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From Wetting-Front Coalescence to Urban Road Collapse: Interpretable Machine Learning of Hydro-Mechanical Failure under Coupled Rainfall and Pipeline Leakage

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Abstract: Urban ground collapse poses a severe threat to public safety, road operation and underground infrastructure in densely developed cities. This study investigates the hydro-mechanical failure mechanism of road collapse induced by coupled rainfall infiltration and pipeline leakage through physical model testing, finite element simulation and interpretable surrogate modelling. A validated numerical model incorporating saturation-dependent strength and stiffness degradation was used to generate 120 cases with different pipe burial depths, rainfall intensities and leakage pressures. The results indicate that collapse develops through shallow-soil pre-wetting, leakage-induced wetting-zone expansion, convergence of the upper and lower wetting fronts, and upward propagation of deformation. Leakage pressure is the dominant factor, contributing 86.42%, 87.79% and 92.77% to the variations in collapse depth, near-saturated zone area and wetting-front depth, respectively. Rainfall mainly dissipates matric suction and lowers the failure threshold, whereas burial depth regulates the wetting-front convergence and deformation-transfer path. GPR/Kriging achieved test-set (R^2) values of 0.997–0.998, while XGBoost-SHAP confirmed the mechanism of leakage-pressure domination, rainfall amplification and burial-depth regulation. Risk zoning further shows that increasing rainfall shifts high-risk conditions towards lower leakage pressures, particularly at intermediate burial depths. The proposed framework provides an efficient tool for identifying vulnerable pipeline sections and supporting targeted inspection and collapse prevention.

Keywords: Urban ground collapse; Pipeline leakage; Rainfall infiltration; Failure mechanism; Surrogate modelling

Introduction

Urban road collapse has become a major geotechnical hazard in rapidly urbanising areas, especially where ageing underground pipelines, intensive traffic and extreme rainfall coexist. Unlike natural karst collapse, urban road collapse is commonly related to defective drainage or water-supply pipelines, localised soil erosion, hidden cavity development, rainfall infiltration and progressive ground deformation. Statistical studies of road collapse accidents in China indicate that pipeline leakage and rainfall are among the most frequent triggering factors (Fig. 1), highlighting the need to clarify the

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hydro-mechanical mechanisms of rainfall–pipeline leakage coupled collapse (Tan and Long, 2021; Wang et al., 2022; Wang and Xu, 2022).

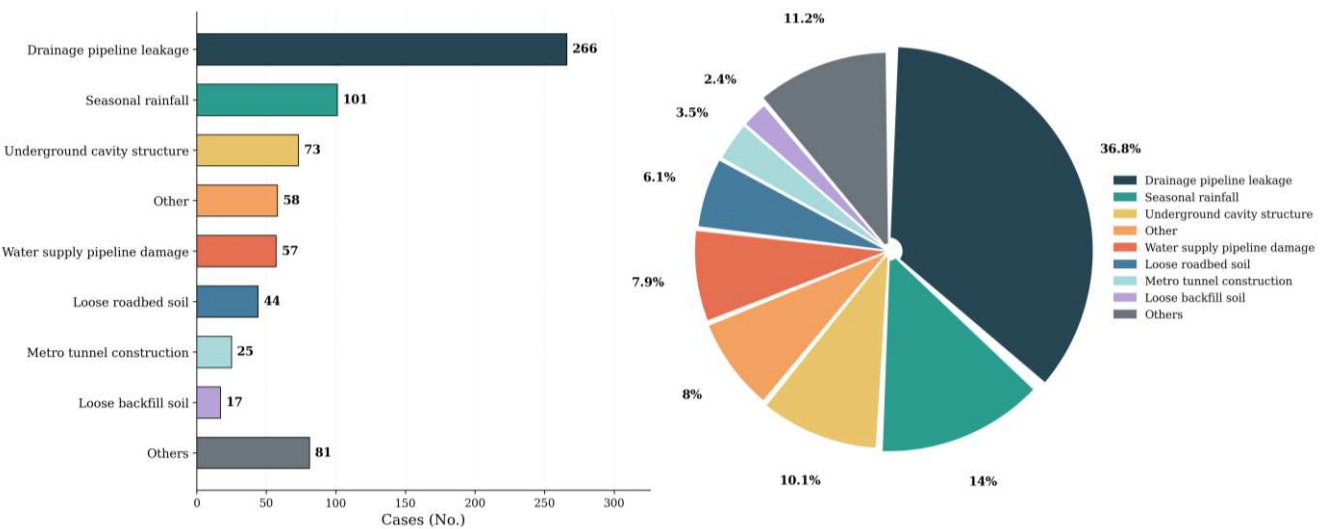


Fig. 1 Statistical Analysis of Urban Sinkhole Triggers and Contributing Factors (Adapted from (Li,2025))

Defective pipes provide preferential paths for seepage and soil-particle migration. Leakage through cracks or openings can induce internal erosion, soil loosening, cavity formation and surface settlement. Previous laboratory, numerical and particle-scale studies have shown that pipe-leakage-induced ground failure is affected by leakage conditions, pipe embedment material, defect geometry and hydraulic boundaries (Davies et al., 2001; Guo and Zhu, 2017; Indiketiya et al., 2017, 2019; Tan et al., 2022; Guo et al., 2023; Li et al., 2023; Yuan et al., 2025b). However, most studies focus on pipe-leakage-induced erosion or cavity development, while the coupling between rainfall infiltration from the ground surface and leakage-induced wetting around buried pipes remains insufficiently quantified.

From a hydro-mechanical perspective, rainfall infiltration and pipeline leakage are not simply additive water sources. Rainfall increases the water content of shallow soil, dissipates matric suction and reduces strength and stiffness, whereas pipeline leakage generates a local hydraulic gradient around the defect and promotes pore-water diffusion, fine-particle migration and localised softening. These processes are closely related to unsaturated soil mechanics and hydraulic conductivity models (Bishop, 1959; Fredlund et al., 1978; Mualem, 1976; van Genuchten, 1980). When the downward rainfall wetting front interacts with the outward-expanding leakage-induced wetted zone, a continuous softened pathway may form, allowing hidden hydraulic disturbance to evolve into surface settlement or collapse. Although damaged sewer pipes and repeated heavy rainfall have been reported to jointly affect cavity initiation and expansion, the convergence of rainfall and leakage-induced wetting zones and its transformation into surface deformation remain insufficiently described (Jung et al., 2023).

Physical model tests, geophysical detection and numerical simulations are widely used to investigate underground cavities and urban ground collapse. Physical tests can reproduce wetting-front migration and surface deformation but are limited by model scale and cost. Geophysical methods, such as ground penetrating radar, can detect underground cavities and weak zones but provide limited explanation of the hydro-mechanical evolution process (Gao et al., 2023; Li et al., 2024). Numerical simulation can extend the analysis to broader parameter spaces, but high-fidelity hydro-mechanical or CFD–DEM simulations remain computationally expensive for rapid screening of numerous urban pipe sections (Li et al., 2023; Lan et al., 2024; Yuan et al., 2025a).

Machine-learning-based surrogate modelling offers an efficient alternative for approximating high-cost numerical simulations. It has been increasingly applied to susceptibility mapping, risk zoning and response prediction in landslides, sinkholes, floods and urban ground-collapse-related hazards (Wang et al., 2021; Kim et al., 2022; Deroliya et al., 2022; Gao et al., 2022; Tang et al., 2023; Jiang et al., 2023; Zhang et al., 2024; Yin et al., 2024). Nevertheless, for geotechnical applications, prediction accuracy alone is insufficient. Surrogate models should also provide uncertainty information when possible, remain interpretable and be consistent with the underlying physical mechanisms. Gaussian process regression/Kriging is suitable for small-sample and low-dimensional parameter spaces and can provide prediction uncertainty, whereas tree-based ensemble models such as random forest and XGBoost can capture nonlinear interactions and be interpreted using SHAP methods (Breiman, 2001; Chen and Guestrin, 2016; Lundberg and Lee, 2017; Lundberg et al., 2020.). Recent studies have further emphasised the need to combine data-driven models with physical constraints and engineering interpretation (Lan et al., 2024; Zhuang et al., 2025.).

Although previous studies have provided an important basis for understanding pipeline-leakage-induced collapse, three limitations remain. First, the interaction between the rainfall wetting front and the leakage-induced wetted zone, as well as its transformation into surface response, is still not fully understood. Second, physical tests are difficult to extend to broad engineering parameter spaces, while case-by-case numerical simulations are inefficient for rapid screening of numerous pipe sections. Third, existing machine learning models often focus mainly on prediction accuracy, with limited discussion of their mechanism consistency, applicability range and extrapolation boundaries.

To address these issues, this study proposes a mechanism-constrained dual-surrogate modelling framework. A full-factorial numerical case library is constructed based on a hydro-mechanical model considering saturation-dependent strength degradation. GPR/Kriging is used as a benchmark for prediction accuracy and uncertainty, while XGBoost is adopted for response prediction, risk classification and SHAP-based interpretation. A comprehensive risk index (RI) is further developed for

relative risk zoning within the designed parameter space. This framework links the physical mechanism of rainfall–pipeline leakage coupled collapse with numerical response prediction and engineering risk screening, providing an interpretable method for rapid identification and graded prevention of urban road collapse.

1 Physical model test, numerical model and validation

1.1 Physical model test and loading scheme

To validate the collapse evolution process induced by the combined effects of rainfall infiltration and pipeline leakage, a large-scale physical model test was used as the basis for numerical model calibration (Fig. 2). The test system consisted of a model box, a rainfall system, a water circulation system and a multi-field monitoring system. The model box had dimensions of 1.5 m × 1.0 m × 1.2 m and was equipped with a rigid frame and transparent side walls to facilitate the observation of wetting-front migration and collapse development. The rainfall system produced uniform rainfall through an array of spray nozzles, while the water circulation system was used to simulate continuous leakage from a damaged pipeline. The monitoring system recorded the volumetric water content, pore-water pressure, surface displacement and soil pressure during the test.

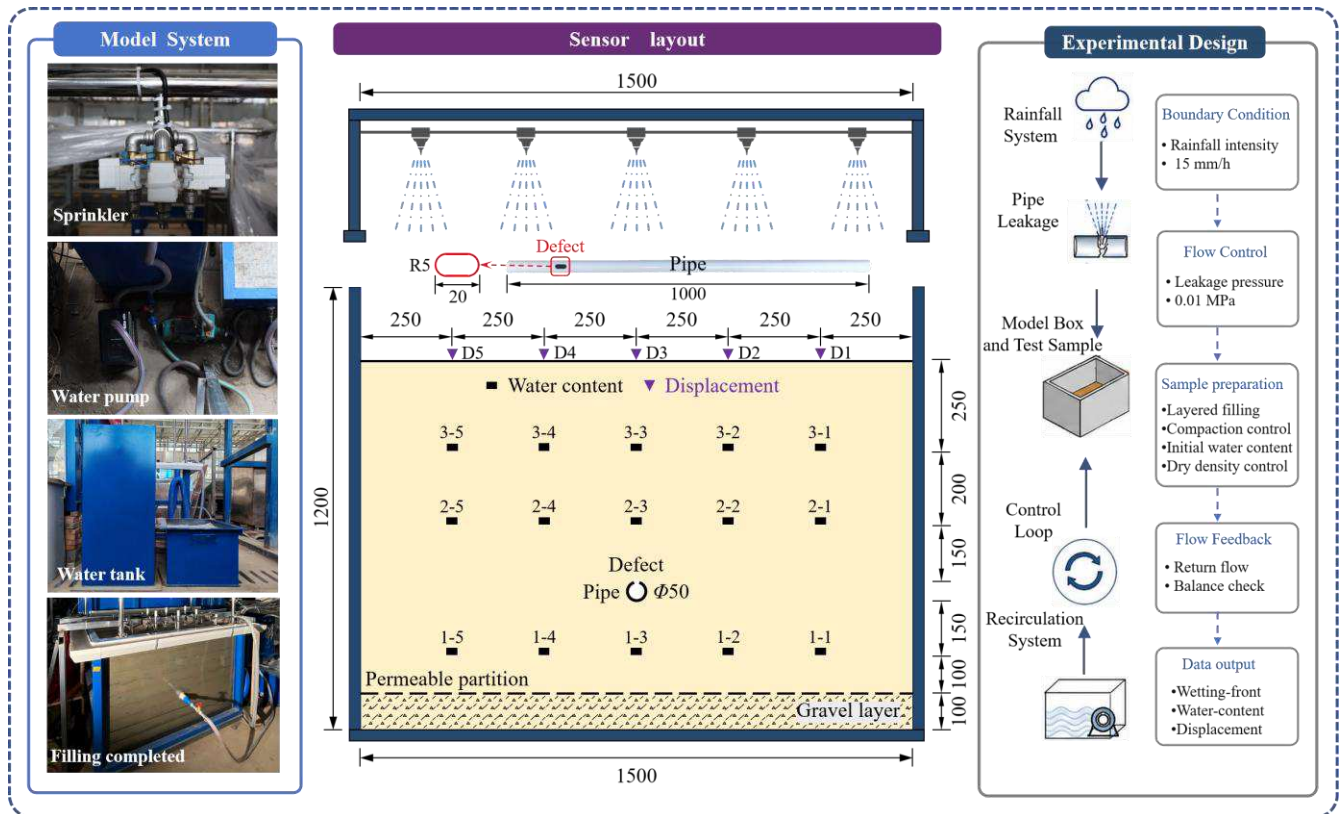


Fig. 2 Physical model test system.

The loading scheme combined intermittent rainfall with continuous pipeline leakage. The rainfall intensity was set to 15 mm/h, and each rainfall cycle consisted of 1 h of rainfall followed by 0.6 h of

rainfall interruption. Five rainfall cycles were applied within 8 h. Pipeline leakage was continuously imposed throughout the test, with the internal pipe pressure maintained at approximately 0.01 MPa to simulate sustained hydraulic disturbance from a defect in a low-pressure drainage or water-supply pipeline. This setup reproduced the full process of downward migration of the upper rainfall wetting front, expansion of the lower leakage-induced wetted zone, convergence of the two wetted zones and subsequent ground collapse.

It should be noted that the physical model test was primarily used to validate the process mechanism of rainfall infiltration, pipeline leakage, wetting-zone convergence and surface settlement, as well as to assess the ability of the numerical model to reproduce key hydro-mechanical responses. The subsequent 120 engineering-scale numerical cases represent a parameter-space extension based on this process-level validation, rather than a one-to-one reproduction of the physical test conditions.

1.2 Hydro-mechanical parameters and strength degradation of unsaturated soil

Rainfall infiltration and pipeline leakage increase the degree of saturation of the surrounding soil, dissipate matric suction and induce degradation of soil strength and stiffness. To describe this process, the internal friction angle (ϕ), cohesion (c), elastic modulus (E), soil-water characteristic curve (SWCC) and relative permeability function were defined as saturation-dependent properties.

Although suction-based shear strength formulations have been widely developed for unsaturated soils (Bishop, 1959; Fredlund et al., 1978;), their practical application is often limited by the difficulty of accurately determining suction-related parameters. Therefore, the degree of saturation S_r was used as a state variable to describe strength degradation. Based on triaxial test results of Hangzhou silty clay under different saturation states, the internal friction angle and cohesion were fitted as empirical functions of saturation:

$$\phi = \begin{cases} \phi' & S_r \geq S_{rc} \\ \phi' + \frac{\phi_d - \phi'}{S_{rc}}(S_{rc} - S_r) & S_r < S_{rc} \end{cases} \quad (1)$$

$$c = \begin{cases} \exp(aS_r + b) & S_r > S_{rv} \\ dS_r + c_d & S_r \leq S_{rv} \end{cases} \quad (2)$$

Where S_r is the degree of saturation. The fitted relationships indicate that the internal friction angle generally decreases with increasing saturation, while cohesion exhibits a nonlinear evolution due to the combined effects of capillary bonding, suction dissipation and wetting-induced softening.

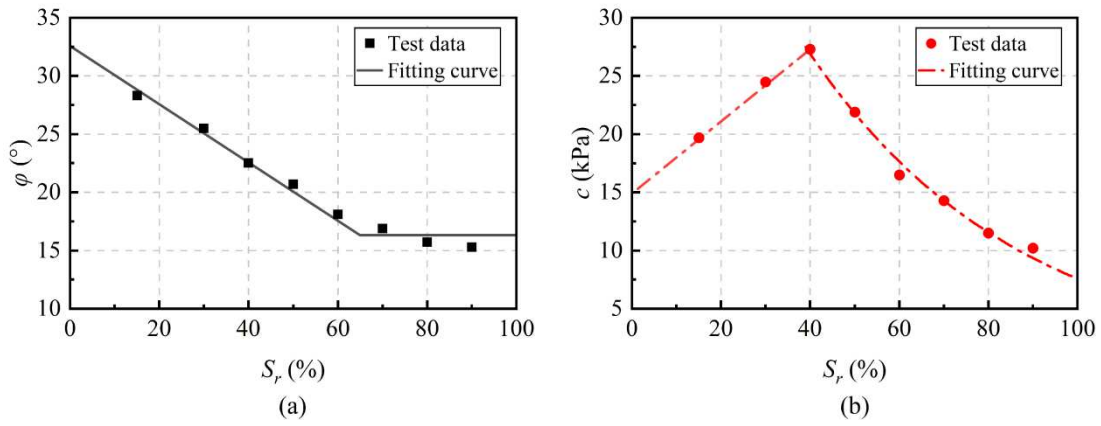


Fig. 3 Relationships between shear strength parameters and degree of saturation. (a) Internal friction angle; (b) cohesion.

The hydraulic behaviour of the unsaturated soil was described using the van Genuchten-Mualem model (Mualem, 1976; van Genuchten, 1980):

$$S_e = \frac{\theta - \theta_r}{\theta_s - \theta_r} = \frac{1}{\left(1 + (\alpha\psi)^n\right)^m} \quad (3)$$

$$K_r = S_e^l \left[1 - \left(1 - S_e^{1/m}\right)^m\right]^2 \quad (4)$$

where S_e is the effective saturation; θ , θ_s and θ_r are the volumetric, saturated and residual water contents, respectively; ψ is the matric suction; K_r is the relative permeability coefficient; α , n and m are SWCC fitting parameters with $m=1+1/n$; and l is the pore-connectivity parameter. The fitted SWCC is shown in Fig. 4, and the air-entry value determined by the tangent-intersection method is approximately 10 kPa.

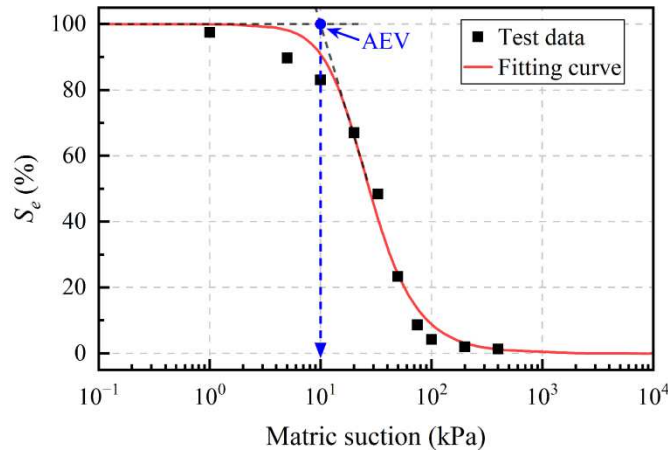
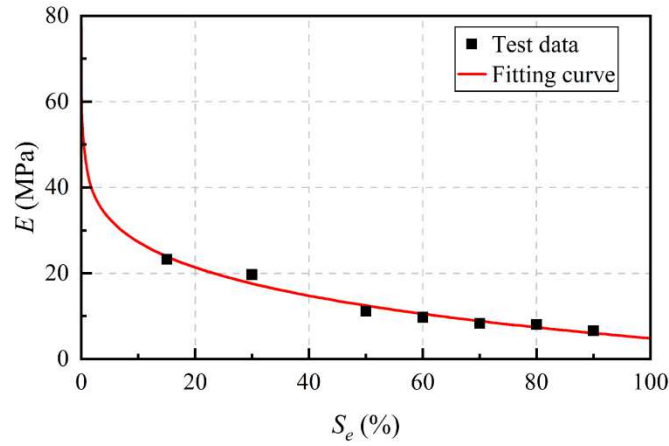


Fig. 4 Soil-water characteristic curve of the Hangzhou silty clay.

The wetting-induced stiffness degradation was described using an empirical power-law relationship:

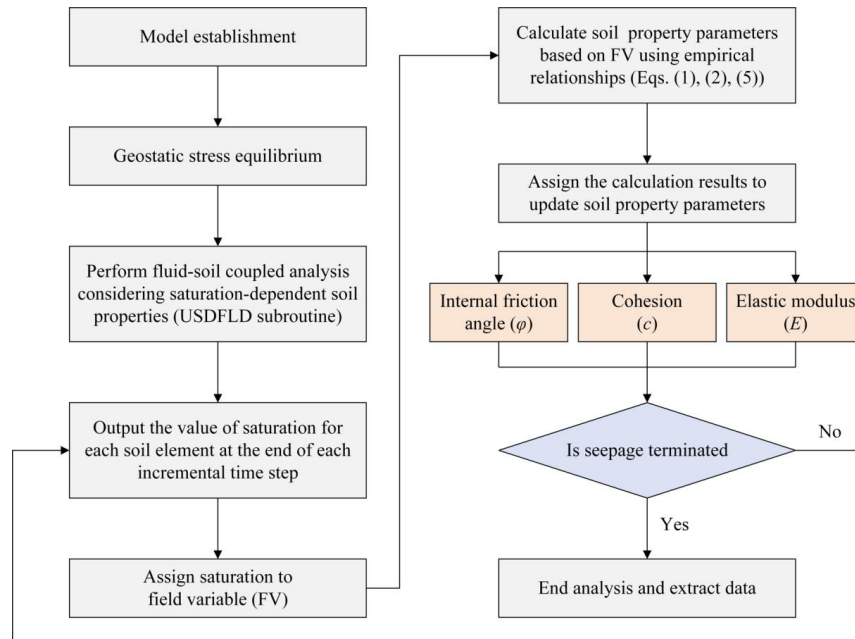
$$E = E_d + (E_w - E_d) \left(\frac{\theta - \theta_d}{\theta_w - \theta_d} \right)^r \quad (5)$$

143 where E_d and E_w are the elastic moduli under dry and wet reference states, respectively; θ_d and θ_w are
 144 the corresponding volumetric water contents; and r is the fitting exponent.



145
 146 Fig. 5 Relationship between elastic modulus and degree of saturation.

147 In the finite element model, the hydraulic response was governed by the VGM model, while the
 148 saturation-dependent strength and stiffness degradation were implemented through the USDFLD
 149 subroutine (Fig. 6) . At each increment, the degree of saturation of each soil element was extracted
 150 from the pore-fluid analysis and assigned to a field variable. The internal friction angle (ϕ), cohesion (c)
 151 and elastic modulus (E) were then updated according to Eqs. (1), (2) and (5). This implementation
 152 allows the Mohr-Coulomb parameters and stiffness to evolve continuously with wetting, thereby
 153 capturing the progressive transition from local saturation increase to strength degradation and surface
 154 settlement under rainfall–pipeline leakage coupling.



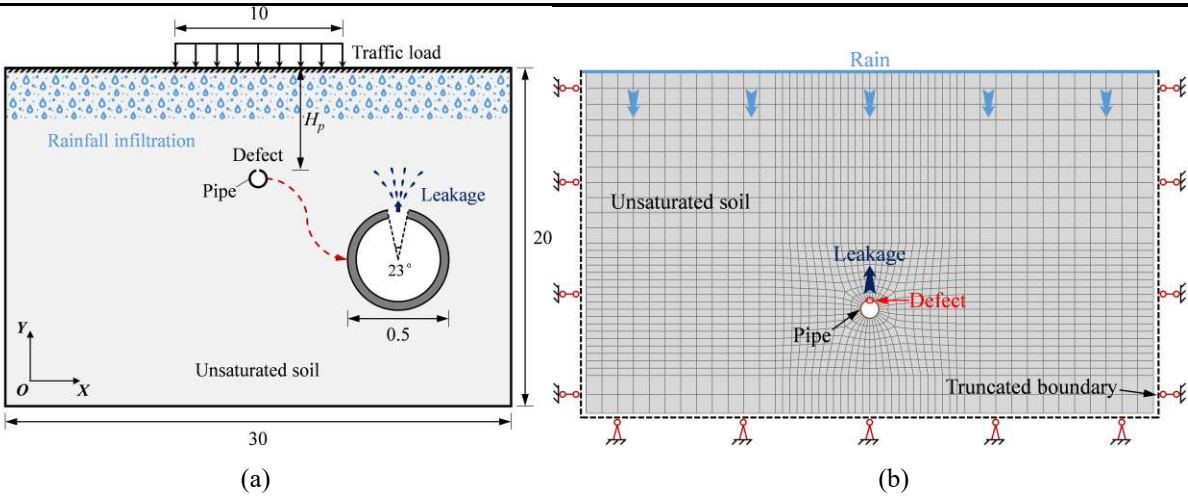
155
 156 Fig. 6 Numerical implementation procedure of saturation-dependent strength and stiffness degradation using the
 157 USDFLD subroutine.

158 1.3 Finite element model

159 An engineering-scale two-dimensional plane-strain finite element model was established. The model
160 domain was 30 m × 20 m to minimise boundary effects. The pipe diameter was 0.5 m, and the pipe
161 burial depth (D) varied from 1 m to 6 m. The model surface was defined as a rainfall infiltration
162 boundary, and the pipeline defect was assigned a pore-pressure boundary to simulate leakage pressure
163 (Fig. 7a) . The bottom boundary was fixed in both the normal and tangential directions, while the
164 lateral boundaries were constrained in the normal direction. Four-node pore-pressure coupled elements
165 were used for the soil, and plane-strain elements were used for the pipeline. Local mesh refinement
166 applied around the pipe and in the potential wetting-front migration zone (Fig. 7b) .The mechanical
167 parameters of the soil and pipeline used in the finite element model are listed in Table 1.

168 Table 1 Mechanical parameters of soil and pipeline.

Material	Density (kg/m ³)	Elastic modulus (MPa)	Poisson's ratio	Permeability coefficient (10 ⁻⁶ m/s)	Friction angle (°)	Cohesion (kPa)
Soil	1520	12.5	0.3	1.86	21.8	20.0
Pipeline	7100	170000	0.28	-	-	-

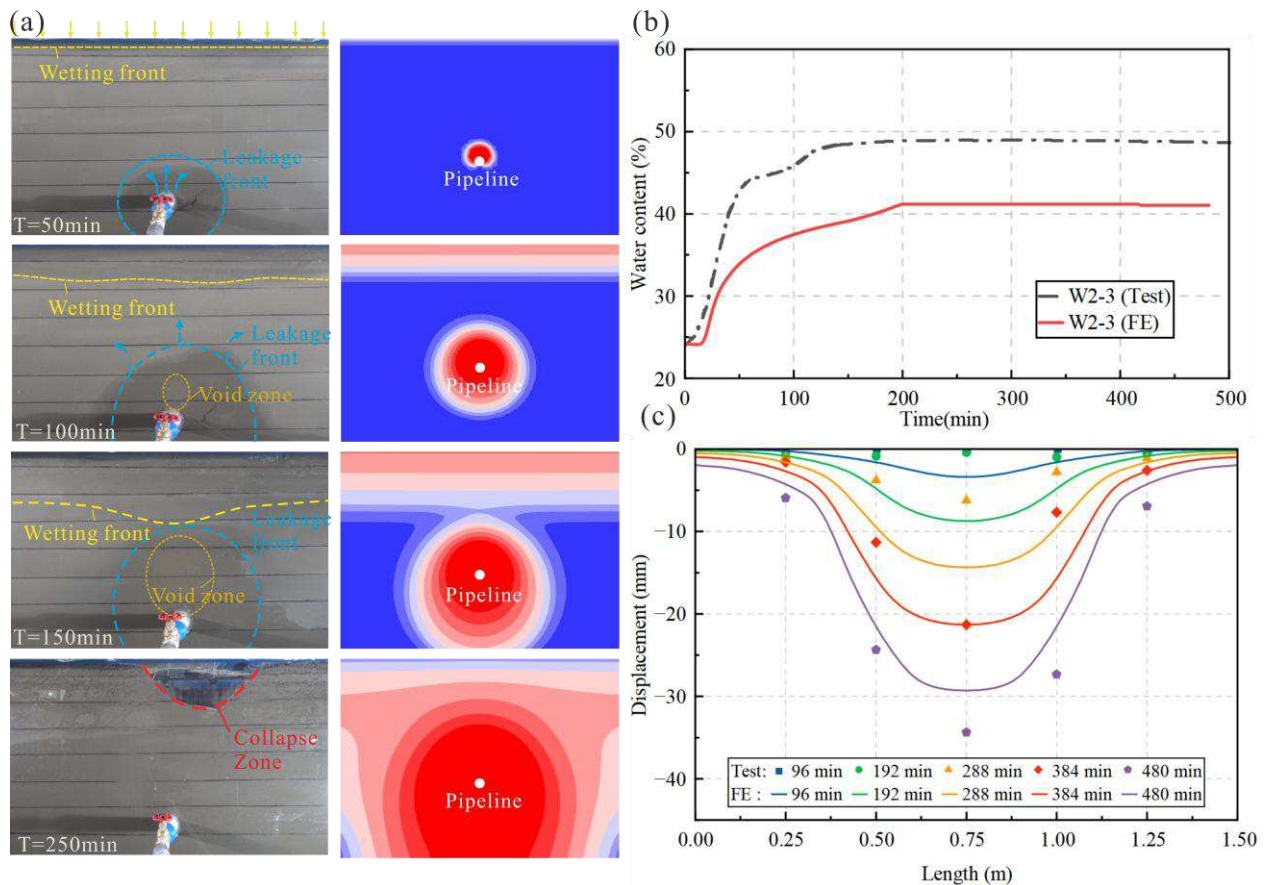


171 Fig. 7 Numerical model. (a) Geometric relationship (unit: m); (b) Mesh and boundary conditions.

172 1.4 Numerical model validation

173 The numerical model was validated from three aspects: wetting-front morphology, volumetric water
174 content and surface displacement. The wetting-front comparison showed that rainfall infiltration
175 generated an approximately horizontal wetting front that migrated downward, whereas pipeline leakage
176 produced an elliptical wetted zone around the defect. As seepage continued, the two wetted zones
177 gradually contacted and merged, forming an inverted Ω -shaped wetting pattern (Fig. 8a) . The
178 simulated wetting-front morphology, convergence process and final wetted range were generally
179 consistent with the physical model observations.

180 The time-history curves of volumetric water content at key monitoring points showed that the points
 181 near the wetting-front convergence zone first experienced rapid wetting under the influence of pipeline
 182 leakage, followed by a short delay in the growth rate (Fig. 8b) . After the rainfall wetting front
 183 connected with the leakage-induced wetted zone, the volumetric water content increased rapidly again
 184 and approached saturation. The numerical model reproduced this staged response reasonably well,
 185 indicating that it can describe the water migration process under rainfall–pipeline leakage coupling.
 186 The surface displacement comparison indicated that the model could reproduce the progressive
 187 settlement and spatial attenuation in the peripheral collapse zone (Fig. 8c) . However, the extreme
 188 displacement near the collapse centre was difficult to match precisely using a continuum model,
 189 because this region was strongly affected by local soil loss, cavity connection and post-collapse
 190 structural rearrangement. Overall, the model reasonably captured the full evolution of rainfall
 191 infiltration, pipeline leakage, wetting-zone convergence and surface settlement, and can therefore be
 192 used as the basis for subsequent parametric numerical cases and machine learning dataset construction.



193
 194 Fig. 8 Experimental-numerical validation. (a) Wetting-front morphology; (b) Water content. (c) Displacement

195 1.5 Construction of the 120-case numerical database

196 Based on the numerical model validated by the physical model test, a full-factorial database containing
 197 120 numerical cases was constructed for subsequent sensitivity analysis and surrogate model training

(Table 2) . Three main variables were considered: pipe burial depth (D), rainfall intensity (R) and leakage pressure (L). Specifically, (D) was set to 1, 2, 3, 4, 5 and 6 m; (R) was set to 20, 40, 60 and 80 mm/d; and (L) was set to 50, 60, 70, 80 and 90 kPa, resulting in ($6 \times 4 \times 5 = 120$) full-factorial cases. The total simulation duration was 15 d, and a traffic load of 20 kPa was applied. The output responses included the surface collapse deformation depth (S), near-saturated zone area (A_s) and wetting-front depth (Z_w), representing the surface deformation consequence, soil softening range and hidden hydraulic disturbance depth, respectively.

Table 2 Loading cases.

pipe burial depth D (m)	Leakage pressure L (kPa)	Rainfall intensity R (mm/d)	Duration t (d)	Traffic loading P_t (kPa)	Output responses
1	50, 60, 70, 80, 90	20, 40, 60, 80	15	20	
2	50, 60, 70, 80, 90	20, 40, 60, 80	15	20	(S)
3	50, 60, 70, 80, 90	20, 40, 60, 80	15	20	(A_s)
4	50, 60, 70, 80, 90	20, 40, 60, 80	15	20	(Z_w)
5	50, 60, 70, 80, 90	20, 40, 60, 80	15	20	
6	50, 60, 70, 80, 90	20, 40, 60, 80	15	20	

2 Numerical simulation-based sensitivity analysis

2.1 Main-effect trends

Fig. 9 shows the main-effect mean curves of pipe burial depth D, rainfall intensity R, and leakage pressure L on surface collapse depth S, near-saturated zone area A_s , and wetting-front depth Z_w . Overall, the three response indicators exhibit distinct sensitivities to the input variables: L shows a continuously increasing effect on all three responses, R mainly acts as a positive amplification factor, whereas D exhibits a more pronounced non-monotonic and path-regulating effect.

For surface collapse depth S, as D increases from 1 m to 3 m, S increases from approximately 171 mm to 191 mm and reaches its peak at an intermediate burial depth. When D further increases to 6 m, S decreases to approximately 168 mm, indicating that intermediate burial depth is more likely to produce a larger surface deformation response. As R increases from 20 mm/d to 80 mm/d, S increases from approximately 156 mm to 206 mm, showing an approximately linear growth trend. By comparison, L has the most significant influence on S. When L increases from 50 kPa to 90 kPa, S increases from approximately 117 mm to 276 mm, with a much larger increase than that caused by D or R.

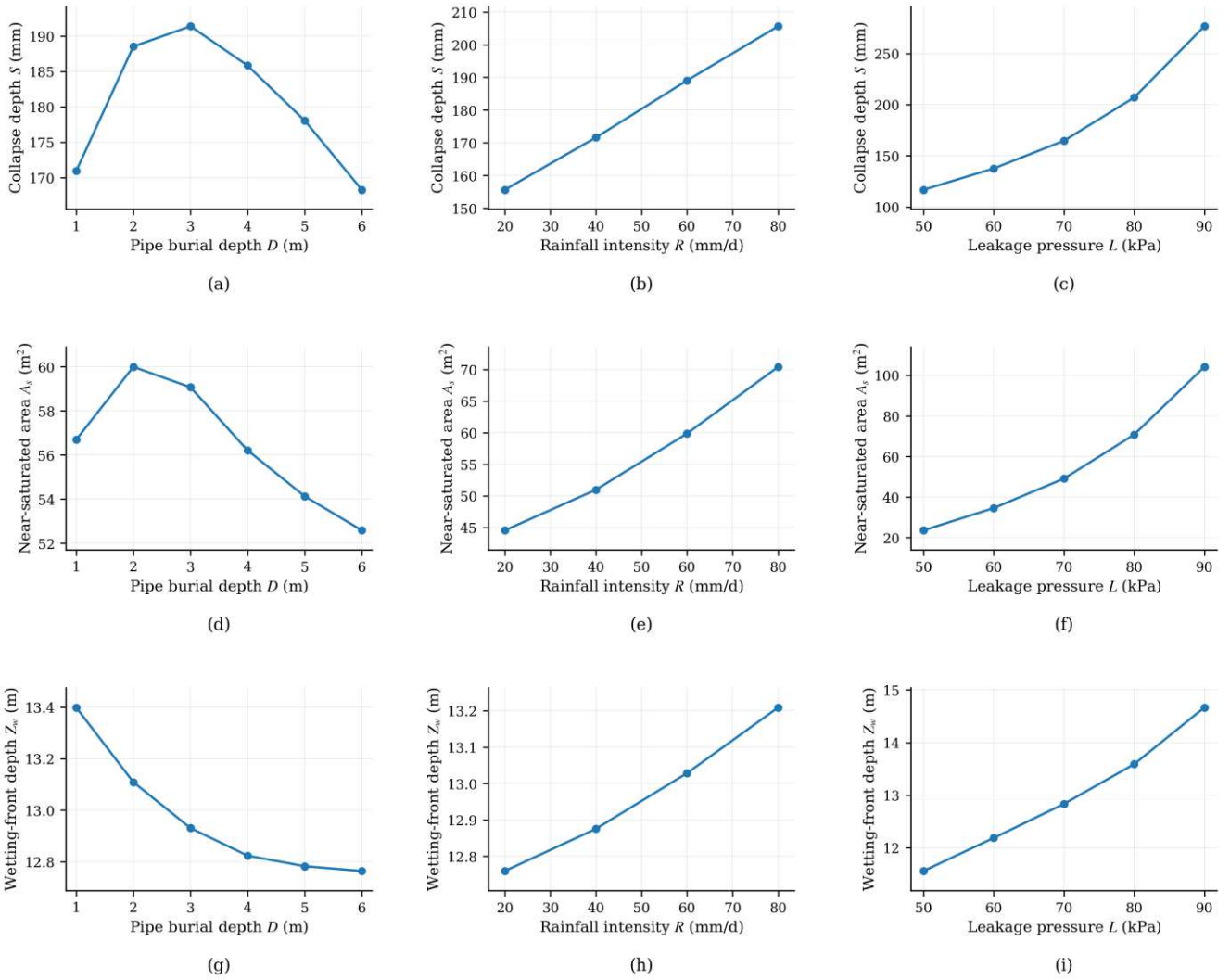


Fig. 9 Main-effect mean curves of (D), (R), and (L) for the three collapse response indicators. (a–c) Effects of pipe burial depth (D), rainfall intensity (R), and leakage pressure (L) on collapse depth (S), respectively; (d–f) effects of (D), (R), and (L) on near-saturated zone area (A_s), respectively; (g–i) effects of (D), (R), and (L) on wetting-front depth (Z_w), respectively.

For the near-saturated zone area A_s , the effect of D also shows a trend of first increasing and then decreasing. When D increases from 1 m to 2 m, A_s increases to approximately 60 m²; thereafter, A_s gradually decreases with increasing D , reaching approximately 53 m² at $D=6$ m. Both R and L promote the expansion of A_s . Specifically, A_s increases from approximately 45 m² to 70 m² as R increases from 20 mm/d to 80 mm/d, whereas it increases from approximately 24 m² to 105 m² as L increases from 50 kPa to 90 kPa. This indicates that leakage pressure exerts a stronger control on the expansion of the softened zone.

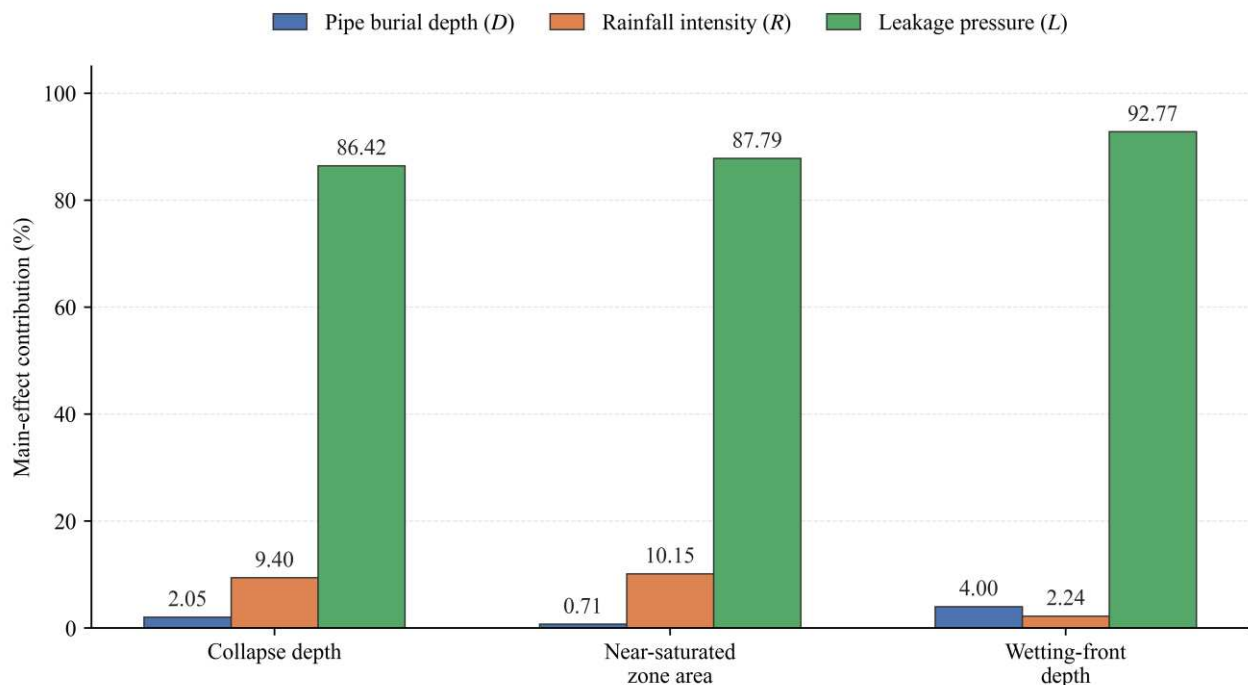
For wetting-front depth Z_w , the effects of D , R , and L are clearer. Z_w decreases from approximately 13.4 m to 12.8 m as D increases, indicating that a larger burial depth lengthens the convergence path between the rainfall wetting front and the leakage-induced wetted zone and weakens the effective

236 propagation of the wetting front. R promotes Z_w to some extent, but the increase is relatively limited.
 237 In contrast, L has the most pronounced effect on Z_w , which increases from approximately 11.6 m to
 238 14.7 m with increasing L . This suggests that leakage pressure directly controls the propagation depth
 239 of hidden hydraulic disturbance.

240 In summary, Fig. 9 indicates that all three response indicators are most sensitive to changes in L .
 241 Rainfall intensity R mainly amplifies collapse responses through infiltration and shallow wetting,
 242 while pipe burial depth D regulates the responses by changing the spatial convergence path between
 243 the rainfall wetting front and the leakage-induced wetted zone.

244 2.2 Main-effect variance contribution

245 To quantitatively compare the influence of the three input variables on the response indicators, a main-
 246 effect variance contribution analysis was conducted based on the 120 full-factorial numerical cases. The
 247 main-effect contribution of each variable was calculated as the ratio of the variance of its level-
 248 averaged response to the sum of the main-effect variances of all input variables. As shown in Fig. 10.
 249 the results show that L dominates all three responses, with main-effect contributions of 86.42%,
 250 87.79%, and 92.77% to S , A_s , and Z_w , respectively. The contributions of R to S and A_s are 9.40%
 251 and 10.15%, respectively, indicating that rainfall mainly amplifies surface deformation and the softened
 252 zone. The contribution of D to Z_w is 4.00%, which is higher than its contributions to S and A_s ,
 253 suggesting that burial depth mainly affects hidden wetting-front development by controlling the water
 254 migration path.



255

256

Fig. 10 Main-effect contribution rates of D , R , and L to the three response indicators.

2.3 Mechanistic relationship among response indicators

The main-effect trends and variance contribution results indicate that S , A_s , and Z_w , although representing surface deformation consequence, internal softened-zone extent, and hidden hydraulic disturbance depth, respectively, are not independent of each other. Instead, they jointly describe the continuous evolution of rainfall–pipeline leakage coupled collapse. An increase in Z_w indicates the propagation of hydraulic disturbance from the pipeline defect to a wider region; the expansion of A_s reflects the development of low-suction and near-saturated softened zones; and the increase in S represents the transformation of internal hydraulic disturbance and strength degradation into surface deformation.

From the perspective of the response chain, leakage pressure L first increases the hydraulic gradient near the pipeline defect, thereby promoting wetting-front expansion and the formation of a near-saturated zone. Rainfall intensity R weakens the stability of the overburden through shallow pre-wetting and matric suction dissipation, making the leakage-induced disturbance more likely to propagate towards the ground surface. Pipe burial depth D controls the spatial distance and convergence path between the upper and lower wetted zones. Under high L and high R conditions, the leakage-induced wetted zone around the pipe is more likely to connect with the rainfall wetting front, forming a continuous softened pathway and promoting the expansion of A_s and the increase of S . By contrast, when D is excessively large, the hydraulic disturbance path towards the surface becomes longer, and the surface deformation response is attenuated.

Therefore, rainfall–pipeline leakage coupled collapse can be summarised as a response chain of hidden hydraulic disturbance development–near-saturated softened zone expansion–surface settlement concentration. L controls the initiation and development intensity of this response chain, R determines the triggering and amplification conditions in the shallow soil, and D governs the spatial transfer efficiency between hydraulic disturbance and surface deformation. This mechanistic interpretation provides a physical basis for the subsequent surrogate model construction and SHAP-based explanation.

3 Interpretable machine-learning surrogate modelling method

3.1 Dataset construction

The machine-learning dataset consisted of 120 validated numerical cases, with each sample containing three input variables and three response variables. The input variables were pipe burial depth D , rainfall intensity R , and leakage pressure L . The response variables were surface collapse depth S , near-saturated zone area A_s , and wetting-front depth Z_w . The selection of D , R , and L was not based purely on data-driven feature screening, but was determined according to the physical model test,

numerical simulation, and mechanism analysis presented above. Specifically, D represents the geometric path and overburden stability reserve, R represents the external hydrological triggering condition, and L represents the hydraulic disturbance intensity at the pipeline defect.

Because the dataset was constructed using a 6×4×5 full-factorial design, it systematically covered the D-R-L parameter space defined in this study. For model training, 75% of the samples were used as the training set and 25% as the independent test set, with random_state = 42. For the classification task, stratified sampling was adopted to maintain the proportions of low-, medium-, and high-risk samples. Five-fold cross-validation was performed on the training set, and learning curves, residual diagnosis, and leave-level validation were further used to evaluate model stability.

It should be noted that the applicability of the model is limited to the soil type, pipe diameter, rainfall intensity, leakage pressure, and boundary conditions considered in this study. For different stratigraphic conditions, pipe diameters, groundwater levels, pipe defect geometries, or extreme rainfall boundaries, the numerical case library should be expanded or field monitoring data should be introduced to recalibrate the model.

3.2 Candidate surrogate models

To avoid conclusions being dependent on a single model, six regression surrogate models were compared: linear regression, polynomial ridge regression, SVR-RBF, GPR/Kriging, random forest, and XGBoost. Linear regression and polynomial ridge regression were used as the linear baseline and second-order response surface model, respectively. SVR-RBF and GPR/Kriging are suitable for small-sample nonlinear mapping, and GPR/Kriging can further provide prediction standard deviations for uncertainty diagnosis. Random forest and XGBoost were used to capture nonlinear thresholds and variable interactions.

Model performance was evaluated using the coefficient of determination R^2 , root mean square error RMSE, and mean absolute error MAE, which measure variance explanation ability, large-error sensitivity, and average prediction deviation, respectively:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (6)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (7)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (8)$$

where y_i is the numerical simulation result, $\hat{y}_i$ is the surrogate-model prediction, $\bar{y}$ is the mean value of the numerical simulation results, and n is the number of samples.

3.3 SHAP interpretation method

It should be emphasised that SHAP explains the prediction decomposition of the XGBoost surrogate model, rather than directly observed physical processes. Therefore, in this study, SHAP was used as a tool for mechanism-consistency check. Only when the variable ranking and dependence trends obtained from SHAP were consistent with the numerical sensitivity analysis were they interpreted as evidence that the model had learned reasonable hydro-mechanical response patterns.

In the dual-surrogate framework, SHAP interpretation was performed using the XGBoost branch. The mean absolute SHAP values were used to quantify the relative contributions of D, R, and L to the model outputs, and SHAP interaction values were used to identify the coupled effects of D×R, D×L, and R×L. SHAP analysis was used not only for variable-importance ranking, but also to examine whether the model learned the mechanism-consistent pattern of L-dominated, R-amplified, and D-regulated responses.

If the SHAP results also show the pattern of L domination, R amplification, and D regulation, the surrogate model can be considered to have not only predictive ability but also a certain degree of mechanism interpretability.

3.4 Comprehensive risk index RI

To convert the three continuous responses S , A_s , and Z_w into an engineering-readable risk ranking, min-max normalization was first applied to obtain S^* , A_s^* , and Z_w^* :

$$S^* = \frac{S - S_{\min}}{S_{\max} - S_{\min}} \quad (9)$$

$$A_s^* = \frac{A_s - A_{s,\min}}{A_{s,\max} - A_{s,\min}} \quad (10)$$

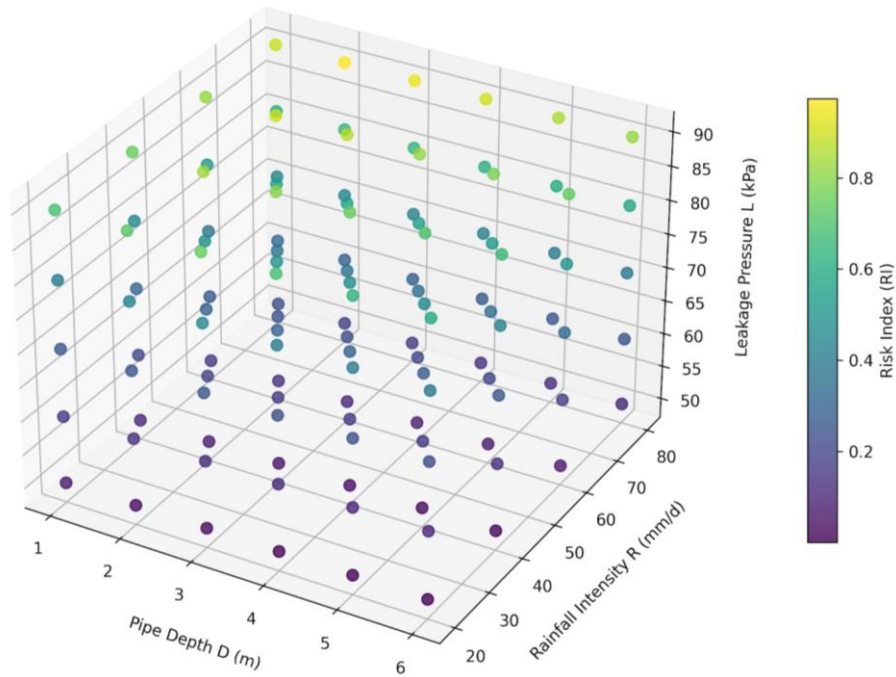
$$Z_w^* = \frac{Z_w - Z_{w,\min}}{Z_{w,\max} - Z_{w,\min}} \quad (11)$$

The comprehensive response risk index RI was then calculated using equal weighting:

$$RI = \frac{S^* + A_s^* + Z_w^*}{3} \quad (12)$$

where S^* , A_s^* , and Z_w^* represent the normalized surface deformation consequence, internal wetting-softening range, and hidden hydraulic disturbance depth, respectively. A larger RI indicates a higher overall development level of the three responses and therefore a higher relative risk. It should be noted that RI is not an absolute field collapse probability, but a relative risk-ranking index within the parameter space considered in this study.

341 The risk levels were classified using the tertiles of RI: $RI \leq 0.2269$ was defined as low risk,
 342 $0.2269 < RI \leq 0.4548$ as medium risk, and $RI > 0.4548$ as high risk. This classification divided the 120
 343 samples into balanced low-, medium-, and high-risk groups of 40 samples each, facilitating subsequent
 344 XGBoost classification model training and evaluation. As shown in Fig. 11, the samples are regularly
 345 distributed in the D-R-L parameter space, and the RI distribution can distinguish the three relative
 346 risk levels. The purpose of the tertile thresholds is to divide the 120 parametric numerical cases into
 347 balanced low-, medium-, and high-risk categories for classification model training and comparison
 348 (Fig. 12) .



349
 350 Fig. 11 Parameter-space distribution of the 120 full-factorial numerical cases.

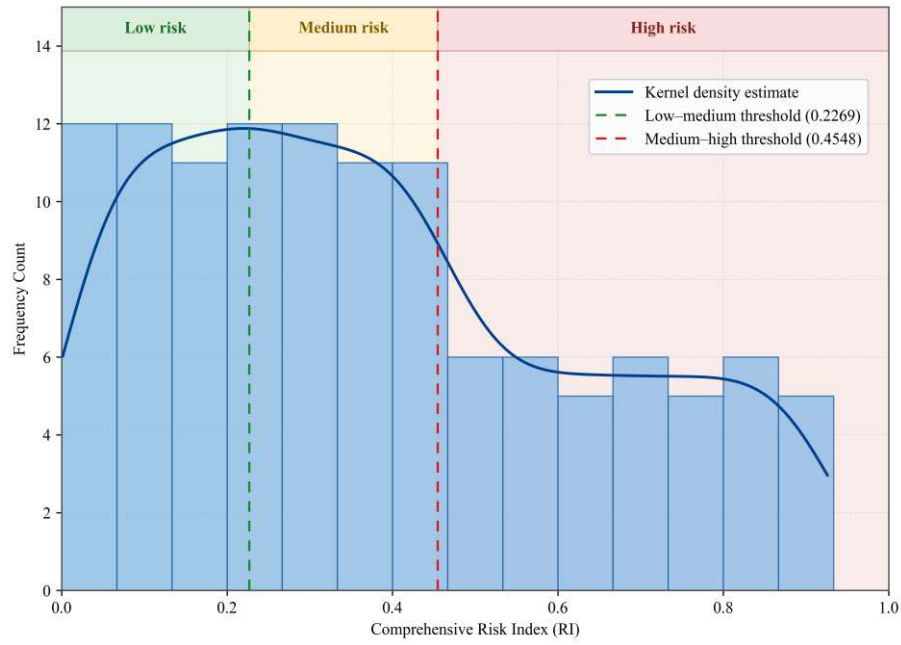


Fig. 12 Distribution of the risk index RI.

4 Machine Learning Results Analysis

4.1 Prediction Comparison of Regression Surrogate Models

Fig. 13 compares the 5-fold cross-validated (R^2) values of the six candidate regression surrogate models. The nonlinear models generally outperform linear regression, indicating that the rainfall–pipeline leakage coupled collapse response is controlled by nonlinear hydro-mechanical interactions. Polynomial ridge regression, SVR-RBF and GPR/Kriging all achieve high prediction accuracy, suggesting that the numerical response surface within the investigated parameter space is relatively smooth and can be effectively approximated by nonlinear surrogate models.

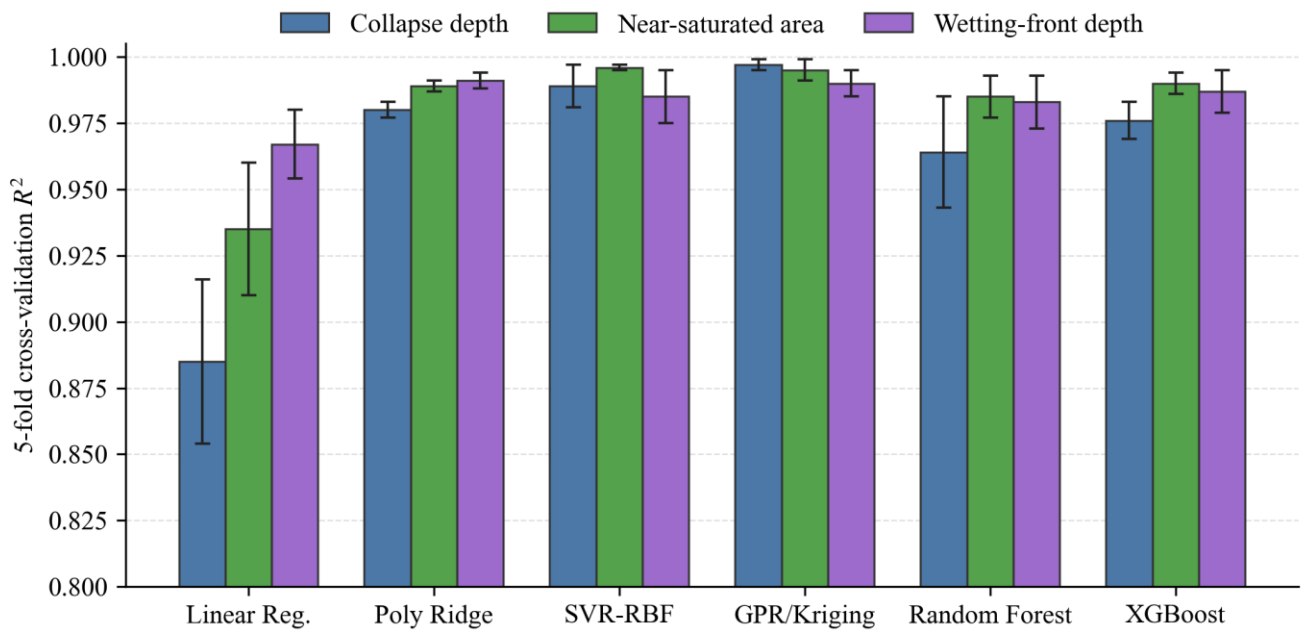


Fig. 13 Comparison of 5-fold cross-validated R^2 values for the six candidate surrogate models

Among the candidate models, GPR/Kriging shows the best overall accuracy and stability in the small-sample and low-dimensional parameter space. In the independent test set, its (R^2) values for (S), (A_s) and (Z_w) reach 0.997, 0.998 and 0.998, respectively, with mean predictive standard deviations of approximately 1.425 mm, 0.824 m² and 0.034 m. Therefore, GPR/Kriging is used as a high-accuracy interpolation and predictive-uncertainty benchmark. Other models also provide useful comparisons: linear regression serves as a baseline, polynomial ridge regression and SVR-RBF reflect the effectiveness of nonlinear approximation, and random forest provides a tree-based ensemble reference.

Although XGBoost does not achieve the highest (R^2) in the regression comparison, it has a specific role. Unlike GPR/Kriging, XGBoost can be directly extended to TreeSHAP-based contribution analysis and low-, medium- and high-risk classification. Therefore, XGBoost is selected not as the most accurate regression model, but as the interpretable prediction and risk-discrimination branch. On this basis, Fig. 14 further evaluates whether the XGBoost branch has sufficient predictive accuracy on the independent test set.

As shown in Fig. 14, the predicted values of (S), (A_s) and (Z_w) are generally distributed close to the 1:1 reference line, with independent test-set (R^2) values of 0.962, 0.990 and 0.985, respectively. These results indicate that XGBoost can effectively approximate the numerical simulation results while retaining its advantage in interpretability and classification. Fig. 15 further shows that, as the number of training samples increases, the test-set (R^2) values gradually improve and stabilize, while the gap between training and test performance narrows. The residuals are mostly distributed around zero without obvious systematic bias, suggesting no evident overfitting within the investigated parameter space.

In summary, the dual-surrogate framework is not based simply on selecting the two models with the highest (R^2). Instead, GPR/Kriging is used as a high-accuracy interpolation and uncertainty benchmark, while XGBoost is used for response prediction, SHAP-based mechanism interpretation and risk classification. The remaining candidate models serve as comparative benchmarks, supporting the necessity of nonlinear modelling and the rationality of the selected dual-surrogate strategy.

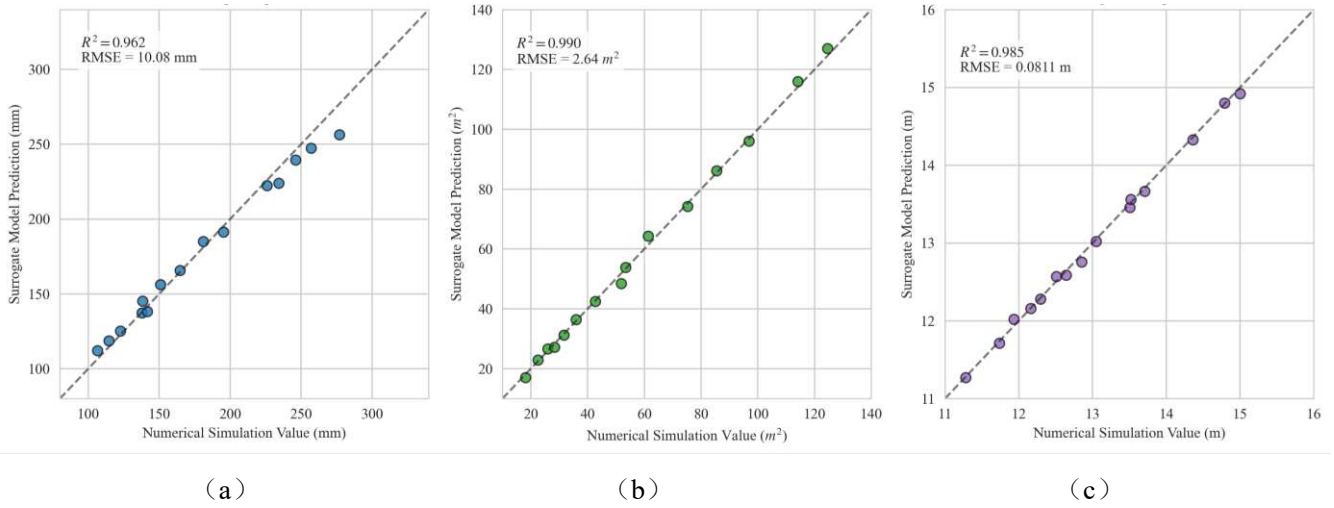


Fig. 14 Comparison between XGBoost-predicted values and numerical simulation values on the independent test set:

(a) Collapse Depth S ; (b) near-saturated zone area A_s ; (c) Wetting Front Depth Z_w

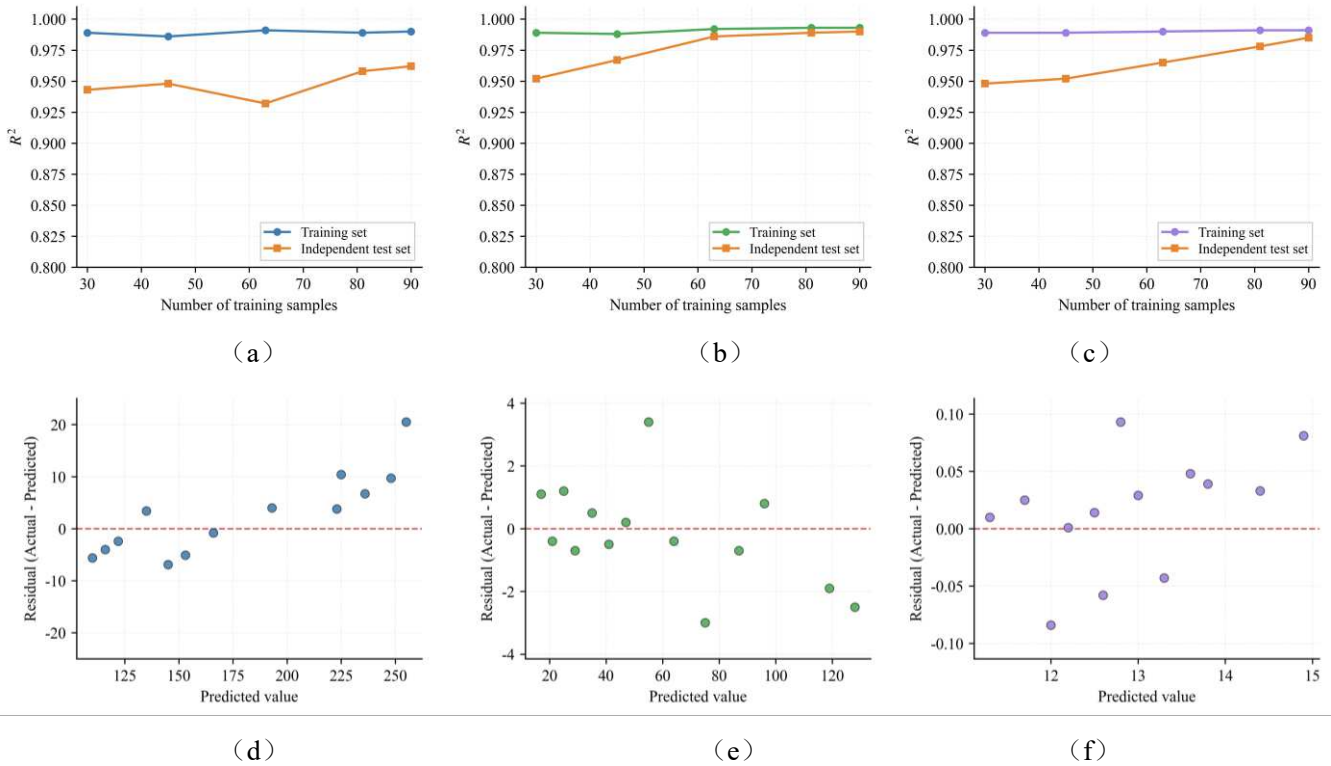


Fig. 15 Sample-size stability and residual diagnosis of the XGBoost branch.(a–c) Learning curves for S , A_s , and Z_w , respectively; (d–f) residual distributions on the independent test set for S , A_s , and Z_w , respectively.

4.2 XGBoost-SHAP Mechanistic Interpretation

The SHAP analysis was used to interpret the contribution and interaction of (D), (R), and (L) in the XGBoost branch. As shown in Fig. 16, leakage pressure (L) is the dominant factor for all three response indicators, contributing 66.62%, 69.69%, and 74.35% to (S), (A_s), and (Z_w), respectively. Rainfall intensity (R) contributes more strongly to (S) and (A_s), indicating its amplification effect on

404 surface deformation and near-saturated zone expansion. Pipe burial depth (D) has a relatively smaller
 405 overall contribution, but its influence on (Z_w) is more evident, suggesting that it mainly regulates the
 406 wetting-front propagation path.

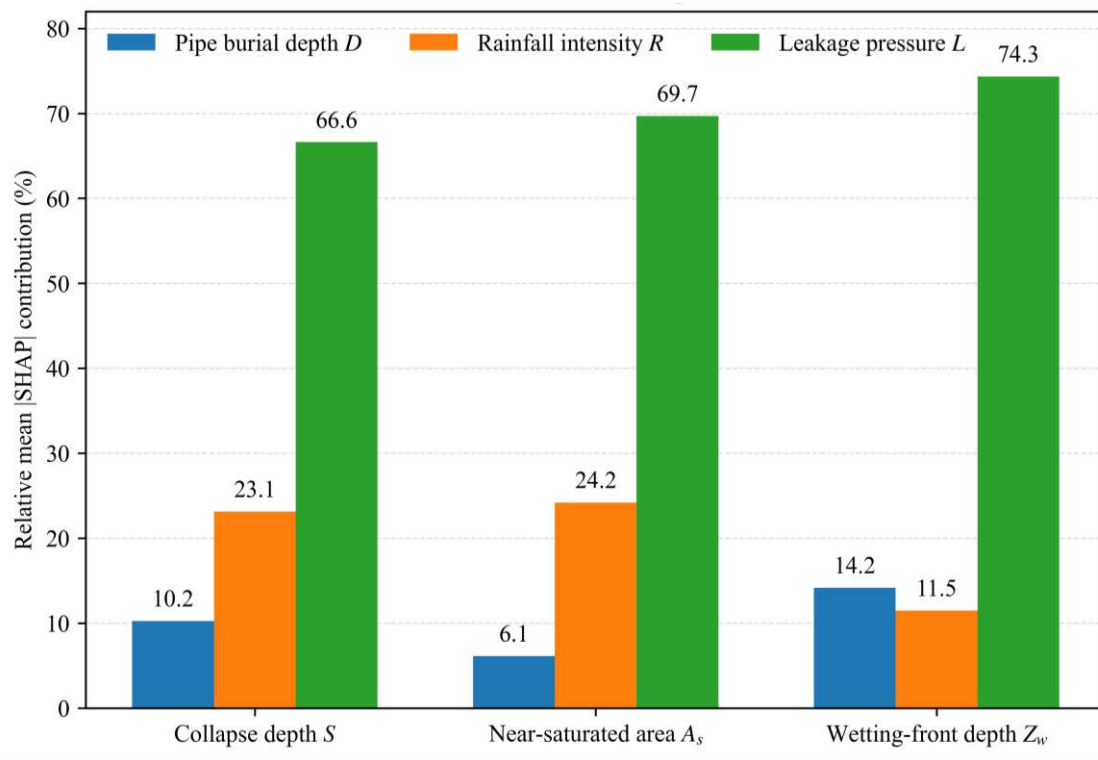
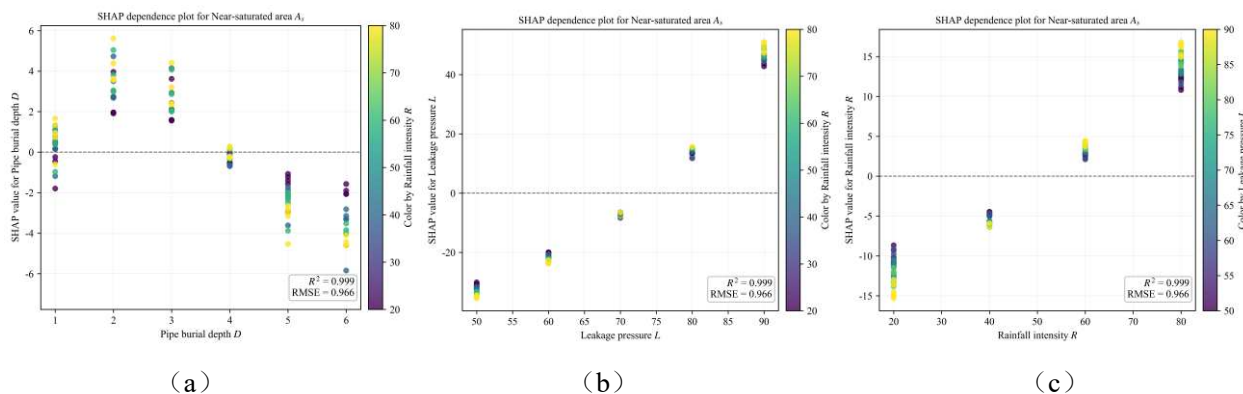


Fig. 16 XGBoost-SHAP interpretation of the feature contributions of D , R , and L .

409 Fig. 17 further shows the SHAP dependence relationships. Increasing (L) shifts the SHAP values from
 410 negative to positive for all three responses, supporting its dominant role in promoting collapse
 411 development. Increasing (R) mainly enhances the positive SHAP values of (S) and (A_s), reflecting its
 412 amplification effect through rainfall infiltration and suction dissipation. The effect of (D) is nonlinear
 413 and response-dependent; intermediate burial depths tend to increase (S) and (A_s), whereas larger burial
 414 depths weaken the upward transfer of hydraulic disturbance and reduce (Z_w).



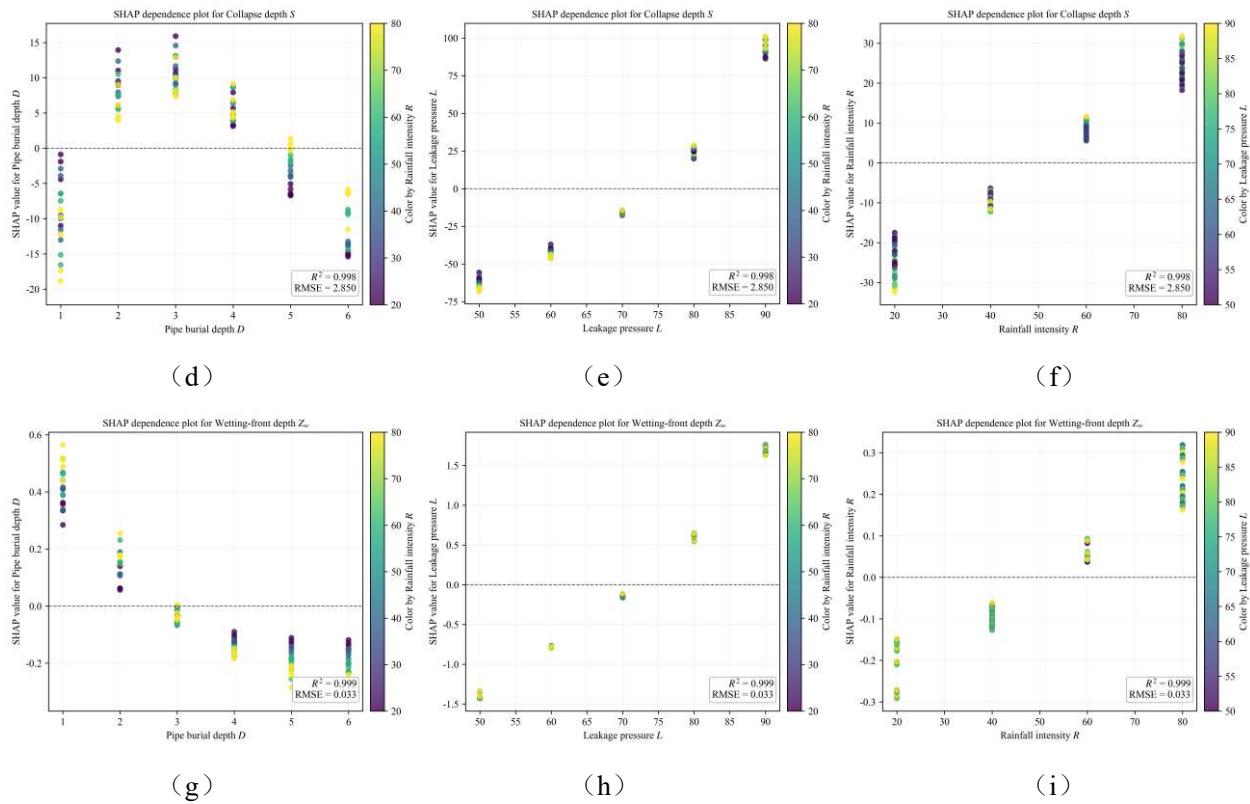


Fig. 17 SHAP dependence plots of the XGBoost branch for the three collapse response indicators.(a-c) Effects of pipe burial depth D on A_s , S , and Z_w , respectively;(d-f) effects of leakage pressure L on A_s , S , and Z_w , respectively;(g-i) effects of rainfall intensity R on A_s , S , and Z_w , respectively.

Overall, the SHAP results are consistent with the numerical sensitivity analysis and further support the mechanism of “(L)-dominated, (R)-amplified, and (D)-regulated” rainfall–pipeline leakage coupled collapse.

4.3 Risk Level Classification

Based on the equal-weighted RI, the 120 working conditions are divided into low-, medium-, and high-relative-risk classes to examine the ability of D , R , and L to support risk-priority identification for pipe sections. It should be noted that the risk level here represents only the relative risk ranking within the parameter space of this study and is not equivalent to the absolute probability of field failure.

Fig. 18 shows that the RI results under different weighting schemes are highly consistent. The Jaccard consistency of high-risk samples between the equal-weighted RI and the settlement-weighted RI is 1.000, and that between the equal-weighted RI and the PCA-weighted RI is 0.951. The overall label agreement rates are all 98.3%. In addition, the PCA-derived weights are close to the equal-weighted assumption, indicating that the risk zoning is not sensitive to the weighting scheme.

The classification results show that the XGBoost classifier achieves a 5-fold cross-validated Accuracy and Macro-F1 of 0.889 ± 0.050 and 0.885 ± 0.052 , respectively, and both metrics reach 0.967 on the

independent test set. The confusion matrix shows that no high-risk samples are missed in the current test set, and the classification errors are mainly concentrated between adjacent risk levels. This suggests that the classification branch can be used for preliminary engineering screening and priority identification of high-risk pipe sections.

Fig. 19 presents the confusion matrix of the XGBoost classification branch on the independent test set. Among the 30 test samples, 29 are correctly classified, yielding an overall Accuracy of 0.967. Low-risk and high-risk samples are both accurately identified, with no high-risk omission. The only error is one medium-risk sample classified as high risk, indicating that the classification error is mainly located near the boundary between adjacent risk levels.

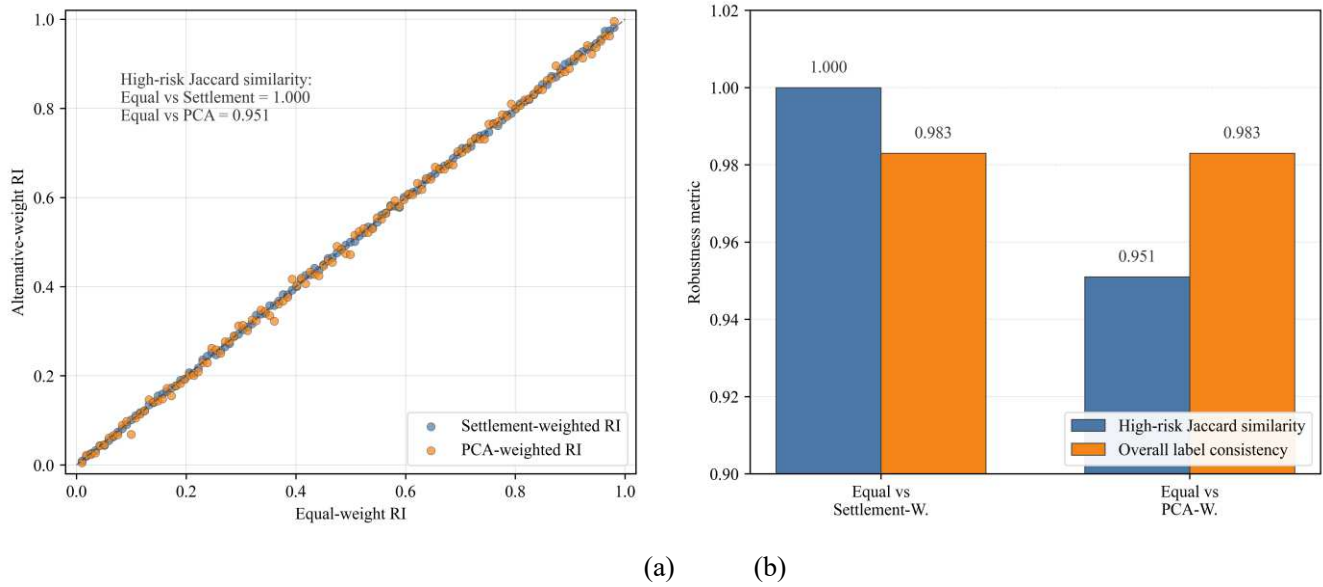


Fig. 18 Robustness test of weighting and threshold schemes for the comprehensive risk index RI:(a) RI weight sensitivity analysis; (b)Robustness metrics across weighting schemes

Table 3 Performance of the low-, medium-, and high-risk classification models

Classification Model	CV Accuracy	CV Macro-F1	Test Accuracy	Test Macro-F1
SVC-RBF	0.925 ± 0.046	0.918 ± 0.047	0.867	0.868
Random Forest	0.875 ± 0.088	0.861 ± 0.100	0.900	0.902
XGBoost	0.889 ± 0.050	0.885 ± 0.052	0.967	0.967

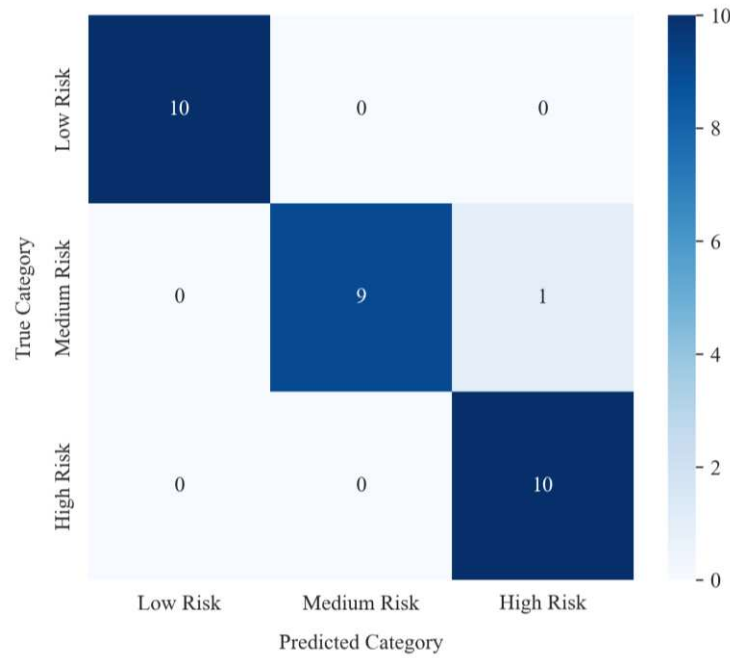


Fig. 19 Confusion matrix of the XGBoost classification branch for risk-level classification

4.4 D-R-L Risk Zoning Map

Fig. 20 presents the averaged distribution of the comprehensive risk index (RI) under the three two-factor combinations (D)–(R), (D)–(L) and (R)–(L). Rather than serving only as a visual comparison of variable effects, these maps translate the sensitivity results and SHAP interpretation into a risk-transfer pattern in the designed parameter space. The (D)–(R) map shows only a moderate variation in (RI), indicating that rainfall and burial depth mainly regulate the development pathway of collapse risk. By contrast, the (D)–(L) and (R)–(L) maps exhibit a much sharper increase in (RI) along the leakage-pressure direction, demonstrating that (L) forms the principal risk-controlling axis. Meanwhile, the gradual increase in (RI) with (R) indicates that rainfall acts as an external amplifier by lowering the threshold for leakage-induced softening to evolve into surface collapse. These interaction maps therefore provide a graphical confirmation of the mechanism identified in the previous sections, namely an (L)-dominated, (R)-amplified and (D)-regulated collapse response.

Fig. 21 further converts the continuous (RI) values into low-, medium- and high-relative-risk zones under different rainfall intensities. The most important feature is the rainfall-dependent migration of risk boundaries. Under lower rainfall intensity, high-risk zones are mainly concentrated at high leakage pressure, whereas increasing rainfall intensity causes the medium- and high-risk zones to expand toward lower leakage-pressure levels. This indicates that rainfall infiltration does not merely increase the absolute value of (RI), but changes the threshold condition under which pipeline leakage evolves into a high-risk collapse scenario. In addition, under high (L) and high (R) conditions, the relatively high-risk region is more evident at intermediate burial depths, especially around (D=2 – 3) m. This

reflects the greater likelihood of effective convergence between the upper rainfall-induced wetting front and the lower leakage-induced wetting zone, which promotes near-saturated softening and upward deformation transfer.

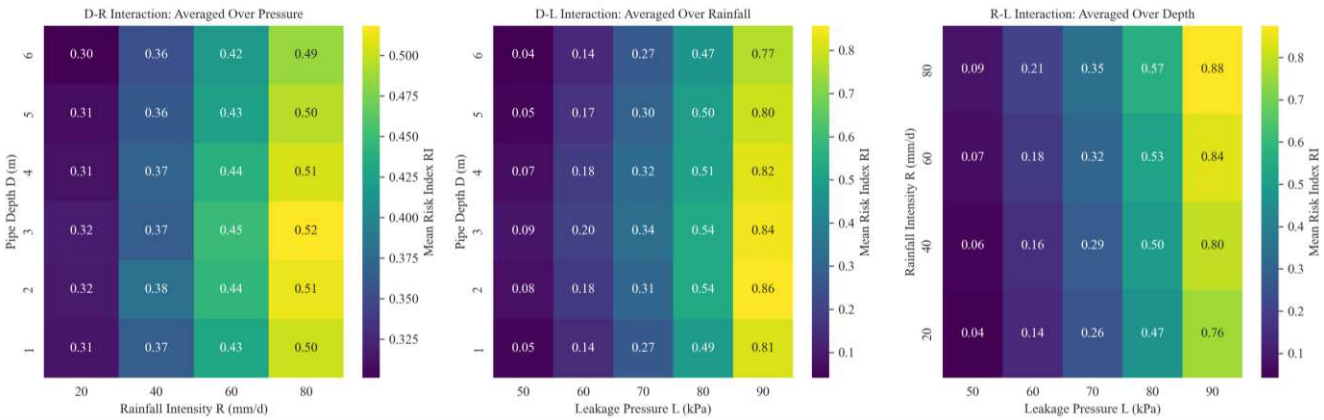


Fig. 20 Influence of multi-factor interactions on the comprehensive collapse risk index RI

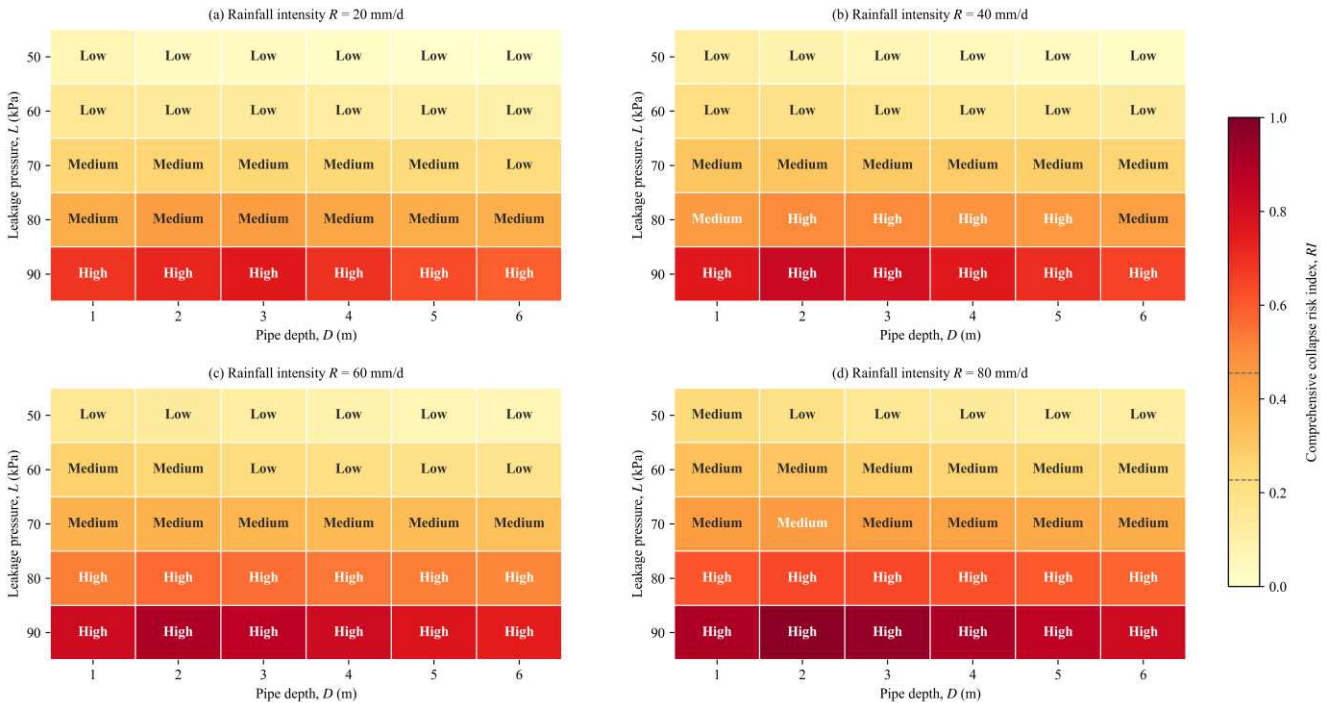


Fig. 21 D-L collapse risk zoning heatmaps under different rainfall intensities

Therefore, Fig. 21 can be interpreted as a rainfall-conditioned relative-risk screening chart for urban pipeline sections. For sections with high leakage pressure, strong rainfall and intermediate burial depth, priority should be given to inspection, leakage control, ground-penetrating radar detection and settlement monitoring. In contrast, low-leakage-pressure sections remain relatively low risk even under moderate rainfall, although rainfall may still shift some cases toward the medium-risk class. This zoning result links the hydro-mechanical mechanism, surrogate-model prediction and engineering

488 decision-making, providing a practical basis for rapid pipe-section screening and graded prevention of
489 rainfall–pipeline leakage induced urban road collapse.

490 **5 Discussion**

491 **5.1 Mechanism of rainfall–pipeline leakage coupled collapse and explainability assessment**

492 The numerical sensitivity analysis and XGBoost-SHAP interpretation consistently identify leakage
493 pressure (L) as the dominant factor controlling surface collapse depth (S), near-saturated zone area (A_s)
494 and wetting-front depth (Z_w). Rainfall intensity (R) mainly amplifies deformation and near-saturated
495 softening, whereas pipe burial depth (D) regulates the convergence path of the upper and lower wetting
496 zones and the upward transfer distance of deformation. Therefore, the pattern of (L)-dominated, (R)-
497 amplified and (D)-regulated responses is not only a statistical feature, but also reflects the hydro-
498 mechanical evolution of rainfall–pipeline leakage coupled collapse.

499 By integrating physical model tests, numerical simulations and machine-learning interpretation, the
500 collapse process can be summarized into four stages (Fig. 22). In the initial rainfall infiltration stage,
501 shallow soil becomes wetter, matric suction dissipates and soil strength and stiffness decrease. In the
502 wetting-front diffusion stage, leakage pressure generates a local hydraulic gradient around the pipe
503 defect, causing the near-saturated and weakened zones to expand outward. In the wetting-front
504 convergence stage, the upper rainfall-induced wetting front connects with the lower leakage-induced
505 wetting zone, forming a continuous softened pathway. Finally, in the surface collapse stage, the
506 weakened zone and plastic deformation propagate upward and develop into concentrated settlement or
507 collapse at the ground surface.

508 This mechanism indicates that rainfall and pipeline leakage do not act as a simple linear superposition
509 of two water sources. Instead, they jointly modify the unsaturated state, seepage path, strength
510 degradation and deformation transfer process of the soil. Compared with previous studies focusing
511 mainly on pipeline leakage, internal erosion or cavity expansion, this study highlights the spatial
512 convergence between rainfall-induced and leakage-induced wetting zones. High leakage pressure
513 controls the intensity of internal hydraulic disturbance, strong rainfall lowers the instability threshold,
514 and intermediate burial depth promotes effective wetting-zone convergence, thereby increasing the
515 likelihood of surface collapse..

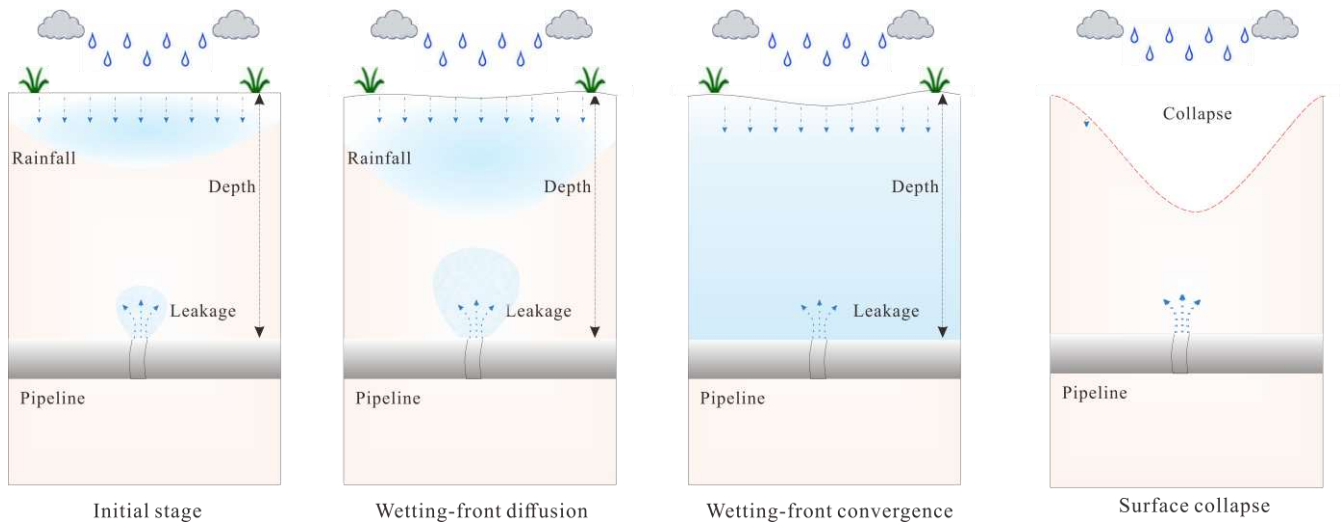


Fig. 22 Integrated mechanism diagram of rainfall – pipeline leakage coupled collapse from hydraulic disturbance to surface response

5.2 Engineering Application and Applicable Boundaries of the Dual-Surrogate Model

As shown in Fig. 23, the mechanism-constrained dual-surrogate modeling framework proposed in this study does not simply pursue the highest accuracy of a single model. Instead, it connects physical-process understanding, numerical case-library construction, surrogate-model prediction, and engineering risk screening. GPR/Kriging, as a classical small-sample numerical surrogate model, is mainly used to examine whether the response surface formed by the 120 full-factorial numerical cases exhibits good smoothness, interpolation accuracy, and uncertainty quantification capability. XGBoost is used to provide a unified implementation of continuous response prediction, risk-level classification, and TreeSHAP-based mechanistic interpretation. The results show that GPR/Kriging achieves higher interpolation accuracy for some continuous responses and provides predictive standard deviation as an uncertainty reference. Although XGBoost does not necessarily achieve the highest accuracy for all indices, it can further identify the variable contributions of D , R , and L and directly support relative risk-level discrimination based on RI . Therefore, the two models play complementary roles in this study rather than representing a simple model competition.

From an engineering application perspective, the proposed framework is more suitable as a graded auxiliary tool for “preliminary screening-priority verification-field calibration.” For road pipe sections where pipe burial depth, operating pressure, and rainfall forecast information are available, the surrogate models can be used to rapidly predict S , A_s , and Z_w , further calculate the comprehensive risk index RI , and classify the pipe sections into low-, medium-, and high-relative-risk levels. For high-risk sections, CCTV inspection, sonar detection, ground-penetrating radar, ground settlement monitoring, or localized refined numerical analysis can be prioritized. For medium-risk sections, inspection and

540 monitoring should be strengthened before and after rainfall events. For low-risk sections, routine
541 inspection can be maintained. This strategy helps allocate limited detection and remediation resources
542 preferentially to highly sensitive combinations such as high leakage pressure, strong rainfall, and
543 intermediate burial depth.

544 It should be emphasized that the proposed model has clear applicability boundaries. First, the dataset is
545 derived from numerical simulations validated by physical model tests; therefore, the model is
546 essentially a fast surrogate of the numerical model and cannot be directly regarded as a predictor of
547 absolute field failure probability. Second, this study only considers three dominant variables, namely D,
548 R, and L. Factors such as pipe defect size, groundwater level, traffic dynamic loading, soil
549 heterogeneity, and particle loss have not yet been explicitly included. Third, RI represents the relative
550 risk ranking within the parameter space of this study. In practical engineering applications, threshold
551 calibration should still be conducted by considering road class, allowable settlement criteria, pipe
552 material, inspection results, and historical defect records.

553 Future research can be further developed in three directions. First, the numerical case library can be
554 expanded by incorporating different stratum types, groundwater levels, pipe defect geometries, and
555 traffic loads as additional input variables. Second, field monitoring data, historical collapse cases, and
556 multi-source detection results can be introduced to construct a hybrid dataset that integrates numerical
557 simulations and field observations. Third, DEM/CFD-DEM, physics-informed machine learning, or
558 Bayesian surrogate models can be adopted to better characterize particle migration, cavity expansion,
559 and engineering risk uncertainty.

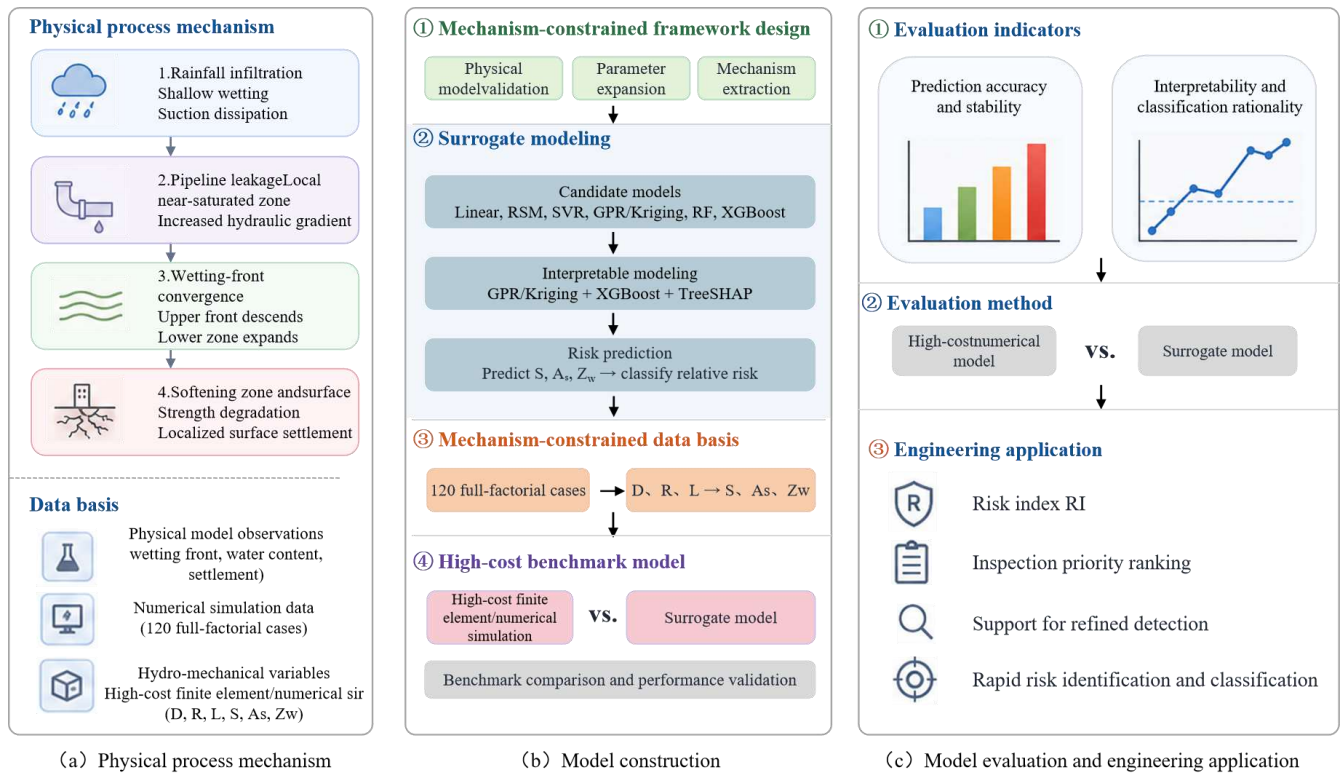


Fig. 23 Mechanism-constrained dual-surrogate modeling and relative risk evaluation framework

6 Conclusions

This study investigated rainfall–pipeline leakage induced urban road collapse using physical model testing, hydro-mechanical simulation and interpretable surrogate modelling. The main conclusions are as follows:

- (1) Rainfall–pipeline leakage induced collapse is a progressive hydro-mechanical failure process involving shallow-soil pre-wetting, expansion of the leakage-induced wetted zone, convergence of the upper and lower wetting fronts, and upward propagation of soil weakening and deformation. The connection of the two wetting zones forms a continuous softened pathway, through which hidden hydraulic disturbance develops into surface settlement and collapse.
- (2) Leakage pressure is the dominant factor controlling collapse development, contributing 86.42%, 87.79% and 92.77% to the variations in surface collapse depth, near-saturated zone area and wetting-front depth, respectively. Rainfall mainly amplifies the failure process by dissipating matric suction and reducing soil strength and stiffness, whereas burial depth regulates the wetting-front convergence path and upward deformation transfer. Intermediate burial depths of approximately 2–3 m produce relatively strong surface responses under the investigated conditions.
- (3) GPR/Kriging accurately reproduced the numerical response surfaces, with independent test-set (R^2) values of 0.997–0.998. XGBoost also achieved satisfactory predictive performance, and its SHAP interpretation was consistent with the numerical sensitivity analysis. The agreement between the

two methods confirms the mechanism of leakage-pressure domination, rainfall amplification and burial-depth regulation.

- (4) Risk zoning shows that increasing rainfall shifts medium- and high-risk zones towards lower leakage pressures. Pipeline sections characterised by high leakage pressure, strong rainfall and intermediate burial depth should therefore be prioritised for leakage inspection, subsurface cavity detection and settlement monitoring.

The proposed framework provides a rapid method for identifying vulnerable pipeline sections. However, the risk levels represent relative rankings within the investigated parameter space rather than absolute field-collapse probabilities. Further calibration using field monitoring, pipeline defect information and local geological conditions is required before practical application.

CRedit authorship contribution statement

Liming Xue: Data curation, Formal analysis, Writing – original draft. Qiangbing Huang: Conceptualization, Methodology, Resources, Funding acquisition, Writing – review & editing. Jiawei Liang: Writing–review & editing. Yuxuan Gou: Formal analysis. Jun Dong: Validation

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

All data generated or analyzed during this study are included in this published article.

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