volcanic ash cloud formed by the volcanic eruption have seriously threatened the safety of global air transportation and local climate and environmental changes [2]. Based on the auxiliary data containing meteorology, geography and geology information, etc., volcanic ash cloud monitoring using remote sensing has become a business norm at present [3]–[6]. To simple the complexity of diffusion model, the traditional monitoring methods contain identification and diffusion of volcanic ash cloud is mostly carried out horizontally, and rarely involves vertical direction [7]–[10]. The actual simulation of volcanic ash cloud diffusion, however, should be performed in both horizontal and vertical directions. Collaborative computing refers to a way of computing that is relatively independent in terms of space and time series, and jointly completes a certain computing task in accordance with pre-established interconnection modes, interaction methods and technologies, and computing strategy [11]–[13]. And it has obvious advantages in monitoring of volcanic ash cloud using the dynamic changes of spatiotemporal data [14]–[16].

As a discrete system in time and space, cellular automaton (CA) can simulate complex systems that are constantly updated via evolution rule [17], [18]. It has great potential in the dynamic monitoring contains identification and diffusion of discrete volcanic ash cloud in time and space. In particular, the diffusion of volcanic ash cloud is affected by multiple factors, such as meteorological conditions (i.e., wind direction, wind speed, temperature, humidity, rainfall, etc.), the weight of volcanic ash debris particles and

The associate editor coordinating the review of this manuscript and approving it for publication was Honghao Gao.

the physiochemical reactions of volcanic gases with the surrounding atmosphere [19]–[25], so the evolution rule is the key to exact monitor and simulate of the volcanic ash cloud diffusion. At present, being widely used in the machine learning, image analysis and recognition, disease prediction and financial data mining, long short term memory (LSTM) neural network can not only effectively handle the relatively long intervals and delays in time series, but also accurately predict the subsequent development trends in the time series [26]. As a time-recurrent neural network, LSTM is very suitable for simulation of dynamic volcanic ash cloud diffusion with time series.

To further understand the sequential characteristics and the diffusion simulation in dynamic volcanic ash cloud monitoring, the current study investigates the simulation of volcanic ash cloud diffusion in three-dimensional space using the LSTM-CA collaborative calculation method. In this method, by constructing first three-dimensional CA model of volcanic ash cloud diffusion and taking the LSTM neural network as the evolution rule of the diffusion model, and then the proposed LSTM-CA collaborative computing method is tested and verified in the simulation experiment and true Etna ash cloud case on December 24, 2018. The results show that the proposed method can accurately simulate the diffusion of volcanic ash cloud in two-dimensional and three-dimensional spaces. Especially in the initial stage of volcanic ash cloud diffusion, the simulation effect in the three-dimensional space is more accurate and realistic.

The aims of this paper are:

(1) To propose LSTM-CA collaborative calculation method for remote sensing data;

(2) To simulate the diffusion of volcanic ash cloud in two-dimensional and three-dimensional spaces; and

(3) To test and verify the proposed method by the simulation data and true Etna volcanic ash cloud case in the experiment.

We will briefly outline the related theoretical basis in the following part. The third Part presents the detailed LSTM-CA collaborative computing method. The simulation experiment and analysis and the true Enta volcanic ash cloud case are devoted in the fourth and fifth Parts, respectively. We conclude our study with conclusion and future work in the last Part.

II. BASIC THEORY AND RELATED WORK

A. LSTM BASIC THEORY

In this part, we introduce the basic theory of LSTM. LSTM can effectively avoid the long-term dependence issue in the traditional recurrent neural network (RNN) [27], [28]. There are input gates, forget gates and output gates in the cell processor. And the key of LSTM is the cell state. When the information is inputted into the LSTM network, the useful information goes to the next step by the judgment, and the useless information is forgotten by the forget gate. The information flow process in the cell is shown below:

(1) Determine the percentage of information is kept from the cell, which is done in the forgotten gate. The output of the network is a value in the range of [0, 1], which is used for subsequent calculation of the degree of retention of old memory.

(2) Judge whether the information is updated to the next cell, which is mainly done in the input gate. It contains two steps, i.e., new information generation and usage of new information. The combination of the two can be performed by the production.

(3) Combine the steps 1) and 2) to get the information of new cell status. The retention part of old information and the new learning information are combined to generate new cell status information at the moment.

(4) Via the new cell status information, the output value of classifier is calculated in the output gate, and the final output value is gotten.

B. CA BASIC THEORY

Cell is the most basic unit of CA model. It can be distributed on discrete Euclidean spaces contains two-dimension and three-dimension, etc. and lattice points of higher-dimensional. These cells combine to form a complete cell space. The combined forms of cell space include triangles, quadrangles and hexagons, etc.

Each cell in the CA continuously iterates and updates in terms of the established rules[29], [30]. A complete CA model includes cell, cell space, neighbor and evolution rule, and can be represented by a quadruple, hence we have:

$$C = (L_d, S, N, f) \tag{1}$$

where L is the cell; d is the cell space; S is the state set of CA; N is the set of neighbor cells contains n different cell vectors, and $N = (s_1, s_2, s_3, \ldots s_n)$; n is the number of neighbor cells; s is an integer from 1 to n; f is the transformation rule of cell, and represent the transformation method for a given cell in CA from time T to time $T+1$.

For CA model, the key to continuously simulate the space change of evolution rule is the change function. In addition, because a cell's evolution rule is only related to its neighbor cells, it is necessary to clear define its neighbor cells when defining the rule. The neighbor cell refers to a set of other cells designated by the periphery rule around the center cell.

The neighbors of the one-dimensional CA are the simplest. Generally speaking, only the cells around the center cell are the neighbors. The definition of two-dimensional CA's neighbors is more complicated than that of one-dimensional CA, which usually includes von Neumann, Moore and extended Moore, etc. And what's more, there are many more complicated neighbor rules are set to meet specific needs in practical applications.

C. RELATED WORK

Initially, the diffusion of volcanic ash cloud is performed by the numerical simulation based on the atmospheric pollution diffusion model. Then there are two high peaks of achievements driven by the powerful eruption of Pinatubo volcano in 1991 and Eyjafjallajokull volcano in 2010.

One early study showed that the temperature of the volcanic ash cloud column gradually decreased from the bottom to the top, and exist a temperature difference of 20 ° [31]. the relationship among zonal distribution of vertical volcanic ash aerosol, radiation intensity of volcanic ash cloud aerosol and climate change were explored and discussed from remote sensing data [3], [32]. Then the key factors (e.g., distribution shape and height) affecting the dynamic diffusion of volcanic ash cloud were tested and verified [4]. To tackle of the inaccurate input parameters in the traditional models of volcanic ash cloud diffusion, the parameter evaluation method with multidiscipline-based was proposed and tested [5]. And what's more, the spectral features of volcanic ash debris particles in the infrared bands were usual used to identify and detect the long-distance diffusion path [6].

In general, these works mainly focus on the only numerical simulation, and lack of the auto-evolutional mechanism in the actual diffusion.

III. MATHODS

In view of the computation complexity and accuracy of simulation, we have proposed a new LSTM-CA collaborative computing so as to simply the computation. Next, we detail the presented method in this work.

(1) Scale setting and neighbors' definition

In practice, volcanic ash cloud is affected by both wind in the horizontal direction and turbulence in the vertical direction, and the adsorption of rain. The effective point source of volcanic ash cloud distribution with a certain height is adopted as the initial position of the three-dimensional CA diffusion model. Due to the diffusion of volcanic ash cloud is in all directions after it formed, so it is necessary to divide the area around the volcanic ash cloud into a rectangular grid $N \times N \times M$ in a three-dimensional CA space. Each grid is looked as a cell, and the cell vale is looked as mean concentration of volcanic ash cloud in the cell. In the three-dimensional CA model, a total 10 cells (i.e., 8 cells in the horizontal direction and 2 cells in the vertical direction) are set around each cell. In view of the diffusion characteristics, the volcanic ash cloud information flows among the different cells, so each cell is separate determined by its surrounding 10 cells at a specific time. In this study, the cell scale of volcanic ash cloud diffusion in the three-dimensional CA model is 500 m × 500 m × 500 m.

(2) Model hypothesis

To facilitate modeling and simplify calculations in the experiment, let us assume:

1) The three-dimensional CA model only considers the influence by wind direction and wind speed on the cells, and ignores the chemical reactions of volcanic ash caused by temperature, humidity and light.

2) There is no upper limit on the amount of volcanic ash can be carried by cells.

3) Real-time wind direction and wind speed in simulation of volcanic ash cloud diffusion can be obtained from probability statistics method.

4) Based on multiple verifications, the step size of three-dimensional CA model is calculated and designated as 6 s.

(3) Evolution rule

Previous works focus primarily on the two-dimensional diffusion in the horizontal direction due to the simplicity of the modeling and computation. Based on the diffusion of horizontal direction, the diffusion of volcanic ash cloud in the vertical direction could be considered in fact.

The LSTM neural network constructed in this experiment includes six layers, such as the first layer is the input layer, the three layers from second to fourth layer are the LSTM layer, and the fifth and sixth layers are the fully connected (FC) layer and the activation layer, respectively. Specifically, there are inputs 13 features and 64 neurons in the first layer. The layers from second to fourth layer are composed by 512, 128 and 64 neurons, respectively. Then the former fourth layers are all taken as the activity function. Based on the LSTM model, it can be seen that the activity function, $f(x)$, has the form:

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{2}$$

where x is the neurons data in separate LSTM layers.

The *sigmoid* function is used as the activation function in sixth layer (activation layer), and the formula can be expressed as:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{3}$$

In the training of LSTM model, the *Adam* algorithm is used to optimize the three-dimensional CA model.

To reduce the computational complexity of three-dimensional CA model, the influence of windless, windy and turbulent diffusion on volcanic ash cloud is only considered while ignoring the chemical reaction and settlement characteristics of volcanic ash cloud. In terms of the structural characteristics of the three-dimensional CA model, the volcanic ash cloud concentration $E_{i,j,k}^{t+1}$ of the cell ijk at the time $t+1$ is determined by the concentration of the cell itself at the time t and the surrounding 10 neighboring cells. The $E_{i,j,k}^{t+1}$ can be solved as:

$$E_{i,j,k}^{t+1} = f(E_{i,j,k}^{t}, \Delta^t E_{1-8}^{h}, \Delta^t E_{9-10}^{v}) \tag{4}$$

where $E_{i,j,k}^{t}$ is the volcanic ash cloud concentration of cell ijk at the time t; $\Delta^t E_{1-8}^{h}$ is the influence from other 8 neighbor cells in the horizontal directions on the cell;, $\Delta^t E_{9-10}^{v}$ is the influence from other 2 neighbor cells in the vertical directions on the cell. And the total influence of cell ijk is determined by the weighting among of the surrounding 10 neighboring cells.

(4) Volcanic ash cloud diffusion

In the LSTM-CA model, the cell ijk is affected by 8 directions, and the volcanic ash cloud concentration of the cell ijk at the moment $t+1$ can be solved as:

$$\begin{aligned}
&\Delta^t E^h_{i,j,k} \\
&= p^t_a[p^t_n(E^t_{i,j-1,k} - E^t_{i,j,k}) + p^t_s(E^t_{i,j+1,k} - E^t_{i,j,k}) \\
&\quad + p^t_e(E^t_{i+1,j,k} - E^t_{i,j,k}) + p^t_w(E^t_{i-1,j,k} - E^t_{i,j,k})] \\
&\quad + p^t_a d[p^t_{ne}(E^t_{i+1,j-1,k} - E^t_{i,j,k}) + p^t_{nw}(E^t_{i-1,j-1,k} - E^t_{i,j,k}) \\
&\quad + p^t_{se}(E^t_{i+1,j+1,k} - E^t_{i,j,k}) + p^t_{sw}(E^t_{i-1,j+1,k} - E^t_{i,j,k})] \quad (5)
\end{aligned}$$

where n, s, e, w, ne, nw, se, sw is the influence of the cell ijk by the wind speed with north, south, east, west, northeast, northwest, southeast and southwest directions at the time t, respectively; d is the bevel coefficient, and $d \subset [0.1, 0.16]$; isosurface is the empirical parameter, and $p^t_a = 0.084$.

The influence of turbulence on the cell ijk in the vertical direction can be solved as:

$$\Delta^t E^v_{i,j,k} = p^t_a[k'_m(E^t_{i,j,k-1} - E^t_{i,j,k}) + k''(E^t_{i,j,k+1} - E^t_{i,j,k})] \quad (6)$$

where k'' is the influence of atmospheric turbulence on the uplift on volcanic ash cloud, $k'' = \sigma$; σ is the atmospheric turbulence parameters calculated from atmospheric stability. In accordance with the Pasquill-Gifford diffusion model of atmospheric stability, the atmospheric turbulence coefficient is finally got in this experiment, and $\sigma = 0.12$; $k'm$ is the comprehensive coefficient that the cell ijk is affected by turbulence and initial velocity in the vertical upward and downward directions, and it is determined by the wind speed and wind direction. Hence, we have the form:

$$k'_m = \begin{cases} c\dfrac{v_c}{v_h}, & m = c \\ 0, & m \neq c \end{cases} \quad (7)$$

where v_c is the wind speed at currently wind direction; v_h is the maximum historical wind speed at this time; c is the diffusion ratio caused by air flow and can be determined by the real test; $k'm$ usually includes the dilution effect of rainfall on gas and the adsorption effect of rainfall on solid particles in volcanic ash cloud.

The state change cell in the LSTM-CA model can be learned and updated by the LSTM neural network automatically. And then the evolutionary rule learned by the proposed method in this paper is used to simulate and predict the possible change of volcanic ash cloud in the two-dimensional and three-dimensional spaces.

IV. SIMULATION EXPERIMENT AND ANALYSIS

In this part, the proposed LSTM-CA collaborative computing method is compared and analyzed from the three aspects. The proposed LSTM-CA collaborative computing method as introduced previously (formulas (5-7)) were implemented, and the definitions of the CA and volcanic ash cloud diffusion were assumed in Part 3. And then, in this experiment, the three-dimensional CA model constructed in this study was evaluated in terms of wind direction and wind speed, step size and cell number. All tests are complemented on the platform with Inter (R) Core (TM) i7-8700 CPU @ 3.20 GHz, 16 GB RAM, Windows 10-x64 platforms, and Matlab R 2014b software.

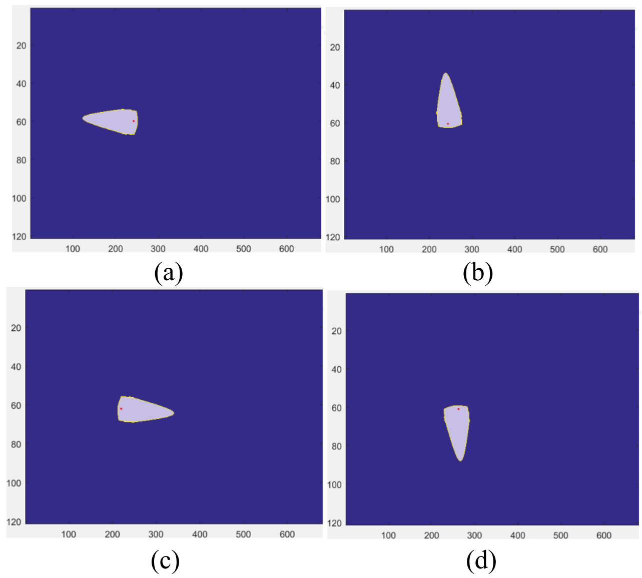

FIGURE 1. Between wind direction and diffusion of volcanic ash cloud, (a) east, (b) south, (c) west, (d) north, the red point is the point source of volcanic ash cloud diffusion, the gray area is the coverage area of volcanic ash cloud diffusion; yellow line is the boundary between the volcanic ash cloud and the outside atmosphere.

A. WIND DIRECTION, WIND SPEED AND DIFFUSION

Due to the ignores the influence of volcanic ash's own weight, chemical reactions and other factors, so the volcanic ash cloud diffuses in the high air only affected by wind direction and wind speed. In this experiment, the point source location of volcanic ash cloud diffusion and wind direction (i.e., east wind, south wind, west wind and north wind) are assumed, the time interval in simulation is set as 3 minutes and the simulation time is set as 180 minutes. The simulation of volcanic ash cloud diffusion under the given wind direction are plotted in Fig. 1.

From Fig. 1, it can be seen that the diffusion of volcanic ash cloud is closely related to the wind direction, and is almost consistent with the change of the wind direction. However, volcanic ash cloud diffusion is affected not only by the horizontal wind direction, but also by the turbulence in vertical direction in practice. In addition, the interaction of different wind directions is more complicated than that in the simulation.

Subsequently, the diffusion distance of volcanic ash cloud can be defined as the straight line distance between the farthest cell that diffuses in a certain direction at the time t and the point source of diffusion. Then the diffusion distances in the east, south, west and north directions are calculated and updated, respectively. Table 1 shows the detailed diffusion distance of volcanic ash cloud at the time $t = 60$.

As shown in Table 1, it can be seen that the volcanic ash cloud in the downwind direction has the largest diffusion distance, which is approximately equal to a few dozen

TABLE 1. Diffusion distance of volcanic ash cloud.

wind direction	diffusion distance (m)			
	east	south	west	north
east	200	550	2350	600
south	550	200	600	2350
west	2400	550	220	550
north	550	2350	600	200

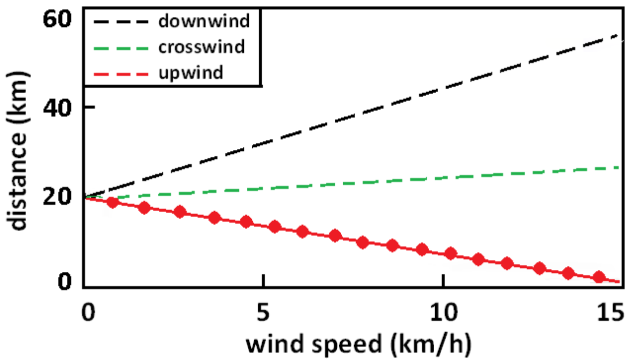

FIGURE 2. Between wind speed and the diffusion distance of volcanic ash cloud.

times of the crosswind direction, followed by the crosswind direction's diffusion distance, while the volcanic ash cloud in the upwind direction has the shortest diffusion distance. Meanwhile, the volcanic ash cloud diffusion tends to show a conical narrow area with the action of wind direction.

In addition, the diffusion distance of volcanic ash cloud is also closely related to wind speed. Via assuming that the simulation time interval and duration are given, in this experiment, the diffusion trend of volcanic ash cloud with downwind, crosswind and upwind can be simulated when the wind speed is within a certain range, and the calculation of diffusion of volcanic ash cloud can be plotted in Fig. 2.

From Fig.2, it can be seen that the diffusion distance of volcanic ash cloud in the downwind, crosswind and upwind directions is basically equal with no winds. As the increase of wind speed, the diffusion distance of volcanic ash cloud increases rapidly in the downwind direction and increases slowly in the crosswind direction whereas rapidly decrease in the upwind direction. Therefore, in the initial stage of volcanic eruption and diffusion, based on to the prevailing wind direction, wind speed and other factors at the same time, it is possible to quickly estimate the possible diffusion position and coverage area of the volcanic ash cloud, and further make the corresponding emergency measures.

B. STEP SIZE AND DIFFUSION

For the diffusion simulation of volcanic ash cloud may randomly begin from any point in the three-dimensional CA space, in the experiment, we set in advance the possible diffusion source point of volcanic ash cloud. Figure 3 shows the simulation of volcanic ash cloud diffusion with the different step size by the proposed LSTM-CA collaborative computing method.

From Figs. 3 (a) – (f), it can be seen that the coverage area and the thickness of the volcanic ash cloud gradually increases with the increase of the step size. The diffusion trend of volcanic ash cloud is becoming more and more obvious. However, the diffusion speed of volcanic ash cloud in the horizontal direction is significantly faster than that in the vertical direction.

C. NUMBER OF CELL AND DIFFUSION

Based on the wind direction is given and constant, the relationship between wind speed and the number of cells involved in the diffusion simulation is discussed in this experiment. And the computation of the relationship is plotted in Fig. 4.

From Fig. 4, it can be seen that when the wind direction remains constant and the wind speed is set as 5 km/h, 10 km/h and 15 km/h, respectively, the number of cells involved in the volcanic ash cloud diffusion simulation are rapidly increasing with the increase of the step size. The greater the wind speed, the faster the number of cells increases. Meanwhile, with the number of cells involved in the diffusion simulation increases, its growth rate gradually increases too. The greater the wind speed, the more obvious the increase rate.

Subsequently, in the experiment, taking the Etna volcanic ash cloud case on December 24, 2018 as an example, the diffusion of volcanic ash cloud in two-dimensional and three-dimensional space was simulated by the proposed LSTM-CA collaborative computing method based on the MODIS remote sensing images of the same period and other auxiliary meteorological data.

V. ENTA VOLCANIC ASH CLOUD DIFUUSION CASE

A. GENERAL SITUATIONS

In this paper, taking the Etna volcanic ash cloud diffusion on December 24, 2018 as the data source, we test and verify the proposed method in the true volcanic ash cloud case.

Etna volcano is the highest active volcano in Europe with a maximum altitude of about 3.5 km. Its base circumference is about 140 km and covers an area of about 1250 km^2. Etna volcano is located at the junction of the Eurasian and African plates, and has frequent volcanic and seismic activities [33]. Etna volcano erupted on December 24, 2018, and caused a series of small earthquakes and further formed a large number of volcanic ash cloud. At the same time, it also led to the air traffic control when seriously reduced the atmospheric visibility around volcano, and a large number of flights were delayed or cancelled.

B. DATA SOURCE AND PREPROCESSING

(1) MODIS data selection and preprocessing

The data source used in this experiment is MOD021KM image from Terra/MODIS sensor, and the imaging time is December 24, 2018.

Before the simulation of volcanic ash cloud diffusion, the data preprocessing of MODIS remote sensing data including geometric correction, radiation correction and image

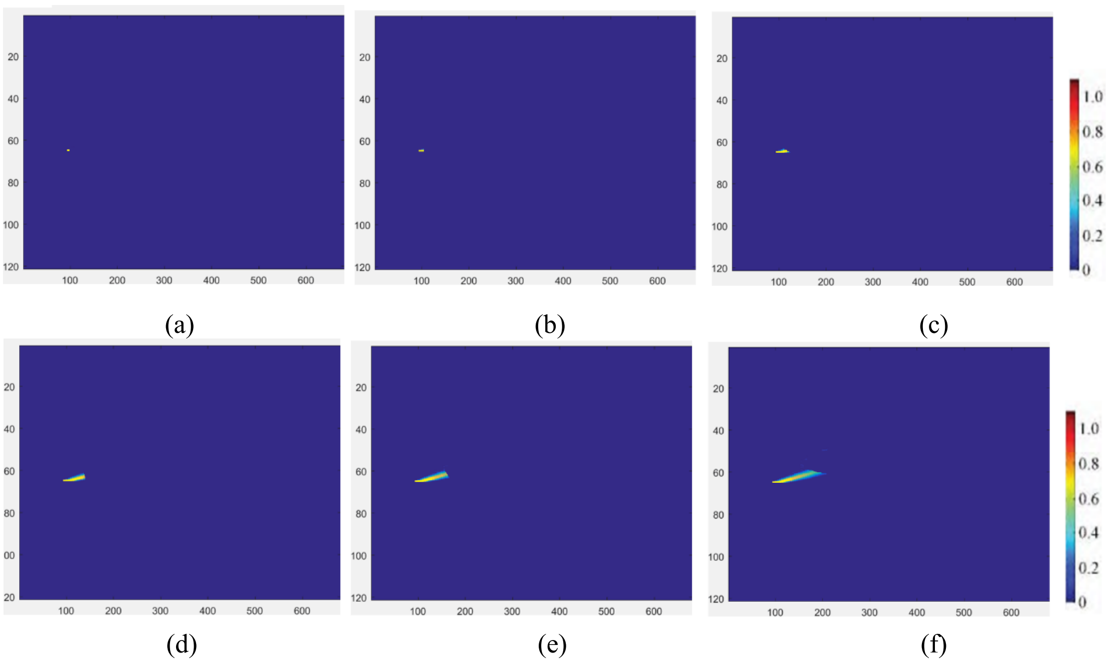

FIGURE 3. Simulation of volcanic ash cloud diffusion with the different step sizes, (a) t=100, (b) t = 200, (c) t = 300, (d) t = 400, (e) t = 500, (f) t = 600.

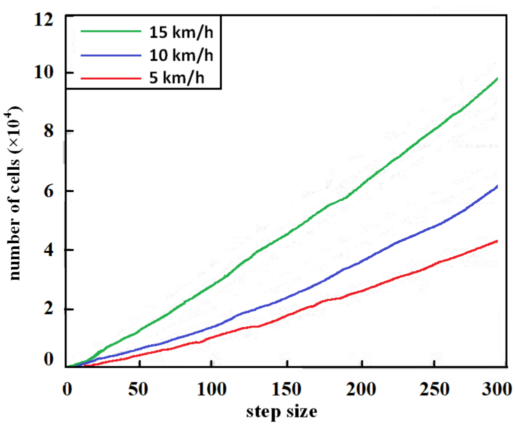

FIGURE 4. Between wind speed and the number of cells.

FIGURE 5. False color preprocessed image of Etna volcanic ash cloud on December 24, 2018.

stitching is performed firstly in the experiment. Figure 5 shows the MODIS false color preprocessed image of Etna volcanic ash cloud on December 24, 2018.

(2) Wind speed and wind directions data selection and preprocessing

The wind data contains wind speed and wind direction is acquired from the website https://gis.ncdc.noaa.gov/, which provides free historical weather data at different time points of various weather stations around the world. In terms of the eruption of Etna volcano on December 24, 2018, the historical data of MESSINA and REGGIO OF CALABRIA weather stations around Etna volcano were finally adopted and download combined with the transit trajectory of MODIS sensor, such as wind direction, wind speed, day visibility, etc.

In view of the early eruption of Etna volcano on December 24, 2018 and the coverage area is small, in this experiment it can cover the volcanic ash cloud area only by the meteorological data of the MESSINA weather station. Therefore, the meteorological data of MESSINA weather station from 1998 to 2018 were obtained in this experiment.

The format of meteorological data provided by websites is mainly.txt, which includes the weather station number, time, wind direction, wind speed, cloud conditions, visibility, visibility with high, medium and low altitude, line-of-sight, etc. Wind direction and wind speed data were used in this experiment based on the model construction and diffusion monitoring. Among them, the wind direction is 360° data and includes 36 directions. Because the diffusion of volcanic ash cloud in the two-dimensional CA model only considers the central cell and its surrounding 8 cell neighbor cells, it is

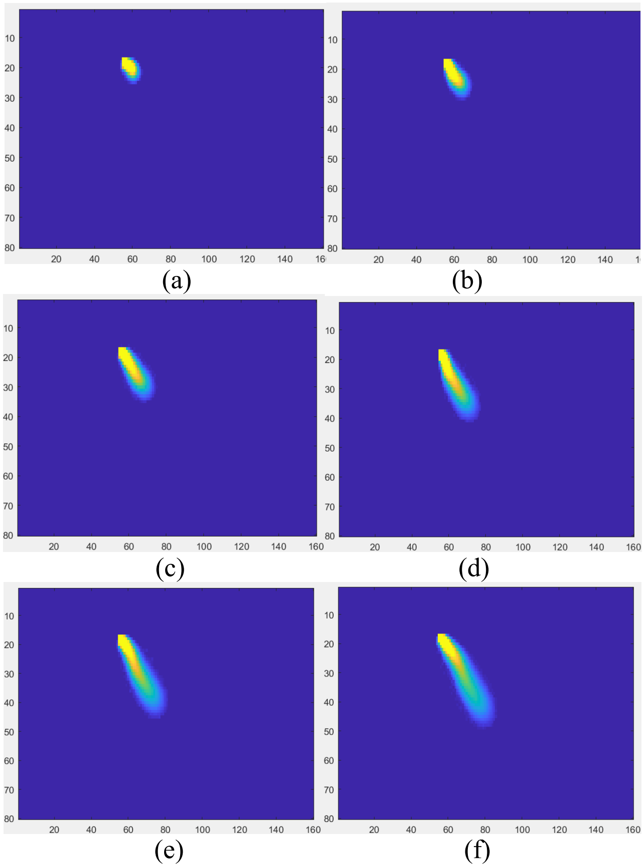

FIGURE 6. Simulation of volcanic ash cloud with different step size on December 24, 2018, (a) t=100, (b) t = 200, (c) t = 300, (d) t = 400, (e) t = 500, (f) t = 600.

necessary to combine the data in 36 directions according to the data in each positive direction angle from 22.5 ° to 67.5 °.

For the volcanic ash cloud formed by the Etna volcano eruption on December 24, 2018, the wind speed and wind direction come from the MESSINA weather station were calculated during the period December, 1998-2018. As shown in statistics, the main wind direction of MESSINA weather station contains southwest, west, northwest, north and northeast. Although it rotated 90° clockwise and flipped left and right for testing and the true orientation in the actual image, the wind direction is exactly the same after flipping. Therefore, the statistical wind direction dataset of MESSINA weather station in the actual test is still southwest, west, northwest, north and northeast. Finally, the average wind speed of the MESSINA weather station during the period December, 1998-2018 is computed and reached 25 m/s.

C. DIFFUSION SIMULATION IN TWO-DIMENSIONAL SPACE

Figure 6 shows the simulation results of the Etna volcanic ash cloud diffusion in two-dimensional space on December 24, 2018 when the step size was set as 100, 200, 300, 400, 500 and 600, respectively. Figure 7 shows the Etna ash cloud distribution over the same period identified from MODIS remote sensing image by the traditional feedback neural network (FNN) method in volcanic ash cloud monitoring.

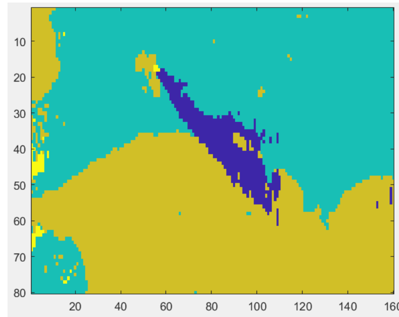

FIGURE 7. Distribution of Etna volcanic ash cloud identified by the FNN method on December 24, 2018.

TABLE 2. Accuracy comparison of volcanic ash cloud.

		the proposed method	
		ash	no ash
FNN method	ash	409	203
	no ash	288	11900
total accuracy = 96.1%			

From Figs. 6 and 7, it can be seen that the simulation result of volcanic ash cloud on December 24, 2018 by the proposed LSTM-CA collaborative computing method is basically consistent with the volcanic ash cloud distribution obtained from the MODIS remote sensing image by traditional FNN method, and have good simulation results of Etna volcanic ash cloud diffusion. Then the accuracy comparison of volcanic ash cloud distribution by the proposed method and FNN method has been performed in the experiment, and is shown in Table 2.

As shown in Table 2, it can be seen that the total accuracy of Etna volcanic ash cloud on December 24, 2018 by the proposed LSTM-CA collaborative computing method from MODIS remote sensing image reached 96.1% compared to the traditional FNN method. It shows that in the two-dimensional space the proposed method can achieve better simulation of volcanic ash cloud diffusion in the initial stage of volcano eruption. However, the volcanic ash cloud is always changing dynamic, and it needs to be further verified the applicability of the proposed method in the middle and late stages of volcanic ash cloud diffusion.

D. DIFFUSION SIMULATION IN THREE-DIMENSIONAL SPACE

In this part, the wind speed, wind direction and atmospheric turbulence were inputted into the proposed LSTM-CA collaborative computing method of volcanic ash cloud, and then the simulation of volcanic ash cloud in three-dimensional space was performed in the Matlab software platform. In addition, to better understand the horizontal and vertical structure of volcanic ash cloud, the contour profile of the Etna volcanic ash cloud on December 24, 2018 was drawn by

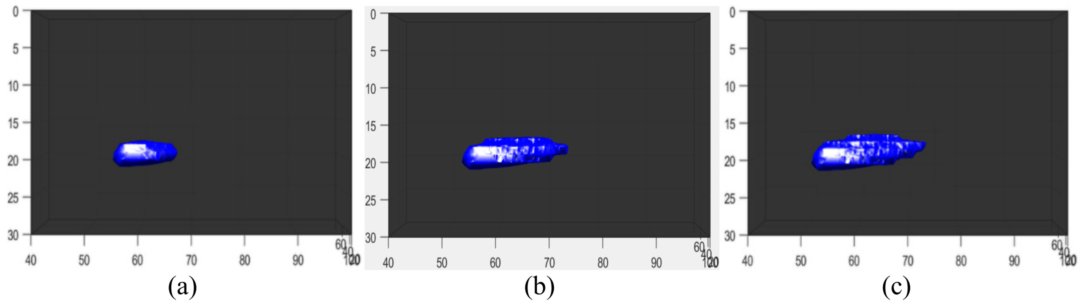

FIGURE 8. Simulation of Etna volcanic ash cloud on December 24, 2018 in the three-dimensional space, (a) t = 200, (b) t = 400, (c) t = 600.

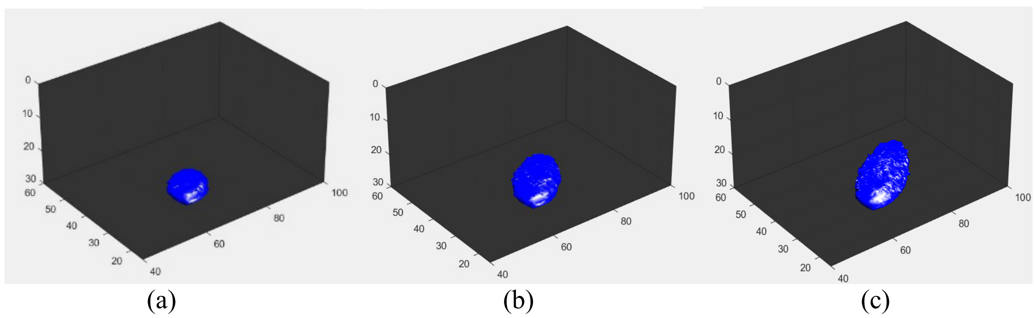

FIGURE 9. Slice of Etna volcanic ash cloud on December 24, 2018 in the three-dimensional space, (a) t = 200, (b) t = 400, (c) t = 600.

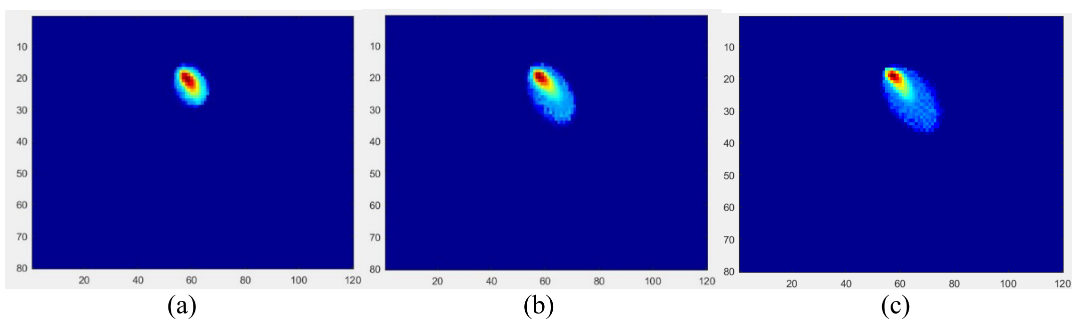

FIGURE 10. Slice of Etna volcanic ash cloud on December 24, 2018 in the three-dimensional space, (a) t = 200, (b) t = 400, (c) t = 600.

the isosurface function in Matlab software platform. Subsequently, the vertical structure of volcanic ash cloud diffusion in the three-dimensional space is discussed and analyzed by slicing including horizontal slice and vertical slice. The simulation of Etna volcanic ash cloud in three-dimensional space on December 24, 2018 with the different step size can be illustrated in Fig. 8.

The horizontal slice of Etna volcanic ash cloud in three-dimensional space on December 24, 2018 with the different step size can be illustrated in Fig. 9.

The vertical slice of Etna volcanic ash cloud in three-dimensional space on December 24, 2018 with the different step size can be illustrated in Fig. 10.

From Figs. 8-10, it can be seen that the cluster distribution of Etna volcanic ash cloud on December 24, 2018 in the diffusion process is very significant. That is to say, the diffusion of volcanic ash cloud in the horizontal direction is rapid and in the vertical direction is slow at the same time, and has a certain mass thickness. It is also consistent with the original intention of proposed LCTM-CA collaborative computing method in the three-dimensional space. Meanwhile, when the step size is set as 200, 400 and 600, the distribution thickness of Etna volcanic ash cloud on December 24, 2018 reached 1.9 km, 2.3 km and 2.5 km, respectively, and shows a trend of steady increase.

E. DISCUSSIONS

1) In the two-dimensional space, the simulation effect of volcanic ash cloud by the proposed LCTM-CA collaborative computing method in the early stage is better than that in

the middle and late stage. And in the early stage of volcanic ash cloud diffusion, the proposed method can more accurately simulate the distribution state of volcanic ash cloud diffusion. For example, the simulation of Etna volcanic ash cloud on December 24, 2018 is better and the total accuracy reached 96.1%.

2) For the proposed LCTM-CA collaborative computing method, the evolution speed of model wills gradually slowdown in the actual calculation process. For example, it took 10 minutes with the step size from 1 to 2400, and 50 minutes with the step size from 2400 to 7200. And as the number of cells involved in the calculation increases in the model, the overall efficiency of the model will decrease.

3) The proposed LCTM-CA collaborative computing method in this paper is able to simulate and obtain more intuitive distribution of volcanic ash cloud and diffusion trends in two-dimensional and three-dimensional spaces. However, in the process of volcanic ash cloud diffusion, it is difficult for the proposed method to accurately simulate changes in meteorological factors in actual. In addition, the changes in meteorological factors (e.g., wind direction and wind speed) have a great impact on the diffusion system in a complex environment. Especially with the time of continuous diffusion and sudden changes of wind direction and wind speed on the diffusion path, it is difficult for the proposed method to fully realize the accurate simulation of volcanic ash cloud diffusion.

4) For the simulation results by the proposed LCTM-CA collaborative computing method in two-dimensional space, it can be compared and evaluated by various documents and reports published. However, in the three-dimensional space of volcanic ash cloud, as few studies currently involve vertical diffusion, there is a lack of corresponding reference standards for evaluation. In our work, the distribution and diffusion of volcanic ash cloud in three-dimensional spaces are only shown and preliminary discussed from the visual effects of horizontal slices and vertical slices, and the true simulation effect needs further verification.

VI. CONCLUSION AND FUTURE WORK

Via analyzing the characteristics of volcanic ash cloud diffusion, CA and LSTM neural network structure, a LSTM-CA method is proposed in this paper for the volcanic ash cloud diffusion from remote sensing data. The core of the diffusion model is the LSTM neural network to learn the volcanic ash cloud diffusion characteristics (i.e., evolution rule in CA model) and modeling of volcanic ash cloud diffusion in the two-dimensional and three-dimensional spaces. The result shows that, the compared with the traditional methods, the proposed LSTM-CA method in this paper has the characteristics of simple calculation, high accuracy and good visual effects, etc., and can provide a new idea of volcanic ash cloud monitoring.

Nevertheless, the traditional works mainly focus on the volcanic ash cloud identification and diffusion in two-dimensional space in the actual monitoring business of volcanic ash cloud. In this experiment, it is only an attempt to simulate the volcanic ash cloud diffusion from the horizontal and vertical directions by the proposed LSTM-CA method, and is an attempt for current volcanic ash cloud monitoring. In the follow-up work, many factors are closed related to the diffusion and simulation of volcanic ash cloud, including more complex meteorological and geographic data, satellite remote sensing image and more simple and accurate mathematical models are all introduced to discuss the actual volcanic ash cloud diffusion.

REFERENCES

[1] R. Inkpen, "'Riskscapes' as a heuristic tool for understanding environmental risks: The Eyjafjallajokull volcanic ash cloud of April 2010," *Int. J. Disaster Risk Reduction*, vol. 121, no. 7, pp. 3534–3547, 2016.

[2] Y. Zhao, Y.-S. Li, Q.-C. Fan, and Z.-F. Guo, "The progress of volcanic ash cloud study in aviation safety," *Bull. Mineral. Petrol. Geochem.*, vol. 33, no. 4, pp. 531–539, 2014.

[3] I. Kirchner, G. L. Stenchikov, H.-F. Graf, A. Robock, and J. C. Antuña, "Climate model simulation of winter warming and summer cooling following the 1991 mount Pinatubo volcanic eruption," *J. Geophys. Res., Atmos.*, vol. 104, no. D16, pp. 19039–19055, Aug. 1999.

[4] P. Daniele, L. Lirer, P. Petrosino, N. Spinelli, and R. Peterson, "Applications of the PUFF model to forecasts of volcanic clouds dispersal from Etna and Vesuvio," *Comput. Geosci.*, vol. 35, no. 5, pp. 1035–1049, May 2009.

[5] L. G. Mastin, M. Guffanti, R. Servranckx, P. Webley, S. Barsotti, K. Dean, A. Durant, J. W. Ewert, A. Neri, W. I. Rose, D. Schneider, L. Siebert, B. Stunder, G. Swanson, A. Tupper, A. Volentik, and C. F. Waythomas, "A multidisciplinary effort to assign realistic source parameters to models of volcanic ash-cloud transport and dispersion during eruptions," *J. Volcanol. Geothermal Res.*, vol. 186, nos. 1–2, pp. 10–21, Sep. 2009.

[6] A. J. Durant, G. Villarosa, W. I. Rose, P. Delmelle, A. J. Prata, and J. G. Viramonte, "Long-range volcanic ash transport and fallout during the 2008 eruption of Chaitén volcano, Chile," *Phys. Chem. Earth, Parts A/B/C*, vols. 45–46, pp. 50–64, Jan. 2012.

[7] A. L. M. Grant, H. F. Dacre, D. J. Thomson, and F. Marenco, "Horizontal and vertical structure of the Eyjafjallajökull ash cloud over the UK: A comparison of airborne lidar observations and simulations," *Atmos. Chem. Phys.*, vol. 12, no. 21, pp. 10145–10159, 2012.

[8] K. L. Wilkins, I. M. Watson, N. I. Kristiansen, H. N. Webster, D. J. Thomson, H. F. Dacre, and A. J. Prata, "Using data insertion with the NAME model to simulate the 8 May 2010 Eyjafjallajökull volcanic ash cloud," *J. Geophys. Res., Atmos.*, vol. 121, no. 1, pp. 306–323, Jan. 2016.

[9] F. S. Marzano, E. Picciotti, S. Di Fabio, M. Montopoli, L. Mereu, W. Degruyter, C. Bonadonna, and M. Ripepe, "Near-real-time detection of tephra eruption onset and mass flow rate using microwave weather radar and infrasonic arrays," *IEEE Trans. Geosci. Remote Sens.*, vol. 54, no. 11, pp. 6292–6306, Nov. 2016.

[10] I. Taylor, S. Mackie, and M. Watson, "Investigating the use of the Saharan dust index as a tool for the detection of volcanic ash in SEVIRI imagery," *J. Volcanol. Geothermal Res.*, vol. 304, pp. 126–141, Oct. 2015.

[11] H. Gao, Y. Duan, L. Shao, and X. Sun, "Transformation-based processing of typed resources for multimedia sources in the IoT environment," *Wireless Netw.*, vol. 26, no. 8, Nov. 2019, doi: 10.1007/s11276-019-02200-6.

[12] J. Yu, M. Tan, H. Zhang, D. Tao, and Y. Rui, "Hierarchical deep click feature prediction for fine-grained image recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, to be published, doi: 10.1109/TPAMI.2019.2932058.

[13] H. Gao, Y. Xu, Y. Yin, W. Zhang, R. Li, and X. Wang, "Context-aware QoS prediction with neural collaborative filtering for Internet-of-Things services," *IEEE Internet Things J.*, to be published, doi: 10.1109/JIOT.2019.2956827.

[14] X. Ma, H. Gao, H. Xu, and M. Bian, "An IoT-based task scheduling optimization scheme considering the deadline and cost-aware scientific workflow for cloud computing," *EURASIP J. Wireless Commun. Netw.*, vol. 2019, no. 1, p. 249, Dec. 2019, doi: 10.1186/s13638-019-1557-3.

[15] J. Yu, Z. Kuang, B. Zhang, W. Zhang, D. Lin, and J. Fan, "Leveraging content sensitiveness and user trustworthiness to recommend fine-grained privacy settings for social image sharing," *IEEE Trans. Inf. Forensics Secur.*, vol. 13, no. 5, pp. 1317–1332, May 2018.

[16] J. Yu, C. Hong, Y. Rui, and D. Tao, ''Multitask autoencoder model for recovering human poses,'' *IEEE Trans. Ind. Electron.*, vol. 65, no. 6, pp. 5060–5068, Jun. 2018.

[17] C. L. Wu, ''Epidemic spread model based on cellular automata,'' *Comput. Knowl. Technol.*, vol. 15, no. 9, pp. 185–186, 2019.

[18] H. J. Zhang and F. Gao, ''Cellular automata modeling of diffusion systems,'' *J. Anhui Inst. Educ.*, vol. 15, no. 3, pp. 17–21, 2006.

[19] M. Gómez-Letona, J. Arístegui, A. G. Ramos, M. F. Montero, and J. Coca, ''Lack of impact of the el Hierro (Canary Islands) submarine volcanic eruption on the local phytoplankton community,'' *Sci. Rep.*, vol. 8, no. 1, p. 4667, Dec. 2018.

[20] J. B. Krippner, A. B. Belousov, M. G. Belousova, and M. S. Ramsey, ''Parametric analysis of lava dome-collapse events and pyroclastic deposits at Shiveluch volcano, Kamchatka, using visible and infrared satellite data,'' *J. Volcanol. Geothermal Res.*, vol. 354, pp. 115–129, Apr. 2018.

[21] W. I. Rose, S. Self, P. J. Murrow, C. Bonadonna, A. J. Durant, and G. G. J. Ernst, ''Nature and significance of small volume fall deposits at composite volcanoes: Insights from the October 14, 1974 Fuego eruption, Guatemala,'' *Bull. Volcanol.*, vol. 70, no. 9, pp. 1043–1067, Sep. 2008.

[22] A. Piscini, S. Corradini, F. Marchese, L. Merucci, N. Pergola, and V. Tramutoli, ''Volcanic ash cloud detection from space: A comparison between the RST_{ASH} technique and the water vapour corrected BTD procedure,'' *Geomatics, Natural Hazards Risk*, vol. 2, no. 3, pp. 263–277, Sep. 2011.

[23] L. Liu, C. Li, Y. Lei, J. Yin, and J. Zhao, ''Volcanic ash cloud detection from MODIS image based on CPIWS method,'' *Acta Geophysica*, vol. 65, no. 1, pp. 151–163, Mar. 2017.

[24] W. F. Giggenbach, Y. Sano, and H. U. Schmincke, ''CO_2-rich gases from Lakes Nyos and Monoun, Cameroon; Laacher See, Germany; Dieng, Indonesia, and Mt. Gambier, Australia—Variations on a common theme,'' *J. Volcanology Geothermal Res.*, vol. 45, nos. 3–4, pp. 311–323, Apr. 1991.

[25] F. S. Marzano, S. Barbieri, G. Vulpiani, and W. I. Rose, ''Volcanic ash cloud retrieval by ground-based microwave weather radar,'' *IEEE Trans. Geosci. Remote Sens.*, vol. 44, no. 11, pp. 3235–3246, Nov. 2006.

[26] Y. M. Wei, J. C. Quan, and Y. Q. Y. Hou, ''UAV sequential localization based on CNN and Bi-LSTM,'' *Electron. Opt. Control*, vol. 24, no. 12, pp. 51–55, 2017.

[27] F. Y. Hei, J. Z. Wang, and L. H. Zhao, ''Public opinion classification of heterogeneous data based on CNN and LSTM,'' *Comput. Sys. App.*, vol. 28, no. 6, pp. 141–147, 2019.

[28] X. K. Liang, C. H. Song, M. R. Hao, J. J. Zhao, and D. Zheng, ''Sequence image visual positioning technology based on LSTM and Siamese network,'' *Mod. Def. Technol.*, vol. 47, no. 5, pp. 65–70, 2019.

[29] C. Li, L. Liu, X. Sun, J. Zhao, and J. Yin, ''Image segmentation based on fuzzy clustering with cellular automata and features weighting,'' *EURASIP J. Image Video Process.*, vol. 2019, no. 1, pp. 1–10, Dec. 2019.

[30] M. Espínola, J. A. Piedra-Fernández, R. Ayala, L. Iribarne, S. Leguizamón, and J. Z. Wang, ''Simulating rainfall, water evaporation and groundwater flow in three-dimensional satellite images with cellular automata,'' *Simul. Model. Pract. Theory*, vol. 67, pp. 89–99, Sep. 2016.

[31] A. W. Woods and S. Self, ''Thermal disequilibrium at the top of volcanic clouds and its effect on estimates of the column height,'' *Nature*, vol. 355, no. 6361, pp. 628–630, Feb. 1992.

[32] G. L. Stenchikov, I. Kirchner, A. Robock, H.-F. Graf, J. C. Antuña, R. G. Grainger, A. Lambert, and L. Thomason, ''Radiative forcing from the 1991 mount Pinatubo volcanic eruption,'' *J. Geophys. Research: Atmos.*, vol. 103, no. D12, pp. 13837–13857, Jun. 1998.

[33] D. Andronico, C. Spinetti, A. Cristaldi, and M. F. Buongiorno, ''Observations of Mt. Etna volcanic ash plumes in 2006: An integrated approach from ground-based and polar satellite NOAA–AVHRR monitoring system,'' *J. Volcanol. Geothermal Res.*, vol. 180, nos. 2–4, pp. 135–147, Mar. 2009.

LAN LIU was born in Jining, Shandong, China, in 1982. She received the M.S. degree from Southwest University, in 2009, and the Ph.D. degree from Shanghai University, China, in 2018. She is currently an Experimentalist with the School of Electronic and Electrical Engineering, Shanghai University of Engineering Science. Her major research is in computer application. Her main research interests include clustering classification, spatial image processing, laboratory management, and information construction.

XIAN-KUN SUN was born in Jinan, Shandong, China, in 1972. He received the M.S. degree in computer science from East China Normal University, China, in 2001. He is currently an Associate Professor with the College of Electronic and Electrical Engineering, Shanghai University of Engineering Science. He has hosted and participated in several national and provincial research projects, and has been published several articles. His main research interests include data mining and satellite remote sensing image processing.