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Artificial Intelligence Based Flood and Landslide Disaster Monitoring and Dynamic Numerical Prediction System



Abstract: - Monitoring and dynamic numerical prediction of flood and landslide disasters are of great significance for reducing disaster risks, ensuring urban safety and stable development. The existing systems have limitations in real-time and dynamic performance, making it difficult to provide effective support for disaster prevention and management. To improve the efficiency of disaster monitoring, this article combined artificial intelligence (AI) to conduct in-depth research on the construction of flood and landslide disaster monitoring and dynamic numerical prediction systems. This article first analyzed the system functional requirements, and then designed the system architecture based on this, dividing it into three levels: user interface layer, application layer, and data layer. Finally, the BP (Back Propagation) neural network algorithm and dynamic numerical model were utilized to analyze the monitoring and dynamic numerical prediction of flood and landslide disasters. To verify the effectiveness of the system, this article compared it with GIS (Geographic Information System) based methods, and conducted testing and analysis on the system from monitoring errors, real-time monitoring, numerical simulation, and several levels. The results showed that in terms of real-time monitoring, compared with GIS based disaster prediction systems, the average response time of the AI based disaster monitoring and prediction system in this paper was shortened by 1.36 milliseconds. The conclusion indicated that the AI-based flood and landslide disaster monitoring and dynamic numerical prediction system in this article could effectively improve the efficiency of disaster monitoring and early warning, and help promote the efficient and intelligent development of disaster prevention.

Keywords: Disaster Monitoring, Dynamic Numerical Prediction, Artificial Intelligence, Flood and Landslide, Back Propagation Neural Network.

I. INTRODUCTION

With the increasingly prominent issue of extreme climate, geological disasters such as floods and landslides occur frequently, posing a great threat to the daily lives of the people [1]. Traditional disaster management and early warning systems are susceptible to interference from other factors, have limited monitoring scope, lack real-time capability, and cannot adapt to complex and ever-changing disaster scenarios, making it difficult to provide timely and effective objective basis for disaster prevention and control work [2-3]. With the mature development of computer science theory, AI algorithms have made great progress. In the monitoring and prevention of flood and landslide disasters, AI algorithms can discover and mine hidden complex patterns from data, strengthen the understanding and prediction ability of disaster mechanisms, and improve the real-time and accuracy of monitoring. The use of AI technology to establish a monitoring and dynamic numerical prediction system for flood and landslide disasters has significant social and economic value in improving disaster prevention and reduction, and reducing the losses caused to people's lives and property by disasters.

Flood and landslide disaster monitoring and dynamic numerical prediction can achieve early warning and take response measures to reduce casualties and property losses [4-5]. With the rapid development and application of geological hazard survey, remote sensing and other technologies, monitoring and prediction of flood and landslide disasters have also achieved certain results. Yan Jianhua applied a numerical technique that combines the discrete element method with the equilibrium finite volume shallow water model to predict the hazards caused by landslide blockages, dam breaches, and flood disaster chains, and selected a dumping slope in a reservoir area in the southeast of the Qinghai Tibet Plateau for research. The results indicated that the hazard map obtained by combining numerical techniques provided a quantitative reference for risk mitigation [6]. Sheng Yifan achieved landslide disaster prediction mapping by combining spatiotemporal probability analysis with time-varying ground deformation velocity derived from multi temporal interferometric radar methods, and used a comprehensive set of statistical indicators to evaluate the effectiveness of these methods. The results indicated that the proposed method could improve the accuracy of landslide disaster prediction and meet the needs of planners and government agencies responsible for managing landslide prone areas and preventing landslide disasters [7]. Takayama S developed a numerical simulation method for predicting the progressive failure flood hydrograph of landslide dams. By reproducing the collapse process of the dam toe, the longitudinal dam shape

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and reservoir water level during reservoir overflow were predicted. The effectiveness of this method was verified through on-site experiments of progressive failure of landslide dams. The progressive failure model successfully reproduced the experimental results of the dam toe collapse process [8]. Goudarzi Shidrokh used a fault-tolerant multi-level framework consisting of wireless sensor networks and unmanned aerial vehicles (UAVs) to monitor river water levels, and proposed an algorithm that combines group method data processing and particle swarm optimization to predict impending flood disasters in an intelligent collaborative environment. Experimental analysis showed that the proposed water level prediction model had high accuracy [9]. Although existing monitoring and prediction methods have certain accuracy in flood and landslide disaster prevention, the monitoring data obtained from them still cannot meet the needs of dynamic and intelligent monitoring and analysis of flood and landslide disasters.

The development of AI provides more possibilities for the dynamic monitoring, prediction and analysis of flood and landslide disasters [10-11]. Zhang Yonggang proposed a dynamic prediction method for landslide displacement based on gated recurrent unit neural network and adaptive noise fully integrated empirical decomposition, and conducted prediction experiments in landslide areas as an example. The results indicated that landslide displacement was carried out in a clear and gradual manner, and the dynamic prediction method used could significantly improve accuracy [12]. Nava Lorenzo combined convolutional neural networks with Long Short-Term Memory (LSTM) neural networks to predict future dynamic displacement of landslides. Experiments showed that the proposed model could make reliable dynamic predictions in landslide areas with high seasonal characteristics, providing valuable assistance for implementing deep learning based landslide warning systems [13]. Li Li-min proposed a dynamic prediction model for landslide displacement based on Singular Spectrum Analysis (SSA) and Stacked LSTM. Through SSA, the accumulated displacement time series data of landslides was decomposed into trend and periodic displacement subsequences, and Stacked LSTM was used to predict periodic displacement subsequences. Finally, the proposed model was validated to have higher prediction accuracy and better simulate the dynamic characteristics of landslides in the Tantan landslide prediction experiment in Hubei Province [14]. AI algorithms can fully consider the complexity and uncertainty of geological changes, and achieve intelligent and real-time analysis of flood and landslide disasters. However, most studies still have certain limitations in terms of monitoring and analysis efficiency.

In order to improve the real-time and dynamic monitoring of geological disasters, and enhance the quality of disaster response and prevention, this paper combined AI and used BP neural network and dynamic numerical model to study the flood and landslide disaster monitoring and dynamic numerical prediction system. To verify the functional effectiveness of the system, this article, taking B city as the object, conducted testing and analysis on the system from the aspects of monitoring error, real-time monitoring, numerical simulation, and user experience, and compared it with traditional GIS based disaster monitoring and prediction systems. In the monitoring error results, compared to the average relative error of the system in precipitation and displacement monitoring in this article, it decreased by 0.03 and 0.04 respectively; in terms of real-time monitoring results, the average response time of the system in this article was 1.36 milliseconds shorter than that of the GIS based disaster monitoring and prediction system; in the numerical simulation results, the precipitation and displacement simulation results in this paper were more dynamic and had more significant fitting with actual natural processes; in user experience testing, the system test results in this article were more ideal, with a higher proportion of users having a satisfactory experience level or above. In practical applications, the AI based flood and landslide disaster monitoring and dynamic numerical prediction system in this article can effectively improve monitoring efficiency and accuracy, providing more timely and reliable support for preventing flood and landslide disasters.

II. CONSTRUCTION OF FLOOD AND LANDSLIDE DISASTER MONITORING AND DYNAMIC NUMERICAL PREDICTION SYSTEM

A. System Functional Requirements

Flood and landslide disasters refer to natural geological disasters caused by sustained, long-term, or intense precipitation leading to an increase in groundwater level and flash floods [15-16]. Continuous, long-term, or high-intensity precipitation often leads to a significant increase in surface runoff and soil saturation, resulting in disasters such as land sliding, mudslides, and river flooding [17]. The functional requirements of the flood and landslide disaster monitoring and dynamic numerical prediction system are mainly considered from five aspects:

(1) Real-time monitoring and early warning

The system requires real-time monitoring of flood and landslide disasters, including the collection and monitoring of information such as rainfall, water level, and geological changes. On this basis, combined with on-

site observation data and numerical simulation results, the occurrence and development of floods and landslides are predicted and warned.

(2) Data analysis and management

By collecting and transmitting data through different monitoring stations, the system should provide analysis and management of relevant information such as the probability of disaster occurrence and the degree of damage, for government decision-making reference. The types of data involved in flood and landslide disasters are extensive, and the system should have different transmission methods and storage formats. In terms of data management, different types of databases should be used to store data. While ensuring data storage security, the spatiotemporal attributes of the data should be maintained as much as possible. Through effective interfaces of the database, it should be connected to the backend server to provide effective data support for overall flood and landslide disaster prevention and control.

(3) Dynamic numerical simulation

As a major function of the system, dynamic numerical simulation should be able to simulate flood and landslide disasters in practical applications, and predict their development trends and scope. The system should not only have high-precision numerical models, but also strong computational capabilities to achieve simulation and prediction of multiple disaster scenarios. The simulation results should have high credibility and accuracy, in order to achieve objective prediction of unexpected events.

(4) Spatial information integration

The system requires the integration of spatial information such as terrain, soil type, vegetation cover, etc., to provide support for disaster prevention and reduction. This means effective storage, management, and analysis of spatial data, and correlation analysis with numerical simulation results, in order to enhance understanding and mastery of the spatiotemporal distribution characteristics of flood and landslide disasters.

(5) User management

The system should have functions such as user permission management and data access control, and provide different levels of services and functions according to the user's role and permission. In other words, user management should have multi-level permission settings, which can flexibly set user permissions according to the user's role and usage requirements to ensure system security and information privacy.

B. System Architecture

Based on functional requirements analysis, this article constructs the overall architecture of the flood and landslide disaster monitoring and dynamic numerical prediction system using the B/S (Browser/Server) model, as shown in Figure 1:

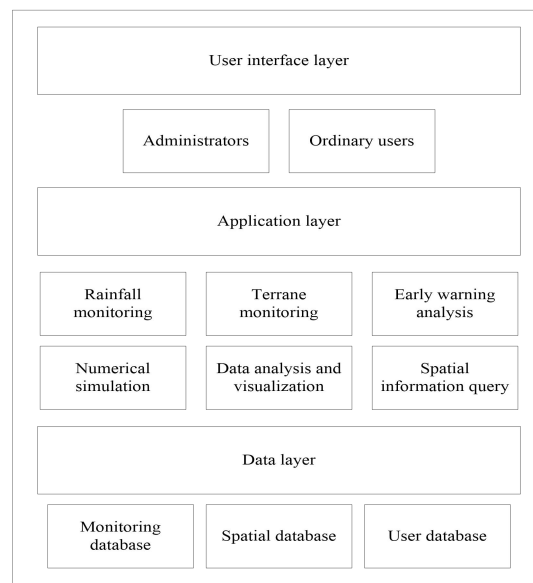


Figure 1. Overall system architecture

From Figure 1, it can be seen that the overall architecture of the flood and landslide disaster monitoring and dynamic numerical prediction system is divided into three levels: user interface layer, application layer, and data layer.

(1) User interface layer

The user interface layer mainly includes system users. In the flood and landslide disaster monitoring and dynamic numerical prediction system, the user group is divided into two categories: administrators and ordinary users. As the operation and maintenance personnel of the system, administrators are mainly responsible for configuring, managing, and maintaining the system. It has all the permissions for monitoring information management, system settings, user management, etc. It can add, modify, delete ordinary users, manage monitoring sites and warning rules, as well as set system parameters and permissions. The operations and permissions that ordinary users can implement within the system are set by administrators and cannot be changed by the system, nor can they manage other users.

After the administrator user enters their account and password, they then enter a randomly generated verification code. After completing the login confirmation, the system user interface is displayed, as shown in Figure 2.

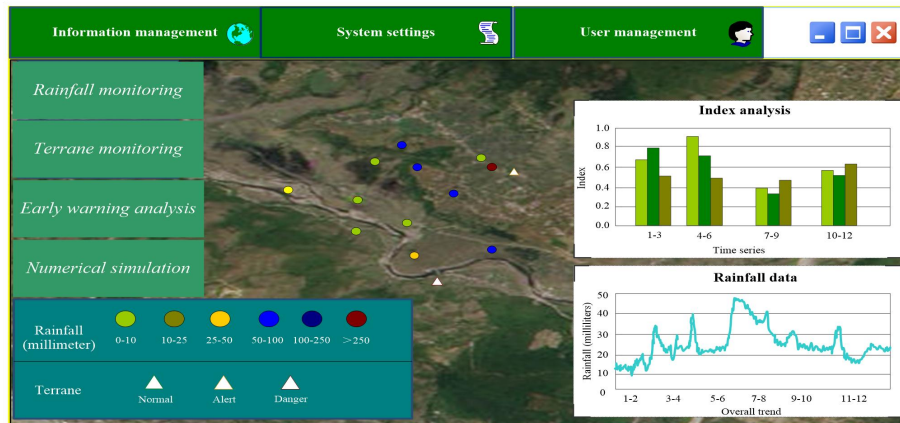


Figure 2. System user test interface

In Figure 2, the upper side of the interface displays the operations that can be implemented by administrator users, while the far right side displays rain monitoring, terrain monitoring, warning analysis, and numerical simulation. These four functional modules are the core parts of the flood and landslide disaster monitoring and dynamic numerical prediction system.

(2) Application layer

The system application layer mainly consists of rain monitoring, ground monitoring, early warning analysis, numerical simulation, data analysis and visualization, and spatial information query. The rain monitoring module mainly realizes real-time collection and monitoring of precipitation information at monitoring stations. By analyzing the precipitation, intensity, and spatial distribution of precipitation at different monitoring stations, precipitation events and regions that may cause flood and landslide disasters are identified, providing data support for early warning and emergency response of flood and landslide disasters, as shown in Figure 3.

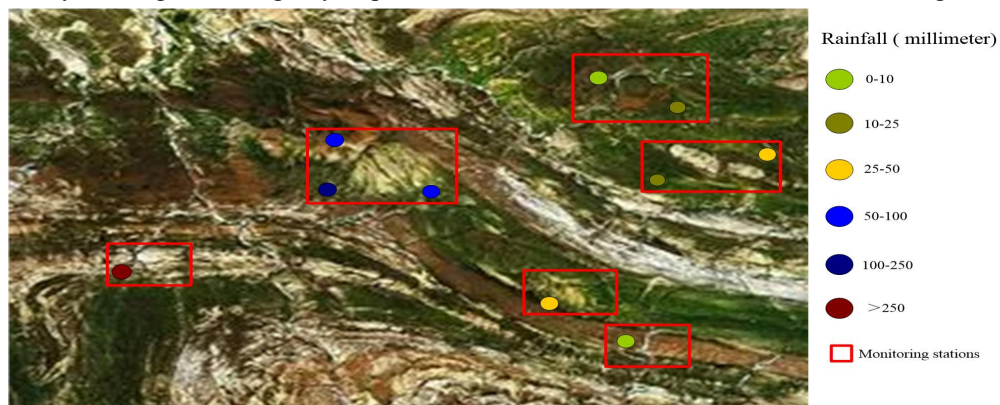


Figure 3. Rain monitoring module

The terrain monitoring module mainly realizes real-time monitoring of the geological conditions and topography of the monitoring station. By monitoring groundwater level, water content, geological structure, etc., effective warning and prevention of geological disasters such as floods and landslides can be achieved, as shown in Figure 4.



Figure 4. Ground monitoring module

The early warning analysis module mainly analyzes and processes monitoring data based on rainfall and terrain monitoring, and evaluates and warns the probability of flood and landslide disasters according to warning criteria, providing different levels of warning information to different users to assist them in making immediate decisions on disaster response.

The numerical simulation module mainly simulates floods and landslides through on-site monitoring data, combined with algorithm results, and uses numerical models to predict the occurrence, development, and impact range of disaster events, providing scientific support for emergency response and disaster relief work. The data analysis and visualization module is responsible for analyzing and visualizing monitoring data and numerical simulation results. The spatial information query module is mainly responsible for implementing disaster geographic information retrieval, map display, and spatial data query. On the basis of this module, users can view the disaster area, distribution of monitoring stations, and scope of the disaster through graphical means, grasp the spatiotemporal distribution patterns of floods and landslides, and provide spatial information support for disaster prevention and reduction work.

(3) Data layer

The data layer mainly consists of monitoring databases, spatial databases, and user databases. In data management, the monitoring database is responsible for storing and calling real-time monitoring data, while the spatial database is responsible for storing and calling geographic object data and remote sensing images; in the user database, it is mainly responsible for storing user data and other attribute data. Three databases constitute the data layer structure of the entire system.

The spatial database adopts a file geographic database to store spatial data such as geographic object data and remote sensing images of flood and landslide disaster monitoring stations, providing spatial data support for subsequent flood and landslide monitoring and dynamic numerical prediction systems. The monitoring database and user database are stored, queried, and managed using Microsoft SQL (Structured Query Language) server2020, which has superior data storage capabilities. The attribute data related to real-time monitoring data and user data is stored, including monitoring device information, real-time transmission data from monitoring points, and user information. The data storage of the system is centered around each monitoring station, achieving detailed recording of monitoring time, monitoring values, and other data for each monitoring station.

The key data tables for flood and landslide monitoring and dynamic numerical prediction system mainly include monitoring station data tables, monitoring information data tables, and user data tables, as shown in Tables 1 to 3.

Table 1. Monitoring station data table

Field	Description	Data type	Length (bytes)
Site-number	Number of monitoring station	Nvarchar	30
Site-name	The name of the monitoring station	Nvarchar	30
Site-location	Geographical location of monitoring station	Nvarchar	40
Site-type	The type of monitoring station	Nvarchar	20
Site-time	The construction time of the monitoring station	Datetime	30
Groundwater-type	Groundwater types at monitoring station	Nvarchar	30
Terrane-type	Ground type of monitoring station	Nvarchar	30
Note	Other descriptions	Nvarchar	100

From Table 1, the monitoring station data table mainly includes the monitoring station number, name, geographical location, type, construction time, groundwater type, terrain type, and remarks.

Table 2. Monitoring information data table

Field	Description	Data type	Length (bytes)
Equipment-number	Monitoring equipment number	Nvarchar	30
Equipment-name	Monitoring equipment name	Nvarchar	100
Date	Monitoring date	Date	30
Time	Monitoring time	Time	30
Value	Monitoring values	Float	30
Location	Monitoring location	Nvarchar	30
Remarks	Other descriptions	Nvarchar	100

From Table 2, the monitoring information data table mainly includes the monitoring equipment number, name, monitoring date, time, monitoring values, location, and remarks.

Table 3. User data table

Field	Description	Data type	Length (bytes)
User-identification	User identification	Int	20
User-name	User Name	Nvarchar	20
User-type	User type	Nvarchar	30
User-area	User's area	Nvarchar	30
User-phone number	User contact phone number	Nvarchar	20
Data	Historical data	Nvarchar	100

From Table 3, the user data table mainly includes user identification, name, type, location, contact phone number, and historical data information.

C. Disaster Monitoring and Dynamic Numerical Simulation Implementation

With the continuous maturity of AI technology, the application of neural network algorithms has made significant progress [18-19]. The BP neural network does not require complex modeling of the problem in advance, and each neuron has a simple nonlinear kernel function that can reflect nonlinear characteristics [20]. By self-organizing and assembling several types of nonlinear kernel functions, a neural network model is established to enable it to learn complex nonlinear mappings and construct complex nonlinear classification discrimination functions.

For the monitoring of flood and landslide disasters, this article uses BP neural network to learn the characteristics of flood and landslide disasters, and realizes the identification and monitoring of flood and landslide disasters. In terms of feature learning, by optimizing the correlation parameters between the network output layer and the hidden layer, training and generalizing the obtained data, the target area is accurately identified at the system application layer. Based on the location information of the disaster, parameters are fitted to achieve real-time monitoring of the disaster.

In flood and landslide monitoring and dynamic numerical prediction systems, most of the monitoring data is transmitted in the form of electrical signals. In order to convert these electrical signals into corresponding physical quantities, the equipment and devices need to be processed accordingly. Throughout the process, it is necessary to fully consider whether the device has the ability to identify abnormal signals, in order to timely identify and delete abnormal signals in monitoring data and convert electrical signals into corresponding physical quantities. The monitoring information of floods and landslides has real-time characteristics, and timely processing of abnormal signals is of great significance for taking timely response measures. Therefore, it is necessary to preprocess the monitoring data. Firstly, the functional relationship between the monitoring value f and time is set to $f(t)$, and the sampling point x contains n monitoring values. From this, the maximum and minimum values of the sampling sample are obtained, and the relevant parameters are calculated [21].

The calculation of the average value of sampling point x is expressed by the formula:

$$\bar{x} = (\sum_{i=1}^n x_i) / n \quad (1)$$

In Formula 1, i represents the degree of deviation of the sampling structure. The standard deviation τ of the sample is calculated as:

$$\tau = \sqrt{\frac{\sum_{i=1}^n x_i^2 - \frac{(\sum_{i=1}^n x_i)^2}{n}}{n-1}} \quad (2)$$

Statistical vectors are calculated:

$$S_1 = \frac{\bar{x} - x_{min}}{\tau} \quad (3)$$

$$S_2 = \frac{x_{max} - \bar{x}}{\tau} \quad (4)$$

Among them, x_{min} and x_{max} represent the minimum and maximum values of the sampled samples, respectively. Two statistical vectors contain the same probability distribution, and for a known risk rate, there exists:

$$\delta(h \geq H(n, r)) = r \quad (5)$$

When the difference between two monitoring values is $D_j = x_j - \bar{x}$, it must meet the following conditions:

$$|D_j| > H(n, r) \cdot \tau \quad (6)$$

If x_j is an abnormal data, then it should be removed. The above steps are repeated, and the remaining data is judged one by one until no abnormal data appears.

On this basis, by setting relevant parameters and selecting different signals, the efficiency and accuracy of flood and landslide disaster monitoring can be improved. Flood and landslide disasters have multiple causative factors. Taking I_s as the input of the algorithm model, and setting corresponding parameters such as the number of nodes N and learning rate η , these parameters can effectively improve the control accuracy of the model and improve its real-time performance. This process is represented by the formula:

$$M(k) = I_s(k) + N(k) + \eta(k) \quad (7)$$

By using the linear function transformation method for standardization, the following results are obtained:

$$y = \frac{x - N_{min}}{N_{max} - N_{min}} \quad (8)$$

The process of learning disaster features using BP neural networks can be divided into two parts: forward propagation of signals and backward propagation of errors [22-23]. In the forward propagation of signals, the signal is first transmitted through the input layer to the hidden layer, and then processed by the hidden layer before being transmitted to the output layer; the backward propagation of error refers to the transmission of the error signal to the party with reduced error when there is a difference between two output signals, averaging all errors and correcting the weights of different levels.

The sum of squared errors ε of all nodes is calculated during the forward propagation of the signal, which is expressed by the formula [24]:

$$\varepsilon = \frac{1}{2} \sum_{j=1}^m (e_j - y_j)^2 w_i M(k) \quad (9)$$

Among them, e_j is the expected value of the output layer node, and y_j is the final output value of the node. When the ε value is less than the given value, it should be trained for the next sampling. Otherwise, it is necessary to perform ε backward propagation and adjust the size of each value accordingly. By repeating the above calculation process, the output error of the network is controlled within the predetermined receiving range [25]. On this basis, the input samples are monitored, and based on the output results, the occurrence of flood and landslide disasters is judged and predicted.

After implementing monitoring of flood and landslide disasters, dynamic numerical simulation methods are used to simulate water level changes and ground displacement under different scenarios, and to provide early warning for potential flood and landslide disasters. In the system architecture, the functionality of the numerical simulation module is mainly achieved through dynamic numerical models.

It is assumed that the X-direction motion formula of water flow is:

$$O_X = \frac{\partial du}{\partial t} + \frac{\partial}{\partial X} (du^2 + \frac{1}{2}gd^2) + \frac{\partial duv}{\partial Y} \quad (10)$$

It is assumed that the Y-direction motion formula of water flow is:

$$O_Y = \frac{\partial dv}{\partial t} + \frac{\partial}{\partial Y} (dv^2 + \frac{1}{2}gd^2) + \frac{\partial dvu}{\partial X} \quad (11)$$

The continuity formula is expressed as [26-27]:

$$q = \frac{\partial d}{\partial t} + \frac{\partial du}{\partial X} + \frac{\partial dv}{\partial Y} \quad (12)$$

The definitions of variables from Formula 10 to Formula 12 are shown in Table 4.

Table 4. Definition of variables from Formula 10 to Formula 12

Sequence	Variables	Meaning
1	d	Water depth
2	g	Gravitational acceleration
3	u	Flow velocity in the X -direction
4	v	Flow velocity in the Y -direction
5	q	Rate of inflow

The numerical method of finite volume integration is used to discretize the continuity formula, and the normal momentum formula after discretization is [28]:

$$u_j^{n+1} = l_j + g \frac{\theta \Delta t}{\alpha_j \rho_j} (\mu_{je(j,2)}^{n+1} - \mu_{je(j,1)}^{n+1}) \tag{13}$$

$$v_j^{n+1} = g_j + g \frac{\theta \Delta t}{\alpha_j \rho_j} (\mu_{j\lambda(j,2)}^{n+1} - \mu_{j\lambda(j,1)}^{n+1}) \tag{14}$$

In dynamic numerical simulation, based on the discrete water flow momentum formula, the period of relatively gentle deformation is selected as the starting stage, with the latest monitored rock and soil mechanics parameters and the stable state of the terrain during this period as the main control factors, and the location, scale, and time of flood landslides are dynamically simulated.

III. TESTING OF FLOOD AND LANDSLIDE DISASTER MONITORING AND DYNAMIC NUMERICAL PREDICTION SYSTEM

In order to verify the effectiveness of the AI-based flood and landslide disaster monitoring and dynamic numerical prediction system, this paper conducted experimental tests on it. B city was selected as the testing area in this paper. The terrain of this city is mainly mountainous, with subtropical monsoon climate characteristics, uneven distribution of seasonal precipitation, and concentrated precipitation in a short period of time, which is prone to trigger flood and landslide disasters. This article tested and analyzed the system from several aspects, including monitoring error, real-time monitoring, numerical simulation, and user experience, and compared it with traditional GIS based disaster monitoring and prediction systems. There were a total of 10 monitoring stations distributed in the city. This article used the precipitation and displacement data of June 2023 from each monitoring station as sample data for system testing, and compared and analyzed the application effects of the two systems. The sample data is shown in Table 5.

Table 5. Sample data

Monitoring stations	Precipitation (millimeters)	Displacement (millimeters)
1	125.66	80.35
2	140.31	106.91
3	90.16	67.23
4	54.29	41.26
5	83.54	59.58
6	101.02	70.44
7	131.65	73.21
8	66.71	50.16
9	58.06	25.32
10	88.13	45.08

From Table 5, it can be seen that there were certain differences in precipitation and displacement data among various monitoring stations in the city based on specific geographical locations and environments.

(1) Monitoring error

Accurate monitoring data is the basis for scientific decision-making. In geological hazard monitoring and early warning systems, accurate monitoring data can provide decision-makers with more accurate information, thereby providing a data foundation and support for formulating effective disaster prevention measures [29-30]. This article compared the monitoring values of rainfall and displacement data from two types of systems with the actual values of the samples, and calculated the final monitoring relative error (RE) of the system. The result is shown in Figure 5.

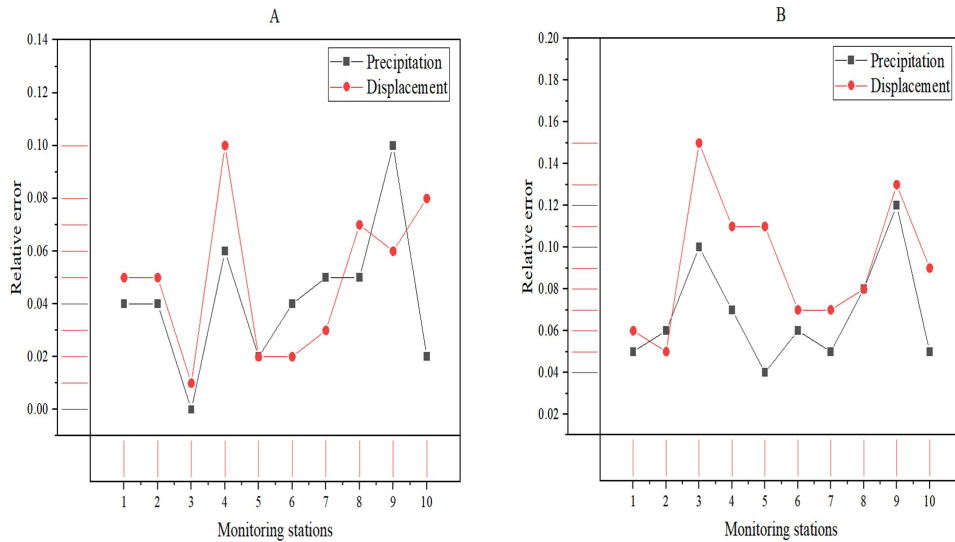


Figure 5. Monitoring error results (Figure 5A shows the RE monitoring results of the system in this article; Figure 5B shows the RE monitoring results of the GIS system)

From Figure 5, it can be seen that the AI based flood and landslide disaster monitoring and dynamic numerical prediction system had generally excellent monitoring errors. In Figure 5A, the average RE of precipitation monitoring at different monitoring stations in this article was about 0.04, and the average RE of ground displacement monitoring was about 0.05. In Figure 5B, the average displacement monitoring precipitation of the traditional GIS system at different monitoring stations was about 0.07, and the average RE of ground displacement monitoring was about 0.09. From the specific comparison results, in terms of monitoring error, compared to traditional GIS systems, the AI based flood and landslide disaster monitoring and dynamic numerical prediction systems in this article have reduced the average RE of precipitation and displacement monitoring by 0.03 and 0.04, respectively.

(2) Real-time monitoring

The real-time monitoring has a crucial impact on the timeliness of flood and landslide warning. On the basis of monitoring error testing, this article tested the real-time monitoring performance of two types of systems, and recorded and compared the response time of requests from different monitoring stations for the two types of systems. The final result is shown in Figure 6.

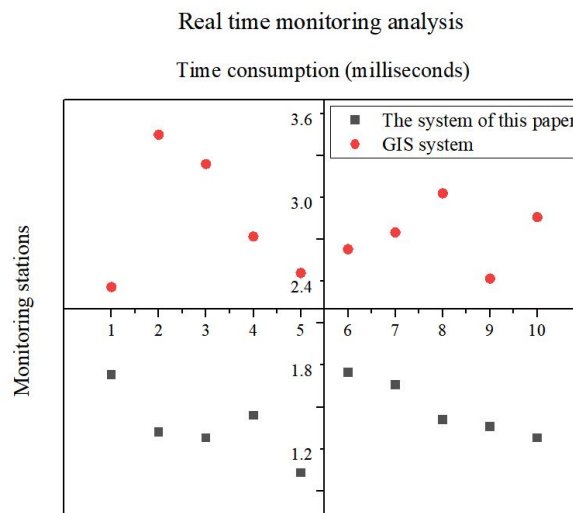


Figure 6. Real-time monitoring

From the specific results in Figure 6, it can be seen that there was a significant difference in the time consumption of site request responses between the two types of systems. In the process of responding to requests from different monitoring sites, the longest response time of the system in this article was 2.05 milliseconds; the

shortest response time was 1.33 milliseconds; the average response time was about 1.73 milliseconds. The GIS based disaster monitoring and prediction system had a maximum response time of 3.75 milliseconds and a minimum response time of 2.66 milliseconds for monitoring station requests, with an average response time of approximately 3.09 milliseconds. At the level of real-time monitoring, GIS based disaster prediction systems typically require processing a large amount of geographic information data. The neural network algorithm used in this system can achieve efficient response by learning and adjusting based on historical and real-time data. Compared with the GIS based disaster prediction system, the average response time of the AI based disaster monitoring and prediction system in this article has been shortened by 1.36 milliseconds.

(3) Numerical simulation

To verify the reliability of system prediction, this article took the Number 2 monitoring station with the highest precipitation and ground displacement as the object, and used different systems to simulate the actual natural processes of rainfall and displacement at this station. The final simulation results are shown in Figure 7.

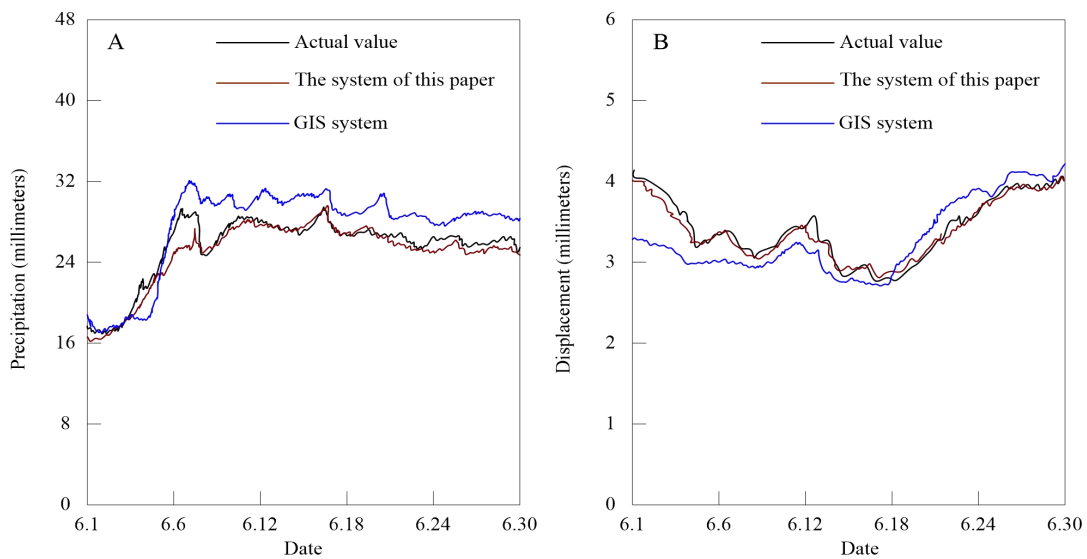


Figure 7. Numerical simulation results

Figure 7A shows the simulation results of precipitation;

Figure 7B shows the displacement simulation results.

Figure 7 shows the numerical simulations of two types of systems on the actual natural processes of rainfall and displacement at monitoring station 2. From the precipitation simulation results in Figure 7A and the displacement simulation results in Figure 7B, it can be seen that the system simulation results in this paper had strong coupling with the observed data of actual rainfall and ground displacement processes. Compared to GIS based disaster monitoring and prediction systems, the simulation results under AI in this article had a more significant fit with the actual natural processes in terms of direction and trend. The simulation results of GIS based systems had significant differences from actual natural processes.

(4) User experience

To analyze the effectiveness of system function usage, this article randomly selected 100 ordinary users from two types of systems through online surveys, and conducted user experience tests from the aspects of information presentation accuracy, timely warning, and system stability. The user experience level was divided into four levels: very satisfied, satisfied, average, and dissatisfied. The final test results are shown in Figure 8.

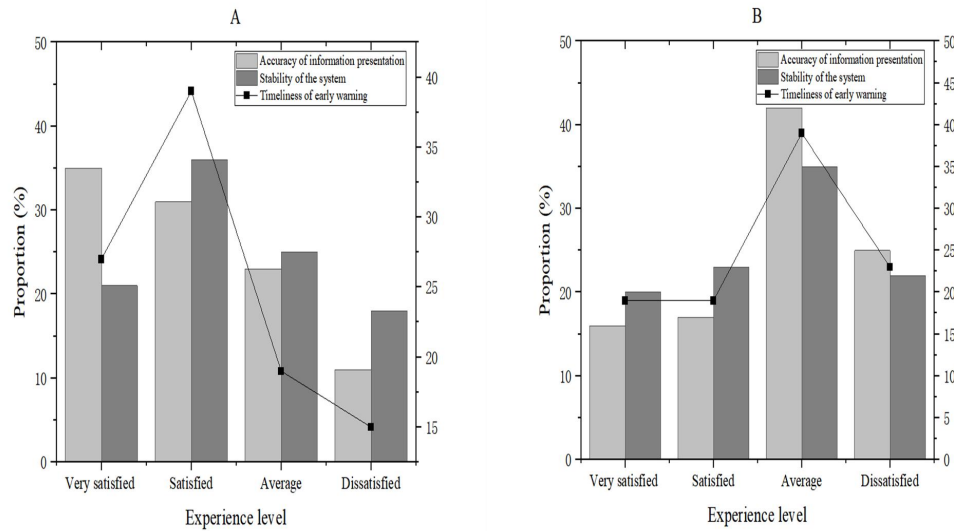


Figure 8. User experience test results (Figure 8A shows the user experience of the system in this article; Figure 8B shows the user experience of the GIS system).

In Figure 8, the left vertical axis represents the accuracy of information presentation and system stability test results, while the right vertical axis represents the timeliness test results of early warning. Among them, the user experience test results of the two types of systems showed significant differences. In Figure 8A, the total proportion of users who were satisfied or above with the accuracy of system information presentation, timely warning, and system stability in this article reached 66%, 66%, and 57%, respectively. In Figure 8B, the total proportion of users who were satisfied or above with the accuracy, timely warning, and system stability of the GIS based disaster monitoring and prediction system information presentation were 33%, 38%, and 43%, respectively. Compared to traditional GIS disaster monitoring and prediction systems, the flood and landslide disaster monitoring and dynamic numerical prediction system under AI in this article had more ideal test results, and the user experience level was generally higher.

IV. DISCUSSION

In the testing section, this article conducted experimental tests on the system from the aspects of monitoring error, real-time monitoring, numerical simulation, and user experience. From the perspective of monitoring error, the flood and landslide disaster monitoring and dynamic numerical prediction system under AI in this article has more ideal monitoring error results. BP neural network has strong adaptability and can achieve effective control of monitoring errors through continuous adjustment and improvement of historical data and real-time feedback. In terms of real-time monitoring, compared with GIS based disaster monitoring and prediction systems, this system, supported by neural network algorithm models, improves the speed and efficiency of monitoring and prediction by synchronously processing multiple sampling points. In numerical simulation, the system presented in this paper exhibits more significant dynamism and can achieve good coupling with actual precipitation and displacement processes. In terms of user experience, the total proportion of users who are satisfied or above with the accuracy of system information presentation, timely warning, and system stability in this article is higher.

V. CONCLUSIONS

With the acceleration of urban construction and climate change, the incidence of floods and landslides is increasing. The current traditional monitoring and prediction systems are difficult to provide timely and efficient early warning responses to natural disasters. In order to improve the real-time and dynamic monitoring of the system and provide objective and effective basis for disaster prevention, this paper combined the BP neural network algorithm under AI to construct a flood and landslide disaster monitoring and dynamic numerical prediction system. This has not only improved monitoring errors to a certain extent, achieving more accurate monitoring of precipitation and displacement, but also enhanced real-time monitoring and numerical simulation effects. On the basis of achieving efficient response and dynamic simulation, the user experience has been improved. In future research, it would be considered to continuously enhance the practical application value of

the system from the perspective of system scalability, and provide more effective technical support for geological disaster prevention and control.

ACKNOWLEDGMENT

Funding: This research was supported by the Science and Technology Innovation Project of Yangling Vocational and Technical College, grant number ZK21-37, JD22-02; and this research was funded by the Key Research and Development Program of Shaanxi, grant number 2023-YBNY-042, 2023-YBNY-223, 2024NC-YBXM-207

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