

Article

Research on the Spatiotemporal Evolution Patterns and Predictive Models of Surface Displacement Induced by Buried Ground Fissure Activity

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Abstract

Differential surface settlement is a critical trigger for engineering disasters, with buried ground fissure activity serving as one of the core factors driving such subsidence. In this study, four groups of physical model tests were conducted. High-precision laser displacement meters were used to monitor real-time settlement at varying distances from the ground fissure. Based on this, the surface displacement evolution patterns of both loess layer structures and interbedded sand–soil structures under slow (0.01 m/h) and rapid (2 m/h) ground fissure activities were summarized. To evaluate the predictive performance of different models for time- and space-dependent nonlinear displacement evolution, five methods, namely polynomial regression, support vector regression (SVR), multilayer perceptron (MLP), random forest (RF), and gradient boosting decision tree (GBDT), were constructed and compared using the experimental displacement dataset. The physical model test results indicate that the interbedded sand–soil structure tends to suppress localized crack propagation while expanding the affected zone range, whereas the loess layer is prone to near-field deformation localization. The activity rate exerts a pronounced influence on fracture propagation within the loess layer, while its influence on the deformation of the interbedded sand–soil structure is relatively limited under the present test conditions. The model comparison results show that a cubic polynomial can effectively describe the displacement evolution pattern under slow and homogeneous conditions. MLP exhibited the most stable performance among the four machine learning algorithms, while SVR, GBDT, and RF provided complementary information for interpreting continuous displacement evolution and local nonlinear displacement variations. Overall, under the present physical model test conditions, the machine learning models provide a useful data-driven basis for quantitatively characterizing displacement evolution trends and interpreting the development of ground fissure-affected zones. Based on the experimental results—scaled up by a similarity ratio of 20:1 and incorporated with a safety factor of 1.1–1.3—the preliminary reference engineering avoidance distance in the ground fissure-affected zone is 20–24 m for the hanging wall and 14–16 m for the footwall, which are broadly consistent with the current codes and regulations. The findings provide controlled experimental evidence and a quantitative reference for ground fissure hazard assessment and engineering protection.

Keywords: ground fissure; surface displacement; physical simulation; affected zone width; spatiotemporal predictive model



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1. Introduction

Ground fissures are surface rupture phenomena caused by tectonic activity, groundwater overexploitation, or surface loading. They are widely developed in areas such as the Fenwei Basin and the North China Plain in China, the western United States, and the East African Rift Valley [1,2]. Most ground fissure activity is manifested as vertical differential settlement, with the hanging wall descending relative to the footwall. This results in a series of engineering hazards, including building cracking and displacement, road subsidence and damage, underground pipeline dislocation and leakage, and the failure of water conservancy facilities. These hazards seriously threaten lives and property and restrict normal urban operations and sustainable development [3]. Available statistics indicate that more than 100 cities in China have suffered from ground fissure disasters, resulting in substantial economic losses [4–6]. Among different types of ground fissures, buried ground fissures are characterized by concealment, gradual deformation, and a wide damage range, with no obvious prior signs of surface rupture. The vertical surface displacement induced by their activity exhibits significant nonlinear spatiotemporal evolution characteristics. Compared with open ground fissures, buried ground fissures are more difficult to monitor, predict, and actively control, and have become a prominent challenge for urban engineering construction, underground space development, and disaster prevention and control.

The risk of ground fissure disasters is mainly concentrated within the ground fissure-affected zone, which can be divided into a main deformation zone with a significant deformation gradient and a micro-deformation zone where deformation gradually attenuates. The damage effects and engineering hazard levels differ significantly among these zones. Therefore, accurately defining the width of the ground fissure-affected zone, the potential maximum dislocation during the engineering service life, and the spatiotemporal deformation laws is essential for determining the engineering avoidance distance of buildings on ground fissure sites, structural protection design, and disaster risk management [7–9]. Currently, the width of the ground fissure-affected zone is mostly determined through extensive ground investigations and long-term monitoring of leveling profiles across ground fissures. In areas where surface signs of ground fissures are unclear and monitoring data are lacking, large exploratory trenches are often excavated to reveal and measure rupture structural characteristics, dislocation amounts, actual deformation ranges, and deformation degrees of ground fissures. Although this approach can provide actual deformation information, it is generally limited by site selection difficulties and high costs. More importantly, the stratigraphic lithology and fissure activity rate strongly influence surface deformation and the extent of the affected zone. However, traditional methods have difficulty conducting comparative analyses across multiple cases and clarifying the differential deformation mechanisms under the coupled effects of these two factors. This leads to uncertainty in the affected zone width and limits refined engineering protection.

Current studies mainly rely on field monitoring, numerical simulations, and physical model tests to investigate ground fissure rupture propagation and surface response patterns [10–12]. Among these methods, field monitoring can provide actual deformation data, but it is limited by the observation period and the density of measuring points, making it difficult to fully reveal spatiotemporal evolution patterns. Numerical simulation methods are highly flexible and can simulate complex cases, but their reliability depends strongly on soil constitutive models and boundary conditions [13]. Due to their strong controllability and high repeatability, physical model tests can reproduce the entire process of fissure propagation and surface settlement under different strata and activity rates. They provide an important approach for revealing ground fissure deformation mechanisms and quantifying deformation evolution patterns [14]. However, existing physical simulation studies often involve limited case designs and mostly focus on the influence of a single factor, such as

the activity rate or lithology, while paying insufficient attention to the coupled effects of the stratigraphic structure and activity rate. Comparative studies involving typical strata, such as homogeneous loess and interbedded sand–soil, and different activity modes, such as slow creep and rapid dislocation, remain limited. Consequently, a quantitative time–space displacement relationship has not yet been fully established, and the predictive capability for nonlinear surface displacement evolution under complex cases remains insufficient.

In recent years, machine learning algorithms have been widely applied to the prediction and assessment of geological disasters such as surface subsidence, ground fissures, and landslides because of their nonlinear fitting and high-dimensional feature-mining capabilities. These methods provide a new approach for addressing the low accuracy and poor adaptability of traditional statistical models [15–23]. However, existing studies lack a systematic comparison between traditional regression and multiple types of machine learning models. The adaptability of different algorithms to different ground fissure cases has not yet been clarified. This makes it difficult to construct a hierarchical prediction system that balances efficiency and accuracy and to effectively support settlement prediction and affected zone delimitation in complex sites.

To address the aforementioned research gaps, this study conducts large-scale physical model tests to investigate the surface displacement response, fissure propagation and affected zone development induced by buried ground fissure activity under different stratigraphic structures and activity rates. Four representative experimental cases are designed by combining two typical stratigraphic lithologies and two ground fissure movement rates. Based on the measured displacement data and observed rupture characteristics, the deformation responses under different lithological and kinetic conditions are quantitatively compared, with particular attention to the development of the main deformation zone, the micro-deformation zone and the affected zone width. Furthermore, several data-driven models, including polynomial regression, support vector regression, multilayer perceptron, random forest and gradient boosting decision tree, are established to quantitatively characterize the relationship among the activity process, spatial position and surface displacement. By integrating controlled physical model observations with data-driven displacement characterization, this study provides experimental evidence for understanding the deformation response of soils overlying buried ground fissures and offers a quantitative basis for affected zone identification, preliminary engineering assessment and subsequent refinement using numerical modeling and field monitoring data.

2. Methods

2.1. Experimental Apparatus and Model Design

A custom-designed physical simulation system for ground fissures was used (Figure 1). The system consists mainly of three components: a model box, a hydraulic control system, and a data acquisition system, which enable controlled simulation of ground fissure activity and real-time acquisition of deformation data. The dimensions of the model box are 5.0 m × 1.5 m × 3.0 m (length × width × height), with high-strength tempered glass on both sides to facilitate the observation of internal soil and surface deformation characteristics. A movable steel plate and jacks are installed at the bottom to simulate the downward movement of the hanging wall of the ground fissure. The movement rate is precisely controlled by a servo motor with an accuracy of up to 0.001 mm/s, which can meet the simulation requirements of different ground fissure activity rates.

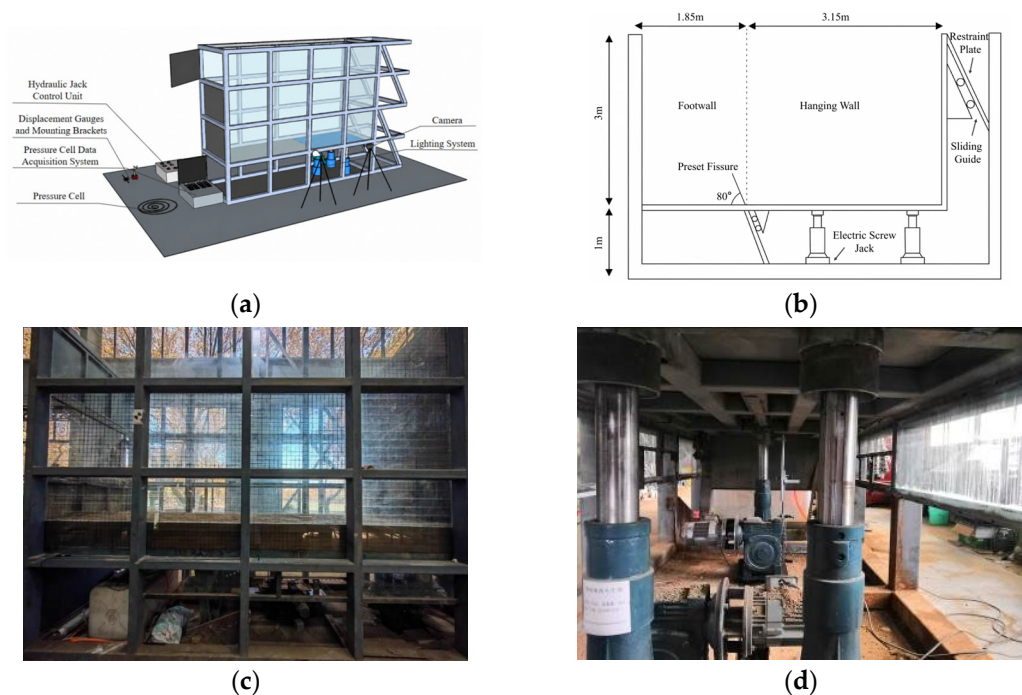


Figure 1. Ground fissure physical simulation test system [24]. (a) Three-dimensional schematic diagram of the model box; (b) side schematic diagram of the model box; (c) physical photograph of the model box; (d) layout diagram of the model box jacks.

2.2. Experimental Condition Design

Four experimental cases were designed in this study to simulate the rupture propagation process of buried ground fissures under the coupled effects of different stratigraphic lithologies and activity rates (Table 1). Two types of stratigraphic lithology were configured: a loess layer (using silty clay) and an interbedded sand–soil structure (using alternately laid silty clay and fine sand). The total thickness of the soil layers is 2.2 m (Figure 2a). The filling soil is compacted layer by layer via ramming, with ramming points arranged in a quincunx pattern, and the thickness of each single filling layer is controlled within 10–15 cm. Two ground fissure activity rates were established: slow (0.01 m/h) and rapid (2 m/h), corresponding to two typical activity modes of ground fissures, namely slow creep and sudden dislocation. The test termination conditions were defined as follows: the cumulative displacement of the hanging wall reached the design value (200 mm), or the soil rupture propagated to the surface. The specific parameters for each case are listed in Table 1. Soil parameters are listed in Tables 2 and 3. The model dimensions, layered structure, soil parameters, prescribed hanging wall displacement and activity rate together define the geometric, material and kinematic boundary conditions of the physical model, providing a controlled basis for comparing the deformation responses under different stratigraphic and activity rate conditions.

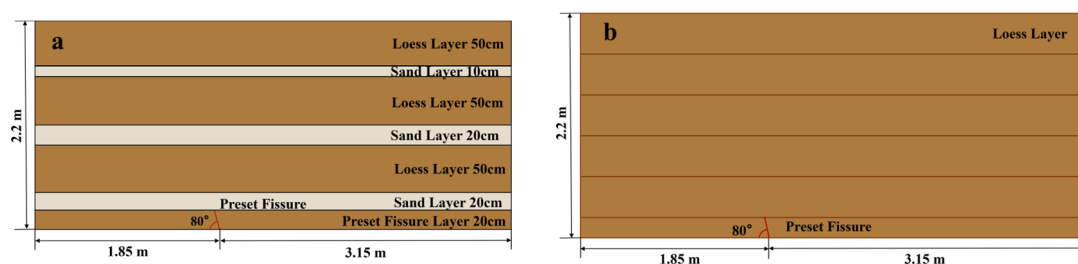


Figure 2. Schematic diagram of laid soil layers [24]. (a) Interbedded sand–soil; (b) loess layer.

Table 1. Experimental design of the model tests.

Scenario No.	Stratum Lithology	Kinematic Rate (m/h)	Cumulative Displacement of Hanging Wall (mm)	Monitoring Duration
Case 1	Interbedded sand–soil	0.01	150	15 h
Case 2	Loess layer	0.01	110	11 h
Case 3	Loess layer	2	140	7 min
Case 4	Interbedded sand–soil	2	120	6 min

Table 2. Particle size distribution.

Particle Size (μm)	Content (%)
<0.074	0.00
0.074~0.185	1.87
0.185~0.466	5.74
0.466~1.171	4.90
1.171~2.941	1.73
2.941~7.384	10.48
7.384~18.54	24.4
18.54~46.55	34.82
46.55~116.8	13.82
116.8~293.5	2.24

Table 3. Soil parameters.

Water Content (%)	Dry Density (g/cm^3)	Void Ratio	Cohesion (Kpa)	Internal Friction Angle ($^\circ$)
15.6	1.48	0.95	27	24

2.3. Displacement Monitoring Layout

High-precision laser displacement meters (with an accuracy of 0.01 mm) were symmetrically arranged on top of the model along the long axis of the model box, covering both the hanging wall and footwall areas, with a measuring point spacing of 0.3 m. The field layout of the displacement meters is shown in Figure 3, and the corresponding plan layout is illustrated in Figure 4. The laser displacement meters had a measurement range of ± 200 mm and an accuracy of up to 10 μm . They do not come into direct contact with the soil during the test, thereby avoiding any damage to the soil structure. The displacement meters were fixed on independent frames to eliminate the influence of model deformation on the sensor positions. Surface settlement was continuously monitored throughout the experiment, and the sampling frequency was set to 1 time/min for the slow activity rate or 1 time/s for the rapid activity rate.

**Figure 3.** Field layout photo of displacement meters.

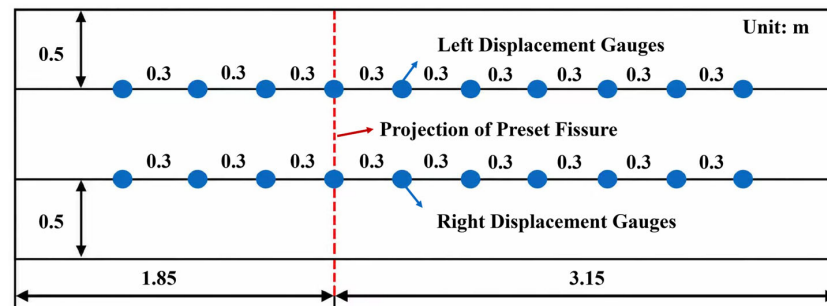


Figure 4. Plan layout schematic diagram of displacement meters [25].

3. Physical Model Test Results and Analysis

Figure 5 shows the surface displacement curves along the distance from the preset fissure at different deformation stages for the four cases, and Figure 6 presents the corresponding surface rupture characteristics. To reduce the subjectivity in identifying the deformation zones, the displacement gradient between adjacent measuring points was calculated at the final deformation stage of each case. The absolute displacement gradient was defined as follows:

$$G = [S(i + 1) - S(i)] / [x(i + 1) - x(i)] \quad (1)$$

where $S(i)$ and $S(i + 1)$ are the measured surface displacements at two adjacent measuring points, and $x(i)$ and $x(i + 1)$ are their distances from the preset fissure. The normalized displacement gradient index G^* was obtained by dividing G by the maximum gradient in each case.

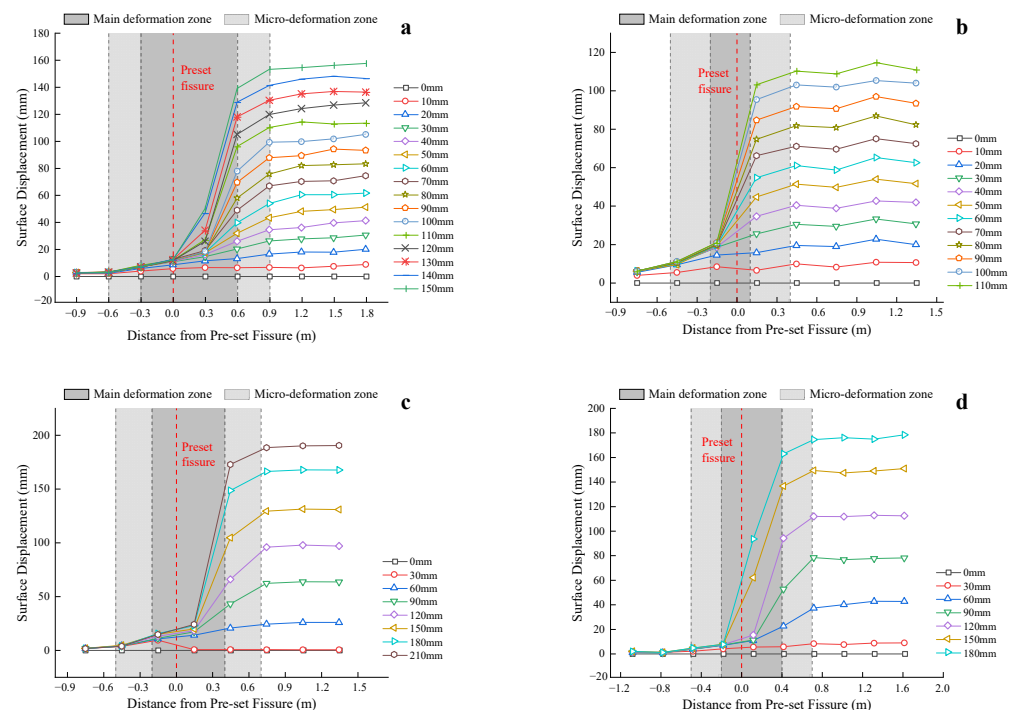


Figure 5. Surface displacement versus distance curves under different dislocations of ground fissures for each case. (a) Case 1; (b) Case 2; (c) Case 3; (d) Case 4.

The normalized displacement gradient within the deformation zones for each case is listed in Table 4. As illustrated schematically in Figure 7, the deformation zone boundaries were identified by integrating the final-stage displacement profiles, the normalized displacement gradient distribution and the observed surface rupture characteristics. The main deformation zone was defined as the continuous area near the preset fissure where the

displacement curve showed abrupt variation, the normalized displacement gradient index exhibited peak or relatively high values, and continuous surface cracking or obvious soil disturbance was observed. The micro-deformation zone was defined as the adjacent transition area outside the main deformation zone, where the displacement gradually attenuated and only discontinuous fine cracks or slight surface disturbance occurred. The external boundary of the affected zone was determined at the position where the displacement curve tended to become stable and visible surface cracks disappeared.



Figure 6. Live photograph of surface rupture propagation (taking Case 4 as an example).

Table 4. Normalized displacement gradient within the deformation zones for each case.

Scenario	Deformation Zone (m)	G*
Case 1	−0.6~−0.3	0.04
	−0.3~−0	0.06
	0~0.3	0.43
	0.3~0.6	1.00
	0.6~0.9	0.16
Case 2	−0.45~−0.15	0.12
	−0.15~0.15	1.00
	0.15~0.45	0.09
Case 3	−0.45~−0.15	0.07
	−0.15~0.15	0.06
	0.15~0.45	1.00
	0.45~0.75	0.10
Case 4	−0.6~−0.3	0.04
	−0.3~0	0.06
	0~0.3	0.43
	0.3~0.6	1.00
	0.6~0.9	0.16

It should be noted that the normalized displacement gradient index was used as auxiliary quantitative evidence rather than as a single fixed threshold, because the gradient distribution is affected by measuring point spacing, stratigraphic structure and local rupture morphology. The spacing of the displacement measuring points was 0.3 m; therefore, the identified boundaries represent approximate ranges corresponding to the experimental observation resolution. Based on this integrated identification criterion, Table 5 summarizes

the ranges of the main deformation zone, micro-deformation zone and affected zone under the four cases.

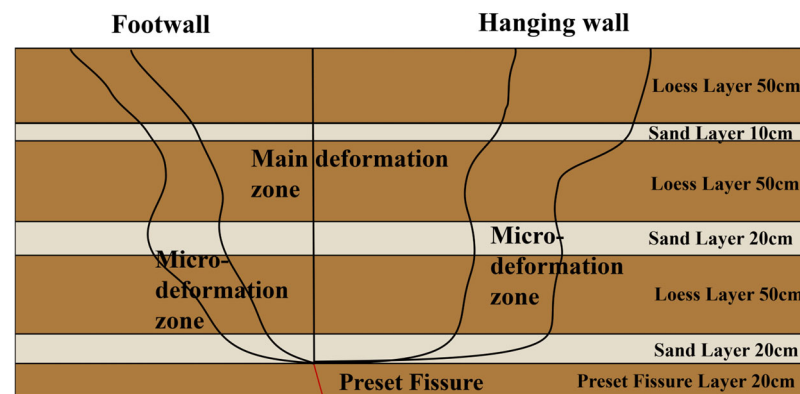


Figure 7. Schematic diagram of the profile of the ground fissure main deformation zone and micro-deformation zone (taking the interbedded sand–soil as an example) [24].

Table 5. Summary table of the surface deformation zone ranges for each case.

Scenario	Footwall		Hanging Wall	
	Main Deformation Zone (m)	Micro-Deformation Zone (m)	Main Deformation Zone (m)	Micro-Deformation Zone (m)
Case 1	−0.3~0	−0.6~−0.3	0~0.6	0.6~0.9
Case 2	−0.2~0	−0.5~−0.2	0~0.1	0.1~0.4
Case 3	−0.2~0	−0.5~−0.2	0~0.4	0.4~0.7
Case 4	−0.2~0	−0.5~−0.2	0~0.4	0.4~0.7

3.1. Influence of Stratigraphic Lithology on Surface Displacement

Comparing the performance of Case 1 (interbedded sand–soil) and Case 2 (loess layer) under slow activity, the surface displacement of the loess layer is more concentrated near the fissure, exhibiting a larger deformation gradient. Conversely, the sand layer within the interbedded sand–soil structure exerts an inhibitory effect on the localized propagation of the ground fissure [26,27], thereby widening the range of the surface deformation impact. The affected zone width of Case 1 is 1.5 m, which is significantly larger than the 0.9 m observed in Case 2. This discrepancy can be explained by the stress transfer mechanism and the soil strength characteristics. From a soil mechanics perspective, under the imposed downward movement of the hanging wall, the overlying soil is subjected to differential settlement accompanied by tensile–shear deformation near the preset fissure. For the homogeneous loess layer, the relatively stronger structural integrity and cohesive bonding make deformation redistribution less pronounced before failure. As a result, shear and tensile deformation tend to concentrate in the near-fissure region, producing a steeper displacement gradient and a narrower affected zone [28–30]. In contrast, in the interbedded sand–soil structure, the sand layers and soil–sand interfaces interrupt the continuous upward propagation of localized rupture. The relatively lower cohesion of the sand layer and the frictional sliding along layer interfaces promote local yielding and deformation redistribution, thereby dissipating part of the deformation energy. Consequently, localized crack propagation is weakened, but the deformation influence is transferred to a wider surface range.

3.2. Influence Mechanism of Activity Rate on Displacement Evolution

Under rapid activity conditions, the displacements in both Case 3 (loess layer) and Case 4 (interbedded sand–soil) develop rapidly, reaching large values within a short period

and then tending to stabilize. The difference between slow and rapid activity reflects the influence of the activity rate on stress redistribution and deformation adjustment in the overlying soil. Under slow activity, the imposed displacement is transferred gradually, allowing the soil mass to undergo progressive stress adjustment and deformation redistribution. Therefore, the surface displacement curves are relatively smooth, and the deformation develops in a more gradual manner. Under rapid activity, however, the displacement boundary is imposed within a short period, and the overlying soil has insufficient time to fully redistribute stress. This promotes concentrated differential settlement, tensile–shear deformation and local void development near the fissure, resulting in abrupt displacement growth and stronger nonlinear deformation characteristics. For the loess layer, comparison between the slow activity case (Case 2) and the rapid activity case (Case 3) shows that, at the same position relative to the preset fissure, the hanging wall displacement in Case 3 is consistently greater than that in Case 2. The maximum displacement in Case 3 reaches 190 mm within 7 min, whereas that in Case 2 reaches 112 mm within 11 h, indicating that the activity rate has an important influence on the displacement amplitude and distribution. The affected zone width of Case 2 is 0.9 m, which is smaller than the 1.2 m of Case 3. This difference may be related to the formation of internal voids and differential settlement under rapid activity, under which the activity rate of the buried fissure has a more pronounced influence on rupture propagation [31,32]. For the interbedded sand–soil structure, comparison between the slow activity case (Case 1) and the rapid activity case (Case 4) shows that the affected zone width in Case 1 is larger than that in Case 4. This suggests that, for the interbedded sand–soil structure, stratigraphic lithology may play a more important role than the activity rate in controlling the spatial distribution of displacement.

3.3. Analysis of Affected Zone Width

The width of the ground fissure-affected zone is jointly determined by the main deformation zone and the micro-deformation zone. As shown in Table 2, the characteristics of the two zones differ among the cases: the hanging wall main deformation zone width ranges from 0.1 to 0.6 m, reflecting the influence of the stratigraphic structure and activity rate; the footwall main deformation zone width ranges from 0.2 to 0.3 m and remains relatively stable; and the micro-deformation zone width is approximately 0.3 m on both the hanging wall and footwall. The hanging wall affected zone width ranges from 0.4 to 0.9 m, whereas the footwall ranges from 0.5 to 0.6 m. Overall, the hanging wall affected zone is wider than the footwall affected zone and shows greater variability. This asymmetric feature stems from the active subsidence effect of the hanging wall in normal fault-type ground fissures, where the hanging wall soil undergoes tension, toppling, and internal shearing, making it easy for ruptures to propagate toward the dip direction. Based on this, basic setback zones can be established by partitioning. Using the similarity ratio of 20:1 to scale up the experimental results and taking the maximum affected zone width on each wall as a conservative reference, the basic engineering avoidance distance is estimated to be no less than 18 m for the hanging wall and 12 m for the footwall. For practical reference, considering complex factors such as soil heterogeneity and groundwater conditions, the above basic values can be multiplied by a safety factor of 1.1 to 1.3. Thus, the preliminary reference avoidance distances are approximately 20~24 m for the hanging wall and 14~16 m for the footwall. These values are broadly consistent with the avoidance distances and protection zone widths for general industrial and civil buildings specified in the current Code for Investigation and Engineering Design of Ground Fissure Sites in Xi'an (DBJ61/T 182-2021), suggesting that the model test results can provide a useful reference for code-based engineering zoning.

4. Spatiotemporal Predictive Models

To investigate the surface displacement evolution laws under the coupled effects of time variables and spatial distance variables, this study utilized five models—polynomial regression, support vector regression (SVR), multilayer perceptron (MLP), gradient boosting decision tree (GBDT), and random forest regression (RF)—to model and predict the surface displacement as a function of time and spatial distance across four cases. For each case, the effective dataset was arranged according to the temporal sequence. The first approximately 80% of the time steps were used for training, and the remaining approximately 20% were used for testing, so as to evaluate the capability of the models to predict later-stage deformation based on earlier-stage observations.

4.1. Cubic Polynomial Regression

Cubic polynomial regression (Deg = 3). It was employed as the baseline reference model. The time t and space x were mapped into a cubic polynomial space, and ridge regression with L2 regularization (regularization coefficient $\alpha = 1.0$) was used to solve the model coefficients, thereby capturing the nonlinear evolution laws of the data:

$$W(t,x) = a_1t + a_2t^2 + a_3t^3 + a_4tx + a_5x^2 + a_6t^3 + a_7t^2x + a_8tx^2 + a_9x^3 + c_1 \quad (2)$$

4.2. Machine Learning Prediction Algorithms

(1) Support Vector Regression (SVR)

SVR employs kernel function techniques to map low-dimensional data into a high-dimensional feature space and solves for the optimal regression hyperplane, thereby achieving the modeling of nonlinear relationships [33]. This study adopted the Radial Basis Function (RBF) kernel. The key hyperparameters were set as follows: the penalty parameter was set to $C = 100$ to enhance the model's capacity to fit nonlinear data distributions [33], and the kernel coefficient γ was determined using the default adaptive scaling ('scale') method [34].

(2) Multilayer Perceptron (MLP)

Multilayer perceptron is a typical artificial neural network model that iteratively adjusts network weights via the backpropagation algorithm to optimize prediction errors. This study adopted a network structure containing two hidden layers, with 64 neurons in each layer, specified as `hidden_layer_sizes = (64, 64)`. The activation function selected was ReLU, the optimizer used was Adam, and the maximum number of iterations was set to `max_iter = 1000` [35]. To accelerate network convergence and prevent gradient explosion, the input data were preprocessed using Z-Score normalization (StandardScaler) before entering the MLP and SVR models.

(3) Gradient Boosting Decision Tree (GBDT)

Gradient boosting decision tree is an ensemble learning algorithm based on the boosting framework. It sequentially combines multiple weak regression trees, where each new tree fits the residuals of the model from the previous round, thereby gradually reducing prediction errors. In this study, the number of base weak learners (decision trees) was set to `n_estimators = 100`. GBDT exhibits strong anti-interference capability against outliers in data [36].

(4) Random Forest Regressor (RF)

Random forest regression is an ensemble learning algorithm based on the bagging framework. By introducing dual perturbations in both sample bootstrapping and feature dimensions, it constructs a large number of independent decision trees and averages their

prediction results to reduce model variance and enhance generalization capability. In this study, the number of decision trees was set to $n_estimators = 100$, and the maximum tree depth was left unrestricted until the leaf nodes reached maximum purity [37]. Random forest does not require data standardization preprocessing and is commonly used for nonlinear regression tasks by reducing model variance through ensemble averaging.

5. Predictive Model Results and Analysis

5.1. Cubic Polynomial Regression Results

The model prediction results are presented in Table 6 and Figure 8. The average coefficient of determination (R^2) across the four cases is 0.9345. For the rapid activity cases, the RMSE of the model increases to 14~16 mm, indicating larger errors than in the slow activity cases and suggesting the greater difficulty of predicting abrupt deformation processes.

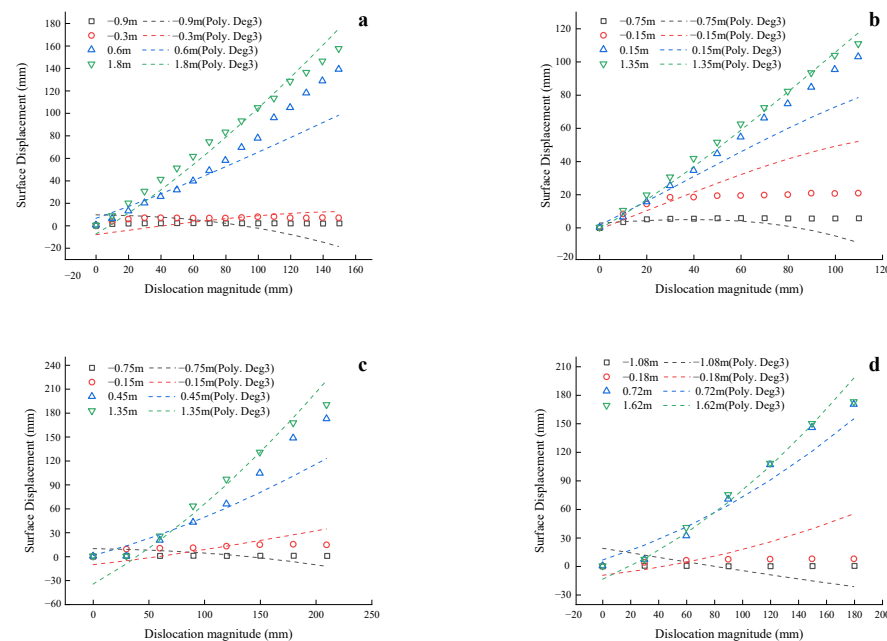


Figure 8. Measured versus predicted results of cubic polynomial regression. (a) Case 1; (b) Case 2; (c) Case 3; (d) Case 4.

Table 6. Cubic polynomial regression coefficients for each case.

Coefficient	Case 1	Case 2	Case 3	Case 4
a1	3.3063	6.8090	72.9100	68.4626
a2	10.7626	4.5523	57.8024	55.0513
a3	−0.0579	−0.0489	8.7712	7.1270
a4	4.9481	6.9614	69.1888	68.3089
a5	25.2938	10.1177	18.9651	8.5075
a6	0.0040	−0.0021	0.9698	0.6845
a7	0.0280	0.0595	8.2220	6.9453
a8	−0.2321	−2.9694	67.1933	75.0256
a9	−18.3121	−11.5713	−24.9021	−17.6409
c1	−8.0599	−1.2207	19.1979	24.3607
R2	0.9428	0.9389	0.9219	0.9344
RMSE/mm	11.3346	8.7986	16.9203	14.8888

5.2. Analysis of Machine Learning Prediction Results

The prediction results of the machine learning models are presented in Table 7, and the measured versus predicted results of the best-performing MLP model are shown in Figure 9. The four models show different levels of prediction performance under the adopted temporally ordered validation strategy. Among them, multilayer perceptron (MLP) exhibits the most stable fitting performance, followed by support vector regression (SVR), whereas gradient boosting decision tree (GBDT) and random forest (RF) show relatively larger prediction deviations.

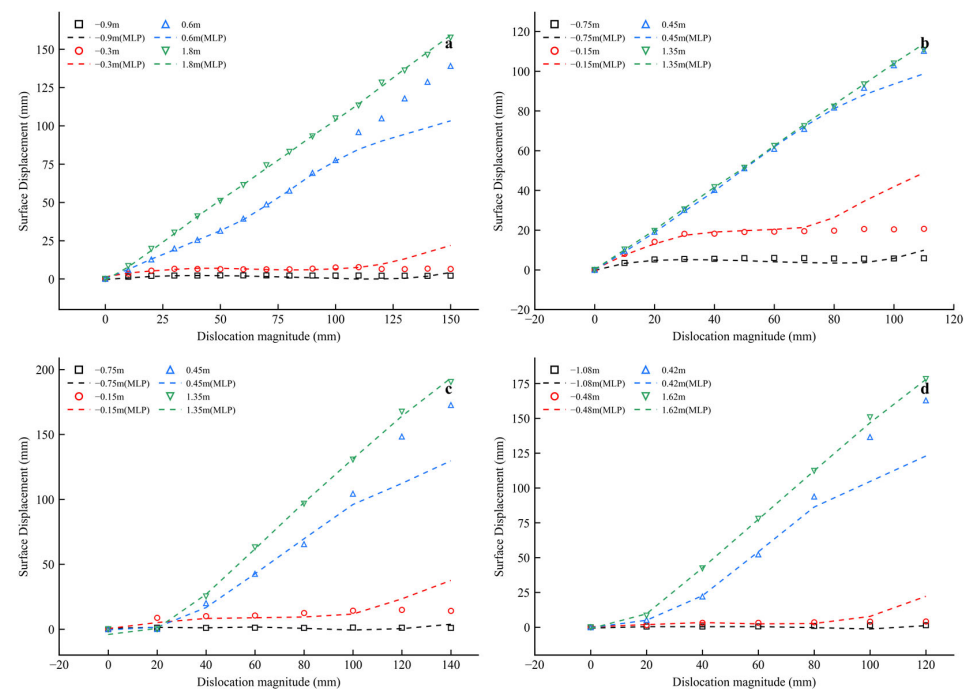


Figure 9. Measured versus predicted results of multilayer perceptron (MLP). (a) Case 1; (b) Case 2; (c) Case 3; (d) Case 4.

Table 7. Comparison of prediction accuracy among machine learning algorithms for each case.

Scenario	Metrics	SVR	MLP	GBDT	RF
Case 1	R ²	0.9367	0.9646	0.8844	0.8719
	RMSE/mm	16.0189	11.9700	21.6410	22.7799
Case 2	R ²	0.9071	0.9373	0.8534	0.8452
	RMSE/mm	13.2753	10.9017	16.6752	17.1330
Case 3	R ²	0.8609	0.9253	0.8056	0.7802
	RMSE/mm	30.7826	22.5625	36.3881	38.6890
Case 4	R ²	0.8716	0.9485	0.6752	0.6616
	RMSE/mm	26.7912	16.9749	42.6175	43.5019

5.3. Comprehensive Comparative Analysis

The cubic polynomial regression model can reasonably describe the macro trends of surface displacement evolution over time and space, showing stable performance especially under conditions of slow ground fissure activity and good stratigraphic homogeneity (such as Case 2). However, under conditions characterized by strong heterogeneity, such as rapid activity or interbedded sand–soil structures (such as Case 3 and Case 4), it struggles to precisely fit surface displacement changes. Therefore, for relatively simple conditions with slow activity and high degrees of homogeneity, cubic polynomial regression may serve

as a transparent and computationally efficient baseline model for preliminary assessment. For the four machine learning models, their applicability differs among the cases. Among them, MLP exhibits the most stable overall performance, with R^2 values of 0.9646, 0.9373, 0.9253 and 0.9485 for Cases 1–4, respectively, and the lowest average RMSE of 15.60 mm. This suggests that MLP has potential for describing the nonlinear relationship among the activity process, spatial position and surface displacement under the present experimental conditions. This characteristic is particularly meaningful for interpreting the rapid activity and interbedded sand–soil cases, where surface displacement evolution is influenced by abrupt stress release, localized void development and widening of the affected zone. SVR also shows acceptable prediction performance. Its kernel-based nonlinear mapping is suitable for capturing relatively continuous displacement evolution, especially under conditions where deformation develops gradually. However, for cases involving sharp displacement gradients near the fissure and evident hanging wall–footwall asymmetry, its adaptability is relatively limited compared with MLP. GBDT and RF can identify local nonlinear features in the displacement field, but their tree-based piecewise prediction characteristics make them less stable in representing continuous later-stage displacement evolution under complex deformation conditions. In particular, under rapid activity and heterogeneous strata, the abrupt growth of near-fissure displacement and the expanded affected zone increase the difficulty of prediction. Therefore, under the present controlled physical model test conditions, MLP appears to be more suitable for describing the nonlinear spatiotemporal evolution of surface displacement, while SVR, GBDT and RF may serve as complementary models for cross-comparison and auxiliary interpretation of local deformation characteristics. These results provide a data-driven reference for identifying displacement evolution trends and optimizing the layout of monitoring points in ground fissure-affected areas.

6. Discussion

The physical model tests provide a controlled experimental representation of the deformation response of soils overlying a buried ground fissure under prescribed displacement boundary conditions. The downward movement of the hanging wall induces differential settlement, tensile–shear deformation, local failure and fissure propagation in the overlying soil. Therefore, the observed surface displacement curves, rupture development and affected zone widths reflect the combined effects of stratigraphic structure, soil strength characteristics and activity rate. In particular, the contrast between the loess layer and the interbedded sand–soil structure indicates that cohesive bonding, internal friction and layer interfaces play important roles in controlling deformation localization, crack propagation and deformation redistribution. These experimental observations provide benchmark data for subsequent numerical simulations and mechanism-based models involving soil constitutive behavior, strength parameters, layer interface effects and fissure propagation.

By combining the spatiotemporal prediction curves of each model with the experimental deformation observations, the deformation response of buried ground fissures can be interpreted from both physical and data-driven perspectives. The model curves do not merely reproduce the measured displacement values; they also help distinguish the continuity, abruptness and nonlinear characteristics of displacement evolution under different lithological and activity rate conditions. Under slow activity, the displacement curves for the two types of strata are relatively smooth and gradual, indicating that the imposed displacement is transferred progressively and that the overlying soil has sufficient time for stress adjustment and deformation redistribution. In contrast, under rapid dislocation, the curves present steep segments and localized fluctuations, reflecting concentrated differential settlement, tensile–shear deformation and local void development near the

fissure. These features explain why polynomial regression can describe the overall trend under relatively simple conditions but has difficulty capturing abrupt local deformation under rapid activity.

The model comparison also provides a useful basis for the hierarchical use of different prediction methods. Cubic polynomial regression has a simple mathematical form and clear physical interpretability, and it may be used as a baseline model for preliminary assessment under relatively simple conditions. Among the machine learning models, MLP shows the most stable overall performance in the present tests, indicating its potential for describing the nonlinear spatiotemporal relationship among the activity process, spatial position and surface displacement. This is meaningful for interpreting deformation conditions involving rapid activity, near-fissure displacement gradients and hanging wall–footwall asymmetry. SVR can serve as a complementary model for relatively continuous displacement evolution, while GBDT and RF may assist in identifying local nonlinear displacement variations within the monitored data range. Therefore, although further field calibration and validation are still required, the proposed modeling framework provides a useful data-driven reference for displacement trend identification, monitoring point layout optimization and preliminary affected zone analysis in ground fissure-affected areas.

Overall, the comparison between physical model observations and model prediction results indicates that the proposed framework can capture the main spatiotemporal deformation characteristics of surface displacement under controlled large-scale model conditions. The temporally ordered validation further examines the ability of the models to characterize later-stage deformation based on earlier-stage observations. Meanwhile, the interpretation of the results should be linked to the experimental conditions, including the 20:1 similarity ratio, the finite model box boundary, the 0.3 m spacing of displacement measuring points and the tested soil properties. These factors do not weaken the observed deformation laws, but define the applicable scope of the quantitative affected zone widths and model prediction results. Therefore, when the results are extended to field conditions, further calibration using site-specific monitoring data and numerical modeling would help improve their engineering adaptability.

In addition, the patterns reflected by the prediction curves, such as the asymmetric deformation of the hanging wall and footwall and the differences in affected zone width among different cases, can provide a useful basis for optimizing engineering avoidance zoning and formulating targeted control measures. For instance, within the ground fissure-affected zone, the main deformation zone should be regarded as the key control area where construction activities should be avoided or strictly controlled, whereas protective measures, such as reinforcing structural components and limiting the structural importance level, may be considered in the micro-deformation zone. Furthermore, the prediction deviations in the models also reflect the possible differences between the controlled experiments and actual engineering conditions. Factors such as groundwater seepage, soil consolidation time effects, and surface dynamic/static loads can alter soil deformation characteristics, leading to minor deviations between actual settlement curves and experimental prediction curves. Therefore, future research should incorporate multi-source in situ monitoring data to calibrate model parameters and improve prediction accuracy, thereby further enhancing the applicability of the models to engineering early warning and ground fissure site planning.

7. Conclusions and Recommendations

This study conducted four controlled physical model tests to obtain surface settlement data of buried ground fissures under different lithologies and activity rates. Based on the measured displacement data, spatiotemporal prediction models covering traditional

regression and four machine learning algorithms were constructed and compared, and the displacement evolution characteristics were interpreted in combination with the observed deformation responses. The main conclusions are as follows:

1. Stratigraphic lithology and the activity rate are important factors influencing the spatiotemporal evolution of surface displacement. The sand layer in the interbedded sand–soil structure can effectively suppress localized crack propagation and expand the scope of the affected zone, whereas the homogeneous loess layer is prone to inducing localized deformation in the near-field, significantly increasing the variation gradient of near-field displacement. Rapid activity may promote the development of internal voids within the soil mass, causing surface displacement to rapidly reach relatively large values and then tend to stabilize within a short period. The activity rate exerts a prominent control over fracture propagation in the loess layer, while its impact on the deformation of the interbedded sand–soil structure is negligible.
2. Traditional cubic polynomial regression can effectively simulate the evolution trends of surface displacement over time and space, making it suitable for cases with slow activity and good stratigraphic homogeneity. Among the four machine learning algorithms, MLP exhibited the most stable performance under the adopted temporally ordered validation strategy. SVR showed acceptable performance for relatively continuous displacement evolution, while GBDT and RF may be used as complementary models for identifying local nonlinear displacement variations within the monitored data range. Overall, the machine learning models provide a useful data-driven reference for displacement trend identification and auxiliary interpretation of affected zone development under the present physical model test conditions.
3. Based on the physical model test results scaled by a similarity ratio of 20:1, with safety factors of 1.1–1.3 applied, the preliminary reference engineering avoidance distances for the ground fissure-affected zone are estimated to be 20–24 m on the hanging wall and 14–16 m on the footwall. These values are broadly consistent with the protection ranges specified in the current relevant regulations for ground fissure site investigation and engineering design, indicating that the physical model results have reference value for preliminary engineering assessment.

The physical model tests and data-driven analysis in this study improve the experimental understanding of surface displacement evolution induced by buried ground fissure activity and provide a quantitative basis for affected zone identification under controlled physical model conditions. Because the predictive models were established from four representative large-scale physical model tests, their applicability is mainly constrained by the tested stratigraphic structures, boundary conditions and soil properties. Although repeated tests under identical conditions were not conducted due to the large model size, high preparation cost and long testing period, the model dimensions, layer thickness, water content and monitoring frequency were strictly controlled to ensure comparability among different cases. Future studies should further combine additional cases, repeated tests where feasible, uncertainty analysis, site-specific monitoring data and numerical modeling that incorporates soil constitutive behavior, strength parameters, layer interface effects and fissure propagation, thereby improving the generalization and engineering applicability of the proposed framework.

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References

1. Zhao, J.Y.; Liu, C.; Peng, J.B.; Qiao, J.; Meng, Z.; Wen, H.; Wang, F.; Ma, P.; Wang, Z.; Jia, Z.; et al. Characteristics and formation mechanism of the Yangjiazhuang-Maguduo ground fissure, western Linfen Basin, Northern China. *J. Asian Earth Sci.* **2022**, *226*, 105043. [\[CrossRef\]](#)
2. Sancio, R.B.; Bray, J.D.; Stewart, J.P.; Youd, T.; Durgunoğlu, H.; Önalp, A.; Seed, R.; Christensen, C.; Baturay, M.; Karadayılar, T. Correlation between ground failure and soil conditions in Adapazari, Turkey. *Soil Dyn. Earthq. Eng.* **2022**, *22*, 1093–1102.
3. Zheng, Y.C.; He, S.Y.; Yu, Y.; Zheng, J.; Zhu, Y.; Liu, T. Characteristics, challenges and countermeasures of giant karst cave: A case study of Yujingshan tunnel in high-speed railway. *Tunn. Undergr. Space Technol.* **2021**, *114*, 103988. [\[CrossRef\]](#)
4. Li, Y.; Liu, H.; Su, L.J.; Chen, S.; Zhu, X.; Zhang, P. Developmental Features, Influencing Factors, and Formation Mechanism of Underground Mining-Induced Ground Fissure Disasters in China: A Review. *Int. J. Environ. Res. Public Health* **2023**, *20*, 3511. [\[CrossRef\]](#) [\[PubMed\]](#)
5. Li, H. Research on the development characteristics of ground fissures in shallow-buried coal seam mining: Taking Yujialiang Coal Mine in Shaanxi as an example. *Shaanxi Coal* **2019**, *38*, 43–46.
6. Xu, J.S.; Peng, J.B.; An, H.B.; Wang, F.; Sun, H.; Hu, H.; Yang, B. Paleochannel-controlled earth fissures in Daming, North China Plain and their implication for underground paleogeomorphology. *Geomorphology* **2019**, *327*, 523–532. [\[CrossRef\]](#)
7. Zang, M.D.; Peng, J.B.; Xu, N.X.; Jia, Z. A probabilistic method for mapping earth fissure hazards. *Sci. Rep.* **2021**, *11*, 8841. [\[CrossRef\]](#) [\[PubMed\]](#)
8. Chang, J.; Deng, Y.H.; Mu, H.D.; You, X.; Ge, C. A microtremor study to reveal the dynamic response of earth fissure site: The case study in Fenwei Basins, China. *Environ. Earth Sci.* **2022**, *81*, 80. [\[CrossRef\]](#)
9. Tian, Y.J.; Xu, Z.P.; Hu, H.W. Numerical simulation of the influence of ground fissures on the deformation characteristics of the surface. *IOP Conf. Ser. Earth Environ. Sci.* **2021**, *638*, 012076. [\[CrossRef\]](#)
10. Bray, D.; Seed, R.B.; Cuff, L.S.; Seed, H. Earthquake fault rupture propagation through soil. *J. Geotech. Eng.* **1994**, *120*, 543–561. [\[CrossRef\]](#)
11. Qi, J.F.; Liu, F.J.; Yang, X.Y.; Zhao, Y. Influence factors on the ground surface rupture zone induced by buried normal fault dislocation. *J. Earthq. Sci.* **2020**, *33*, 62–71. [\[CrossRef\]](#)
12. Ng, C.W.W.; Cai, Q.P.; Hu, P. Centrifuge and numerical modeling of normal fault rupture propagation in clay with and without a preexisting fracture. *J. Geotech. Geoenvironmental Eng.* **2012**, *138*, 1492–1502. [\[CrossRef\]](#)
13. Zhao, J.D.; Shan, T. Coupled CFD–DEM simulation of fluid–particle interaction in geomechanics. *Powder Technol.* **2013**, *239*, 248–258. [\[CrossRef\]](#)
14. Chu, S.S.; Lin, M.L.; Huang, W.C.; Nien, W.-T.; Liu, H.-C.; Chan, P.-C. Simulation of growth normal fault sand box tests using the 2D discrete element method. *Comput. Geosci.* **2015**, *74*, 1–12. [\[CrossRef\]](#)
15. Yu, H.B.; Wang, M.C.; Wang, F.Y. Geological hazard susceptibility assessment in Panshi, Jilin based on coupled models of statistical methods and machine learning. *World Geol.* **2025**, *44*, 433–445.
16. Wang, X.B.; Wang, L.Q.; Zhang, W.G.; Zhang, C.; Tan, C.; Yan, P.; Zhang, Z.; Guo, J. Ground fissure susceptibility mapping based on factor optimization and support vector machines. *Bull. Eng. Geol. Environ.* **2022**, *81*, 341. [\[CrossRef\]](#)
17. Hu, X.J.; Shentu, J.; Xie, N.; Huang, Y.; Lei, G.; Hu, H.; Guo, P.; Gong, X. Predicting triaxial compressive strength of high-temperature treated rock using machine learning techniques. *J. Rock Mech. Geotech. Eng.* **2023**, *15*, 2072–2082. [\[CrossRef\]](#)
18. Zhao, D.; Yan, L.; Kun, Z.; Li, R.; Li, Y.; Yao, C. Loess Collapsibility Prediction and Influencing Factor Analysis Using Multiple Machine Learning Algorithms in Xi'an Region. *Appl. Sci.* **2025**, *15*, 12095. [\[CrossRef\]](#)

19. Yu, B.; Xing, H.; Yan, J.; Li, Y. Small-scale, large impact: Utilizing machine learning to assess susceptibility to urban geological disasters—a case study of urban road collapses in Hangzhou. *Bull. Eng. Geol. Environ.* **2024**, *83*, 454. [\[CrossRef\]](#)
20. Ma, J.W.; Dou, J. Machine Learning Modeling for Spatial-Temporal Prediction of Geohazard. *Sensors* **2023**, *23*, 9262. [\[CrossRef\]](#) [\[PubMed\]](#)
21. Mohammady, M.; Pourghasemi, R.H.; Amiri, M. Land subsidence susceptibility assessment using random forest machine learning algorithm. *Environ. Earth Sci.* **2019**, *78*, 503. [\[CrossRef\]](#)
22. Ma, E.; Lai, J.; Su, X.; Peng, T.; Qiu, J. Failure characteristics of tunnels neighbouring karst fissures: Insights from laboratory observations and machine learning-interpreted simulations. *TunnW. Undergr. Space Technol.* **2025**, *156*, 106252. [\[CrossRef\]](#)
23. Pachano, F.; Cagua, B.; Birrell, M.; Medalla, M.; Astroza, R. A machine learning-based ground motion model for the Chilean subduction zone and its application to probabilistic seismic hazard analysis. *Soil Dyn. Earthq. Eng.* **2026**, *200*, 109862. [\[CrossRef\]](#)
24. Wang, P.R. A Study of Rupture Extension and Surface Rupture Effects of Hidden Ground Fracture. Ph.D. Thesis, Chang'an University, Xi'an, China, 2024.
25. Lu, Q.Z.; Ke, C.Y.; Li, C.; Li, Y.; Wu, Y.; Luo, W.; Mao, X.; Wang, Y.; Chen, X. Simulation study on fracture propagation of normal buried ground fissure with a dip of 60°. *J. Eng. Geol.* **2025**, *33*, 135–145.
26. Ferrill, A.D.; Morris, P.A.; McGinnis, N.R.; Smart, K.J.; Wigginton, S.S.; Hill, N.J. Mechanical stratigraphy and normal faulting. *J. Struct. Geol.* **2017**, *94*, 275–302. [\[CrossRef\]](#)
27. Withjack, M.O.; Schlische, R.W.; Henza, A.A. Scaled Experimental Models of Extension: Dry Sand vs. Wet Clay. *Bull. (Houst. Geol. Soc.)* **2007**, *49*, 31–49.
28. Ferrill, A.D.; Morris, P.A. Fault zone deformation controlled by carbonate mechanical stratigraphy, Balcones fault system, Texas. *AAPG Bull.* **2008**, *43*, 359–380. [\[CrossRef\]](#)
29. Chatzidakis, D.; Tsompanakis, Y.; Psarropoulos, P.N. Numerical investigation of secondary-fault rupture propagation through sandy deposits. *Eng. Geol.* **2021**, *292*, 106258. [\[CrossRef\]](#)
30. Liang, Z.Z.; Dong, Z.C.; Zi, L.Z. Modeling shear behavior of sand-clay interfaces through two-dimensional distinct element method analysis. *Environ. Earth Sci.* **2022**, *81*, 140. [\[CrossRef\]](#)
31. Xu, J.S.; Peng, J.B.; Deng, Y.; An, H.; Meng, Z.; Wang, Y.; Li, Z. Characteristics, causes and significance of subsurface stress field of Beijing earth fissures group. *Geomat. Nat. Hazards Risk* **2024**, *15*, 1–21.
32. Jan, V.; Kryštof, V.; Karel, M.; Hroch, T.; Buriánek, D.; Megerssa, L.A.; Boháč, J.; Kassa, M.; Legesse, F.; Yakob, M.; et al. Ground fissures within the Main Ethiopian Rift: Tectonic, lithological and piping controls. *Earth Surf. Process. Landf.* **2021**, *46*, 3158–3174. [\[CrossRef\]](#)
33. Smola, J.A.; Schölkopf, B. A tutorial on support vector regression. *Stat. Comput.* **2004**, *14*, 199–222. [\[CrossRef\]](#)
34. Antosz, K.; Jasiulewicz-Kaczmarek, M.; Husar, J.; Sá, J.C.; Hallioui, A. Machine Learning Methods in Quality Prediction: A Comparative Analysis of Regression Models—Case study. *IFAC-PapersOnLine* **2025**, *59*, 287–292. [\[CrossRef\]](#)
35. Shi, S.Z.; Gu, J.Y.; Feng, J.; Duan, P.F.; Qi, Y.C.; Han, Q. Intelligent identification method for near-surface ground fissures based on seismic data. *Appl. Geophys. Bull. Chin. Geophys. Soc.* **2020**, *17*, 639–648. [\[CrossRef\]](#)
36. Friedman, H.J. Greedy Function Approximation: A Gradient Boosting Machine. *Ann. Stat.* **2001**, *29*, 1189–1232. [\[CrossRef\]](#)
37. Zhang, W.; Wu, C.; Zhong, H.; Li, Y.; Wang, L. Prediction of undrained shear strength using extreme gradient boosting and random forest based on Bayesian optimization. *Geosci. Front.* **2020**, *12*, 469–477. [\[CrossRef\]](#)

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