Journal of Engineering, Project, and Production Management
2026, 16(2), 2025-182

Cloud Model-Driven Digital Twin Security Assessment for Water Conservancy

Deling Chen
Associate Professor, Director of the Academic Affairs Department, Dean's Office, Yunnan Water Resources and Hydropower Vocational College, Kunming, 650400, China, E-mail: Cdl9527@yeah.net (corresponding author).

Project Management
Received August 25, 2025; revised October 14, 2025; accepted October 17, 2025
Available online March 7, 2026

Abstract: Long-term water conservancy engineering projects face safety issues during operation, and effective assessment is key to ensuring stable operation. Therefore, this study proposes an intelligent digital evaluation technology for water conservancy engineering based on digital twin technology. The study uses a cloud model to quantify safety indicators and utilizes three parameters, namely expectation, entropy, and super entropy, to establish a two-way mapping between qualitative concepts and quantitative values. This mapping is used to construct a four-level safety status discrimination criterion. Second, the study combines an improved mutation series method with deep learning models, integrating physical interpretability with data-driven advantages to construct a hybrid evaluation framework. In a case study of a certain water conservancy hub, the cloud model achieved 100% consistency between its evaluation results for 32 indicators, including horizontal displacement and uplift pressure, and the actual conditions, outperforming comparable technologies. In water conservancy parameter identification, the research model had an error rate of 0.017, with an anomaly detection accuracy of 97.25%, demonstrating the best performance. Finally, an overall assessment of water conservancy engineering was conducted, with a total mutation level of 0.93 to 0.95, all of which were classified as "normal". In summary, this research technology has good application results and provides more efficient and reliable technical support for digital twin security assessment for water conservancy engineering.

Keywords: Cloud model, digital twin, mutation algorithm, safety and security, water conservancy.

DOI 10.32738/JEPPM-2025-182

1. Introduction

Water conservancy engineering (WCE) is closely related to the national economy and people's livelihood, and its safety and stability are important guarantees for economic and social development. Digital twin technology empowers the entire life cycle management of engineering projects through virtual-physical mapping, providing a new paradigm for safety supervision (Wang et al., 2023). Security assessments are at the core work of WCE operations. By combining digital twins and deep learning, it is possible to provide accurate and effective technical support for WCE operations and security assessments. The integration of these three elements has become a key direction for the development of the industry. When cloud models are combined with digital twins at the provincial level, they significantly improve the accuracy of building risk assessments. Cloud models use expectation, entropy, and super entropy to map qualitative concepts (QCs) to quantitative values (QVs) in both directions, balancing fuzziness and randomness. Their forward and inverse transformation algorithms enable applications such as granular computing and system assessment (Cantiello et al., 2023). Currently, the most common model is the normal cloud model, which has also given rise to multi-dimensional clouds, similarity metrics, and generic concept trees. These models have widespread applications in the field of engineering safety (Jamion et al., 2023). Related scholars have conducted extensive research on this topic. For example, Xiashi et al. (2023) studied the issue of insufficient accuracy in the evaluation of dual prevention mechanisms in non-coal mining areas and proposed an evaluation model combining the weighting method. The technical process involved establishing a dual evaluation indicator system and introducing cloud model theory (CMT). Experiments revealed that this study had outstanding overall accuracy and resolved the subjectivity and randomness problems of conventional approaches. Huang et al. (2024) proposed an assessment method based on a three-dimensional cloud model to address the issue of ambiguity in risk assessment for deep foundation pit construction. This technology established an evaluation index system by identifying risk sources, which was preliminarily determined using the Delphi method. Finally, a dimensional cloud was generated using a forward cloud generator and applied to foundation pit engineering. Tests showed that this technology

had good reliability, but its accuracy was low in extreme risk scenarios. Sarwar (2023) combined interval rough numbers and cloud models to address multiple uncertainties in the evaluation of early-stage products. This technology obtained evaluation ranking schemes through a combination of subjective and objective weighting methods and cloud computing, which were then used in the development of refrigerator products. Tests showed that this technology could improve product evaluation quality and reduce data analysis processes.

The mutation series originates from Tom's mutation theory, which studies the series expansion of system mutations. In recent years, it has been used for ecological and financial tipping point early warning, combined with machine learning to improve prediction accuracy. Kaining et al. (2023) conducted research on the frequent occurrence of geological disasters in Ping Shan County, Hebei Province. The study proposed a combined model integrating the analytic hierarchy process (AHP), mutation theory, and the minimum information entropy weighting method. The study selected nine evaluation factors, including terrain elevation, and calculated their weights using the AHP and mutation theory. The study then combined the minimum information entropy weighting method to establish a model and compared the results of the three methods. The results indicated that the combined model achieved high accuracy and aligned with the developmental characteristics of geological disasters. Lu et al. (2023) established a system comprising five primary indicators and 21 secondary indicators for assessing construction risks in prefabricated building projects. The study used the AHP, the importance criterion of inter-attribute correlation, and the theory of sudden change to create an assessment model. This model used combination weighting and the sudden change series method. The findings demonstrated that the examination of four businesses was successful and that metrics such as the caliber of prefabricated components had significant weights. Zhang et al. (2023) addressed the issue of evaluating the quality of cold chain logistics services for fresh food e-commerce. They constructed an indicator system from the perspective of service recipients and used maximum deviation and fuzzy set theory for combined weighting. Furthermore, this study employed the sudden change series method to determine indicator priority and ranking, and applied it to two companies to validate its effectiveness. Xu et al. (2023) addressed the evaluation of farmland system resilience by establishing a framework based on production, ecological, and economic elasticity. The results showed significant spatiotemporal differences that steadily increased over time. Key driving forces were identified, but the sudden change model's inability to smooth fluctuations in long-term data affected trend judgments.

In summary, cloud models have significant advantages in handling ambiguity and randomness and are widely used in many fields. However, they suffer from low processing efficiency for high-dimensional indicators and poor adaptability to small samples (Wang et al., 2023). Additionally, the mutation series is useful for analyzing critical points in systems and is effective in disaster and engineering risk assessments. However, it has issues such as sensitivity to extreme factors and low efficiency when dealing with complex, hierarchical structures (Shao et al., 2023). A digital twin security assessment for WCE involves multi-source uncertainty, multi-level complex indicators, and diverse data characteristics. These factors make it difficult to adapt existing single methods (Chauhan et al., 2023). Therefore, to address the inadequacy of WCE security assessments, this study proposes a new assessment method. This method uses cloud models and an improved mutation series to ensure the safety and stable operation of WCE. This study has two innovative aspects. The first is the proposal of a cloud-model-driven quantitative method for digital twin security metrics, enabling qualitative-to-quantitative mapping and precise identification of four-level states. Second, the study introduces an improved Transformer (I-Transformer) network hybrid evaluation framework with an enhanced mutation order. This framework uses a temporal convolutional network (TCN) to improve feature extraction and enhance evaluation accuracy and adaptability through the hybrid structure. This study will provide more precise and efficient technical support for digital twin security assessment in WCE.

2. Methods and Materials

2.1. Cloud-Based Digital Twin Safety Index Analysis for WCE

To meet the safety and stability requirements of WCE, an effective WCE security assessment is crucial. Therefore, this study proposes a digital twin security assessment technology for the field of WCE. Based on CMT, this technology provides accurate security threshold references for digital twin platforms. Fig. 1 displays the framework for the cloud model.

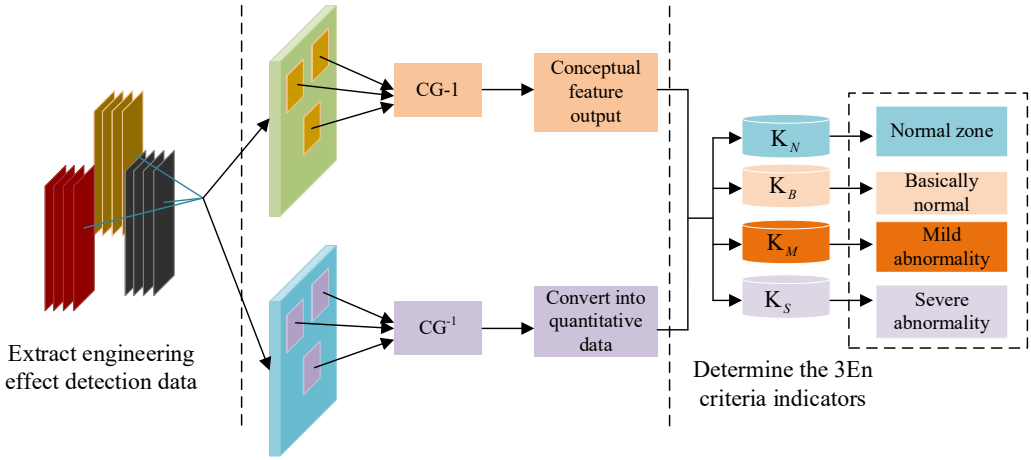


Fig. 1. Basic theory and digital features of cloud models

Fig. 1 displays that the core of the cloud model is to reflect the uncertainty of the engineering operation status through quantitative indicators. The analysis process primarily includes four stages: monitoring data preprocessing, calculation of cloud model feature parameters, implementation of forward and inverse cloud generators, and formulation of safety metrics based on the "3En criteria". This method identifies randomness and fuzziness characteristics within monitoring data. The cloud model describes QCs through three feature parameters: expectation (Ex), entropy (En), and hyperentropy (He) (Zhu, 2024). It is assumed that domain U is a set of QVs, and C is a QC on U. For any $x \in U$, its certainty $\mu(x) \in [0,1]$ on C is a random variable, then $\mu(x)$ on U is called a cloud distribution, denoted as $C(x)$. Each $[x, \mu(x)]$ is called a cloud drop. The QC is described as shown in Eq. (1) (Wang et al., 2023).

$$\mu : U \to [0,1], \forall x \in U, x \to \mu(x) \tag{1}$$

In Eq. (1), U is the quantitative domain. x is the QV within the domain. $\mu(x)$ is the degree of certainty of x for the QC C. For the normal cloud model, its characteristic parameters will reflect the engineering change relationship. Among them, the expectation (Ex) is the center value of the cloud droplet distribution, representing the core of the QC, as shown in Eq. (2).

$$Ex = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{2}$$

In Eq. (2), n is the sample size. x_i is the ith monitoring data. Eq. (3) illustrates how the feature parameter entropy (En), which integrates fuzziness and unpredictability, represents the measurement concept's uncertainty.

$$En = \sqrt{\frac{\pi}{2}} \cdot \frac{1}{n}\sum_{i=1}^{n} |x_i - Ex| \tag{3}$$

In Eq. (3), $|x_i - Ex|$ is the absolute deviation between the ith data point and the expected value (EV), reflecting the degree of data dispersion. Eq. (4) illustrates how the dispersion thickness of the cloud droplet distribution is reflected in the uncertainty of entropy, which is described by hyperentropy (He).

$$He = \sqrt{S^2 - En^2} \tag{4}$$

In Eq. (4), $S^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \overline{x})^2$ is the sample variance. $\overline{x} = Ex$ represents the sample mean, reflecting the volatility characteristics of the data. To effectively reflect the mapping relationship between the standardized concept and the quantitative concept in the WCE digital twin system, this process needs to be converted through a cloud generator. The principle diagram is shown in Fig. 2 (Bitarafan et al., 2023).

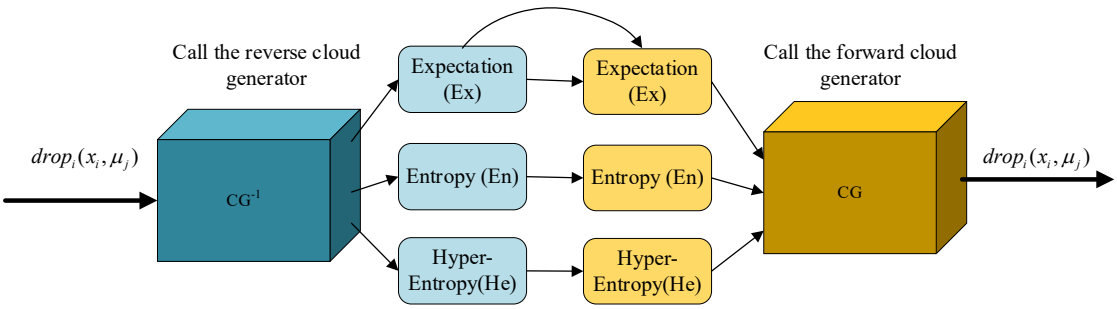


Fig. 2. Schematic diagram of cloud generator

In Fig. 2, the cloud generator includes two types: forward and reverse. It uses three parameters, "expectation, entropy, and super-entropy", to transform fuzzy concepts into random cloud droplets with membership degrees. Conversely, it estimates these three parameters from data, thereby achieving a qualitative-quantitative exchange. In the forward cloud generator, cloud droplets are generated using feature parameters, producing a normal random number En' with En as the expectation and He as the Standard Deviation (SD), as displayed in Eq. (5) (Jin et al., 2024).

$$En' \sim N(En, He^2) \tag{5}$$

In Eq. (5), $N(\cdot)$ is the normal distribution function. En' is the random entropy value. A normal random number x

with EV Ex and SD En' is generated, as shown in Eq. (6).

$$x \sim N(Ex,(En')^2) \tag{6}$$

In Eq. (6), x is the cloud droplet value within the domain. Further calculations based on the above analysis determine the certainty $\mu(x)$ as shown in Eq. (7).

$$\mu(x)=\exp\left[-\frac{(x-Ex)^2}{2(En')^2}\right] \tag{7}$$

In Eq. (7), $\mu(x)$ reflects the extent to which x belongs to a QC, with a value range of [0,1]. In the reverse cloud generator, feature parameters (Ex, En, and He) are inferred from cloud droplet samples. This is achieved by calculating the sample mean, absolute central moment, and variance. These calculations are consistent with forward inference, which extracts cloud model features from monitoring data. Subsequently, safety metrics based on the "3En criterion" are established, serving as the core basis for safety metrics. The contribution distribution of cloud droplet groups to QCs is shown in Fig. 3 (Li et al., 2023).

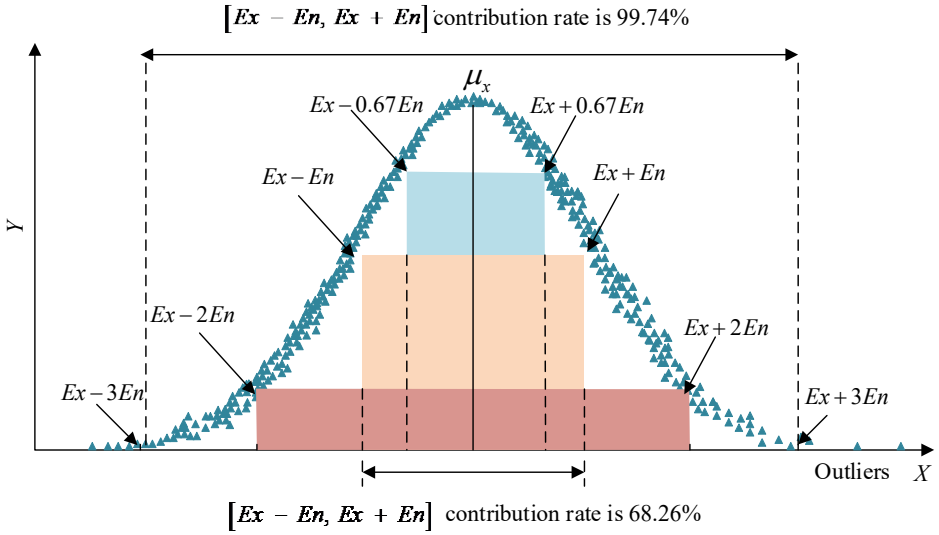


Fig. 3 Distribution of cloud droplet group's contribution to QCs

In Fig. 3, four safety zones can be divided within zone $[Ex-3En, Ex+3En]$. Cloud drops contribute 99.74% to QCs, and values outside the zone can be considered outliers. The normal zone $[Ex-En, Ex+En]$ contributes 68.26% and corresponds to the "normal" state. The basic normal interval $[Ex-2En,Ex-En]\cup[Ex+En,Ex+2En]$ has a contribution rate of 27.18%, corresponding to the "basic normal" state. The light abnormal (LA) interval $[Ex-3En,Ex-2En]\cup[Ex+2En,Ex+3En]$ has a contribution rate of 4.3%, corresponding to the "LA" state. The severely abnormal (SA) interval $(-\infty,Ex-3En)\cup(Ex+3En,+\infty)$ has a contribution rate of 0.26%, corresponding to the "SA" state. The safety indicators are shown in Eq. (8).

$$\begin{cases} \mathrm{K}_N : |x-Ex| \le En \\ \mathrm{K}_B : En < |x-Ex| \le 2En \\ \mathrm{K}_M : 2En < |x-Ex| \le 3En \\ \mathrm{K}_S : |x-Ex| > 3En \end{cases} \tag{8}$$

In Eq. (8), x is the monitored value. Ex is the EV. En is the entropy. K_N, K_B, K_M, and K_S correspond to normal, Basically Normal (BN), LA, and SA, respectively. This interval division can be used to quantify and distinguish safety status.

2.2. Security Assessment Modeling based on Improved Mutation Series and Deep Learning

After the cloud model has completed the quantification of safety indicators and interval division, a comprehensive assessment model is needed to identify the overall safety status of the digital twin of WCE. Therefore, this study proposes a hybrid assessment framework based on a combination of an improved mutation series method and a deep learning model. The entire technical process is shown in Fig. 4.

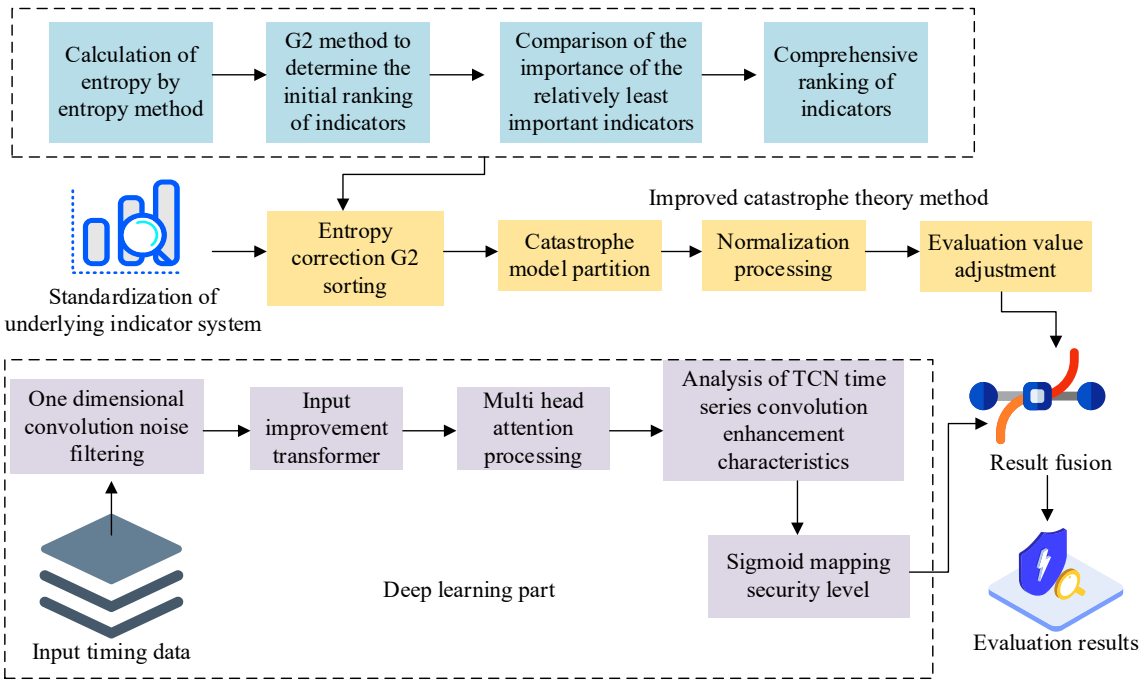


Fig. 4. Security assessment process based on improved mutation level and deep learning (https://www.svgrepo.com/vectors/vector/3; https://www.svgrepo.com/vectors/assessment/; https://www.svgrepo.com/vectors/data/; https://www.svgrepo.com/vectors/data/3)

In Fig. 4, this technology utilizes an improved mutation series to analyze the hierarchical relationships between indicators, thereby enabling deterministic assessment. Meanwhile, deep learning models optimize assessment accuracy by capturing deep-level correlations in the data. Together, these two approaches provide dynamic, high-precision security assessment results for digital twin platforms. In the assessment model, the improved mutation series method employs an entropy-corrected G2 method to address the issue of strong subjectivity in indicator weights in traditional methods. The appropriate mutation model is selected based on the number of sub-indicators, such as the spike mutation model for two sub-indicators. The potential function is shown in Eq. (9) (Gerçek and Güven, 2023).

$$f(x) = x^4 + ax^2 + bx \tag{9}$$

In Eq. (9), x is the state variable. a and b are control variables that describe the transition law of the system from stable to abrupt change. The three sub-indicators reflect the swallowtail abrupt change model. The normalization formula is shown in Eq. (10).

$$x_a = a^{1/2}, x_b = b^{1/3}, x_c = c^{1/4} \tag{10}$$

In Eq. (10), a, b, and c display the standardized values of the sub-indicators. x_a, x_b, and x_c are the normalized mutation order values, achieved through square root operations to perform a nonlinear transformation of the indicators. To avoid the influence of indicator ranking on the results, a combined ranking strategy using the entropy method and the G2 method is adopted. Entropy calculation is used to measure the information utility of the indicators, as shown in Eq. (11) (Sajjad et al., 2023).

$$e_j = -\frac{1}{\ln(m)} \sum_{i=1}^{n} f_{ij} \ln(f_{ij}), f_{ij} = y_{ij} / \sum_{j=1}^{n} y_{ij} \tag{11}$$

In Eq. (11), e_j is the entropy value of the j th indicator. m is the number of samples. y_{ij} is the standardized value of the j th indicator of the i th sample. f_{ij} is the indicator weight. Eq. (12) illustrates how the study determines the relative relevance of other indicators by using the least important indication as the baseline.

$$r_{ik} = \begin{cases} e_{jk} / e_{jn} & (e_{jn} < e_{jk}) \\ 1 & (e_{jn} \geq e_{jk}) \end{cases} \tag{12}$$

In Eq. (12), r_{ik} is the ratio of the entropy value e_{jn} between the k th indicator and the least important indicator. The

larger the value of $r_{ik} \geq 1$, the more important the indicator. To solve the problem of value concentration in traditional mutation series methods, the results are distributed to a uniform interval through linear mapping, as shown in Eq. (13).

$$H_{j'} = (d_{i+1} - d_i) \cdot \frac{H_j - h_i}{h_{i+1} - h_i} + d_i \tag{13}$$

In Eq. (13), $H_{j'}$ represents the adjusted evaluation value. H_j is the original evaluation value. $[h_i, h_{i+1}]$ is the original grade interval. $[d_i, d_{i+1}]$ is the target uniform interval, such as [0,0.3) corresponding to "severe anomaly" and [0.85,1] corresponding to "normal." Considering the temporal and high-noise characteristics of WCE monitoring data, a slightly improved deep learning model is introduced to extract nonlinear features and correct the evaluation results of the sudden change series method. This model integrates convolutional neural networks (CNN), Transformers, and TCNs, enhancing feature capture capabilities through two structural improvements (Luo et al., 2023). First, the study uses 1D-CNN to filter noise and extract local features, as shown in Eq. (14).

$$z_t = \sigma\left(\sum_{k=1}^{K} w_k \cdot x_{t-k+1} + b\right) \tag{14}$$

In Eq. (14), z_t represents the convolution output. K denotes the convolution kernel (CK) size. w_k refers to the weights. x_{t-k+1} signifies the input time-series data. b represents the bias. σ denotes the ReLU activation function. Considering that the various indicator data in WCE vary with time, the study employs an I-Transformer to capture long-range dependencies among indicators. The I-Transformer network structure is illustrated in Fig. 5.

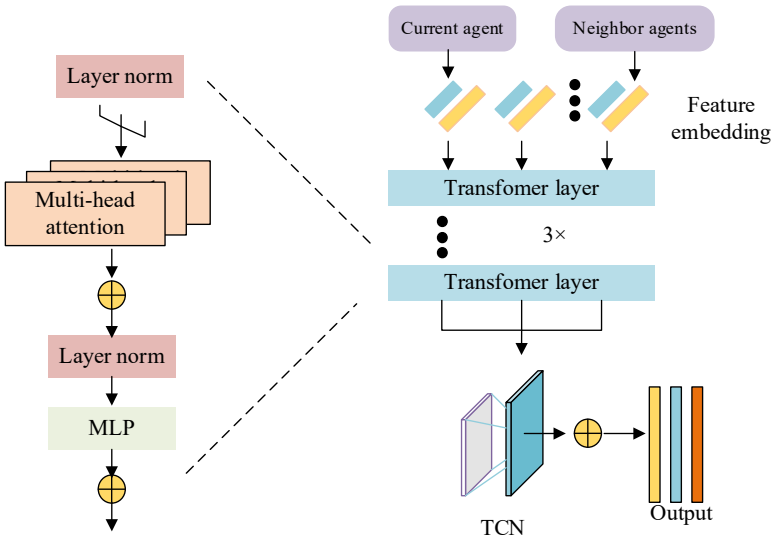


Fig. 5. I-Transformer network structure

In I-Transformer network structure, it strengthens the capture of time-dependent relationships through a multi-head attention mechanism, enhancing the analysis of detailed features. At the same time, the study also needs to consider the seasonal and cyclical characteristics of WCE data. TCN is introduced into the output layer of the Transformer network to capture long-term time series patterns using dilated convolutions, strengthening the analysis of key features. The output of the Transformer network attention layer is shown in Eq. (15).

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{15}$$

In Eq. (15), Q, K, and V represent the query, key, and value matrices, respectively. d_k is the feature dimension, and the metric correlation weights are calculated through scaled dot-product attention. Subsequently, TCN is introduced into the output layer of Transformer to strengthen the analysis of temporal features, as shown in Eq. (16).

$$y_t = \sum_{k=0}^{K-1} w_k \cdot x_{t-s \cdot k} \tag{16}$$

In Eq. (16), S is the expansion rate. K is the CK size. w_k is the weight. Jump sampling is used to expand the receptive field to adapt to the seasonal and periodic characteristics of WCE data. After reinforcing the engineering feature extraction, the deep learning model outputs a standardized score $\hat{y} \in [0,1]$, which is mapped to a safety level through the Sigmoid function, as shown in Eq. (17).

$$\hat{y} = \sigma\left(W \cdot \mathrm{TCN}(\mathrm{Transformer}(\mathrm{CNN}(X))) + b\right) \tag{17}$$

In Eq. (17), X represents the time series data output by the cloud model. W and b represent the parameters of the fully connected layer. σ represents the Sigmoid function, which implements the nonlinear mapping of the evaluation value. Finally, the research results fusion strategy integrates and improves the results of the mutation series method $H_{j'}$ and the deep learning results $\hat{y}$ through weighted fusion, as shown in Eq. (18).

$$S = \alpha \cdot H_{j'} + (1-\alpha) \cdot \hat{y} \tag{18}$$

In Eq. (18), S is the final safety evaluation value. $\alpha \in [0,1]$ is the weight, which is optimized through cross-validation and typically set to 0.6 to highlight the physical interpretability of the mutation series method. The entire digital twin security assessment system for WCE framework is shown in Fig. 6.

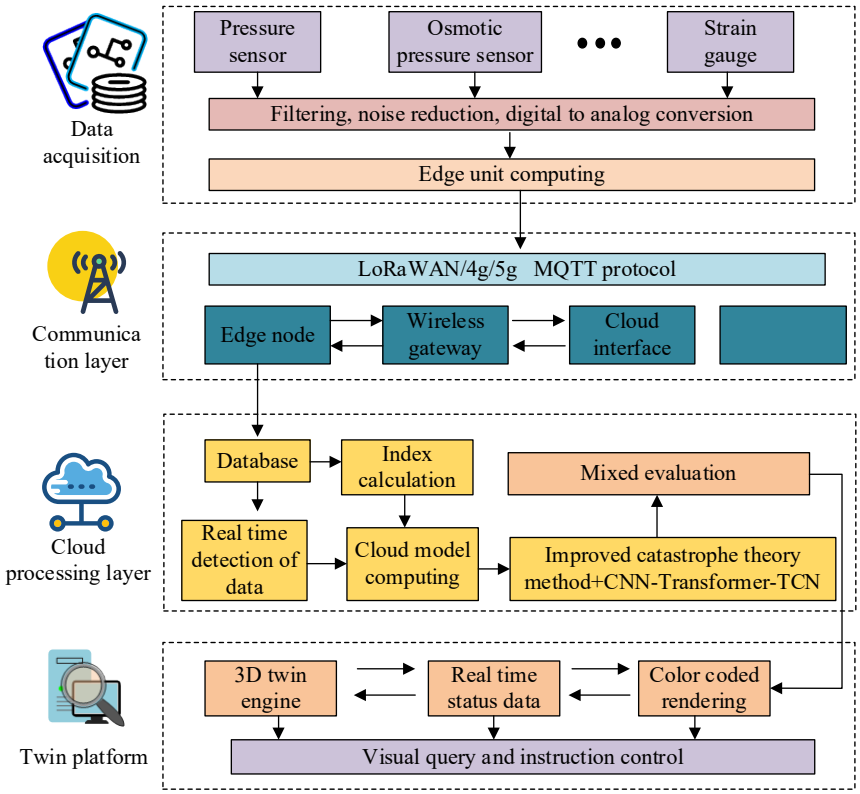


Fig. 6. Framework of the digital twin security assessment system for WCE (https://www.svgrepo.com/vectors/cloud-computing/2; https://www.svgrepo.com/vectors/database/3; https://www.svgrepo.com/vectors/communication/5; https://www.svgrepo.com/vectors/system/3)

Fig. 6 shows that the entire system consists of a data collection layer, a communication layer, a cloud processing layer, and a digital twin platform. Among them, various node sensors are deployed in the collection layer, combined with project monitoring data, such as YHD type tension line meter, JLX type static level meter, etc. The cloud processing outputs four-level safety indicators, and the final safety status is evaluated using a hybrid evaluation meter. The entire system framework requires tension gauges for measuring displacement and pressure gauges for measuring seepage. The cloud platform adopts Huawei Cloud, and the system detection adopts the Mantu MTW460SI terminal, combined with the MQTT+LoRa protocol for a complete design.

3. Results

3.1. Cloud-Based Model Evaluation Grade Analysis

A water conservancy hub of a tributary of the Yangtze River, which is a concrete gravity dam, is selected for the study.

The monitoring system is laid out as follows: Hardware equipment: YHD-type lead tensiometer is used for horizontal displacement, JLX-type static level meter is used for vertical displacement, JFX-type seam gauge is used for joint cracks, and SYC-type seepage pressure meter is used for dam base lifting pressure. The data are transmitted to the database through the automated collection terminal. Software environment: The data preprocessing is done using Python 3.8 (Pandas library) and the cloud modeling calculation is implemented based on MATLAB 2022a. It contains forward, inverse cloud generator algorithms and 3En criterion interval division module. The study gives the project status security assessment system based on the operational safety standards for WCE dam projects as displayed in Table 1.

Table 1. Digital twin security system for WCE

Target layer	Primary indicator	Secondary index	Level IV index (measuring point area)
Safe operation status of the dam	Deformation monitoring	Horizontal displacement	SX1-1, SX1-2 (tension line measuring point)
		Vertical displacement	CZ1-1, CZ1-2 (static leveling point)
		Seam opening and closing degree	JF1-1, JF1-2 (measuring point of joint meter)
	Seepage monitoring	Foundation seepage uplift	YL1-1, YL1-2 (measuring point of osmometer)
	Stress monitoring	Dam heel stress	YL1-1, YL1-2 (measuring point of stress meter)
		Dam toe stress	BY1-1 (strain gauge group)
		Local stress	JY1-1 (strain gauge group)

In Table 1, the dam safety state mainly analyzes WCE state safety from three directions: deformation, seepage, and pressure. The study selects the overflow section 11 monitoring data of this water conservancy project to verify the validity of the cloud model. The monitoring data from 2015 to 2022 are shown in Table 2.

Table 2. Monitoring data and cloud model parameters of overflow section 11 of water conservancy project

Index	Measurement point number	2015	2016	2017	2018	2019	2020	2021	2022	Mean value	Cloud characteristic parameters
Horizontal displacement (mm)	SX1-1	3.2	2.8	4.1	1.9	2.5	5.3	2.2	3.8	3.09	Ex=3.09, En=1.12, He=0.18
	SX1-2	3.0	2.6	3.9	1.7	2.3	5.1	2.0	3.6		
	SX1-3	3.5	3.1	4.3	2.1	2.7	5.5	2.4	4.0		
Vertical displacement (mm)	CZ1-1	-1.5	-2.1	-3.8	-0.9	-2.4	-4.5	-1.8	-3.2	-2.53	Ex=-2.53, En=1.05, He=0.15
	CZ1-2	-1.8	-2.4	-4.1	-1.2	-2.7	-4.8	-2.1	-3.5		
	CZ1-3	-1.2	-1.8	-3.5	-0.6	-2.1	-4.2	-1.5	-2.9		
Seam crack (mm)	JF1-1	0.8	1.2	2.5	0.6	1.5	3.8	0.9	2.1	1.66	Ex=1.66, En=0.98, He=0.12
	JF1-2	0.6	1.0	2.3	0.4	1.3	3.6	0.7	1.9		
	JF1-3	1.0	1.4	2.7	0.8	1.7	4.0	1.1	2.3		
Foundation seepage uplift (mH_2O)	YL1-1	34.2	33.8	36.5	32.9	34.7	38.1	33.5	35.9	34.71	Ex=34.71, En=1.63, He=0.21
	YL1-2	33.5	33.1	35.8	32.2	34	37.4	32.8	35.2		
	YL1-3	32.8	32.4	35.1	31.5	33.3	36.7	32.1	34.5		

In Table 2, the index data of overflow section of the water conservancy project are recorded for a total of 8 years from 2015 to 2022. Among them, the mean value (MV) of horizontal displacement of overflow section is 3.09, the MV of vertical displacement is -2.53m, the MV of joint crack is 1.66mm, while the MV of dam base head pressure is 34.71. According to the above data can be obtained the parameters related to the cloud characteristics of the cloud model. The study introduces confidence interval method evaluation, confidence interval method evaluation, and fuzzy comprehensive evaluation method evaluation to compare the cloud model evaluation method and verify the rationality of its evaluation level. Among them, four major indicators are set according to the cloud model, which are normal (N), BN, LA, and SA. Table 3 displays the test results.

The multi-measurement point evaluation results in Table 3 show that the deviation of the indicator level cloud parameter Ex from the MV of the representative value is <3%, e.g., the horizontal displacement is Ex=3.09 mm, the MV of the representative value is 3.09 mm, and En covers 82% of the fluctuating range of the data at the measurement points, and He<0.25. This indicates that the parameter can accurately characterize the randomness and ambiguity of the data at the multi-measurement points. The evaluation results of the cloud model for 32 groups of samples are completely consistent with the actual state, which is 100%. 100% consistency indicates that the cloud model's determination of the safety status determination of 32 monitoring indicators, such as horizontal displacement and vertical displacement, fully matches the actual operating status confirmed by the dam site survey, with no misjudgments. In contrast, the confidence interval method and fuzzy synthesis method consistency are 68.75% and 56.25%, respectively. For example, the confidence interval method misjudges the horizontal displacement of 5.3mm in 2020 as “A”, but it is actually a reasonable response during the flood

period. Whereas, the subjective assignment of the fuzzy synthesis method ignores the difference in the location of the measurement points, resulting in the settlement of the dam bottom of -2.4mm in 2019 being misjudged as "BN". The actual state is N, which is consistent with the base consolidation law.

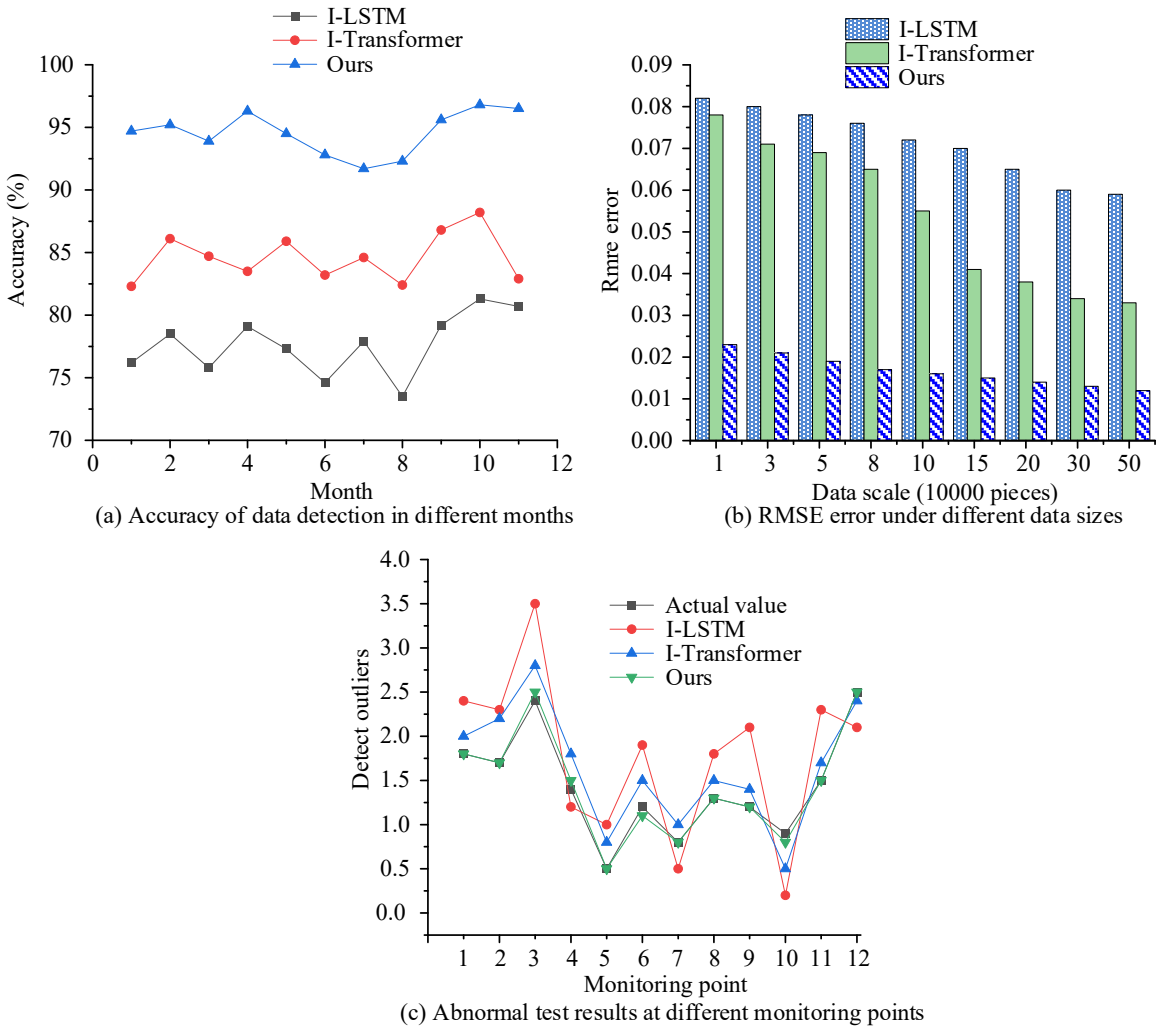
Table 3. Comparison of multi point evaluation results of three methods with actual status

Index	Year	Multi sensor data	Representative value	Cloud model	Confidence interval approach	Fuzzy comprehensive method	Actual state	Cloud model consistency
Horizontal displacement	2015	SX1-1=3.2, SX1-2=3.0, SX1-3=3.5(mm)	3.2mm	N	N	N	N	100%
	2017	SX1-1=4.1, SX1-2=3.9, SX1-3=4.3(mm)	4.1mm	N	N	BN	N	100%
	2020	SX1-1=5.3, SX1-2=5.1, SX1-3=5.5(mm)	5.3mm	BN	A	LA	BN	100%
Vertical displacement	2016	CZ1-1=-2.1, CZ1-2=-2.4, CZ1-3=-1.8(mm)	-2.1mm	N	N	N	N	100%
	2019	CZ1-1=-2.4, CZ1-2=-2.7, CZ1-3=-2.1(mm)	-2.4mm	N	N	BN	N	100%
	2020	CZ1-1=-4.5, CZ1-2=-4.8, CZ1-3=-4.2(mm)	-4.5mm	BN	A	LA	BN	100%
Seam crack	2017	JF1-1=2.5, JF1-2=2.3, JF1-3=2.7(mm)	2.5mm	N	N	BN	N	100%
	2020	JF1-1=3.8, JF1-2=3.6, JF1-3=4.0(mm)	3.8mm	LA	A	SA	LA	100%
	2022	JF1-1=2.1, JF1-2=1.9, JF1-3=2.3(mm)	2.1mm	N	N	N	N	100%
Foundation seepage uplift	2018	YL1-1=32.9, YL1-2=32.2, YL1-3=31.5(mH2O)	32.2mH2O	BN	A	N	BN	100%
	2020	YL1-1=38.1, YL1-2=37.4, YL1-3=36.7(mH2O)	37.4mH2O	BN	A	LA	BN	100%
	2022	YL1-1=35.9, YL1-2=35.2, YL1-3=34.5(mH2O)	35.2mH2O	N	N	N	N	100%

3.2. Comprehensive Assessment of the Operational Status of Dam Segments

This part will assess the operational status of the water project based on the evaluation level of the cloud model. The deep learning model in the study is set up as follows: the CK is 3×1, the output channel is 64, the number of multi-attention heads is 8, and the hidden layer dimension is 128. The deep learning is implemented based on Python 3.8 with PyTorch 1.12, and the data is obtained from the monitoring system data of the Xiajiang River Water Conservancy Hub from 2016 to 2022. The study compares the performance of improved long short-term memory (I-LSTM), I-Transformer, and the proposed method based on overflow section 11 monitoring data. The results are shown in Fig. 7.

Fig. 7(a) shows the data selected for December 2022 to test the accuracy of different models. The research model significantly outperforms similar techniques in detecting the effect, achieving an average accuracy of 95.21%. In comparison, the I-Transformer and I-LSTM achieve 86.1% and 78.2%, respectively. Especially during the rainy season (June-July), the research model is able to recognize seasonal fluctuation data more accurately with higher accuracy. Fig. 7(b) displays the root mean square error (RMSE) for different data sizes. With the increase of data size, different models gradually decrease the data detection error. However, the research model performs better overall under large scale and multiple source counts. For example, at 150,000 data, its error is 0.017, while the I-Transformer and I-LSTM are 0.044 and 0.073, respectively. Fig. 7(c) 12 data monitoring points are selected for testing to compare the effect of different models on abnormal data recognition. Among them, the range of abnormal values 0-8 (0-2 normal, 3-4 LA, 4-6 abnormal, 6-8 severe abnormal) is set to compare the model output with the actual values. The proposed model output has the smallest deviation from the actual outliers, with an average outlier judgment accuracy of 97.25%, compared to 84.52% and 90.25% for I-LSTM and I-Transformer, respectively. As monitored in June-August overflow section 11, I-LSTM has the largest overall deviation of more than 13.52%, and only the research model has the best performance with a deviation of 0.56%. Additionally, the study uses a deep learning model to adjust the mutation evaluation value, which ranges from 0 to 1. Higher values indicate safer indicator status. Normal values range from 0.85 to 1. Values between 0.6 and 0.85 are considered BN. Values between 0.3 and 0.6 are considered LA. Values below 0.3 are considered SA. The test results are shown in Fig. 8.

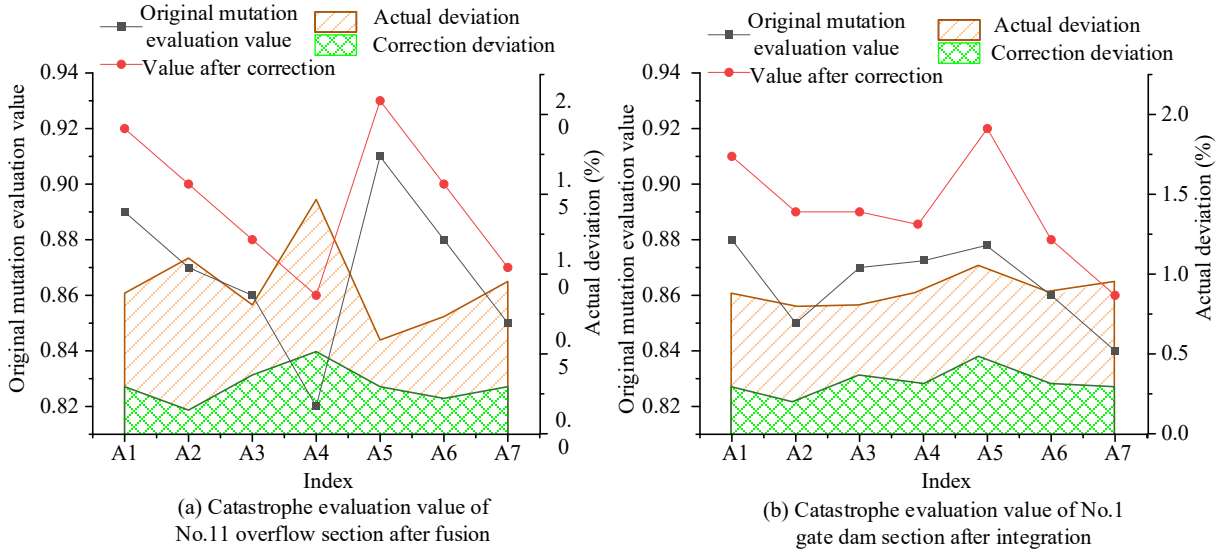


(a) Accuracy of data detection in different months

(b) RMSE error under different data sizes

(c) Abnormal test results at different monitoring points

Fig. 7. Analysis of the recognition effect of water conservancy parameters in deep learning models



(a) Catastrophe evaluation value of No.11 overflow section after fusion

(b) Catastrophe evaluation value of No.1 gate dam section after integration

Fig. 8. Comparison of mutation evaluation values after fusion

Fig. 8(a) shows the results of overflow section 11 mutation value correction, after the correction of the seven major indicators, the deviation value of the indicators are controlled within 0.50%. For example, the deviation of indicator A4 is 1.42% without correction and 0.49% with correction. Correcting the mutation value of the indicator improves the assessment effect on WCE further. Fig. 8(b) shows the results of the correction of the mutation value of gate dam section

No.1. Similarly, the deviation of each index of correction is controlled within 0.50%, which is better than the maximum deviation of 1.11% before correction. Finally, according to the corrected mutation evaluation value, overflow section 11, right bank retaining dam No.8, and gate dam section No.1 are selected for the study. Nine samples are collected from each region, and the improved mutation level method is utilized to calculate the evaluation value of each indicator and the total mutation level. The total mutation level results of the project are also obtained by swallow-tail mutation, as shown in Table 4.

Table 4. Comprehensive evaluation of WCE projects

Region	Index	Bottom level testing and evaluation value	Evaluation value of upper-level indicators	Total mutation level	Security level
Overflow section 11	A1	0.93	0.95	0.94	Normal (N)
	A2	0.91	0.93		
	A3	0.9	0.92		
	A4	0.88	0.9		
	A5	0.94	0.96		
	A6	0.92	0.94		
	A7	0.9	0.92		
Right bank retaining dam No.8	A1	0.92	0.94	0.93	Normal (N)
	A2	0.89	0.91		
	A3	0.91	0.93		
	A4	0.87	0.89		
	A5	0.93	0.95		
	A6	0.91	0.93		
	A7	0.89	0.91		
Gate dam section No.1	A1	0.94	0.96	0.95	Normal (N)
	A2	0.92	0.94		
	A3	0.91	0.93		
	A4	0.89	0.91		
	A5	0.95	0.97		
	A6	0.93	0.95		
	A7	0.91	0.93		

The comprehensive assessment results in Table 4 show that the total mutation grades of the three regions are in the range of 0.93-0.95, and the safety grades are all normal (N). For instance, the lowest evaluation value for the gate dam section (No. 1A5) is 0.95. After calculating the dovetail mutation model, the upper evaluation value reaches 0.97, which is significantly higher than the other indexes. This reflects the structural stress stability advantage of the gate dam section. Moreover, the total mutation level of right bank retaining dam No.8 is 0.93, which is slightly lower than the other two regions, mainly due to the lower A4 (dam base head pressure) bottom evaluation value of 0.87. Therefore, based on the results, it is necessary to strengthen monitoring of this area of the green bias and combine it with the digital twin platform to track the correlation with the upstream water level in real time. This will ensure the safety and stability of the WCE project.

4. Conclusion

This study proposed a hybrid assessment framework that integrated the advantages of physical interpretability and data-driven approaches. The outcomes revealed that the cloud model performed exceptionally well in indicator evaluation. Evaluation results for 32 indicators, including horizontal displacement and uplift pressure, showed 100% consistency with actual conditions. This result significantly outperformed the 68.75% achieved by the confidence interval method and the 56.25% achieved by the fuzzy comprehensive method. Its characteristic parameters could accurately characterize the randomness and fuzziness of the data. In the comprehensive assessment, the total sudden change index for overflow section 11, right bank retaining dam No. 8, and gate dam section No. 1 was 0.93 to 0.95, all of which were judged to be “normal”. After deep learning correction, the index deviation was controlled within 0.50%, and the assessment stability was significantly improved.

The research model can be integrated with current dam safety guidelines (such as deformation and seepage limit requirements) and environmental impact standards. The consistency of indicator evaluation also provides a quantitative basis for supervision. For example, the evaluation of various parts of the project is “normal”, which solves the problem of vague standard implementation in traditional governance. At the same time, the model’s real-time evaluation capability of the model can help policymakers build data-driven inspection frameworks and assist regulatory agencies in developing high-precision early warning systems with 97.25% anomaly recognition accuracy. It can also support the optimization of inspection mechanisms for water departments and promote the transformation of water safety supervision from empirical to precise. This technology can be adapted to various water conservation projects in the real world and used for risk supervision and assessment in scenarios involving dams, reservoirs, and gates. It provides managers with a basis for

decision-making. For example, engineers can use cloud models to quantify indicators such as deformation and seepage pressure and divide them into safe zones. Operators rely on a hybrid evaluation framework to monitor data in real-time and trigger alerts when anomalies occur, while management personnel refer to the total mutation level to coordinate operations and follow the "monitoring evaluation decision-making" process to efficiently manage engineering safety.

In summary, the proposed technology is more accurate and reliable for assessing the security of digital twins in WCE. However, there are still shortcomings. For example, the efficiency of cloud models in processing ultra-high-dimensional indicators needs improvement, and they are relatively sensitive to sudden changes in extreme conditions. In the future, it will be necessary to optimize the processing capacity of high-dimensional indicators, integrate multi-source monitoring data, and refine the model to improve its adaptability and stability in complex water conservancy scenarios.

Institutional Review Board Statement

Not applicable.

Declaration of Artificial Intelligence (AI) Tools

The author confirmed that no AI tools were used in the preparation of this manuscript.

Fundings

The research is supported by the 2024 Yunnan Provincial Department of Education Science Research Fund Project "Research on Mechanism and Data Driven Urban Flood Simulation and Risk Warning" 2024J1839.

References

Bitarafan, M., Hosseini, A., and Zolfani, H. (2023). Identification and assessment of man-made threats to cities using integrated Grey BWM-Grey MARCOS method. Decision Making: *Applications in Management and Engineering*, 6(2), 581-599. doi: 10.31181/dmame622023747

Cantiello, P., Di Martino, B., Mastroianni, M., Colucci Cante, L., and Graziano, M. (2023). Towards a cloud model choice evaluation: comparison between cost/features and ontology-based analysis. *International Journal of Grid and Utility Computing,* 14(1), 15-28. doi: 10.1504/IJGUC.2023.129700

Chauhan, P., Gupta, A., and Malhotra, T. (2023). A novel cloud model based on multiplicative unbalanced linguistic term set. *The Journal of Supercomputing,* 79(14), 16378-16408. doi: 10.1007/s11227-023-05295-z

Gerçek, D. and Güven, T. (2023). Urban earthquake vulnerability assessment and mapping at the microscale based on the catastrophe progression method. International *Journal of Disaster Risk Science,* 14(5), 768-781. doi: 10.1007/s13753-023-00512-y

Huang, Z., Cao, C., and Zhang, W. (2024). Risk assessment method of deep foundation pit construction based on two-dimensional cloud model. *Journal of Northeastern University (Natural Science),* 45(10), 1504. doi: 10.12068/j.issn.1005-3026.2024.10.017

Jamion, A., Lee, E., Mokhtar, M., Goh, L., Simon, N., Goh, T., and Bhat, H. (2023). The integration of nature values and services in the nature-based solution assessment framework of constructed wetlands for carbon – water nexus in carbon sequestration and water security. *Environmental Geochemistry and Health,* 45(5), 1201-1230. doi: 10.1007/s10653-022-01322-9

Jin, L., Ju, G., Chen, Z., Xiao, Q., Fu, W., Ye, F., and Wei, Y. (2024). An analytical solution to predict slip-buckling failure of bedding rock slopes under the influence of top loading and earthquakes: case studies of Hejia landslide and Tangjiashan landslide. *Landslides,* 21(7), 1617-1627. doi: 10.1007/s10346-024-02232-w

Yu, N., Wu, T., and Wei, H. (2023). Geological hazard assessment based on the models of AHP, catastrophe theory and their combination: A case study in Pingshan County of Hebei Province. *The Chinese Journal of Geological Hazard and Control,* 34(2), 146-155. doi: 10.16031/j.cnki.issn.1003-8035.202201012

Li, Y., Hu, N., Ye, Y., and Wu, M. (2023). Improved catastrophe progression method of underground goaf risk evaluation. *Journal of Intelligent & Fuzzy Systems*, 44(3), 4521-4536. doi: 10.3233/JIFS-2220

Lu, W., Fang, L., and Ai, L. (2023). A novel risk assessment model for prefabricated building construction based on combination weight and catastrophe progression method. *Tehnički vjesnik,* 30(6), 1959-1967. doi: 10.17559/TV-20230802000846

Luo, N., Yu, H., You, Z., and Li, T. (2023). Fuzzy logic and neural network-based risk assessment model for import and export enterprises: A review. *Journal of Data Science and Intelligent Syste*ms, 1(1), 2-11. doi: 10.47852/bonviewJDSIS32021078

Sajjad, M., Ali, Z., and Waleed, M. (2023). Has Pakistan learned from disasters over the decades? Dynamic resilience insights based on catastrophe progression and geo-information models. *Natural Hazards,* 117(3), 3021-3042. doi: 10.1007/s11069-023-05976-1

Sarwar, M. (2023). Decision making model for design concept evaluation based on interval rough integrated cloud VIKOR. *Journal of Ambient Intelligence and Humanized Computing,* 14(4), 3875-3897. doi: 10.1007/s12652-022-04459-8

Shao, L., He, J., Zeng, X., Hu, H., and Yang, W. (2023). Fire risk assessment of airborne lithium battery based on entropy weight improved cloud model. *Aircraft Engineering and Aerospace Technology*, 95(6), 869-877. doi: 10.1108/AEAT-05-2022-0135

Wang, Q., Chen, L., Wang, P., Wang, B., and Yang, T. (2023). Evolution of County Socio – Ecological Systems in Nature Reserves in Western China Over the Past 30 Years. *Natural Resources Research,* 32(4), 1809-1822. doi: 10.1007/s11053-023-10211-6

Wang, W., Liang, X., Niu, Q., Wang, Q., Zhuo, J., and Su, X. (2023). Reformability evaluation of blasting-enhanced permeability in in situ leaching mining of low-permeability sandstone-type uranium deposits. *Nuclear Engineering and Technology,* 55(8), 2773-2784. doi: 10.1016/j.net.2023.03.034

Wang, Y. (2023). A novel evaluation model based on connection cloud model and game theory under multiple uncertainties. *Soft Computing,* 27(2), 645-656. doi: 10.1007/s00500-022-07615-6

Xiashi, J. Xue, feng L., I, Shanda, D., Xuxing, H., Yihao, Y., and Wuning, X. (2023). Evaluation on construction of dual prevention mechanism in non-coal mine mountains based on combination weighting-cloud model. *Mining Safety & Environmental Protection,* 50(5), 149-155. doi: 10.19835/j.issn.1008-4495.2023.05.024

Zhu, Z. (2024). Indoor evaluation algorithm for ecological environment design materials based on cloud data processing and wireless communication. *Wireless Networks,* 30(1), 37-50. doi: 10.1007/s11227-023-03447-w

Professor Deling Chen graduated from Northwest A&F University with a Master's degree in Engineering. He currently serves as the Director of the Academic Affairs Department and an Associate Professor at Yunnan Water Resources and Hydropower Vocational College. Additionally, he holds several positions in academic organizations. In the field of water conservancy and hydropower engineering, he has achieved outstanding results, having led and participated in seven research projects. These projects cover cutting-edge areas such as sponge city construction, urban flood simulation, and risk warning. In terms of teaching, he has edited and co-authored three professional textbooks. He has also obtained four utility model patents, providing innovative technical support for practical engineering applications. In academic exchanges, he has published more than ten high-quality papers focusing on areas such as safety assessment of digital twins in water conservancy, demonstrating his in-depth research.