Research on Engineering Structures & Materials
www.jresm.org
MIM Research Group

Research Article

RK-OBGRNet-based high-precision sensing model for landslide detection and geological disaster emergency response

Jian Wang [*,a], Shuai Zhang [b], Shuai Zhang [c]

State Grid Xinyuan Zhejiang Jinyun Pumped Storage Power Co., Ltd, Lishui, Zhejiang, 323000, China

Article Info

Article History:

Received 17 Sep 2025

Accepted 26 Nov 2025

Keywords:

Geological disasters, emergency response; Early warning systems, Landslide hazards; Sensing and monitoring; Runge Kutta Optimized Backpropagate Gated Layered RecurrenceNet (RK-OBGRNet)

Abstract

Geological disasters, such as landslides, are vital in terms of life and property preservation and requires timely and accurate monitoring to adequately react to them and respond appropriately. Such catastrophes are to be monitored and acted on by advanced sensor technology that need advanced sensing technologies to operate in-person to detect and track them. This work utilizes satellite remote sensing data with several environmental and geological variables to produce high-precision landslide influence factors. These are the foundations of advanced sensors and monitoring techniques in geological disaster response. The RK-OBGRNet, an integrated recurrence and monitoring model for landslides which uses remote sensing images, is designed to detect and monitor landslides. The preprocessing methods for satellite images are z-score normalization, Fourier Transform, FT which improves the quality of the satellite images by eliminating noise and making data synchronized to the analyzer. It utilizes feature extraction such as principal component analysis to identify characteristics of landslides that dominate their presence. The impact of model parameters on landslide detection accuracy has been analyzed. The performance of RK-OBGRNet is better compared to the RNN-Autoencoder and Cascade R-CNN with improved accuracy of 95%, precision of 94%, recall of 93%, and F1-Score of 92%. The results indicate that RK-OBGRNet achieves better and demonstrates its effectiveness for high-precision landslide detection. This research provides valuable insights for enhancing geological disaster monitoring and emergency response. It offers a reference for applying high-precision sensing technologies to early warning systems and rapid response strategies in the management of landslide hazards.

© 2026 MIM Research Group. All rights reserved.

1. Introduction

In disaster management and disaster risk reduction (DRR), the majority of nations utilize the single-hazard approach because hazards are viewed and handled as distinct, separate events. A proactive approach to disaster risk reduction by minimizing vulnerability and strengthening vulnerability against natural hazards. But occasionally, several danger categories overlap and interact in the ways listed below: Human activities can cause natural hazards by generating one or more hazard events, by generating natural hazards, intensifying the triggering of natural hazards, establishing networks of interconnections between hazards, and generating two or more hazard events simultaneously [1]. Research on emergency planning and Geographic Information System (GIS) based emergency command systems for geologic hazards is essential. A system that captures, stores, analyzes, and visualizes geographic and spatial data for decision-making and planning.

[*]Corresponding author: 18357885701@139.com

[a]orcid.org/0009-0006-2335-5551; [b]orcid.org/0009-0001-4101-7410; [c]orcid.org/0009-0000-3155-9040

DOI: http://dx.doi.org/10.17515/resm2025-1168sc0917rs

All levels of emergency management agencies have noticed improvements in rescue operations and response times due to emergency plans and command systems [2]. Geological catastrophes are frequent natural occurrences that have a significant impact on human existence because of their abruptness and extreme destructiveness. Therefore, multiple investigations both domestically and internationally have developed catastrophe emergency management programs, for the sake of human survival and the normal development of human civilization [3]. As the social economy expands, large-scale projects, like the railways, may be constructed. Therefore, an increasing number of economies at risk from the hidden dangers of geological disasters, especially long-term landslide threats. However, earthquakes and geological hazard chains may become more apparent when the effects of extreme weather, such as typhoons, drought, and heavy rain, worsen [4]. Reducing catastrophe losses after natural disasters occur is mostly dependent on decision-making based on big data, both geographical and non-spatial, to enable quick emergency response and rescue. A disaster emergency management system's primary component, GIS technology, aids decision-makers in rapidly integrating, processing, and analyzing catastrophe data [5]. The shortest distance, the shortest time, and the highest rescue effect are the goals of emergency resource dispatch models, which typically have particular features. To disperse resources for prompt rescue, emergency management departments typically set up many resource centers. The quantity and kind of vehicles at each resource center are unknown due to the abruptness of geological disasters. Furthermore, roadways can sustain damage and new places can be affected by the effects of secondary catastrophes [6]. The RK-OBGRNet model is aided by GIS systems for integration of spatial data, multi-hazard management principles for the integrated response to disasters, and satellite communication for real-time transmission of data

Emergency communication greatly benefits from satellite networks, while the conventional approach mostly uses a single satellite vehicle or satellite portable station to build the network. While this plan can help with communication issues to a certain degree, satellite vehicles have limited network coverage and poor mobility in crises. The role of satellite vehicles is limited by the aforementioned issues [7]. Seismological monitoring has been made possible by advances in seismology, and the Global Seismographic Network (GSN) offers almost consistent worldwide monitoring. The network, which has more than 150 stations globally, reduces the number of fatalities and financial losses caused by significant earthquakes [8]. Meteorology, geology, and seismology are among the sciences that apply technological methods to avoid and lessen natural disasters. GPS measures crustal movements, weather radar detects precipitation, satellites collect data, and autonomous weather stations track data in real-time [9]. Imaging spectroscopy, another name for hyperspectral imaging, is a technique that uses space-based, airborne, or unmanned aerial systems or lab-based imaging systems to capture images of geologic or outdoor environments. Each pixel of the images contains a reflective/emissive spectrum of the material present. Each pixel can be analyzed to identify items in the obtained image or scene, given context, and a reference library [10]. One of the primary trends in global catastrophe prevention and reduction is community-based disaster risk management (CBDRM) extensively adopted and used by national, international, and local organizations. A participatory process of participatory participation of local communities in how they identify, assess, and manage disaster risk to reduce vulnerability. In recent years, some nations have embraced the development of community-centered disaster reduction strategies to construct the policies, plans, and schemes of CBDRM to address the increasing difficulties of catastrophe risks [11]. Geological disasters, including collapses, landslides, and debris flows, happen all over the world and have a major negative impact on property, human life, the environment, and sustainable economic growth, particularly in developed countries [12]. Runge-Kutta optimization enhances convergence and stability through the optimization of model parameters, and gated layers increase the temporal learning capability, providing dynamic adjustment towards geological information over time. The limitations include,

- Handling real-time, high-dimensional data: Processing high-dimensional data in real-time remains computationally intensive, requiring advanced optimization methods that can be prone to resource constraints.

- Optimizing sensor placement through Runge Kutta: Runge Kutta optimization may struggle with non-stationary or unpredictable data, potentially leading to suboptimal sensor placement in rapidly changing environments.
- Using gated layers for better temporal data learning: Gated layers can become prone to overfitting when trained on insufficient or noisy data, limiting their generalization ability in diverse real-world disaster scenarios.

The integration of high-precision sensing and monitoring technologies in geological disaster emergency response plays a crucial role in promoting climate-responsive and sustainable infrastructure development. With the increasing frequency of extreme climatic events, such as intense rainfall, drought, and temperature fluctuations, the stability and resilience of smart construction systems have become vital concerns. The proposed RK-OBGRNet-based sensing framework not only enhances the accuracy of geological disaster prediction but also contributes to climate-adaptive infrastructure planning by enabling real-time monitoring of environmental parameters such as soil moisture, rainfall intensity, and ground deformation. Through intelligent sensor deployment, AI-driven analytics, and adaptive learning, the system supports early warning and proactive maintenance strategies that reduce the vulnerability of critical infrastructure to climate-induced geohazards. By integrating geological sensing with climate-responsive design principles, this research provides a pathway toward smart, sustainable, and resilient construction ecosystem that can dynamically adapt to evolving environmental conditions and ensure long-term structural stability under the influence of changing climate patterns.

1.1. Objective of the Research

In research focused on landslide detection, the aim is to develop high-precision sensing and monitoring systems to enhance emergency response for geological catastrophes. In improving accuracy as well as the efficiency in landslide monitoring and early warnings, this research explores the combination of satellite remote sensing data, complex pre-processing methods, and the use of the RK-OBGRNet model.

1.2. Key Contribution

- For continuous monitoring, high-precision landslide influencing variables in this research are produced by the combination of both geology and environmental data from satellite remote sensing.
- The suggested RK-OBGRNet model enhanced by applying Runge Kutta, proves to have surpassed conventional methods for landslide detection.
- This research helps enhance emergency response tactics and raise the level of effectiveness of disaster management through offering a useful tool for landslide early warning systems.
- The RK-OBGRNet model greatly enhances the accuracy of disaster detection via sophisticated optimization methods and deep learning, providing an effective tool for early warning systems. Its ability to incorporate dynamic sensor placement and temporal learning maximizes real-time monitoring ability, pushing forward disaster management practices.

1.3 The Remaining Research

Phase 2 includes the literature review, Phase 3 discusses the methodology, Phase 4 evaluates the experimental findings and the discussion, and Phase 5 establishes the conclusions.

1.4 Literature Review

The Sichuan-Tibet Railway, a complex and elaborate project across the Qinghai-Tibetan Plateau, was at risk of disasters because its terrain was extremely difficult. The Sichuan-Tibet Fund special project focused on five studies: geological structure, hazard-inducing processes, tunnel engineering and disaster identification to address these problems and advance technology [13]. The probability of landslides, intensity, and location as well as time and place, are considered as the predictive factors for emergency rescue risk in a landslide catastrophe scenario [14]. For a country on the coast, it examined the effects of risk perception and protective motive theory in disaster preparedness in China. In their analysis, people’s desire to participate in protective activities was greatly influenced by their own assessment of coping and risk attitudes and this is reflected in the need to do more than just managing risk [15]. Real-time data collection and enhanced agency collaboration in emergency management are made possible by the Internet of Emergency Services (IoES). It discussed the difficulties, possibilities, risks, restrictions, and possible effects on the public safety of sensors and Internet of Things (IoT) devices [16]. Forecasting and monitoring were necessary to reduce the dangers associated with large-scale landslides in Zhouqu County, Gansu Province, China. Global Navigation Satellite System monitoring and unmanned aerial vehicle imaging were combined techniques for threat reference and emergency decision-making [17]. With an emphasis on their suddenness, mass occurrence, induction, geographical variation, and social effect, the research investigated the reasons for frequent geological disasters in mined regions. It created a risk assessment system with 10 indicators and emphasized the relationship between environmental geology and breeding, inducing, and forming geology [18]. Public involvement in disaster mitigation programs in both model and nonmodel towns in a geologically vulnerable area was examined. The findings indicated that while catastrophe experience and perceived behavioral control impacted the behavior of nonmodel societies, model communities participated more in evacuation drills and self-help skills training [19]. Earthquake catastrophes in China, an earthquake-prone region, result in direct loss of life and property, secondary natural disasters, and societal repercussions. Researching the main earthquake risks aids in mitigation prediction and prevention. The special issue compiles the most recent findings in research on significant earthquake hazards, such as active structure evolution, occurrence mechanisms, prediction, risk assessment, mitigation, emergency response, and rescue following big earthquakes [20]. For catastrophe scenarios, remote sensing was essential; however, user applications and science restrict its potential. Through the use of social surveys and case studies, it investigated the non-technical aspects that affect RSES. The objective was to enhance RSES administration and comprehension, provide a framework and software for authorities, and direct RSES procedures during crises [21]. The research examined the safety of pipelines that were suspended as a result of natural disasters, with a particular emphasis on plastic deformation and nonlinear finite element techniques (FEM). When the hung length surpasses 50 meters, irreversible plastic stresses happen, reaching 2% at 340 meters. It suggested promoting the sustainable expansion of oil and natural gas pipelines in areas that frequently encounter natural disasters [22]. To lower the expenses of disaster management and the number of fatalities, the Chinese government implemented the Public Participation Monitoring and Warning (PPMW) system. The method, which was used in landslides in Boli village, organizes inhabitants to evacuate ahead of time and distributes timely emergency information. For other nations dealing with comparable circumstances, the system can develop into an inexpensive catastrophe risk management tool [23]. The Yellow River Basin (YRB) was vulnerable to significant calamities due to its diverse climate, fast evolution, and active geological processes. Ecosystems can be destroyed by these catastrophes, which can have serious repercussions. The research examined the YRB's geological processes, significant catastrophe impacts, and risk mitigation studies, highlighting important scientific issues and outlining potential directions for further research based on earth system science ideas [24,25]. Kadiyala et al. (2025) presents a cloud-integrated IoT-based healthcare monitoring and emergency response system using deep learning. RK-OBGRNet adopts similar strategies by integrating satellite IoT sensors with cloud computing for real-time geological monitoring and applying deep learning algorithms for analyzing spatiotemporal data. This integration improves real-time monitoring, enhances disaster prediction accuracy, and ensures scalability for various disaster scenarios, offering a robust solution for geological hazard management [26]. It incorporates ConvLSTM networks and satellite images to enhance predictive modeling for natural hazards such as floods, landslides, and earthquakes, describing its capability in learning spatiotemporal relationships between remote sensing data. It presents a modern example of AI/ML use in disaster sensing, which might be contrasted with the models such as U-Net. Adding this study in your literature review provides a critical evaluation of the development in disaster management technologies [27].

2. Methodology

The technique includes RK-OBGRNet optimization for real-time landslide detection, sensor placement, improved geological disaster monitoring, PCA for feature extraction, and data preprocessing using Z-Score normalization and Fourier Transform. Primary geological disaster data, including information on landslides, tsunamis, floods, and earthquakes, were directly collected through satellite imagery. Figure 1 represents the proposed methodology flow.

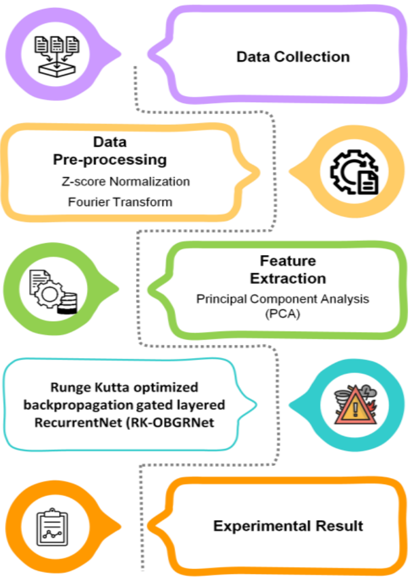


Fig. 1. Flow of proposed methodology

2.1 Data Preprocessing Using Z-Score Normalization and Fourier Transform (FT) For Geological Disaster Monitoring

2.1.1. Z-Score Normalization

In the preprocessing stage of the geological disaster monitoring system, the Z-Score normalization method is used to normalize the data collected from different high-precision sensing technologies, such as seismic activity, soil movement, and atmospheric pressure. The technique is useful in real-time disaster response systems, as it ensures all the features are on the same scale and, hence, improves the accuracy and performance of DL models. Equation (1) follows for standardizing the data:

$$N = N - \frac{mean(N)}{standarddeviation(N)} \tag{1}$$

By removing the biasing in units of data, there is an improvement of RK-OBGRNet models regarding predictions about geological risk hazards and emergency response. This implies with the processing of various source data, it ensures the model can perform, and generate timely results, which will lead to improving tactics for response and disaster management.

2.1.2. Fourier Transform (FT)

The application of FT techniques improves the procedure for the feature extraction of geocatastrophe monitoring. Combined with the data of high accuracy, FT enables real-time processing of frequency terms in data signals related to environmental and seismic events. It converts time-domain information to frequency-domain representation as it unfolds critical frequency content, such as ground acceleration or angular velocity; which is required to understand geologic activity, such as an earthquake, landslides, or volcanic activity. These are frequency components on which traditional correct identification and prediction of disaster scenarios are based. The mathematical expression of a constant FT of a time-domain signal $Y(s)$, which is an expression of geological monitoring equipment or seismic data, is given by equation (2):

$$y = (e) = \int_{-\infty}^{\infty} Y(s) f^{-j2\pi ds} ds \tag{2}$$

Here, $y(e)$ corresponds to the signal in frequency domains, $y(s)$ or the signal in a time domain, and symbols $c\ and\ j$ correspond for frequency and imaginary units respectively. This domain transformation is required in order to produce elements according to frequency analysis in order to characterize behavior geology in a natural catastrophe. Subsequently after the conversion formula in equation (3), the average of converted signal with respect to mean frequency can be calculated as an imperative component of disaster management surveillance:

$$Mean\ Frequency = \frac{1}{n}\sum_{k=0}^{n-1}|y[k]| \tag{3}$$

The equation represents the amplitude of each frequency component by Y[k] whereas n is the number of frequency samples. The proposed solution can improve on monitoring knowledge accuracy through the study of such frequency aspects, therefore, facilitating real-time monitoring and prediction of geological disasters. Z-score normalization was used over min-max scaling because it is able to only normalize data and does not eliminate bias, and all features are equally contributing and their range is not limited hence more stable with other data distributions. The application of Fourier Transform (FT) was based on the fact that it is able to convert time-domain signals into frequency-domain characteristics, which allows a researcher to study a periodic nature and anomalies typical with geological events, including seismic occurrences. This mixture enhances the model to effectively handle dynamic and noisy geological data.

2.2 Feature Extraction Using Principal Component Analysis (PCA)

PCA is a significant preprocess technique, which can be applied to data of high-resolution sensor systems. Typically, such geological factors are the monitoring of the climatic conditions, soil movement, and seismic activity, which generate large amounts of information and have a high level of dimensionality. This is easy to understand and can easily be facilitated to achieve the real-time analysis of response to disasters because the most salient features of this data created by the process of PCA are removed. The initial procedure is the normalization of data matrix Z that is a representation of geological measurements. Principal Component Analysis (PCA) is important in lowering the dimensionality of geological data, determining the most significant features for precise disaster forecasting by recognizing major patterns in seismicity, soil movement, and other environmental conditions. In this case, parameters might be on varied scales e.g., pressure in Pascal, displacement in meters hence the standardization procedure would ensure that all features contribute equally to this research. Subtracting the mean of each feature and dividing by the standard deviation yields the standardized data matrix, or Z_{stand} in equation (4):

$$Z_{stand} = \frac{Z - mean\ (Z)}{std\ (Z)} \tag{4}$$

The matrix of covariance B is calculated to comprehend the connections among the dataset's characteristics. Understanding the correlations and fluctuations between feature pairs is provided by the covariance matrix, which depicts how fluctuate together. The following standardized data is used to compute it in equation (5):

$$X = \frac{1}{p-1} Y_{stand}^{B} Z_{stand} \tag{5}$$

The standardized form of the data matrix is called Y_{stand}, and p is the number of observations in the dataset. To determine the most significant directions of variation in the data, the covariance matrix is essential. The covariance matrix A is used to compute the eigenvalues and eigenvectors. The associated eigenvectors characterize the directions of maximal variance, whereas the eigenvalues, represented by λ, show the variance along with each primary component. The following equation (6) is an expression for the connection between eigenvalues and eigenvectors:

$$Xa = \lambda a \tag{6}$$

This equation demonstrates how each eigenvalue λ scales the corresponding eigenvector a. The primary components, or the directions in which the data fluctuates are represented by the eigenvectors. Components with eigenvalues greater than one are typically retained when using the Kaiser criterion, as they account for the majority of the variation in the data. The following is how top T components are chosen in equation (7):

$$Top\ T\ components\ a_1, a_2, \ldots., a_T \tag{7}$$

These particular elements are the most crucial for comprehending the main causes of geological disasters. The regular data Z_{stand} must be predictable into the new coordinate system that the chosen primary components have specified. While keeping the most significant attributes, this alteration lowers the dimensionality of the data. The covered datasetZ_{PCA} is provided by the equation (8):

$$Z_{PCA} = Z_{stand} U_T \tag{8}$$

$U_T$is the matrix of the selected eigenvectors. By reducing the dataset and emphasizing its prime components, this revolution facilitates data analysis and understanding. The most important elements of the concentrated data can be highlighted while maintaining critical information by reconstructing it to roughly be similar to the dataset. During the renewal process, the following equations (9& 10) are used:

$$F = U_T^B \tag{9}$$

$$V = mean\ (Z) + U_T f \tag{10}$$

The reconstructed data is denoted by F in these equations, and the reconstructed dataset with the mean added back is denoted by V. By using PCA on the data collected by high-precision sensing systems, the research determines the main causes of geological catastrophes, such as changes in the environment, shifting seismic activity, or soil displacement. PCA was employed to compress data dimensionality while retaining essential features, maximizing high-precision sensor data fusion, and enabling effective analysis in dynamic geological monitoring systems. PCA outputs, which constitute important geological features, were incorporated in the RK-OBGRNet model to enhance the predictive performance by enabling the modeling process with a compressed, but meaningful, feature set. The model relies on the assumption of frequent satellite image data availability with high-frequent updates, and the data-collecting sensors are usually high-precision geological sensors that can sense seismic activity, soil movement, and changes in atmospheric pressure.

2.3 Landslide Detection and Monitoring Using Runge Kutta Optimized Backpropagate Gated Layered RecurrenceNet (RK-OBGRNet) from Remote Sensing Images

The images of remote sensing are used in landslide detection and monitoring landslide occurrences. Nevertheless, the accuracy of the prediction can be increased by employing the design of the OBGRNet, which incorporates the usage of backpropagation and the gated recurrent layers; however, the efficiency of the model can be optimized using RK. This improves the accurate geographical and time nature of the landslide processes in real-time monitors. RK-OBGRNet is particularly useful in geological disaster observation, as it is capable of work with high-dimensional time-series, adapting to changes in disasters with gated layers, RK optimization of sensor placement positioning, and real-time observation at high precision.

2.3.1 Backpropagation

The Backpropagation Algorithm is used to optimise sensor data, predict danger and validate the results through error functions, including the Mean Squared Error (MSE) when high precision sensing data is required to respond to geological disasters. Minimizing prediction accuracy through error correction Backpropagation can be used to minimize prediction errors, gated layers allow the learning of real-time temporal predictions and RK optimization can be used to maximize the performance of sensors by the prediction of geological occurrences.

Forward Pass Calculations: The weather and cloud cover are external factors that are known to distort satellite remote sensing data and this may affect the prediction by a model. RK-OBGRNet responses to this by incorporating preprocessing techniques such as Fourier Transform and PCA in order to eliminate noise and capture useful information in noisy satellite pictures. The normalized input variables are received by the input layer and are positioned based on geological features (ground displacement or seismic). Each input is given significance by initializing the weights $Xj, l, and\ i$ at random. The output W_1 for the first hidden layer is computed as follows in equation (11):

$$Z_{1,1} = e(net_{1,1}) \tag{11}$$

Where the first layer's input is in equation (12):

$$net_{1,1} = \sum_{j=1}^{n} X_{j,1,1} \tag{12}$$

- Activation Function: The Sigmoid activation function is used to normalize the output of each neuron in equation (13):

$$\hat{Z}_c = \frac{1}{1 + f^{\sum_l (net_{l,i} + g_i)}} \tag{13}$$

Where, the predictable output, such as the anticipated danger of a geological disaster, is represented by$\hat{Z}_c$.

- **Error Function and Validation:** The discrepancy between the expected and intended output Z_b. The MSE is used to measure $\hat{Z}_c$ in equation (14):

$$MSE = \frac{1}{m} \sum_{c=1}^{m} (Z_b - \hat{Z}_c)^2 \tag{14}$$

To guarantee accurate forecasts for geological disaster management, this error function is utilized to assess the model's correctness.

2.3.2 Gated Layered

Multi-layered sensing systems that are able to analyze are a gated layered approach. selective choice of important data in real-time. This method prioritizes and filters data of different layers of sensors, based on urgency and relevance, when there is a geological crisis, e.g. an earthquake, landslide, or volcanic eruption, using gated mechanisms. It enhances the accuracy and efficiency of monitoring systems by integrating the state-of-the-art sensors with intelligent data filtering mechanisms, thereby making prompt and informed decisions respectively on disaster response and mitigation.

2.3.3 Runge Kutta (RK) Optimization

RK optimization algorithm is a strong optimization technique, which applies the concepts of the Runge-Kutta algorithm in solving ordinary differential equations. The RK in the geological disaster emergency response is applied to enhance the precision of real-time sensor selection and location to sense and monitor. This is because the estimation of gradients was made through the RK technique to guide the search of optimal design and placement of the sensors. This is to trade exploration and exploitation with the solution space to attain high-precision sensing information regarding early warning and disaster relief. RKOBGRNet framework enables an easy coordination of sensing units by integrating resilient communication schemes, which adjusts the placement of sensors and transmit data in response to realtime feedback and monitoring requirements.

Backpropagation, RK optimization, and gated layers provide a high level of synergy by combining the three mechanisms, namely, error correction, dynamic sensor placement, and temporal learning. Backpropagation is used to optimize model accuracy, RK optimization is used to optimize locations of response sensors in real time and gated layers enhance temporal behavior of geological processes to model performance, in comparison with traditional models.

- Search Mechanism to Disaster Monitoring:

The RK optimization identifies regions of the solution space that represent the zones of interest that include seismic activity or prone landscape areas or areas that are at risk of flooding in geological disaster monitoring. The system is operated to guarantee a balance between exploration (of finding new potentially valuable sensor placements) and exploitation (finer-tuning of existing sensor placements based upon the information gathered), with initial sensor placements being randomly assigned to these areas. As examples of the RK optimization of geological sensing, the following equations (15 and 16) are illustrations of the search mechanism (SM):

$$SM = \frac{1}{6} w_{RK} \tag{15}$$

$$w_{RK} = l_1 + 2.\ l_2 + 2.\ l_3 + l_4 \tag{16}$$

Where, w is the positional adjustment of sensors inside the monitoring network and $l_1, l_2, l_3,\ and\ l_4$ are coefficients obtained through the RK approach.

- Solution Update in Disaster Monitoring Systems:

The initial inputs of the RK optimization method are a randomly distributed population of sensors, which are potential locations of monitoring. The locations of these sensors are updated at every cycle with the RK technique. The sensor network is altered to suit the real-time information of geological processes such as earthquakes, landslides, or floods. The sensor location updating process is regulated by the following equations (17 & 18) that ensure the exploration of the new territories as well as the usage of the existing information to manage the disaster:

$$if\ rand < 0.5\quad w_{m+1} = (w_d + q.SF.h.w_d) + SF.SM + \mu.randm.(w_n - w_d)\quad exploration \tag{17}$$

$$else\ \ w_{m+1} = (w_n + q.SF.h.w_n) + SF.SM + \mu.randm.\left(w_q 1 - w_q 2\right)\ \ exploitation \tag{18}$$

With SF the adaptive scaling factor that varies the search intensity in accordance with the iteration progression, and q and h random integers controlling exploration and exploitation respectively equation (18).

- Enhanced Solution Quality (ESQ) in Monitoring Systems:

To ensure that the sensor placement quality is steadily improved with the iteration progression, the RK algorithm ensures that q and �acute are random integers that regulate exploration and exploitation, respectively. This enhancement called the Enhanced Solution Quality (ESQ) is ensured by a feedback mechanism which entails real-time sensor data, which ensures that the system keeps on improving its search to the best monitoring locations. The ESQ process of sensor placement are the equations below (19-21):

$$if\ rand < 0.5 \tag{19}$$

$$if\ x < 1\quad w_{new2} = w_{new1} + q.x.\left|w_{new1} - w_{avg}\right| + randm \tag{20}$$

$$else\ w_{new2} = \left(w_{new1} - w_{avg}\right) + q.x.\left|v.w_{new1} - w_{avg}\right| + randm \tag{21}$$

Where x is a parameter which is dynamically modified to control the work of the algorithm. Ensuring the new sensor placement points are moved towards the region of high-risk activities like the fault lines or floodplains by continuously setting the average location of sensors w_{avg} to optimally and efficiently improve sensor network. The program experiment with additional configurations in the event that the addition of further sensors does not improve the data collecting (i.e., the fitness function is not maximized). Improvement of sensor location is achieved by shifting the sensor in the direction which is shown by the subsequent equation (22):

$$if\ rand < x \quad w_{new3} = (w_{new2} - rand.w_{new2}) + SF.(rand.w_{RK} + u.w_a - w_{new2}) \tag{22}$$

To ensure the algorithm continues to search regions which have the highest probability of locating an important geological process, say a tremor, change in the surface, or rising water levels, u is a random integer that determines the search direction. The hybrid RK-OBGRNet is represented in algorithm 1.

- Algorithm 1: Hybrid RK-OBGRNet

```
Main Loop: Iteration over − optimization and sensor placement
for each iteration in range(MaxIterations):
Backpropagation (BPA) Step to adjust weights based on prediction error
Input data received (e.g., remote sensing images or sensor data)
 input_data = normalize(remote_sensing_data)
  hidden_layer_output = activate(input_data)  Forward pass
   predicted_output = forward_pass(hidden_layer_output)
Calculate error using MSE (Mean Squared Error)
error = calculate_MSE(predicted_output, true_output)
Backpropagate error to adjust weights and improve prediction accuracy
backpropagate(error)
Gated Layered Approach: Real − time data filtering based on geological events
 if geological_event_detected(): # Check if a disaster event (e.g., landslide) is detected
if data_urgency_level() > threshold:
 Prioritize data from critical sensors based on urgency
filtered_data = filter_critical_data(input_data)
 Else:
 Process all available data (non − urgent)
filtered_data = filter_all_data(input_data)
   Else:
filtered_data = input_data # No event detected, use normal data
Runge − Kutta Optimization (RK) for sensor placement
for the sensor in sensors:
Step 1: Update sensor placement using the RK search mechanism
 search_mechanism = calculate_search_mechanism(sensor_position)
 Step 2: Exploration vs Exploitation (Balance between new and existing placements)
if random() < 0.5:
 Exploration: Search for new sensor placements
sensor_position = exploration(sensor_position, search_mechanism)
Else:
Exploitation: Refine current sensor placements
        sensor_position = exploitation(sensor_position, search_mechanism)
 Step 3: Update sensor placement with Enhanced Solution Quality (ESQ)
if random() < 0.5:
Enhance solution quality to avoid local minima
sensor_position = enhanced_solution_quality(sensor_position)
Sensor Network Update: Adjust sensor locations based on real − time data
For sensor in sensors:
Update sensor position based on new geological event data
      sensor_position = update_sensor_position(sensor_position)
Check if optimization has converged (no significant improvement in results)
 if check_convergence():
break  Exit loop if optimization converges
```

The system incorporates gated layers for real-time data prioritization during geological events, backpropagation for error correction-based model prediction optimization, and RK optimization for dynamic sensor placement. This combination of RK-OBGRNet methods improves the reaction to geological risks by increasing forecast accuracy, fine-tuning sensor placements, and guaranteeing effective disaster monitoring.

3. Case Studies

3.1 Case Study 1: Wayanad Landslide Disaster (2024)

This paper presents a detailed investigation into the 2024 Wayanad landslide in India, determining the major factors (geological instability, heavy rainfall) and far-reaching effects on indigenous communities. The research indicates how RK-OBGRNet's dynamic sensor deployment and real-time monitoring could have enhanced early warning systems, saved lives and minimized damage. The model's potential to learn temporal relationships and sensor placement optimization would give more effective disaster response plans in other high-risk territories [28].

3.2 Case Study 2: Pettimudi Landslide Case Study (2020)

This research examines the environmental and social effects of the Pettimudi landslide in Kerala that occurred in 2020 with special focus on how geographic and human factors contribute to disaster management. Incorporating RK-OBGRNet in such a case would have been able to yield improved spatial and temporal analysis of vulnerability in the region, providing early warning mechanisms to avoid such a massive loss. The model's high-level feature learning and temporal ability would improve the predictive power for landslide events, with real-time guidance for enhanced evacuation and resource deployment [29].

4. Experimental Results

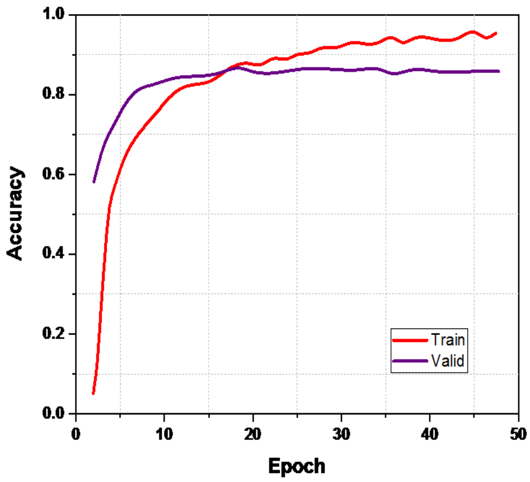
The recommended fix was implemented on a desktop computer running Windows 10 with a 64-bit processor, an 18th-generation Intel Core i7 CPU, and a 4 GB GPU driver that supports CUDA and other components. The suggested structure was constructed using Keras with TensorFlow software capabilities and Python 3.5 software tools for the backend toolkits. The accuracy, precision, recall, and F1-Score of this research's comparison to the traditional models monitoring technology in geological disaster emergency response RNN-Auto encoder [30], and Cascade R-CNN [31] clarify the extent to which the proposed RK-OBGRNet model accurately monitors the geological disaster emergency response. The data used here is the satellite image obtained using Landsat-8 and Sentinel-2 satellites, targeted for geological disaster observation. Landsat-8 offers a spatial resolution of 30 meters with a temporal resolution of 16 days, whereas Sentinel-2 offers a higher spatial resolution of 10 meters and a temporal resolution of 5 days. The data consists of around 5,000 tagged images in different disaster situations, including landslides, earthquakes, and floods, with ground truth information hand-marked on the basis of past records and field observations. The RK-OBGRNet model integrates convolution layers for feature extraction, gated recurrent units (GRUs) for recognizing temporal relationships in sequential data, and Runge-Kutta optimization for dynamic sensor placement and real-time adaptation of data. The hyperparameters for the model are a learning rate of 0.001, 10 layers, the Adam optimizer, 50 epochs, and a batch size of 32, selected based on initial experiments to balance performance and training time.

4.1. Accuracy Loss

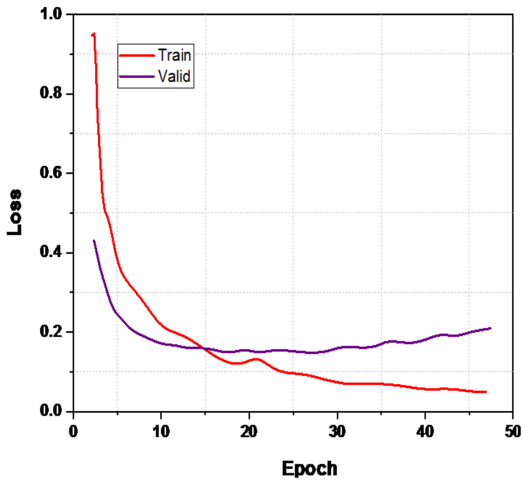
Accuracy loss, as it relates to high-precision sensing monitoring for geological catastrophes, is the deterioration in the model's capacity to accurately identify landslides as a result of inconsistent data or model restrictions. Figure 2 represents the accuracy loss.

4.2. Confusion Matrix

The RK-OBGRNet model's accuracy in landslide detection is evaluated using a confusion matrix, which displays true positives, false positives, true negatives, and false negatives in monitoring. The confusion matrix, which displays the real labels vs, expected labels for landslides, earthquakes, floods, and tsunamis, with color intensity representing occurrences, displays the categorization performance of geological catastrophe categories. Figure 3 displays the confusion matrix for geological disaster classification.



(a)



(b)

Fig. 2. a) Accuracy and b) Loss

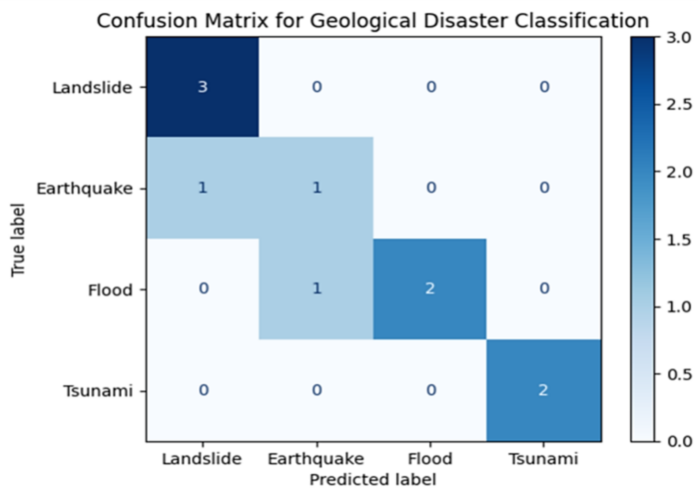


Fig. 3.: Confusion matrix

4.3. Accuracy

The degree to which sensor data, such as from environmental, displacement, or seismic sensors reflects real-world circumstances during geological events is known as accuracy. It is essential to ensure that disasters like earthquakes, landslides, and floods are reliably detected and monitored. This enables prompt warnings and efficient decision-making in emergency response operations. Table 1 and Figure 4 illustrate the comparison results of accuracy.

Table 1. Outcomes of accuracy

Method	Accuracy (%)
RNN-Autoencoder [25]	68%
RK-OBGRNet [Proposed]	95%

For geological disaster monitoring, the RK-OBGRNet technique outperforms the RNN-Autoencoder method, which achieves 68% accuracy, with an accuracy of 95%. These notable enhancements show how well the RK-OBGRNet model detects and tracks geological hazard occurrences using remote sensing data.

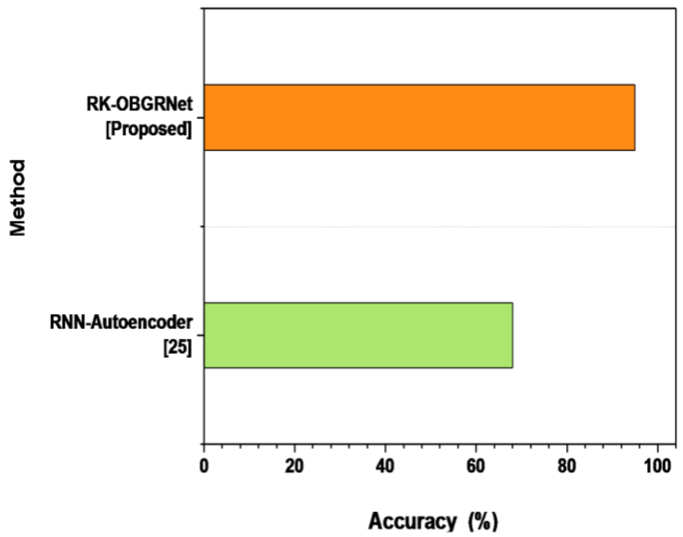


Fig. 4. Analysis of accuracy

4.4. Precision

The precision of identifying and quantifying geological occurrences is referred to as precision in high-precision sensing monitoring technology for geological disorder response. It guarantees low sensor reading error, precise position determination, and trustworthy forecasts, facilitating prompt, well-informed disaster management decision-making and improving response efficiency. Table 2 and Figure 5 depict the comparison results of precision.

Table 2: Outcomes of precision

Method	Precision (%)
RNN-Autoencoder [30]	70%
Cascade R-CNN [31]	93.15%
RK-OBGRNet [Proposed]	94%

The suggested RK-OBGRNet outperforms the RNN-Autoencoder (70%) and Cascade R-CNN (93.15%) with a precision of 94%. This illustrates how well RK-OBGRNet detects geological catastrophes and how well it optimizes high-precision sensing and monitoring systems for emergency response in areas affected by geological disasters.

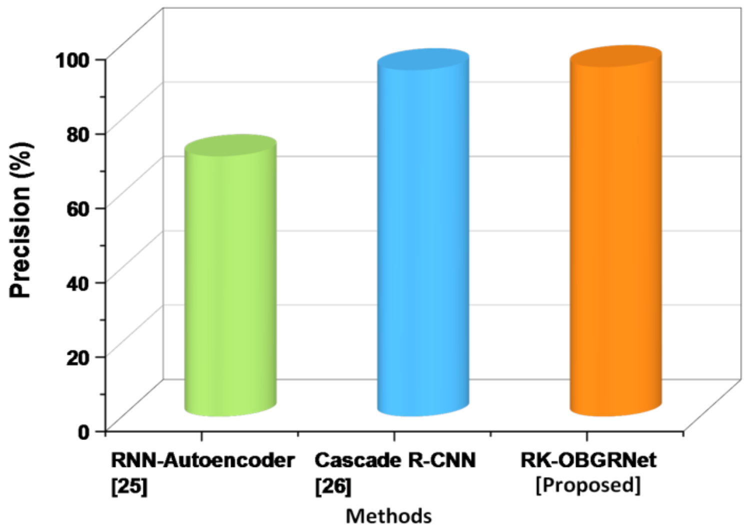


Fig. 5. Analysis of precision

4.5. Recall

Recall refers to a sensory monitoring system's capacity to accurately identify and detect real catastrophe occurrences, such as earthquakes or landslides, in the context of geological disaster emergency response. High recall guarantees low false negatives and enhances the dependability of the system for early warning as well as effective catastrophe mitigation techniques. Table 3 and Figure 6 represent the comparison results of recall.

Table 3. Outcomes of Recall

Method	Recall (%)
RNN-Autoencoder [30]	72%
Cascade R-CNN [31]	89.32%
RK-OBGRNet [Proposed]	93%

From the numerical result, it indicates that RK-OBGRNet performs better than the Cascade R-CNN by 89.32% and then RNN-Autoencoder by 72%. The best value of the recall rate reaches up to 93%. Hence, it presents how RK-OBGRNet exhibits superior capability for accurately identifying and responding to geological disaster occurrences.

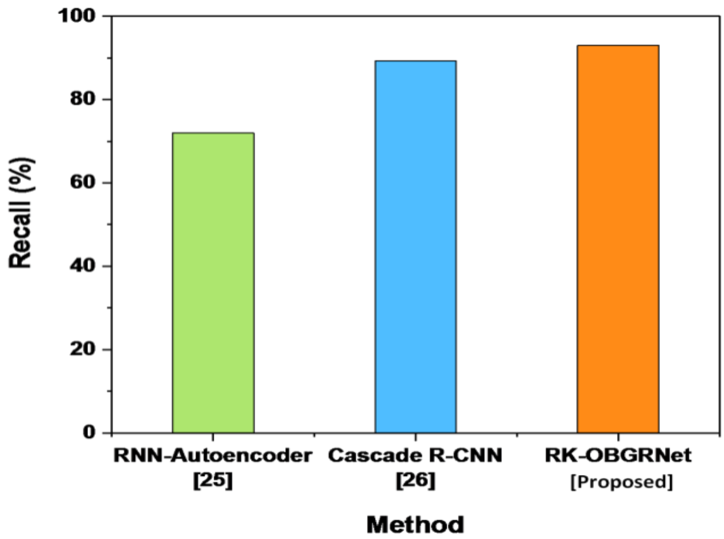


Fig. 6. Analysis of recall

4.6. F1-Score

In high-precision sensing related to geological disaster monitoring, the F1-Score balances precision and recall of estimating its accuracy. It is considered crucial for evaluating how efficiently sensor networks and precision models identify and react to events leading to geological disasters, reducing false alarms while being responsive toward actual events. Table 4 and Figure 7 show the comparison results in terms of F1-score.

Table 4. Outcomes of F1-Score

Method	F1-Score (%)
RNN-Autoencoder [30]	71%
RK-OBGRNet [Proposed]	92%

With an F1-Score of 92% compared to 71% for the RNN-Autoencoder, the suggested RK-OBGRNet model is better than the RNN-Auto encoder model and thus, suitable for geological disaster monitoring. This means that regarding achieving equilibrium between recall and precision, the suggested model offers much higher accuracy in disaster warning and response.

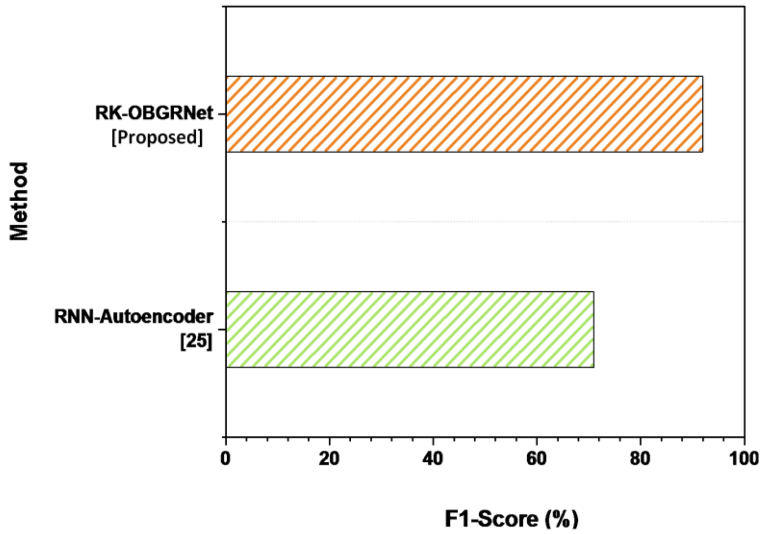


Fig. 7. Analysis of F1-score

4.7. Discussion

Despite its utility for anomaly detection in monitoring geological catastrophes, the RNN-Autoencoder [30] has limitations concerning accuracy and online adaptability. It performs less than other models when it is concerned with predicting and responding to changing geological hazards, as it fails to handle complex spatial-temporal relationships and environmental changes. The computational complexity and difficulty in processing real-time, high-resolution remote sensing data make the approach of Cascade R-CNN [31,32] unsuitable for geological hazard monitoring, even though it performs well for object recognition. This might cause delays in critical disaster reaction situations. The proposed RK-OBGRNet method based on RK optimization of dynamic sensor placement, the application of back propagation to improve accuracy, and the Gated Layered methods of real-time adaptation help to overcome the drawbacks and cope successfully with the complicated spatial-temporal data, which will guarantee the faster and more precise responses to disasters.

5. Conclusion

Geological catastrophes such as landslides are very dangerous to human life and assets, therefore, needs prompt and precise monitoring to control instances of emergencies. Complex sensory technology was crucial in the real-time identification and control of such incidences. This study combines the information of satellite remote sensing and various geological and environmental variables to design high-quality landslide factors that influence factors. On the basis of these features, it was predicted that advanced sensing and monitoring of geological catastrophe emergency response would be created. The RK-OBGRNet was used to identify and monitor landslides using remote sensing photographs in a model. In order to enhance the quality of the satellite images, preprocessing techniques such as FT and z-score normalization are applied to remove noise, and to give the same data to perform the analysis. PCA and other feature extraction methods were embraced in order to distinguish the significant features that characterize presence or absence of landslides. The effect of the model parameters on the accuracy of landslide prediction was assessed. RK-OBGRNet is better than RNN-Autoencoder and Cascade R-CNN with a higher F1-Score of 92%, accuracy of 95%, precision of 94% and recall of 93%. As per the outcomes, RK-OBGRNet got the lowest overall error and it was shown to be applicable in identification of landslides with high precision. On the theoretical level, this study can be used in forming adaptive, real-time, and data-driven solutions in disaster management as they would enhance the effectiveness of early warning systems and response time, which could transform the exercise of disaster risk reduction. RK-OBGRNet is perfectly applicable to existing disaster response systems due to extreme weather conditions, sparsity of data, and real-time adaptation, which may affect the precision of the model during dynamic and large-scale disasters. High computational demands in it would inhibit its scalability especially in systems with resource constraints. The unpredictability of data based on the quality of satellite images and capacity of the sensors may lower predictions and this would be challenging to the model strength in its real application. The study assists in the improvement of emergency reaction and geological disasters observation. It offered a blueprint on how the management of landslide risks could be done through the combination of high-precision monitoring devices and early warning systems and rapid response strategies.One of the limitations is that it depends on satellite data, which has weather fluctuations. Future studies could explore the combining deep learning with real-time sensor networks can enhance predictive accuracy.

References

[1] Mavroulis S, Mavrouli M, Kourou A, Thoma T, Lekkas E. Multi-hazard emergency response for geological hazards amid the evolving COVID-19 pandemic: good practices and lessons learned from earthquake disaster management in Greece. Sustainability. 2022 Jul;14(14):8486. https://doi.org/10.3390/su14148486

[2] Liu X, Liu Z, Liu Y, Tian J. Integration of a geo-ontology-based knowledge model and spatial analysis into emergency response for geologic hazards. Nat Hazards. 2021 Aug;108(2):1489-514. https://doi.org/10.1007/s11069-021-04742-5

[3] Qian X. Regional geological disasters emergency management system monitored by big data platform. Processes. 2022 Dec;10(12):2741. https://doi.org/10.3390/pr10122741

[4] Jiang W, Jiao Q, Luo Y, Li Y, Li Q, Li B. Risk investigation of landslide hazard and disaster emergency based on multi-platform remote sensing techniques. In: IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium. Waikoloa (HI): IEEE; 2020. p. 5211-4. https://doi.org/10.1109/IGARSS39084.2020.9324550

[5] Yang Z, Li J, Hyyppä J, Gong J, Liu J, Yang B. A comprehensive and up-to-date web-based interactive 3D emergency response and visualization system using Cesium Digital Earth: taking landslide disaster as an example. Big Earth Data. 2023;7(4):1058-80. https://doi.org/10.1080/20964471.2023.2172823

[6] Fang W, Haixiang G, Jinling L, Mingyun G, Wenwen P. Multi-objective emergency scheduling for geological disasters. Nat Hazards. 2021;105:1323-58. https://doi.org/10.1007/s11069-020-04356-3

[7] Zhou J, Zhou C, Kang Y, Tu S. Integrated satellite-ground post-disaster emergency communication networking technology. Nat Hazards Res. 2021;1(1):4-10. https://doi.org/10.1016/j.nhres.2020.12.002

[8] Zhao R, Liu X, Xu W. Integration of coseismic deformation into WebGIS for near real-time disaster evaluation and emergency response. Environ Earth Sci. 2020;79(18):414. https://doi.org/10.1007/s12665-020-09153-6

[9] Xu C, Xue Z. Applications and challenges of artificial intelligence in the field of disaster prevention, reduction, and relief. Nat Hazards Res. 2024;4(1):169-72. https://doi.org/10.1016/j.nhres.2023.11.011

[10] Krekeler MP, Burke M, Allen S, Sather B, Chappell C, McLeod CL, et al. A novel hyperspectral remote sensing tool for detecting and analyzing human materials in the environment: a geoenvironmental approach to aid in emergency response. Environ Earth Sci. 2023;82(4):109. https://doi.org/10.1007/s12665-023-10761-1

[11] Xu Y, Qiu X, Yang X, Lu X, Chen G. Disaster risk management models for rural relocation communities of mountainous southwestern China under the stress of geological disasters. Int J Disaster Risk Reduct. 2020;50:101697. https://doi.org/10.1016/j.ijdrr.2020.101697

[12] Zhang D, Feng D. Mine geological disaster risk assessment and management based on multisensor information fusion. Mob Inf Syst. 2022;2022(1):1757026. https://doi.org/10.1155/2022/1757026

[13] Cui P, Ge Y, Li S, Li Z, Xu X, Zhou GG, et al. Scientific challenges in disaster risk reduction for the Sichuan-Tibet Railway. Eng Geol. 2022;309:106837. https://doi.org/10.1016/j.enggeo.2022.106837

[14] Wang M, Wang W, Dai C, Ma C, Luo Y, Xu M. Risk analysis and evaluation of emergency rescue in landslide disaster. Nat Hazards. 2024:1-27. https://doi.org/10.1007/s11069-024-06811-x

[15] Hu SY, Yu M, Que T, Fan G, Xing HG. Individual willingness to prepare for disasters in a geological hazard risk area: an empirical study based on the protection motivation theory. Nat Hazards. 2022:1-25.

[16] Damaševičius R, Bacanin N, Misra S. From sensors to safety: Internet of Emergency Services (IoES) for emergency response and disaster management. J Sens Actuator Netw. 2023;12(3):41. https://doi.org/10.3390/jsan12030041

[17] Guo FY, Meng XM, Qi TJ, Dijkstra T, Thorkildsen JK, Yue DX, et al. Rapid onset hazards, fault-controlled landslides, and multi-method emergency decision-making. J Mt Sci. 2022;19(5):1357-69. https://doi.org/10.1007/s11629-021-6941-x

[18] Yan B, Liu J, Qi Q, Liu W, Li X. Study on chain relationship and risk assessment model of coal mine geological disasters. Arab J Geosci. 2022;15(9):900. https://doi.org/10.1007/s12517-022-10184-5

[19] Que T, Wu Y, Hu S, Cai J, Jiang N, Xing H. Factors influencing public participation in community disaster mitigation activities: A comparison of model and nonmodel disaster mitigation communities. Int J Environ Res Public Health. 2022;19(19):12278. https://doi.org/10.3390/ijerph191912278
[20] He Z, Wang D, Fang L, Ren Z, Xu X. Preface to the special issue on major earthquake hazards and disaster reduction. Nat Hazards Res. 2021;1(2):33-5. https://doi.org/10.1016/j.nhres.2021.06.006
[21] Zheng X, Wang F, Qi M, Meng Q. Planning remote sensing emergency services: Bridging the gap between remote sensing science and emergency practice in China. Saf Sci. 2021;141:105346. https://doi.org/10.1016/j.ssci.2021.105346
[22] Yu J, Chen C, Li C. Safety analysis and emergency response of suspended oil and gas pipelines triggered by natural disasters. Sustainability. 2022;14(24):17045. https://doi.org/10.3390/su142417045
[23] Wu SN, Lei Y, Cui P, Chen R, Yin PH. Chinese public participation monitoring and warning system for geological hazards. J Mt Sci. 2020;17(7):1553-64. https://doi.org/10.1007/s11629-019-5933-6
[24] Lan H, Peng J, Zhu Y, Li L, Pan B, Huang Q, et al. Research on geological and surficial processes and major disaster effects in the Yellow River Basin. Sci China Earth Sci. 2022;65(2):234-56. https://doi.org/10.1007/s11430-021-9830-8
[25] Brighenti F, Caspani VF, Costa G, Giordano PF, Limongelli MP, Zonta D. Bridge management systems: A review on current practice in a digitizing world. Eng Struct. 2024;321:118971. https://doi.org/10.1016/j.engstruct.2024.118971
[26] Kadiyala B, Alavilli SK, Nippatla RP, Boyapati S, Vasamsetty C. Cloud-Integrated IoT-based healthcare monitoring and emergency response system with deep learning. Int J Recent Adv Multidiscip Res. 2025;12(03):10877-81.
[27] Akash R, Mouli KV, Vidhya V. Leveraging Convlstm and satellite imagery for predictive modeling of floods, landslides, and earthquakes. i-Manager's J Future Eng Technol. 2025;20(2). https://doi.org/10.26634/jfet.20.2.21545
[28] Wang Q, Xu C, Ma J, Huang Y, Zhang S, Gao H. Preliminary analysis of the July 30, 2024, Wayanad landslide disaster in India: causes and impacts. Nat Hazards Res. 2025. https://doi.org/10.1016/j.nhres.2025.04.005
[29] Irshad SM, Solaman SC. Identity, space and disaster: a case study of Pettimudi landslide in Kerala. Sociol Bull. 2022;71(3):437-53. https://doi.org/10.1177/00380229221094785
[30] Infante D, Di Martire D, Confuorto P, Tessitore S, Tòmas R, Calcaterra D, et al. Assessment of building behavior in slow-moving landslide-affected areas through DInSAR data and structural analysis. Eng Struct. 2019;199:109638. https://doi.org/10.1016/j.engstruct.2019.109638
[31] Tang J, Yang R, Dai Q, Yuan G, Mao Y. Research on feature extraction of meteorological disaster emergency response capability based on an RNN autoencoder. Appl Sci. 2023;13(8):5153. https://doi.org/10.3390/app13085153
[32] Wang L, Xu Y, Chen Q, Wu J, Luo J, Li X, et al. Research on remote-sensing identification method of typical disaster-bearing body based on deep learning and spatial constraint strategy. Remote Sens. 2024;16(7):1161. https://doi.org/10.3390/rs16071161