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Original Article

Machine Learning-Based Assessment of Soil Dispersibility and Erosion Types in Earthfill Dam: A Case Study from South Central Vietnam

Tam Sy Ho[1], Quan Duy Tran[1], Huong Thi Pham[1], Hong Thi Pham[2], Vung Van Tran[3], Hien Thi Thu Dinh[4], Phi Quang Nguyen[5], Nga Thi Hang Nguyen[5*]

[1]*Faculty of Civil Engineering, Thuyloi University, Hanoi, Vietnam.*
[2]*Faculty of Chemistry and Environment, Thuyloi University, Hanoi, Vietnam.*
[3]*Institute of Education and Applied Sciences, Central Vietnam (IEAS), Thuyloi University, Hanoi, Vietnam.*
[4]*Faculty of Science and Engineering, Iwate University, 3-18-8 Ueda, Morioka, Iwate 020-8550 Japan.*
[5]*Faculty of Water Resources Engineering, Thuyloi University, Hanoi, Vietnam.*

[*]*Corresponding Author : nt_hangnga@tlu.edu.vn*

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Abstract *- The stability of earthfill dam foundations is crucial for ensuring a reliable water supply and protecting downstream infrastructure. Currently, assessments of soil dispersibility and erosion in earthfill dams primarily rely on empirical formulas and expert judgment. However, traditional formulas often fail to cover the full range of real-world classification scenarios and require the continuous development of new thresholds for each specific case, making management challenging. We propose using machine learning combined with field survey data to offer a new approach for classifying soil dispersity and erosion types. This study focuses on comparing machine learning-based classifications with traditional expert-based methods to predict soil dispersity and erosion types across dams in South-Central Vietnam. Machine learning models, particularly Random Forests, outperformed traditional methods in both accuracy ($R^2 = 0.92$ for soil dispersity and $R^2 = 0.92$ for erosion type) and consistency, especially in complex cases. The classifications generated by the machine learning model were consistent with traditional models while better addressing complex scenarios. Key predictors such as quartz content, moisture, and mineralogy were identified as important factors influencing soil behavior.*

Keywords *- Dam soil stability, Machine learning application, Dam structure safety, Soil erosion.*

1. Introduction

Earthfill dams, primarily built from compacted soil, play a vital role in water resource management in developing countries. They are essential for securing substantial water supplies for agriculture, domestic needs, and industry. In addition to water storage, they help control floods by regulating river flow and minimizing downstream risks [1]. Earth dams also support soil conservation by reducing erosion through managed runoff [2].

In many developing countries, these dams have been constructed to support agricultural activities due to their cost-effectiveness and the use of locally available materials, making them practical and widely accessible [3]. However, over time, the structural quality of earth dams can deteriorate. Since most earthfill dams were built before 1850, many are now in need of significant repairs. This aging infrastructure increases the risk of damage or failure, especially during extreme events such as floods or earthquakes [4]. The stability of earthfill dam foundation is often compromised by the inherent properties of the soil, especially soil chemical components. Therefore, dam safety becomes critically important to prevent failures that could result in catastrophic flooding, loss of life, and environmental damage [5, 6]. Ensuring dam safety can protect ecosystems and economic activities that rely on a consistent water supply from hydrological impacts and heavy precipitation, especially in the face of climate change.

The primary cause of dam failure is often the presence of soils with high dispersibility or susceptibility to dissolution, as these properties can greatly compromise the earth dam stability and structural integrity [7]. Since dams are artificial structures, the dispersive nature of soil becomes particularly evident, especially during the early stages of dam operation [8]. Previous research confirms that the primary cause of failure lies in the poor quality of embankment soils, including highly permeable soils, expansive soils, dispersive clays [9], and soils susceptible to erosion [10]. Therefore, checking soil characteristics of earth dams is crucial for monitoring dam safety [11].

Traditional methods for assessing soil quality in earthfill dams play a crucial role in ensuring the stability and safety of these structures [12]. One of the most common approaches is to collect soil samples directly from the field and then analyze them in the laboratory for key physical and mechanical properties such as moisture content, compaction, permeability, swelling potential, and dispersibility [13]. Sampling can be carried out using hand augers, drilling machines, or test pits. The collected parameters are then evaluated using empirical formulas or geotechnical analysis methods to assess the stability of the dam. However, these empirical formulas have some limitations. At first, the empirical formulas require a large number of parameters and multiple samples, which demands significant effort and financial resources.

In addition, the rigidity of empirical formulas in handling complex soil conditions poses challenges for accurate classification. On the other hand, previous studies have indicated that laboratory-based classification results are often inconsistent with field observations [14]. In response to these limitations, several studies have attempted to develop solutions to address such shortcomings. For instance, Sadettin Topçu and Evren Seyrek improved the dispersity classification of soils by integrating both physical and chemical tests. Although this modification enhanced the accuracy and applicability of the empirical method, it also resulted in increased labour, time, and cost burdens [15]. Due to earth dams' highly diverse soil properties, several researchers have re-evaluated specific sites and modified existing chemical standards for soil dispersity by incorporating additional chemical parameters [16, 17]. This highlights the need for region-specific studies to establish revised classification standards.

Recently, machine learning has been increasingly applied in soil management and soil engineering [18], particularly in areas such as quantitative risk assessment for overtopping [4], spatiotemporal pore pressure prediction in earth dams [19], and deformation monitoring [20]. The algorithm of Artificial Neural Network (ANN) has been applied to various geotechnical and environmental problems, including the estimation of thermal conductivity in fine-grained soils, spatial-temporal modelling of soil moisture, prediction of key strong ground motion parameters, and estimation of soil organic carbon [21, 22]. More recently, ANN and Support Vector Machine (SVM) algorithms have also been employed for dispersive soil classification [23]. In this study, we propose using the Random Forest algorithm, which combines bootstrap aggregating algorithms as an alternative to traditional classification formulas for identifying soil dispersibility, dissolution, and erosion in earth dams in Vietnam, with the aim of enabling faster and more accurate assessment of dam-related risks.

In Vietnam, there are approximately 7000 dams that play a vital role in water supply, hydroelectric power generation, flood control, and recreation [24]. According to 2020 statistics from the Water Resource Directorate of the Vietnam Ministry of Agriculture and Rural Development, the South-Central Coast region has the highest concentration of irrigation and hydropower dams in Vietnam, with 517 large and small dams. However, the current state of these dams reveals several critical issues that must be addressed to ensure structural integrity, investment efficiency, and alignment with modernization goals. A widespread problem is the severe erosion of earth embankment slopes, especially those constructed from compacted fill [25]. Many of these structures suffer from inconsistent design and construction practices, poor quality materials, and inadequate safety standards [26, 27]. As a result, evaluating the quality of foundation soils is essential for predicting erosion risks and assessing dam safety. This study aims to compare the performance of empirical formulas and ensemble machine learning models in classifying soil dispersibility and solubility based on a total of 128 soil samples collected from the downstream slope materials of 128 dams in the South Central Coast region of Vietnam.

2. Materials and Methods

2.1. Study Area

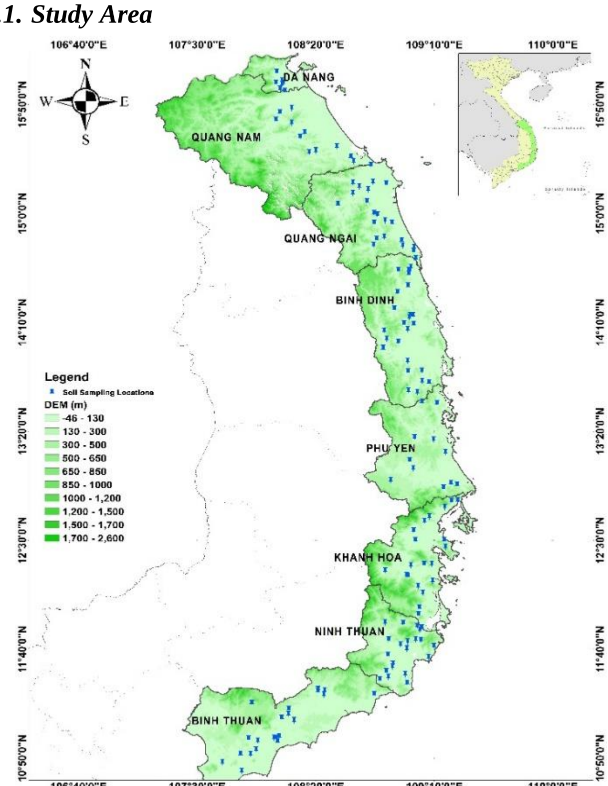

Fig. 1 Map of soil sampling locations

In this study, 128 soil samples were selected from 128 dams distributed across 8 provinces in the South-Central Coast region of Vietnam. The dams were chosen based on several criteria: ensuring geographical distribution (each district with dams had at least one surveyed), diversity in construction time (including newly built dams, older dams without maintenance, and recently repaired or upgraded dams), and variety in scale, height, structure, and slope protection methods. Additionally, the selected dams reflect a range of operating conditions—primarily meteorological and hydrological-as well as differing geological settings and embankment materials. The map of the surveyed dams and soil sampling locations is shown in Figure 1.

From such selected dams and the soil sampled, the authors conducted statistical investigations to classify the current erosion of the dams' downstream slope. In addition, hundreds of laboratory experiments were conducted to determine the dispersive characteristics of the downstream slope of the dams' soil samples, with the aim of identifying a possible correlation between the current state of downstream slope erosion and the dispersive properties of the embankment soil in the study area.

2.2. Sampling and Sample Analysis

Based on survey results of earth dams in Vietnam's South Central Coast region, erosion commonly occurs at depths ranging from 0 to 5 meters below the soil surface. In this study, soil samples were collected at an average depth of 0–5 meters, corresponding to the typical depth of erosion cracks on dam embankments. The samples were air-dried at room temperature and analysed for their physicochemical properties. For soil sample analysis, the soil fraction with an equivalent spherical diameter of less than 1 mm was used. Mineralogical composition was determined for four particle size categories - clay, silt, fine sand, and coarse sand using X-ray diffraction (RINT-2000V, Rigaku), following the procedures outlined by Wada, S.-I. and Y. Umegaki (2001) [28], with Cu Kα radiation at 40 kV and 20 mA.

Exchangeable cations and Cation Exchange Capacity (CEC) were measured using 1 mol L^{-1} NH_4OAc extraction, in accordance with the method of Sumner and Miller (1996) [29]. Two grams of soil were extracted three times with 30 mL of NH_4OAc solution. The resulting extracts were analysed for Ca^{2+}, Mg^{2+}, Na^+, and K^+ using atomic absorption spectroscopy (Savant AA, GBC, Australia). Soil pH (pH_{KCl}) was determined using the electrode method. Soil samples were extracted with a 1N KCl solution at a 1:5 soil-to-solution ratio and measured with a pH electrode meter [30]. Electrical Conductivity (EC) and salt content were measured using a 1:5 soil-to-deionized water extract with a conductivity meter [31]. The soil erosion rate (%/s) was determined using the floating test as defined by the TCVN 8718:2012 standard. The test measured mass loss of the soil placed on a sample grid, with a force sensor (accuracy 0.01N) attached. The sample's weight was continuously recorded on the force sensor display, and the soil mass remaining in the cylinder was tracked over time.

The soil erosion rate (%/s) was calculated using the following formula:

$$D_{tr} = \frac{(F_o - F_t)}{(F_o - F_z)} . 100\% \qquad (1)$$

Where: F_o – is the reading on the sensor at the initial time; F_t – is the reading on the load cell at time t; F_z – is the reading on the load cell at the final time when the test soil sample has completely dissolved.

The Soil dispersion classification is based on calculating the Sodium Adsorption Ratio (SAR) [32] using the following formula:

$$SAR = \frac{[Na^+]}{\sqrt{\frac{1}{2}([Ca^{2+}]+[Mg^{2+}])}} \qquad (2)$$

Where Concentrations are given in milliequivalents per liter (meq/L). Na^+, Ca^{2+} and Mg^{2+} refer to the sodium, calcium, and magnesium concentrations in the soil solution. The Exchangeable Sodium Percentage (ESP) [32] using the following formula:

$$ESP = \left(\frac{Exchangeable\ Na^+}{CEC}\right) \times 100 \qquad (3)$$

The classification of soil dispersion consists of three levels, with an *ESP* of 5–15 (~*SAR* 6–13) serving as the threshold. Soils below this limit are regarded as non-dispersive, whereas soils exceeding it are categorized as severely dispersive.

Table 1. Thresholds in the classification of dispersive soil

Index	Non-dispersive	Intermediate	Dispersive
ESP	< 5	5–15	> 15
SAR	< 6	6–13	> 13

Soil erosion types are determined by observation based on the erosion type described by [33]: 1) Splash erosion happens when raindrops dislodge soil particles, 2) sheet erosion removes a thin layer of topsoil over a wide area. 3) Rill erosion forms small channels in the soil during runoff, which can usually be corrected through regular tillage. More severe is 4) gully erosion, where water cuts deep grooves in the land, and 5) ravine erosion, which is a wide, deep cut.

2.3. Machine Learning Algorithms

To compare classification using empirical formulas with machine learning-based classification, this study employs an enhanced version of the Random Forest algorithm. The Random Forest (RF) algorithm is an ensemble learning method that combines bootstrap aggregating (bagging) [34] with the random subspace method [35]. RF constructs multiple decision trees and aggregates their predictions, which results in robust performance. However, the output is limited to the range defined by the values of the output parameters. In the bagging process, n bootstrap samples are generated by random sampling with replacement from the original training set (of size N). Each bootstrap sample is used to train an individual decision tree. Every node defines a decision rule, and every leaf defines an output label. The tree classifies samples by randomly selecting features at each node, creating a regression space across the ensemble.

Figure 2 follows a comparative framework designed to evaluate soil classification using both traditional and machine learning approaches. The first step involves collecting critical input variables: $Na^+/Ca^{2+}/Mg^{2+}$ ratios, mineralogical composition, salt concentration, soil pH, dispersibility test outcomes (Dtr), and erosion type observations. In the traditional classification pathway, soil dispersibility is assessed using empirical indices such as Exchangeable Sodium Percentage (ESP) and Sodium Adsorption Ratio (SAR), while erosion types are determined through expert interpretation and D_{tr} values. Concurrently, the machine learning pathway applies ensemble algorithms, specifically Random Forest and Bagging classifiers, to predict soil dispersibility and erosion types based on the same input variables. Finally, the classification outcomes from both approaches are compared to assess their relative accuracy and consistency.

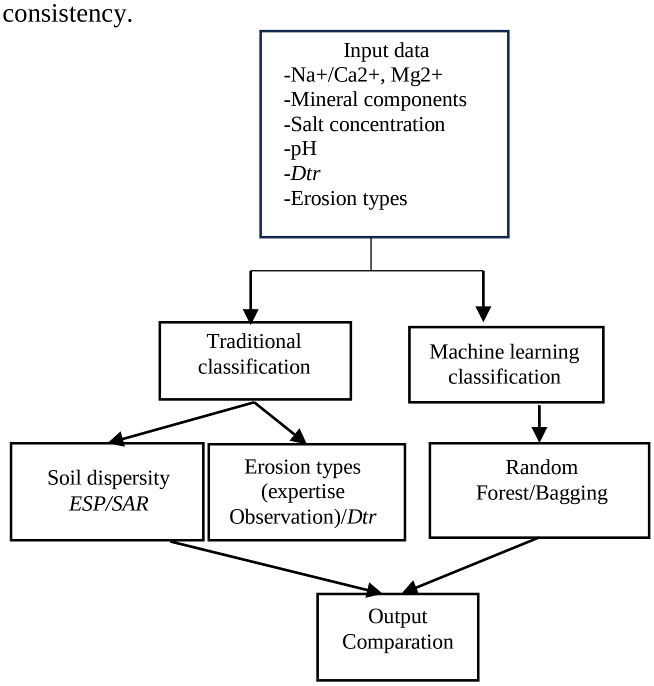

Fig. 2 Flow chart of the study method

3. Results and Discussion

3.1. Machine Learning Applies to Dispersive soil Classification

To classify dispersive soil classes, the traditional approach first uses data on Ca^{2+}, Mg^{2+}, and Na^+ to calculate the SAR and ESP indices using Equations (2) and (3). Then, the classification thresholds for dispersive soils in Table 1 are applied to determine the dispersion level. These classification results are used as ground truth for training and validating the machine learning classification model.

Table 2. Statistics of the obtained model

Class	Name of class	F1-score	Accuracy
1	Non-dispersive	0.96	1
2	Intermediate	0.92	1
3	Dispersive	0.83	0.71

The machine learning model demonstrated strong performance in classifying soil dispersity indices, achieving an overall accuracy of 92% (Table 2).

The classification report highlights high precision across all classes, with perfect precision (1.00) for both class non-dispersive and class Intermediate, indicating that predictions for these classes were highly reliable. Notably, Dispersive, which likely represents highly dispersive soils, achieved a recall of 1.00, meaning all actual cases were correctly identified-a critical outcome for dam safety and risk mitigation. Although the precision for class “Dispersive” was lower (0.71), suggesting some over-prediction, this trade-off is acceptable given the importance of not missing high-risk soils. The confusion matrix in Figure 3 supports these findings, showing minimal misclassifications and no false negatives for class “Dispersive”. Overall, the model provides a reliable tool for predicting soil dispersity, particularly effective in identifying problematic cases that require attention in geotechnical design.

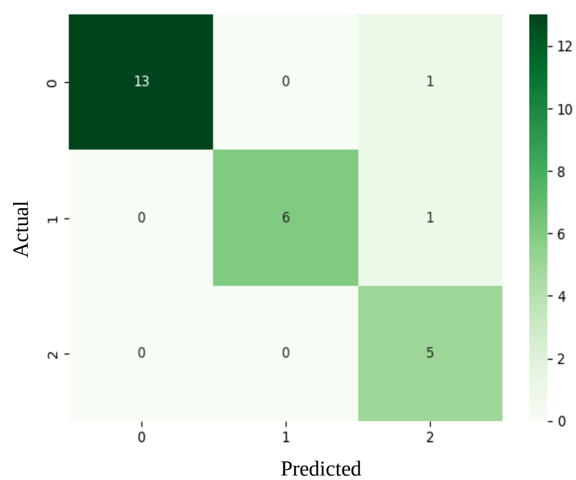

Fig. 3 Confusion matrix of soil diversity classification

In practice, soil dispersibility depends on key factors such as the concentrations of Na^+, Ca^{2+}, and Mg^{2+}, and additional factors like clay mineral type, pH, and organic matter content. Therefore, in this study, when applying the Random Forest algorithm for reclassification, the input variables included not only the traditional parameters (Na^+, Ca^{2+}, and Mg^{2+}) but also factors such as pH, organic matter content, and mineral composition [36]. The classification results of the model showed that for the "Non-dispersive" and "Intermediate" classes, the machine learning model closely matched the traditional classification. However, for the "Dispersive" class, there were noticeable discrepancies between the two prediction methods.

From Figure 4, the feature importance analysis reveals that Quartz (Qz) and (Mc) are the most influential variables in predicting soil dispersity indices. Quartz is significantly more impactful than the others. This suggests that soils with higher quartz content may demonstrate distinct dispersive behavior, potentially due to reduced particle cohesion or the chemically inert nature of quartz. The findings correspond well with earlier reported results [37, 38]. Electrical Conductivity (EC) and clay mineral types like Vt (likely vermiculite) and Na (sodium) also contribute meaningfully, highlighting the role of salinity and mineralogy in soil dispersity classification. Traditional chemical indicators such as pH, CEC, and exchangeable cations (Ca, Mg, K, Na) show lower importance than expected, indicating that mineralogical and textural characteristics might have a stronger influence in this specific dataset.

The imbalance negatively affects soil properties, most notably by reducing aggregate stability due to the pH and dispersion of clay particles [39]. As salt increases, it promotes surface sealing and enhances the risk of crusting, runoff, and erosion [40]. It also alters or narrows the soil's pore size distribution [41], collectively leading to soil dispersity. In fact, the ratio of lime to silica also plays an important role in maintaining the structure of stabilized soil [42]. However, it is important to emphasize that, due to the complex nature of soil structure, many other factors can influence soil stability beyond those considered in traditional formulas. These findings emphasize the value of using machine learning to uncover nuanced patterns that go beyond conventional thresholds like *SAR* and *ESP*, ultimately enhancing predictive accuracy in dam soil evaluations.

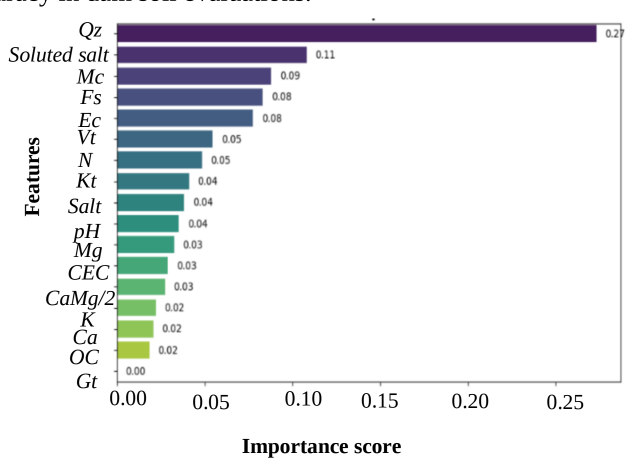

Fig. 4 Feature importance analysis of diversity classification

Figure 5 shows the evaluation of the machine learning model using an ESP vs SAR scatter plot, which demonstrates its strong capability in predicting soil dispersity classes with enhanced accuracy over traditional threshold methods. The model effectively identifies highly dispersive soils (Class 3) in regions where ESP exceeds 15 or SAR exceeds 13, aligning well with established geotechnical criteria. More notably, it performs intelligently within the intermediate zone (ESP 5–15, SAR 6–13), where conventional classification often falls short. Many scientists are currently working to determine the most appropriate threshold values for ESP and SAR based on specific soil conditions [43]. By incorporating additional features beyond ESP and SAR, the machine learning model successfully differentiates between non-dispersive, moderately dispersive, and highly dispersive soils. Although a few samples in class “Dispersive” predictions appear outside the high-risk zones, these are acceptable within the context of conservative engineering design, prioritizing safety over false negatives. Overall, the model demonstrates strong generalization, particularly in complex or borderline cases, confirming its value as a robust tool for assessing soil dispersity in dam engineering applications. Compared with previous studies employing ANN and SVM for dispersive soil classification [23], which capture complex non-linear relationships but require large datasets, careful tuning, and often act as “black-box” models, Random Forest (RF) offers greater robustness and interpretability. RF reduces overfitting through tree aggregation, identifies key soil parameters influencing dispersity, and achieves high accuracy even with limited or noisy data, making it particularly well-suited for dispersive soil classification.

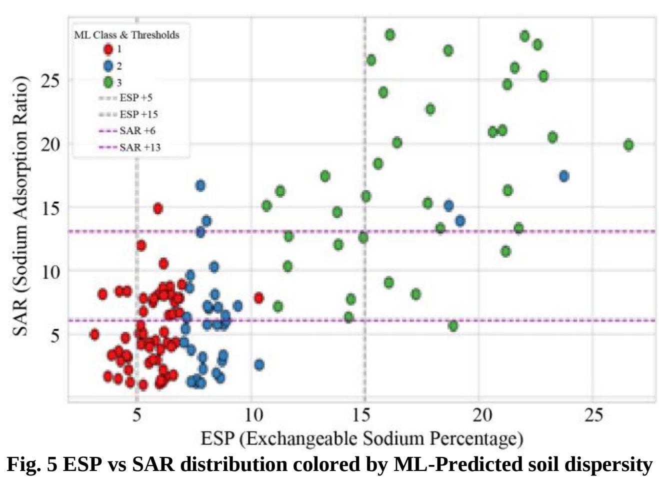

Fig. 5 ESP vs SAR distribution colored by ML-Predicted soil dispersity classes

The result shows machine learning offers a powerful alternative to traditional empirical approaches for predicting soil dispersity, particularly when dealing with complex, nonlinear relationships among multiple soil parameters. While indices like Sodium Adsorption Ratio (SAR) and Exchangeable Sodium Percentage (ESP) have long been used to classify dispersive soils, they rely on fixed thresholds that may oversimplify soil behavior. These models frequently overlook the complex interactions between variables such as clay content, pH, electrical conductivity, and cation exchange capacity, all of which significantly influence dispersity. As a result, conventional approaches may misclassify soils that do not fall neatly within standard limits or exhibit borderline behavior. Machine learning is particularly valuable for uncovering subtle nonlinear patterns and enabling data-driven predictions from extensive or incomplete data. By using algorithms such as decision trees, random forests, or support vector machines, engineers can develop models that adapt to complex site conditions and improve the reliability of risk assessments. This leads to more informed decision-making in dam design, soil treatment, and material selection, ultimately enhancing the safety and efficiency of geotechnical projects.

3.2. Machine Learning Applies to Dispersive Soil Classification

Based on field observations of erosion conditions at the base of earth dams and classification guidelines, experts categorized the erosion status of 128 dams into four types: non-erosion, sheet erosion, rill erosion, and gully erosion. In this study, we used a random forest model to verify the classification capability using input data related to: mineral composition, pH, CEC, Na^{+}, Ca^{2+}, Mg^{2+}, organic matter content, and soluble salt content.

Table 3. Statistics of the obtained soil erosion classification model

Class	Name of class	F1-score	Accuracy
1	Non-erosion	0.96	1
2	Sheet erosion	1	1
3	Rill erosion	0.67	0.5
4	Gully erosion	1	1

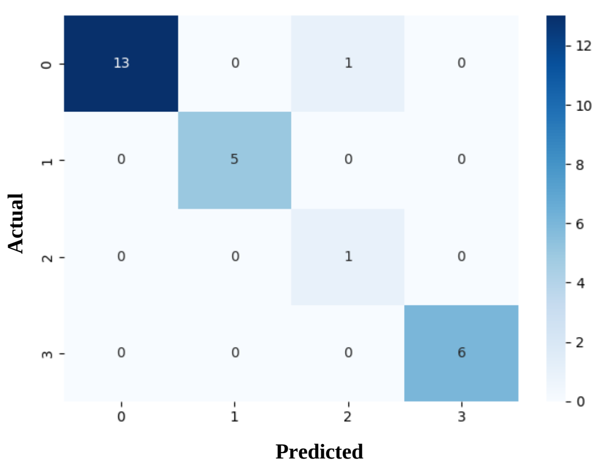

Fig. 6 Confusion matrix of erosion type classification

The erosion type classification model (Table 3, Figure 6) demonstrated excellent classification performance, achieving an overall accuracy of 96% on the test dataset. It correctly identified all instances of sheet erosion (Class 2) and Gully erosion (Class 4), with perfect precision, recall, and F1-scores. The model also performed strongly on Non-erosion (Class 1), correctly classifying 13 out of 14 cases. Although one low-risk sample was misclassified as rill erosion (Class 3), this did not compromise the model's conservative bias, a desirable characteristic in erosion risk assessment. Class 3, which had only one sample in the dataset, was correctly identified but showed lower precision due to the small support size. Overall, the model's ability to reliably detect moderate to severe erosion risk makes it a valuable tool for proactive land and infrastructure management, especially in contexts where the cost of underestimating erosion risk is high.

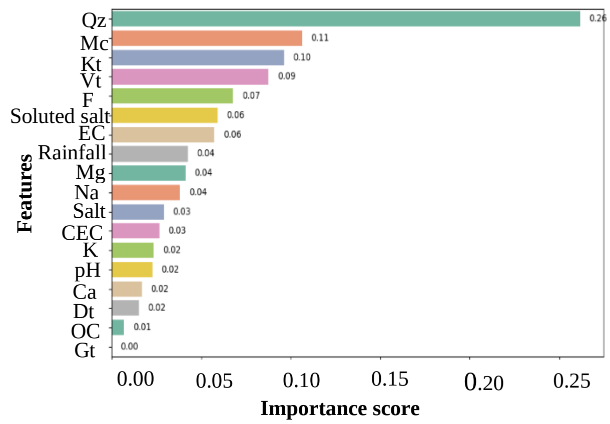

Fig. 7 Feature importance analysis of erosion type classification

The feature importance analysis (Figure 7) shows that Quartz Content (Qz) is the most influential predictor of erosion type, significantly outweighing the contributions of other variables. This is due to the attributed dominance of quartz being the primary mineral in the soil, comprising 41–45% of its composition [44]. These findings highlight that the mineralogical makeup, especially the abundance of quartz, has a major impact on soil erosion dynamics in the study area. Mica (Mc) and kaolinite (Kt), as well as vermiculite (Vt), also show strong predictive power, indicating that both water-related properties and clay mineral types significantly affect erosion susceptibility. Other relevant contributors include Feldspar (Fs), solute salt, and Electrical Conductivity (EC), which likely reflect the combined influence of mineral dissolution and salinity on soil stability. These findings are consistent with those reported in previous research about the important impact of mineral components in soil erosion. Conversely, Organic Carbon (OC), gypsum (Gt), and calcium (Ca) appear to have minimal influence in this dataset. The physicochemical interactions between Soil Organic Carbon (SOC) and minerals are important for the long-term stabilization of soil [45] however in this case the Organic Carbon (OC) and gypsum (Gt), and calcium (Ca) ranked low important level in erosion type classification because they has limited variation in OC, gypsum, or calcium levels across studying sites so their statistical influence in models like Random Forests will naturally be low. Erosion classification (sheet, rill, gully) depends most heavily on how soil physically responds to water action, things like texture, structure, porosity, and cohesion [46]. Elements like OC, Ca^{2+}, and gypsum stabilize soil over time [47], but they may not tend to dictate immediate erosion forms, especially under strong hydrodynamic forces. These results underscore the value of integrating mineralogical and physicochemical parameters in machine learning models for accurate erosion risk assessment. While previous studies have mainly utilized environmental data such as rainfall, soil type, topography, land cover, and land use [48], this study adopts an approach based on the chemical and physical properties of dam soils. These parameters directly affect soil cohesion in earth dams, thereby supporting classification and enabling meaningful comparison with traditional empirical formulas. By integrating diverse datasets, including physicochemical soil properties, mineralogical composition, topography, climate variables (e.g., rainfall), and remote sensing data, ML algorithms can uncover hidden, nonlinear relationships that drive erosion processes. Random Forests are particularly effective for these tasks due to their ability to handle high-dimensional, noisy, and non-normal data. Classification models can assign erosion types based on a wide range of features. By labeling erosion type in historical or experimental datasets, machine learning models can be trained to predict the most likely failure mechanism at a given location. Overall, integrating machine learning into erosion risk assessments enhances accuracy, efficiency, and scalability, especially in data-rich or spatially diverse dam catchments. It supports proactive decision-making, reduces reliance on exhaustive fieldwork, and helps ensure long-term dam safety and sustainable land management.

4. Conclusion

This study compared empirical and ensemble machine learning models for predicting soil dispersity and erosion types in dams across south-central Vietnam. Machine learning models, especially Random Forests, outperformed traditional methods in accuracy and consistency, particularly in complex or intermediate cases. Key predictors such as quartz content, moisture, and mineralogy were identified as critical factors influencing soil behaviors. The models also enabled effective erosion type classification and high-resolution risk mapping. Overall, machine learning offers a robust, data-driven approach to improving dam safety assessment and management.

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