Bulletin of Computational Intelligence
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Article

Development of Interpretable Regression Models for Slope Stability of Nano-Silica Stabilised Soils in Mountainous Terrain

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How To Cite: Thapa, I.; Ghani, S. Development of Interpretable Regression Models for Slope Stability of Nano-Silica Stabilised Soils in Mountainous Terrain. *Bulletin of Computational Intelligence* **2026**, *2*(1), 103–133. https://doi.org/10.53941/bci.2026.100006

Received: 4 November 2025
Revised: 10 December 2025
Accepted: 12 January 2026
Published: 4 February 2026

Abstract: Mountainous regions, particularly the Lesser Himalayas, face persistent slope stability challenges due to complex geological formations and extreme climatic variability. This study investigates the potential of Nano-silica (NS) as an eco-efficient soil stabilizer for enhancing the mechanical behaviour of fine-grained soils in these terrains. Consolidated undrained (CU) triaxial tests were performed on clay of intermediate plasticity (CI), silt of intermediate plasticity (MI), and low-plasticity clay-silt (CL-ML) soil types treated with different NS contents and subjected to various curing durations. To develop reliable predictive insights, both linear and non-linear regression models were constructed using essential geotechnical parameters, including cohesion, internal friction angle, and the pore-water pressure ratio. A novel model simplification process was employed to derive explicit closed-form equations for the Factor of Safety (FoS), retaining only the most influential terms. The non-linear models demonstrated high predictive accuracy, with R^2 values exceeding 0.97, outperforming their linear models for all the soil types stabilized with NS. These interpretable regression models offer a practical tool for slope stability assessments in NS-stabilized soils. The integration of material innovation with simplified computational models contributes to resilient and sustainable infrastructure design in data-scarce highland regions.

Keywords: nano-silica; slope stability; regression modelling; Himalayan region; geotechnical sustainability

1. Introduction

Slope stability analysis in the Lesser Himalayas remains difficult as the complex geological and climatic conditions involved introduce large uncertainties in soil behaviour [1]. Conventional deterministic slope stability analyses rely on single representative values for geotechnical parameters and therefore fail to capture the natural variability and uncertainty inherent in soil and rock properties. This limitation often results in misleading estimations of the factor of safety because the deterministic framework cannot quantify parameter variability or the associated risk of failure [2,3].

Nano-silica has properties such as fine particle size, large surface area and pozzolanic activity and has been verified with profound efficacy in soil stabilization through better binding of the soil matrix. The influence of pore water pressure on slope stability under both static and dynamic loading conditions is widely recognized, as elevated pore pressures reduce effective stress and consequently diminish shear strength the primary parameter governing resistance to slope failure [4–6]. Numerous experimental, numerical, and field studies consistently demonstrate that rising pore water pressure accelerates instability by weakening the soil's shear resistance, thereby increasing the likelihood of failure. At the same time, recent advances in nanomaterial-based soil stabilization, particularly with nano-silica (NS), show significant improvements in shear strength and enhanced resistance against pore-pressure-induced degradation [7–10].

Several experimental studies have demonstrated that incorporating NS enhances soil properties by promoting denser particle packing. Researchers have also noted that the effectiveness of NS is highly dependent on its concentration and the soil type. The incorporation of NS in soil improves particle packing density, as demonstrated by various experimental studies [11,12]. However, other researchers have reported that the effectiveness of NS is predominantly dependent on its concentration and the soil type [13].

The stability of slopes in reduced Himalayan areas is a significant problem specifically in mountainous terrains because of the intricate interaction between geological, hydrological, and climatological factors [14]. With weak geological formations and active tectonics, landslides occur within this region that cause major consequences to infrastructure and safety. Conventional approaches of slope stabilization are usually ineffective in meeting these hindrances due to their inflexibility against the immediate diverse environmental circumstances and considerable non-uniformity amongst the soil characteristics of this region [15]. This region, characterized by fragile geological formations and active tectonic processes, experiences frequent slope failures, significantly impacting infrastructure and safety. Traditional methods of slope stabilization often fall short in addressing these challenges due to their inability to adapt to the region's dynamic environmental conditions and the inherent variability in soil properties.

Nano-materials, specifically NS, have shown reliable and sustainable solutions for soil stabilisation. It has been established that the fine particle size of NS coupled with its high pozzolanic reactivity not only enhances soil strength but also improves stability, which is ideal for the earthwork subject to slope failures in these geotechnically challenging regions [16]. Despite this, the use of NS for slope stabilization needs greater attention, particularly under Lesser Himalayan conditions where a landscape associated with pore pressure induced by rainfall and clayey soils is prominent such as in Lesser Himalayas.

Despite the successful use, the application of NS in slope stabilization has not been thoroughly explored yet, particularly concerning conditions specific to the Lesser Himalayas which are largely characterized by rainfall-induced pore pressure and weak clayey soils. Previous studies such as those related to large-scale landslides in the Lesser Himalaya region suggest a requirement of combining detailed geotechnical study with new stabilization methods to provide for the complex nature of slope instability in this area [17].

Regression analysis, both linear and non-linear, has emerged as a valuable tool for developing empirical relationships in geotechnical engineering. Linear and Non-linear regression equations have not been used to correlate soil stabilization variables like NS content, moisture, and compressive strength. Therefore there is a need for detailed statistical analysis using both linear and non-linear regression models to develop a better fit for complex relationships, especially when multiple variables interact in non-proportional ways. In slope stability, statistical models developed through regression can offer predictive capabilities by linking nano-silica concentration to soil strength and slope stability factors, providing a quantitative basis for the design and optimization of stabilization interventions. Furthermore, Table 1 consolidates the major ML-based investigations on slope stability, the majority of which concentrate on predicting the Factor of Safety (FoS) for unstabilised soil conditions using conventional geotechnical parameters. While these studies demonstrate the potential of data-driven approaches, an important methodological limitation persists: most machine-learning models operate as opaque, black-box systems, making it difficult to understand how individual input variables influence the predicted stability outcomes. To address this challenge, a rigorous statistical examination of the underlying database combined with the development of both linear and non-linear regression models is required. Such complementary analyses not only enhance interpretability but also serve as essential validation layers, ensuring that future machine-learning predictions are grounded in transparent, physically meaningful relationships rather than solely in algorithmic correlations.

Table 1. Overview of machine learning models for slope stability by soil type.

References	Soil Types	Sample Size	Model Used
[18]	Cohesive soil	210	DT, SVM, KNN
[19]	Expansive soil	66	LSSVM-TE, LSSVM-GSA, LSSVM-WOA
[20]	Cohesive soil	70	MLP, SVR, DT, KNN, RF
[21]	Cohesive soil	349	SVM, GBR, Bagging
[22]	Silty soil	600	CNN
[23]	Loess soil	100	DT, SVM, RF
[24]	Cohesive soil	117	SVM, RF, GBR, KNN
[25]	Cohesive soil	211	RF, LightGBM, CatBoost
[26]	Sandy soil	43	ANN, ANN-SSA, ANN-MVO

1.1. Novelty of Research

The novelty of this research lies in its innovative approach to addressing slope stability challenges in the Lesser Himalayan region through the use of NS as a soil stabilization additive. This study uniquely tailors the pozzolanic properties of NS and its ability to enhance soil bonding to the complex geological and climatic conditions of the area. By conducting consolidated undrained triaxial tests, the research provides a detailed analysis of the effects of varying NS concentrations on key geotechnical properties such as cohesion, internal friction angle, and pore water pressure over different curing periods. Furthermore, the study integrates advanced regression modelling, employing both linear and non-linear approaches to accurately predict the factor of safety (FoS) for different soil types (CI, MI, and CL-ML soils). This modelling captures the inherent complexities of geotechnical parameters, particularly in MI soils with high variability. Additionally, the research emphasizes the need for region-specific optimization, tailoring NS concentrations and stabilization techniques to the specific conditions of the Himalayan soils. By adopting probabilistic modelling, the study moves beyond traditional deterministic analyses, offering a reliable framework for assessing slope stability under diverse environmental conditions. These combined innovations contribute significantly to geotechnical engineering by providing a robust, adaptable, and region-specific solution for enhancing slope resilience in mountainous terrains.

1.2. Study Area

Figures 1 and 2 illustrate the spatial distribution of different soil types and slopes across Gandaki Province in central Nepal. The map's legend identifies three distinct soil types: CL-ML, CI, and MI, along with their respective coverage percentages. The dominant soil type, CL-ML, covers 85.71% of the region and is represented by green on the map. This classification corresponds to low to medium plasticity silty clay soils, commonly associated with alluvial or colluvial deposits. These soils are generally suitable for agriculture and construction due to their moderate plasticity and stable properties. The second soil type, CI, covers 11.99% of the province and is shown in red. This category represents medium plasticity clay soils, which tend to have higher water retention capacity and cohesive strength. However, their plasticity may pose challenges in geotechnical applications, requiring careful consideration for construction projects. The least prevalent soil type, MI, accounts for only 2.3% of the area and is marked in blue. These soils are characterized by low plasticity silts, often found in floodplain regions. Their loose to medium-dense granular nature makes them less cohesive and more prone to erosion, but they can be valuable for specific types of farming or as foundation material under controlled conditions. Geographically, the map outlines the boundaries of Gandaki Province, with a north arrow for orientation and a scale of 1:1,350,000 to provide spatial context. The distribution of these soil types reflects the province's diverse topography and geomorphological processes. The predominance of CL-ML soils indicates extensive alluvial plains and colluvial deposits, while the presence of CI and MI soils highlights localized variations in geological and hydrological conditions.

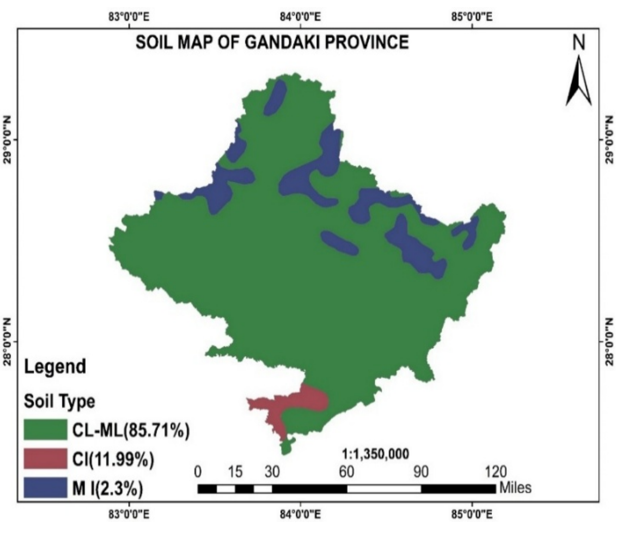


Figure 1. Soil classification map of Gandaki Province, Nepal, showing the spatial distribution of three major soil groups derived from national soil datasets. The dominant soil type is CL-ML (85.71%), followed by CI (11.99%) and MI (2.3%). The map illustrates the prevalence of low-plasticity clay-silt mixtures across the province, with medium-plasticity clays concentrated in the southern belt and isolated pockets of inorganic silts scattered across the region. Scale: 1:1,350,000.

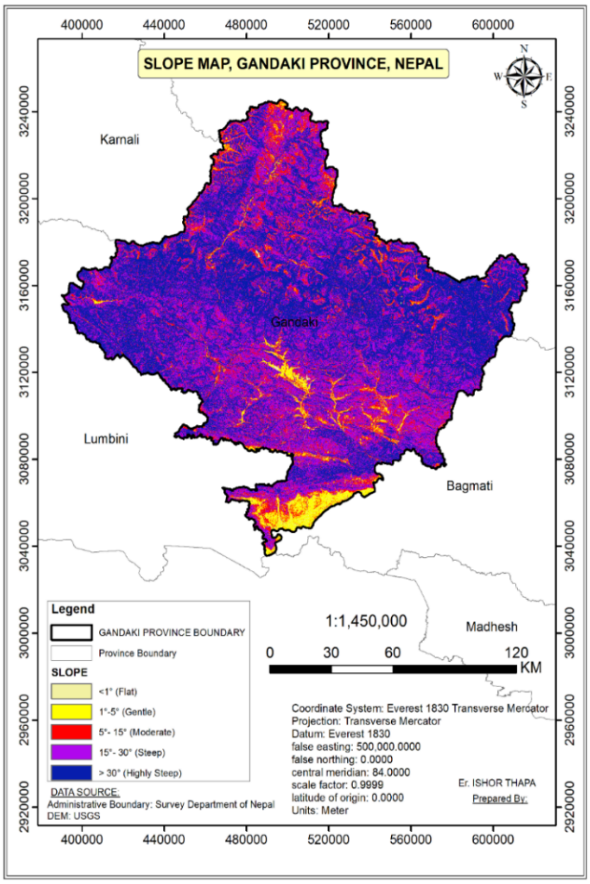


Figure 2. Slope map of Gandaki Province, Nepal, generated from USGS DEM data and classified into <1°, 1–5°, 5–15°, 15–30°, and >30° slope intervals. The spatial distribution highlights dominant steep terrains in the central and northern regions and gentler slopes in the southern lowlands. Mapping was performed using the Everest 1830 Transverse Mercator projection (Central Meridian: 84° E, Scale Factor: 0.9999).

2. Regression Analysis

2.1. Linear Regression

Linear regression analysis is a statistical method used to model and analyze relationships between a dependent variable (response) and one or more independent variables (predictors). In geotechnical and civil engineering, linear regression can be applied to predict key parameters, such as soil stability metrics, based on factors like material properties, environmental conditions, and stabilization techniques. The simplicity and interpretability of linear regression make it a powerful tool for developing predictive equations that can inform engineering decisions.

In slope stability analysis, linear regression can model relationships between stability metrics (e.g., the factor of safety) and influential factors like soil properties, slope angle, and stabilizing additives like NS. For example, a regression model might relate the factor of safety FoS to NS concentration, curing days as shown in Equation (1).

$$\text{FoS} = \beta_0 + \beta_1(\text{NS}) + \beta_2(CD) + \beta_3(c) + \beta_4(\phi) + \beta_5(H) + \beta_6(\beta) + \beta_7(\gamma) + \beta_8(r_u) + \varepsilon \tag{1}$$

where parameters of the Equation (1) as define below as dependent and independent variables and modle parameters respectively.

- Dependent Variable

FoS = Factor of Safety

- Independent Variables

NS = Nano-silica content (%), CD = Curing days (days),
c = Cohesion (kPa), ϕ = Internal friction angle (degrees),
H = Slope height (m), β = Slope angle (degrees),
γ = Unit weight of soil (kN/m^3), r_u = Pore-pressure ratio (dimensionless)

- Model Parameters

β_0 = Regression intercept

$\beta_1 \ldots \beta_8$ = Regression coefficients representing the influence of each variable on FoS

ε = Error term accounting for unexplained variability

2.2. Non-Linear Regression

Non-linear regression is a statistical method used to model interactions between variables when these do not follow a straight-line pattern. Unlike linear regression, which assumes a direct proportionality between predictors and the response variable, non-linear regression can capture complex, curved trends that frequently occur in engineering and natural sciences. In geotechnical engineering, it is particularly valuable for modelling soil behaviour and stability, where the connections between variables are often intricate and multi-dimensional.

In non-linear regression, the relationship between the dependent variable FoS and independent variables X_1, $X_2 \ldots X_p$ is expressed by a non-linear function:

$$\mathrm{FoS} = f(X;\beta) + \varepsilon \tag{2}$$

where, $f(X;\beta)$ is a non-linear function of the predictors $X = (X_1, X_2 \ldots, X_p)$ and parameters $\beta = (\beta_0, \beta_1 \ldots, \beta_k)$ ε is the error term representing variability not explained by the model.

The function $f(X;\beta)$ can take various forms, including exponential, logarithmic, polynomial, or power functions. Choosing the appropriate form depends on the expected relationship between the response and predictors.

Power models are useful when the rate of change of Y varies non-linearly or when soil shear strength might exhibit a power relationship with nano-silica concentration due to non-linear compaction effects. The power model developed in this study, based on the statistical analysis of the experimental dataset, is presented in the Equation (3) below.

$$\mathrm{FoS} = \beta_0 X^{\beta_1} + \varepsilon \tag{3}$$

3. Experimental Database

3.1. Experimental Work

Soil samples taken from the Lesser Himalayan region were used to collect data for CU triaxial tests for the soil stabilized with NS. These areas were selected for their geological significance and the abundance of medium-clay soils prone to slope instability. The tests were conducted to assess the soil's mechanical properties and stability traits with various NS stabilization conditions. In the laboratory, undisturbed soil samples were carefully prepared and subjected to consolidation to simulate field conditions. In the consolidated undrained triaxial tests, axial loads were applied while keeping the lateral confinement pressure constant to determine characteristics like cohesion, internal friction angle, and pore water pressure behaviour. For stabilized soil samples, varying proportions of NS (0.5%, 1.5%, 3% and 4%) were added to assess its impact on enhancing soil stability in various curing periods. Figure 3 illustrates the setup for the CU test conducted on soil samples. The test apparatus includes a soil sample confined within a cylindrical container, typically made of rigid materials such as steel. The top and bottom of the sample are covered with porous stones or filters to allow drainage. Pressure is applied uniformly to the sample through a loading device, while measurements of deformation and pore water pressure are recorded throughout the test. This setup is crucial for studying the shear strength and consolidation characteristics of soils under various loading conditions, providing valuable insights into their engineering behavior [27].

Figure 4 shows the Mohr circles obtained from CU triaxial tests for soil samples with and without NS stabilization across different curing durations. Figure 4a represents the Mohr circle for an untreated soil specimen containing 0% NS, tested immediately on day 0 that is, without any curing. Figure 4b illustrates the Mohr circle for a soil specimen treated with 4% NS after a 90-day curing period. This context makes it easier to see how NS affects the mechanical characteristics of the soil because the Mohr circle is a graphical depiction used to determine the level of stress at a spot. Lower cohesiveness and internal friction are shown by a smaller Mohr circle in Figure 4a of the original soil sample that did not include any NS. This means the soil can withstand only a specific level of shear stress before collapsing. On the contrary, the soil parameters in Figure 4b exhibit a significant enhancement after being treated with 4% NS for 90 days. In this case, the Mohr circle is significantly bigger, indicating better cohesion and internal friction angle, resulting in increased stability and shear strength of the soil. The alterations in look emphasize the effectiveness of NS in enhancing soil stability. This is crucial for slope stabilization and other geotechnical engineering areas because a wider Mohr circle after NS treatment suggests the soil can endure increased stress without collapsing. The illustration clearly shows NS's gradual enhancement of soil strength characteristics and emphasizes its potential usefulness in soil stabilization.

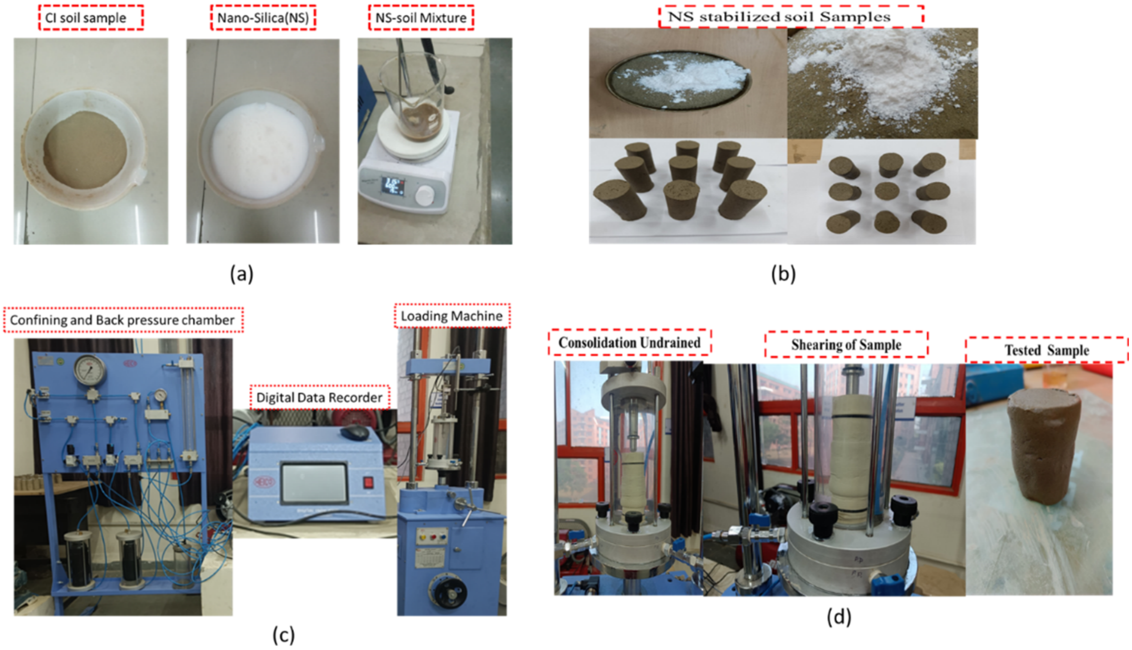


Figure 3. Soil and NS (**a**) soil samples (**b**) CU test setup(**c**) Shearing of sample(**d**).

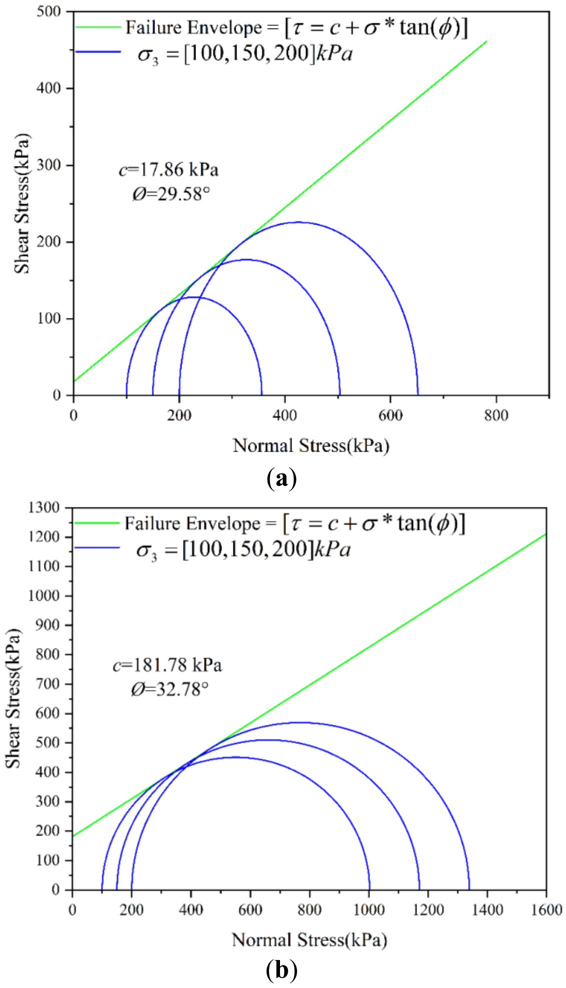


Figure 4. Mohr circle of the triaxial test (**a**) 0% NS at 0 days and (**b**) 4%NS at 90 days.

3.2. Experimental Factor of Safety Calculation

The detailed description of the infinite slope equations may be found in other studies in this section, providing a brief overview to establish context for the upcoming numerical studies and to ensure uniformity in notation (Dolojan et al., 2021; Liu et al., 2021). An infinite slope analysis's fundamental presumption is that the slope is extremely long about the possible failure surface's vertical depth (H). The side forces on either side of a typical slice within a long slope, as depicted in Figure 5, can be thought of as equal and opposite; hence, it is not necessary to know the magnitude of these forces because they cancel out. As a result, every vertical soil column inside the infinite slope is identical to every other vertical column and can be regarded as representative of the total potential sliding mass.

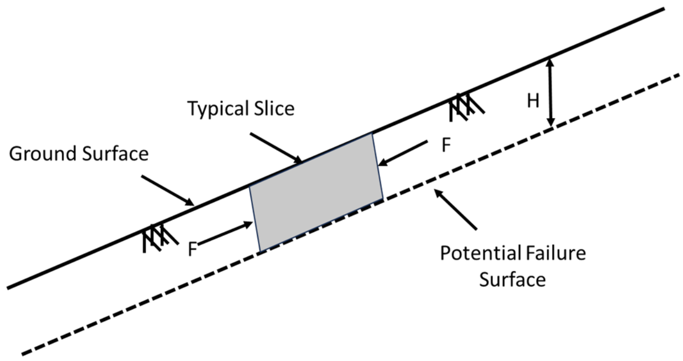


Figure 5. Illustration of infinite slope problem that displays a normal slice with opposing and equal side forces.

The general arrangement and forces acting on a typical slice of a *c′*-*u′* soil of width *L* are depicted in Figure 6a, where c_{sat}, cm and *c′* are the soil's saturated, moist, and buoyant unit weights, respectively, and *H* and *b* are the depth and inclination of the potential failure plane. The water surface is represented by d_w, which is assumed to be parallel to the ground surface in this study. The steady flow net and the formula for calculating the pore pressure at any depth below the water's surface are depicted in Figure 6b. Figure 6a depicts how a standard slice of *c′*-*u′* soil with width *L* is laid out and the forces acting on it. The soil's saturated, moist, and buoyant unit weights are labelled as c_{sat}, c_m, and *c′*, with *H* and *b* indicating the depth and slope of the potential failure plane. This study assumes that d_w represents the water surface and is parallel to the ground surface. In Figure 6b, the continuous flow network and the equation are used to calculate the pore pressure at different depths beneath the water's surface.

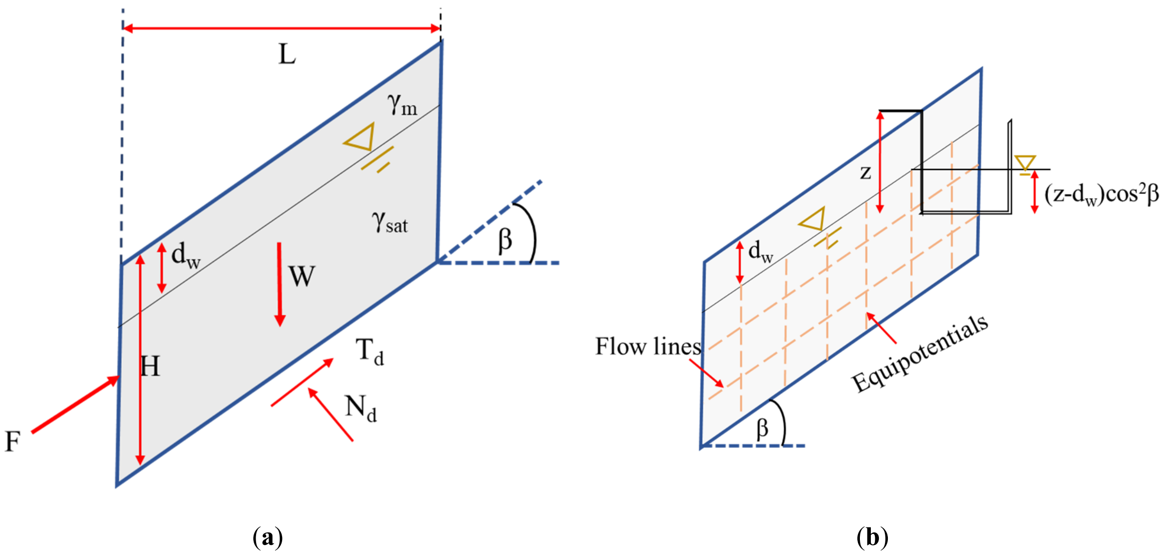


Figure 6. (**a**) Size and pressures at a regular section with a water level and constant seepage parallel to the surface; and (**b**) the continuous flow pattern and equation for calculating the pore pressure at any depth under the water level.

Based on limited equilibrium considerations as shown in Equation (4) below

$$\mathrm{FoS} = \frac{c'}{((\mathrm{H}-\mathrm{d_w})\gamma_{sat} + d_w\gamma_m)cos\beta sin\beta} + \frac{((\mathrm{H}-\mathrm{d_w})\gamma' + d_w\gamma_m)tan\phi}{((\mathrm{H}-\mathrm{d_w})\gamma_{sat} + d_w\gamma_m)tan\beta} \quad (4)$$

Equation (4) is the standard formula for an infinite slope's Factor of Safety, where the water's surface runs parallel to the ground and the soil's unit weights above and below the water's surface differ. Under the cautious assumption that $\gamma_m \approx \gamma_{sat}$, the formula reduces as shown in Equation (5).

$$\mathrm{FoS} = \frac{c'}{H\gamma_{sat} cos\beta sin\beta} + \frac{(H\gamma_{sat} - (H - d_{w)}\gamma_m) tan\phi}{H\gamma_{sat} tan\beta} \tag{5}$$

where paramters of Equations (4) and (5) are describe below:

FoS: Factor of Safety against slope failure, defined as the ratio of available shear strength to the mobilized shear stress along the potential failure surface.

c': Effective cohesion of the soil (kPa), representing the cohesive component of shear strength after excluding pore-water pressure effects.

γ_{sat}: Saturated unit weight of soil (kN/m^3), used for the portion of the slope located below the groundwater table.

γ_m: Moist or natural unit weight of soil (kN/m^3), applicable for the soil above the water table.

γ': Effective (submerged) unit weight of soil (kN/m^3)

H: Total height of the slope (m).

d_w: Depth of the water table measured vertically from the ground surface (m).

β: Slope angle (degrees) measured from the horizontal.

ϕ: Effective internal friction angle of the soil (degrees), representing the frictional resistance along the potential shear plane.

γ_w: Unit weight of water (kN/m^3), used when determining the submerged unit weight.

3.3. Pore Pressure Parameter (r_u)

A different method of determining the pore pressures on the possible failure plane is by using the pore pressure parameter (r_u), which is generally described as in Equation (6).

$$r_u = \frac{u}{\sigma_V} \tag{6}$$

where σ_v is the total vertical stress, u is generated pore-water pressure

Therefore with constant seepage parallel to the ground surface in the scenario depicted in Figure 6b, pore water pressure ratio can be calculated as shown in Equation (7).

$$r_u = \frac{(H - d_w)\gamma_w cos^2\beta}{H\gamma_{sat}} \tag{7}$$

Equation (7) indicates that r_u is also a function of the slope angle β when there is steady seepage parallel to the ground surface and the water surface at depth d_w. This, upon substituting in Equation (5), yields Equation (8).

$$\mathrm{FoS} = \frac{c'}{H\gamma_{sat} cos\beta sin\beta} + (1 - \frac{r_u}{\cos^2\beta}) \frac{tan\phi}{tan\beta} \tag{8}$$

3.4. Infinite Slope Analysis

Equation (5) can be rearranged by dividing through by $tan\phi$, which yields the formula for FoS is represented as shown in Equation (9).

$$\frac{\mathrm{FoS}}{tan\phi} = \frac{c'}{H\gamma tan\phi} \mathrm{x} \frac{1}{cos\beta sin\beta} + (1 - \frac{r_u}{cos^2\beta}) \frac{1}{tan\beta} \tag{9}$$

where ϕ denotes the effective angle of internal friction, c denotes the effective cohesion, γ denotes the unit weight of the soil, H denotes the height of the slope, β denotes the slope angle, and r_u denotes the pore water pressure ratio. This equation considers both the elements that increase slope stability and those that decrease it, providing a comprehensive assessment of FoS.

4. Statistical Description of Database

4.1. Database of CI Soil

Table 2 provides a statistical summary of various parameters associated with CI soil, including data on factor of safety (FoS), unit weight (γ), curing days (CD), nano-silica content (NS), cohesion (c), an unspecified variable, height (H), slope angle (β), and pore pressure ratio (r_u), across 1053 observations. The wide FoS range (0.052–7.467) reflects the deliberate inclusion of both failure-prone and highly stable slope configurations in the regression modelling framework. Extremely low values (<1) correspond to simulated near-failure conditions driven by high pore pressures, steep slope geometries, and minimal shear strength, while the higher FoS values represent highly stable cases arising from favourable geotechnical parameters and NS-induced strengthening. This broad spectrum was necessary to capture the full behavioural variability of CI soils in the geologically complex Lesser Himalayan region and to ensure robust machine-learning generalisation across diverse stability conditions. This broad range suggests considerable variability in soil stability within the CI soil category, highlighting different conditions or strengths across samples. The γ remains constant at 16 kN/m^3 with no variation across observations, indicating that all CI soil samples analyzed possess the same density, which is typical when testing soils with consistent material composition. The curing days (CD) show wide variation, ranging from 0 to 90 degrees, with a mean of 41.538 and a standard deviation of 37.3. This high variability suggests differing levels of soil compaction, likely influenced by local conditions or site-specific soil handling. The NS content, a stabilizing additive, ranges from 0% to 4%, averaging 2.077% with a standard deviation of 1.426, indicating that nano-silica is present in varying but modest amounts across samples. Higher nano-silica content could correlate with increased stability, as suggested by other studies on soil stabilization. The cohesion (*c*), a key factor in soil shear strength, spans a large range, from 34.56 kPa to 259.88 kPa, with an average of 126.338 kPa and a high standard deviation of 65.565 kPa, underscoring significant diversity in the cohesive properties of CI soils. The next variable, which lacks a label, ranges narrowly from 29.24 to 31.85 with a mean of 30.504 and a standard deviation of 0.853. Given this low variability, it might represent a relatively stable soil property.

Table 2. Statistics of CI soil.

Variable	Observations	Minimum	Maximum	Mean	Std. Deviation
FoS	1053	0.052	7.467	1.737	1.223
γ	1053	16	16	16	0
CD	1053	0	90	41.538	37.3
NS (%)	1053	0	4	2.077	1.426
c	1053	34.56	259.88	126.338	65.565
ϕ	1053	29.24	31.85	30.504	0.853
H	1053	6	18	12	4.901
β	1053	20	60	40	12.916
r_u	1053	0	0.5	0.231	0.207

Height (*H*) of the slope or soil depth ranges from 6 to 18 m, with a mean of 12 m and a standard deviation of 4.901, indicating moderate variability in height. The slope angle (*β*) varies from 20 to 60 degrees, with an average of 40 degrees and a standard deviation of 12.916, reflecting the range of inclinations typical in natural or engineered slopes of CI soils. Finally, the pore pressure ratio (r_u) varies from 0 to 0.5, with a mean of 0.231 and a standard deviation of 0.207, suggesting some instances of high pore pressure, which could significantly affect slope stability. This statistical breakdown provides essential insights into the properties of CI soil, useful for evaluating stability, compaction, and shear strength, as well as understanding the influence of additives like nano-silica. The variability across parameters like FoS, CD, and *c* highlights the diverse nature of CI soils, with implications for site-specific geotechnical analysis and design.

Table 3 and Figure 7 show the correlation matrix offers insights into the relationships between key variables influencing CI soil behaviour, including unit weight (*γ*), nano-silica content (NS), curing days (CD), cohesion (*c*), an unspecified parameter, height (*H*), slope angle (*β*), pore pressure ratio (r_u), and factor of safety (FoS). Correlation coefficients range from −1 to 1, with values closer to 1 or −1 indicating strong positive or negative correlations, respectively. NS content shows a moderate positive correlation with cohesion (*c*) (0.508) and factor of safety (FoS) (0.296). This suggests that higher NS content may enhance the cohesion and stability of CI soil, contributing to increased shear strength and potentially greater slope stability. NS has a weak correlation with curing days (CD) (0.135), indicating only a slight association with soil density improvements, which may depend on other factors like compaction methods.

The curing days (CD) display strong positive correlations with both cohesion (*c*) (0.880) and FoS (0.580), highlighting its significant role in improving soil stability. High compaction levels tend to enhance cohesion, which directly contributes to the soil's resistance against shear failure, reflected in the higher factor of safety. The correlation between CD and the unspecified parameter (0.985) and with NS content (0.135) suggests that, in this dataset, compaction is influenced more by soil properties than by additives. Cohesion (*c*) also shows strong correlations with the factor of safety (FoS) (0.644) and CD (0.880), underscoring cohesion's importance in overall soil stability. This strong link suggests that cohesion is a key contributor to the factor of safety, particularly in soils with good compaction and possibly due to the effects of nano-silica. The height (H) and slope angle (β) of the soil or slope have moderate negative correlations with FoS (−0.567 for H and −0.287 for β), indicating that as slope height and steepness increase, stability tends to decrease. This reflects typical geotechnical behaviour where taller and steeper slopes are generally less stable due to increased shear stress. The slight correlation of H with FoS (−0.567) suggests that slope height plays a notable role in stability assessments. The pore pressure ratio (r_u) has a low positive correlation with FoS (0.296), suggesting a complex, potentially indirect relationship with stability. While increased pore pressure typically decreases stability in geotechnics, here the low positive correlation may reflect interactions with other factors like compaction and cohesion.

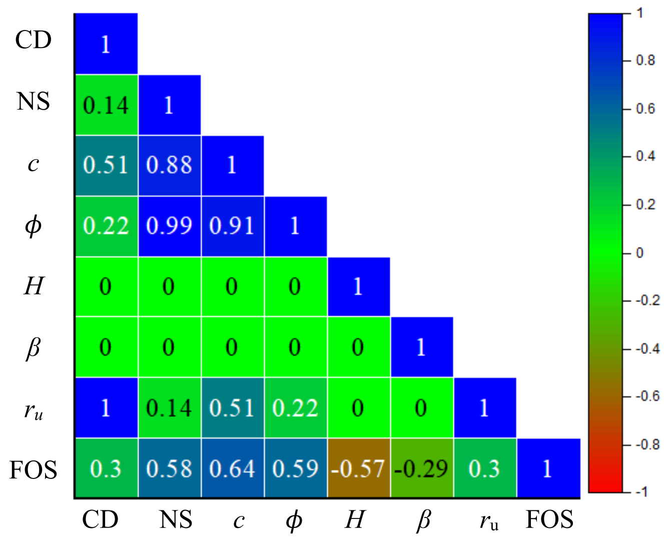


Figure 7. Correlation matrix of CI soil.

Table 3. Correlation matrix of CI soil.

Variable	γ	NS (%)	CD	c	ϕ	H	β	r_u	FoS
γ	0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
NS (%)	0	1	0.135	0.508	0.218	0.000	0.000	1.000	0.296
CD	0	0.135	1	0.880	0.985	0.000	0.000	0.135	0.580
c	0	0.508	0.880	1	0.908	0.000	0.000	0.508	0.644
ϕ	0	0.218	0.985	0.908	1	0.000	0.000	0.218	0.596
H	0	0.000	0.000	0.000	0.000	1	0.000	0.000	−0.567
β	0	0.000	0.000	0.000	0.000	0.000	1	0.000	−0.287
r_u	0	1.000	0.135	0.508	0.218	0.000	0.000	1	0.296
FoS	0	0.296	0.580	0.644	0.596	−0.567	−0.287	0.296	1

The factor of safety (FoS) itself correlates most strongly with cohesion (0.644) and compaction (0.580), indicating that these two parameters are the primary contributors to stability in CI soil. Weak correlations with NS and CD also imply that stability can be enhanced with proper compaction and the right balance of cohesive additives. Negative correlations with slope height (H) and angle (β) further emphasize the destabilizing effect of taller and steeper slopes. In summary, the matrix highlights key relationships among factors influencing CI soil stability, suggesting that curing days and cohesion are primary drivers of stability, while nano-silica content provides additional strength benefits. The results underscore that, while slope characteristics like height and angle negatively impact stability, adequate compaction and cohesive strength can significantly mitigate failure risks in CI soil.

4.2. Database of MI Soil

Table 4 provides a summary of statistical data for MI soil, detailing key variables across 1053 observations. The variables analyzed include the factor of safety (FoS), unit weight (γ), curing days (CD), nano-silica content (NS), cohesion (c), an unspecified variable, height (H), slope angle (β), and pore pressure ratio (r_u). The factor of safety (FoS) ranges from −0.023 to 4.659, with a mean of 1.274 and a standard deviation of 0.823. This variation, including negative values, indicates potential instability in some samples, where soils may be susceptible to failure. The unit weight (γ) of the MI soil is constant at 18.98 kN/m^3, showing no variation, suggesting uniformity in material density across samples, which is typical for controlled soil testing conditions.

Table 4. Statistics of MI soil.

Variable	Observations	Minimum	Maximum	Mean	Std. Deviation
FOS	1053	−0.023	4.659	1.274	0.823
γ	1053	18.98	18.98	18.98	0
CD	1053	0	90	41.538	37.3
NS (%)	1053	0	4	2.077	1.426
c	1053	23.89	156.99	88.852	39.199
ϕ	1053	29.28	31.96	30.354	0.739
H	1053	6	18	12	4.901
β	1053	20	60	40	12.916
r_u	1053	0	0.5	0.231	0.207

The curing days (CD) vary significantly from 0 to 90 degrees, with a mean of 41.538 and a high standard deviation of 37.3. This indicates a broad range of soil compaction levels, reflecting differences in soil density and preparation methods. Variability in CD often affects stability, as higher compaction can increase the soil's load-bearing capacity and resistance to shear. The nano-silica content (NS) ranges from 0% to 4%, averaging 2.077% with a standard deviation of 1.426, showing a moderate addition of nano-silica across samples. This stabilizing additive may be used to enhance soil strength, though its impact likely varies depending on its concentration and interaction with other factors like compaction. The cohesion (c) values range from 23.89 kPa to 156.99 kPa, with an average of 88.852 kPa and a standard deviation of 39.199 kPa. Cohesion, a critical factor in soil shear strength, shows moderate variability, suggesting that MI soils exhibit diverse cohesive properties. This variation influences the overall stability and bearing capacity, making cohesion a crucial parameter for understanding soil behaviour under load.

The next variable, which is unspecified, ranges from 29.28 to 31.96 with a mean of 30.354 and a low standard deviation of 0.739. This limited range and low variability may indicate a stable soil characteristic, potentially related to moisture content or some physical soil trait. The height (H) of the soil layer or slope ranges from 6 to 18 m, with a mean of 12 m and a standard deviation of 4.901. This distribution of height values indicates different slope or soil column conditions, affecting stability, as taller slopes often face increased shear forces. The slope angle (β) varies between 20 and 60 degrees, with an average of 40 degrees and a standard deviation of 12.916. Such variability in slope angle reflects a range of inclinations that would impact the factor of safety, as steeper slopes are generally less stable and more prone to failure.

The pore pressure ratio (r_u) spans from 0 to 0.5, with a mean of 0.231 and a standard deviation of 0.207. This variation in pore pressure reflects changes in soil saturation and drainage conditions, which can directly influence stability. Higher r_u values generally reduce stability by increasing internal pore pressure, reducing effective stress, and thus, decreasing soil strength. In summary, the MI soil statistics illustrate considerable variability across compaction, cohesion, slope angle, and pore pressure, each significantly affecting soil stability and performance. While the consistent unit weight and nano-silica content indicate material uniformity, variations in factors of safety, compaction, and cohesion highlight the complexity of MI soils. These factors, in combination with slope characteristics, play a vital role in assessing the soil's stability, bearing capacity, and susceptibility to failure in geotechnical applications.

Table 5 and Figure 8 explain the correlation matrix reveals the relationships between several key parameters in MI soil, including unit weight (γ), curing days (CD), nano-silica content (NS), cohesion (c), an unspecified variable, height (H), slope angle (β), pore pressure ratio (r_u), and factor of safety (FoS). These correlations offer insights into how these parameters influence soil stability and strength, each represented by correlation coefficients ranging from −1 to 1. Higher absolute values indicate stronger relationships, while values near 0 reflect weaker or negligible relationships. Curing days (CD) show positive correlations with cohesion (c) (0.339) and factor of safety (FOS) (0.141). This suggests that higher compaction can lead to increased soil stability, with improved cohesion contributing to greater resistance against shear failure. The CD also correlates positively with the unspecified variable (0.322) and nano-silica content (NS) (0.135), indicating a potential interaction where higher compaction and added stabilizers, like nano-silica, may work together to strengthen the soil.

Nano-silica content (NS) shows a strong positive correlation with cohesion (0.963) and the factor of safety (0.562), suggesting that higher nano-silica content significantly enhances soil cohesion, which in turn boosts stability. This additive's positive effect on FoS underscores the stabilizing benefits of nano-silica for MI soil. NS also has strong positive correlations with the unspecified variable (0.895), suggesting that it may also influence other stability-related soil properties. Cohesion (c) is strongly correlated with FOS (0.572), highlighting its crucial role in soil stability and shear resistance. Additionally, its strong positive relationship with NS (0.963) and the unspecified variable (0.927) suggests that these factors contribute to cohesion in MI soils. This correlation pattern underlines the importance of cohesive strength as a stabilizing factor, especially with the inclusion of nano-silica. The unspecified variable shares high correlations with NS (0.895), cohesion (0.927), and FoS (0.53), suggesting it may represent a parameter closely related to soil strength, such as internal friction or specific moisture content. Height (*H*) and slope angle (*β*) both exhibit negative correlations with FoS (−0.592 for H and −0.369 for *β*), reflecting the typical destabilizing impact of taller and steeper slopes on soil stability. As slope height and angle increase, the factor of safety tends to decrease due to higher shear stresses and potential instability in steeper conditions. The pore pressure ratio (r_u) has low correlations with other parameters, including a very slight positive correlation with FoS (0.141). In geotechnical contexts, higher pore pressure often reduces soil stability, but here the weak positive relationship might indicate a minor or indirect effect in the presence of other stabilizing factors like compaction and cohesion.

The factor of safety (FoS) itself shows strong positive correlations with cohesion (0.572), NS (0.562), and the unspecified variable (0.53), and a weaker positive correlation with curing days (0.141). These relationships highlight that cohesion, enhanced by additives like nano-silica, plays the most significant role in stabilizing MI soil, while compaction provides additional stability benefits. The negative correlations between FoS and slope characteristics (*H* and *β*) further reinforce the tendency of steeper, taller slopes to decrease stability. Overall, this matrix indicates that cohesion, nano-silica content, and curing days are the primary contributors to MI soil stability. The addition of nano-silica strongly enhances cohesive strength, which in turn boosts the factor of safety, while slope height and angle remain critical factors in stability considerations for geotechnical applications.

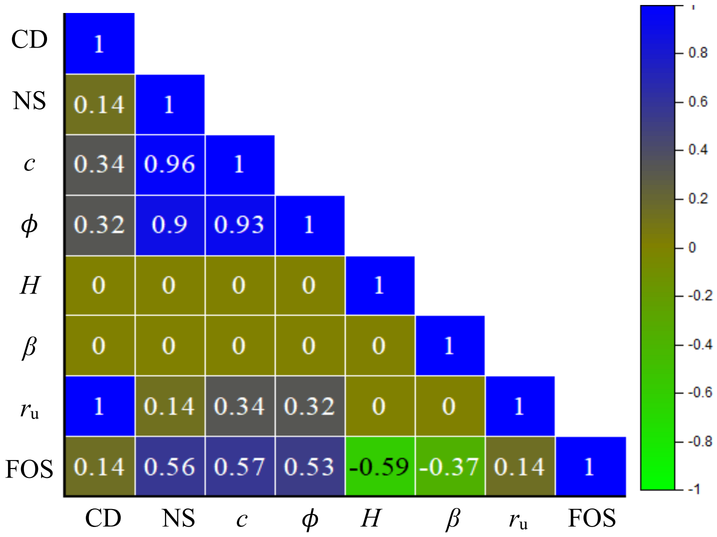


Figure 8. Correlation matrix of MI soil.

Table 5. Correlation matrix of MI soil.

Variable	γ	CD	NS (%)	c	ϕ	H	β	r_u	FoS
γ	0	0	0	0	0	0	0	0	0
CD	0	1	0.135	0.339	0.322	0	0	1	0.141
NS (%)	0	0.135	1	0.963	0.895	0	0	0.135	0.562
c	0	0.339	0.963	1	0.927	0	0	0.339	0.572
ϕ	0	0.322	0.895	0.927	1	0	0	0.322	0.53
H	0	0	0	0	0	1	0	0	−0.592
β	0	0	0	0	0	0	1	0	−0.369
r_u	0	1	0.135	0.339	0.322	0	0	1	0.141
FoS	0	0.141	0.562	0.572	0.53	−0.592	−0.369	0.141	1

4.2. Database of CL-ML Soil

Table 6 provides a summary of statistical properties for CL-ML soil, describing 1053 observations across various key parameters including factor of safety (FoS), unit weight (γ), curing days (CD), nano-silica content (NS), cohesion (c), an unspecified variable, height (H), slope angle (β), and pore pressure ratio (r_u). The factor of safety (FoS) ranges from −0.063 to 5.348, with a mean of 1.292 and a standard deviation of 0.950. This variation, which includes negative values, indicates instances where CL-ML soil samples are potentially unstable, underscoring a range of stability conditions across the samples. The unit weight (γ) is consistent at 18.98 kN/m^3

with no variation, reflecting uniformity in density across samples, which is common in controlled laboratory settings. The curing days (CD) show a broad range, from 0 to 90, with a mean of 41.538 and a standard deviation of 37.3. This high variability highlights differences in soil density, likely due to varying degrees of compaction, which can have significant implications for soil strength and load-bearing capacity. Nano-silica content (NS), a stabilizing additive, varies from 0% to 4% with a mean of 2.077% and a standard deviation of 1.426, indicating that different levels of nano-silica are used across samples. Nano-silica additions may improve soil stability, depending on the proportion added and its interaction with other properties like cohesion and compaction. The cohesion (c) values range widely, from 17.860 kPa to 181.780 kPa, with a mean of 89.918 kPa and a standard deviation of 52.397 kPa. Cohesion, which contributes to shear strength, exhibits considerable variability, suggesting that CL-ML soils have diverse binding properties. This range indicates different degrees of soil stability, with higher cohesion contributing positively to stability.

Table 6. Statistics of CL-ML soil.

Variable	Observations	Minimum	Maximum	Mean	Std. Deviation
FoS	1053	−0.063	5.348	1.292	0.950
γ	1053	19.500	19.500	19.500	0.000
CD	1053	0.000	90.000	41.538	37.300
NS (%)	1053	0.000	4.000	2.077	1.426
c	1053	17.860	181.780	89.918	52.397
ϕ	1053	29.580	32.780	31.114	0.847
H	1053	6.000	18.000	12.000	4.901
β	1053	20.000	60.000	40.000	12.916
r_u	1053	0.000	0.500	0.231	0.207

The angle of internal friction (ϕ) ranges from 29.580 to 32.780, with a mean of 31.114 and a standard deviation of 0.847. Given its low variability, this parameter might represent a relatively stable soil trait, potentially related to moisture or a specific material property. The height (H) of the slope or soil layer varies from 6 to 18 m, with a mean height of 12 m and a standard deviation of 4.901. This variation in slope height influences stability since taller slopes generally have increased shear stress and are more prone to potential failure. The slope angle (β) ranges from 20 to 60 degrees, with a mean of 40 degrees and a standard deviation of 12.916. The range in slope angle reflects different inclinations that affect stability, as steeper slopes tend to be less stable under load. Lastly, the pore pressure ratio (r_u) varies from 0 to 0.5, with a mean of 0.231 and a standard deviation of 0.207. Pore pressure influences soil stability; higher values of r_u generally reduce effective stress, thereby decreasing soil shear strength and increasing the likelihood of slope failure. In summary, this table illustrates the diverse characteristics of CL-ML soils, particularly in cohesion, compaction, and slope characteristics, which are critical factors for geotechnical stability. High cohesion and proper compaction enhance stability, while greater height, steeper slopes, and increased pore pressure can reduce the factor of safety, underscoring the importance of careful assessment of these parameters for designing stable slopes and foundations with CL-ML soils.

Table 7 and Figure 9 describe the correlation matrix for CL-ML soil and illustrates the relationships between key geotechnical parameters, including unit weight (γ), curing days (CD), nano-silica content (NS), cohesion (c), an unspecified variable, height (H), slope angle (β), pore pressure ratio (r_u), and factor of safety (FoS). The values in the matrix indicate the strength and direction of correlations, which range from −1 to 1, where higher absolute values suggest stronger relationships. The curing days (CD) show positive correlations with cohesion (c) (0.463) and factor of safety (FoS) (0.265). This suggests that increased compaction improves soil cohesion and stability, contributing positively to the factor of safety. Additionally, the CD has a moderate positive correlation with the unspecified variable (0.543) and a strong correlation with r_u (1.0), suggesting potential interactions between compaction, moisture retention, and soil stability.

Nano-silica content (NS) has a strong positive correlation with cohesion (0.917) and factor of safety (FoS) (0.621), indicating that adding nano-silica significantly enhances soil cohesion, which in turn improves stability. NS also correlates positively with the unspecified variable (0.882), indicating that nano-silica additions may interact with other soil properties to further enhance stability. Cohesion (c) shows a strong positive correlation with FoS (0.660), highlighting its crucial role in soil stability. Higher cohesion contributes directly to resistance against shear failure, and its positive correlations with NS (0.917), CD (0.463), and the unspecified variable (0.935) suggest that cohesion is influenced by compaction, stabilizers, and other intrinsic soil factors, all of which contribute to increased stability in CL-ML soils. The unspecified variable also shares high positive correlations with cohesion (0.935), NS (0.882), and FoS (0.613), suggesting it might represent a factor closely linked to soil stability, such as internal friction or some physical or chemical property influencing soil binding strength.

Height (*H*) and slope angle (β) both exhibit negative correlations with FoS (−0.519 for H and −0.326 for β), indicating that as the slope height and angle increase, the factor of safety decreases. This reduction in FoS with increased height and steepness is consistent with geotechnical principles, as taller and steeper slopes face greater shear stress and are therefore more prone to potential failure. The pore pressure ratio (r_u) has a modest positive correlation with FoS (0.265), but it strongly correlates with CD (1.0), suggesting that increased compaction may influence pore pressure conditions. While higher r_u values are generally destabilizing in geotechnical terms, here the positive relationship might indicate that compaction stabilizes the soil by altering pore water conditions under controlled conditions. FoS itself is strongly influenced by cohesion (0.660), NS content (0.621), and the unspecified variable (0.613). These strong positive relationships suggest that improvements in cohesive strength and NS additions are essential to enhancing the overall stability of CL-ML soils. The moderate positive correlation with CD (0.265) and negative correlations with slope height and angle (*H* and β) emphasize the role of compaction and slope geometry in maintaining stability. In summary, this matrix underscores the primary role of cohesion and NS content in enhancing CL-ML soil stability. While compaction and slope characteristics contribute to safety, higher cohesion supported by additives like NS is key in preventing soil failure. These findings are essential for designing stable slopes and structures involving CL-ML soils in geotechnical engineering applications.

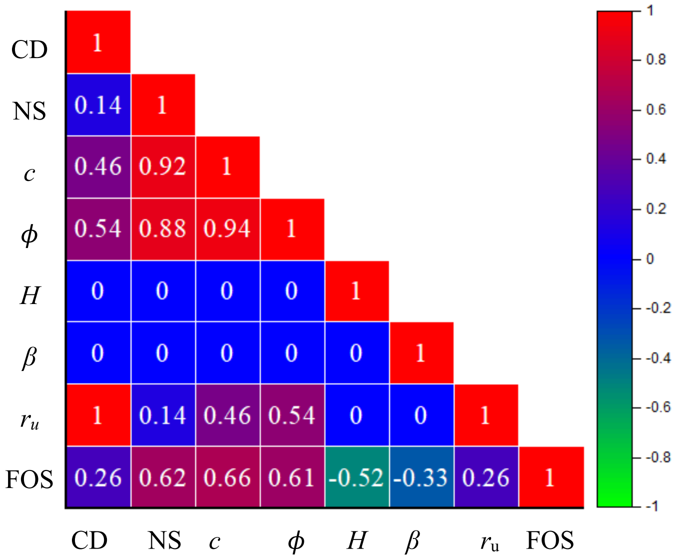


Figure 9. Correlation matrix of CL-ML soil.

Table 7. Correlation matrix of CL-ML soil.

	γ	CD	NS (%)	c	ϕ	H	β	r_u	FoS
γ	0	0	0	0	0	0	0	0	0
CD	0	1	0.135	0.463	0.543	0.000	0.000	1.000	0.265
NS (%)	0	0.135	1	0.917	0.882	0.000	0.000	0.135	0.621
c	0	0.463	0.917	1	0.935	0.000	0.000	0.463	0.660
ϕ	0	0.543	0.882	0.935	1	0.000	0.000	0.543	0.613
H	0	0.000	0.000	0.000	0.000	1	0.000	0.000	−0.519
β	0	0.000	0.000	0.000	0.000	0.000	1	0.000	−0.326
r_u	0	1.000	0.135	0.463	0.543	0.000	0.000	1	0.265
FoS	0	0.265	0.621	0.660	0.613	−0.519	−0.326	0.265	1

5. Results and Discussion

This section presents a detailed analysis of the developed regression and non-regression models to estimate the Factor of Safety (FoS) for slopes stabilized with nano-silica (NS)—treated fine-grained soils. The results are structured by soil classification CI, CL-ML, and MI to provide targeted insights into the behavior of each soil type under varying geotechnical and treatment conditions. Both linear and non-linear regression models are evaluated and compared based on statistical performance metrics such as the coefficient of determination (R^2), root mean squared error (RMSE), and mean absolute error (MAE), with validation supported by 5-fold cross-validation and bootstrapping techniques. Diagnostic plots, SHAP-based feature interpretability, and sensitivity analyses further support the robustness and transparency of the models. The discussion emphasizes not only predictive accuracy but also the physical interpretability of model coefficients and their alignment with established geotechnical principles. By integrating empirical data with statistical and machine learning techniques, this study offers practical and generalizable models for assessing slope stability in NS-stabilized soils.

5.1. Linear Regression Model CI Soil

The linear regression model developed for CI-type soil offers a clear, interpretable relationship between key geotechnical parameters and the Factor of Safety (FoS). The model is expressed as in Equation (10).

$$\text{FoS} = 4.7651 + (-0.1413 \times H) + (-0.0601 \times \phi) + (0.377 \times \text{NS}(\%)) + (-0.0272 \times \beta) + (0.0123 \times c) \quad (10)$$

This equation indicates that the FoS is influenced by the slope height (H), internal friction angle (ϕ), nano-silica content (NS%), slope angle (β), and soil cohesion (c). Among these, the most substantial negative impact on FoS comes from the slope height, where each additional meter in height reduces the safety factor by approximately 0.1413 units, reflecting the increased driving force associated with taller slopes. Similarly, a steeper slope angle (β) contributes negatively to slope stability, with each degree of inclination decreasing FoS by 0.0272. Interestingly, the model suggests a slight negative influence of internal friction angle (ϕ), which, although counterintuitive from a theoretical standpoint, may be attributed to complex interactions in the dataset or specific behaviours of the CI soil under nano-silica treatment.

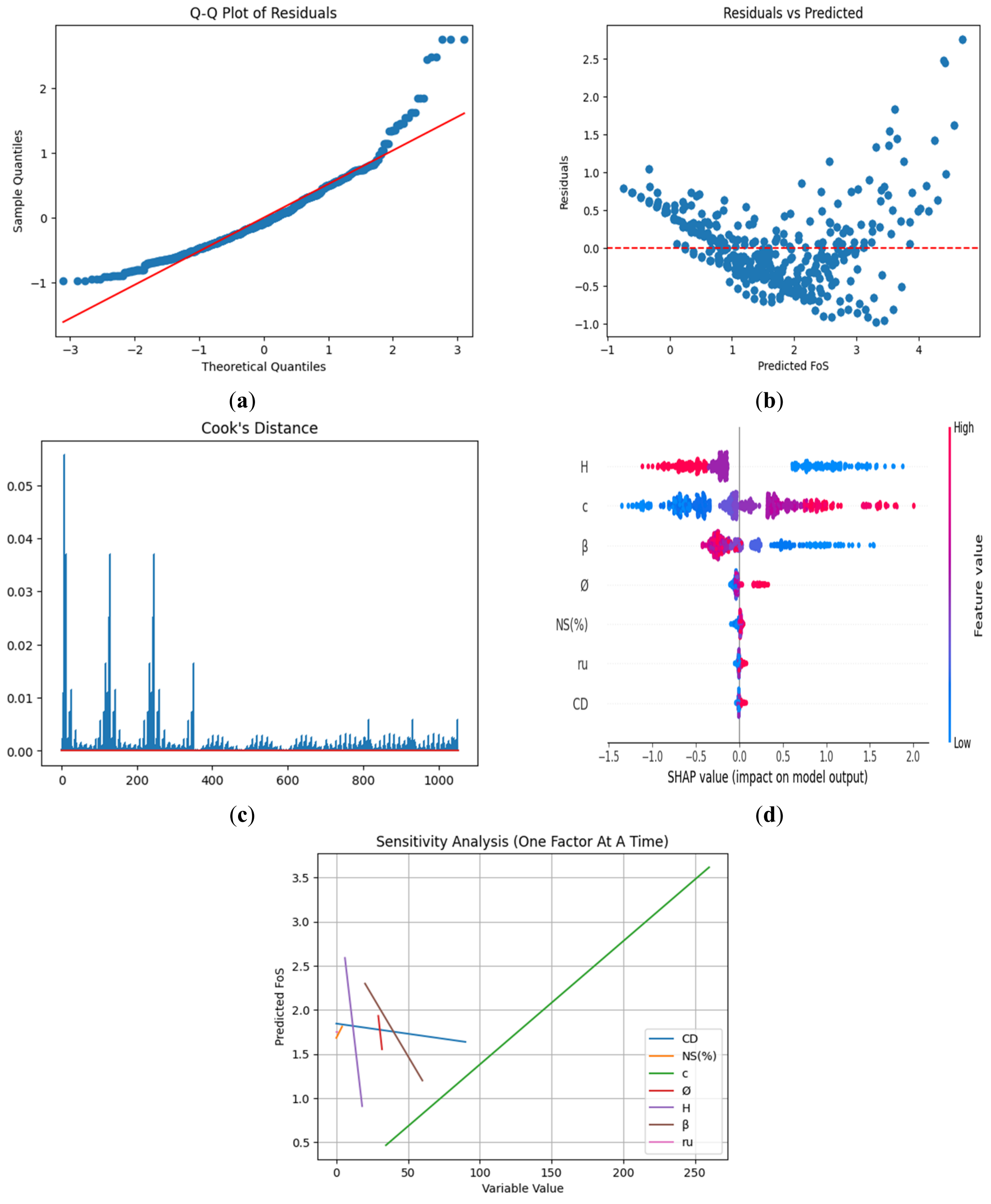
On the positive side, the incorporation of nano-silica demonstrates a clear stabilizing effect; for every 1% increase in NS content, the FoS improves by 0.0377, highlighting the effectiveness of NS in enhancing soil structure and shear resistance. Additionally, soil cohesion (c) contributes positively to stability, where each 1 kPa increase in cohesion improves the FoS by 0.0123. The model's structure reflects the balance between destabilizing geometric factors and stabilizing material improvements, making it both physically meaningful and practically useful. Overall, this equation serves as a reliable, simplified tool for estimating slope stability in NS-treated CI soils and offers valuable guidance for preliminary design and field assessments in mountainous regions.

Table 8 presents the statistical validation results of the linear regression model developed to predict the Factor of Safety (FoS) for nano-silica–stabilized CI soil. The model demonstrates robust predictive performance, as reflected by a mean cross-validated R^2 value of 0.8161, indicating that approximately 82% of the variability in FoS is explained by the input variables across different validation folds. The corresponding mean Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) values are 0.5198 and 0.3982, respectively, which reflect a good level of accuracy in the model's predictions with relatively low error margins. The standalone R^2 value for the linear model on the full dataset is 0.8198, showing consistency with the cross-validation results and confirming the model's stability and generalizability. For benchmarking purposes, a Random Forest (RF) model was also evaluated, achieving an R^2 value of 0.9999, which, while exceptionally high, may reflect potential overfitting given the simplicity and interpretability goals of the current study. Furthermore, a 1000-iteration bootstrapping analysis was performed to assess the uncertainty and robustness of the linear model. The 95% confidence interval for R^2 ranges narrowly from 0.8158 to 0.8195, while the RMSE lies between 0.5192 and 0.5246, reinforcing the reliability and repeatability of the regression outcomes. Overall, the metrics in Table 3 confirm that the linear regression model provides a strong, interpretable, and statistically valid framework for estimating FoS in CI soils treated with nano-silica.

Table 8. Validation results of the linear regression model for FoS prediction in NS-treated CI soil.

Parameters	Values
CrossVal_R^2_Mean	0.8161
CrossVal_RMSE_Mean	0.5198
CrossVal_MAE_Mean	0.3982
Linear_R^2	0.8198
RF_R^2	0.9999
Boot_R^2_CI_Low	0.8158
Boot_R^2_CI_High	0.8195
Boot_RMSE_CI_Low	0.5192
Boot_RMSE_CI_High	0.5246

Figure 10 presents a comprehensive set of diagnostic and interpretability plots for the linear regression model developed to predict the Factor of Safety (FoS) in nano-silica (NS)-treated clay of intermediate plasticity (CI soil). These plots are crucial for validating the statistical assumptions of the model and for interpreting the influence of geotechnical parameters on slope stability. Figure 10a shows the Q-Q plot of residuals, where most points closely follow the red reference line, indicating that the residuals are approximately normally distributed—a key assumption for the validity of linear regression. Figure 10b plots residuals against predicted FoS values, demonstrating a fairly random distribution with no clear pattern, suggesting homoscedasticity and the absence of systematic bias in predictions. The horizontal spread of residuals also implies consistent prediction errors across the range of FoS values.



(**a**) (**b**) (**c**) (**d**) (**e**)

Figure 10. Diagnostic and interpretability plots for the linear regression model predicting Factor of Safety (FoS) in NS-treated CI soil.

Figure 10c, Cook's Distance plot, identifies the influence of individual observations on the regression model. All values remain below the conventional threshold of 1, indicating that there are no highly influential outliers skewing the model, thus confirming its stability and generalizability. Figure 10d is a SHAP (SHapley Additive exPlanations) summary plot, which ranks the importance of input features in determining the predicted FoS. Features such as slope height (H), cohesion (c), and slope angle (β) show the most substantial impact. The colour gradient shows how high and low feature values shift the predictions: for instance, high H and β tend to reduce

FoS, while higher cohesion contributes positively, enhancing slope stability. Figure 10e provides a sensitivity analysis using a one-factor-at-a-time approach. Here, each input variable is varied independently while holding others constant to observe its isolated effect on FoS. The analysis reveals that an increase in pore pressure ratio (r_u) and slope height (H) significantly decreases FoS, aligning with geotechnical principles, while cohesion (c) and friction angle ($Ø$) contribute positively to slope stability. Nano-silica percentage (NS%) and curing days (CD) also exhibit positive, albeit moderate, influence on stability improvement. Together, these visualizations confirm that the linear regression model is statistically valid and offers meaningful insights into the behaviour of NS-treated CI soil. The interpretability components enhance the model's transparency, making it a valuable tool for geotechnical design and decision-making.

5.2. Linear Regression Model CL-ML Soil

The linear regression equation developed for CL-ML soil, treated with nano-silica (NS), provides a simplified yet interpretable model for estimating the Factor of Safety (FoS) based on three critical geotechnical parameters. The equation is expressed as in Equation (11).

$$\mathrm{FoS(CL\text{-}ML)} = 2.2509 + (-0.1006 \times H) + (-0.0240 \times \beta) + (0.0122 \times c) \quad (11)$$

This model includes the height of the slope (H), slope angle (β), and soil cohesion (c) as predictive variables. The intercept value of 2.2509 represents the baseline FoS when all input parameters are assumed to be zero. Although this is a theoretical condition and not practically achievable, it serves as the foundational offset in the regression model. The coefficient for slope height (H) is −0.1006, indicating that each 1 m increase in the height of the slope results in a decrease of 0.1006 units in the FoS. This reflects the increased driving forces associated with taller slopes, which aligns with classical geotechnical understanding. Similarly, the slope angle (β) has a negative coefficient of −0.0240, suggesting that steeper slopes inherently exhibit lower stability due to increased shear stresses acting along the potential failure surface.

In contrast, the soil cohesion (c) exhibits a positive influence on FoS, with a coefficient of +0.0122. This means that for every 1 kPa increase in cohesive strength, the FoS improves by 0.0122 units, reinforcing the well-established role of cohesion in enhancing the shear strength of fine-grained soils. Overall, this equation provides a reliable and straightforward tool for preliminary assessment of slope stability in CL-ML soils stabilized with nano-silica. By isolating the most influential parameters, it aids in quick decision-making while maintaining consistency with geotechnical principles. Despite its simplicity, the model successfully captures the essential soil and geometric factors that govern slope stability in highland regions.

Table 9 presents the validation outcomes of the linear regression model formulated to estimate the Factor of Safety (FoS) for CL-ML soil treated with nano-silica (NS). The model shows strong predictive performance, achieving a mean cross-validated R^2 of 0.8091, indicating that approximately 81% of the variance in FoS can be explained by the selected input parameters across multiple data folds. The associated cross-validated Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) are 0.4119 and 0.3195, respectively, confirming the model's capability to deliver accurate predictions with low residual error.

Table 9. Validation results of the linear regression model for FoS prediction in NS-treated CL-ML Soil.

Parameters	Values
CrossVal_R^2_Mean	0.8091
CrossVal_RMSE_Mean	0.4119
CrossVal_MAE_Mean	0.3195
Linear_R^2	0.8133
RF_R^2	1.0000
Boot_R^2_CL-ML_Low	0.8094
Boot_R^2_CL-ML_High	0.8130
Boot_RMSE_CL-ML_Low	0.4108
Boot_RMSE_CL-ML_High	0.4147

The linear regression model also performs consistently on the full dataset, with a standalone R^2 value of 0.8133, closely aligning with the cross-validation outcome, which suggests strong model generalizability and minimal overfitting. For benchmarking, a Random Forest (RF) model was trained on the same dataset, yielding an R^2 value of 1.0000, indicating a perfect fit. While this underscores the capacity of advanced machine learning models to capture complex patterns, it also emphasizes the interpretability advantage of linear models in engineering decision-making. To further evaluate the model's robustness, a bootstrapping analysis with 1000 resamples was conducted. The 95% confidence interval for the R^2 metric lies between 0.8094 and 0.8130, while the RMSE falls within the range of 0.4108 to 0.4147. These narrow confidence intervals indicate high model stability and reinforce its reliability under resampled conditions. Overall, the results in Table 4 validate the effectiveness of the linear regression model as a practical and interpretable tool for assessing slope stability in NS-stabilized CL-ML soils.

Figure 11 presents a comprehensive suite of diagnostic and interpretability plots that validate and elucidate the performance of a linear regression model developed to predict the Factor of Safety (FoS) in nano-silica (NS) treated CL-ML soil. Figure 11a displays a Q-Q plot of the residuals, which assesses the normality assumption of the regression model. The residuals largely align along the reference line, indicating that the residuals are approximately normally distributed—a key assumption of linear regression. Figure 11b illustrates the residuals versus predicted FoS values, revealing a relatively random scatter without a clear pattern, suggesting homoscedasticity (constant variance of residuals) and absence of significant model bias. In Figure 11c, Cook's Distance is plotted to identify influential data points. The low Cook's Distance values across observations imply that no single data point unduly influences the regression model, affirming its robustness.

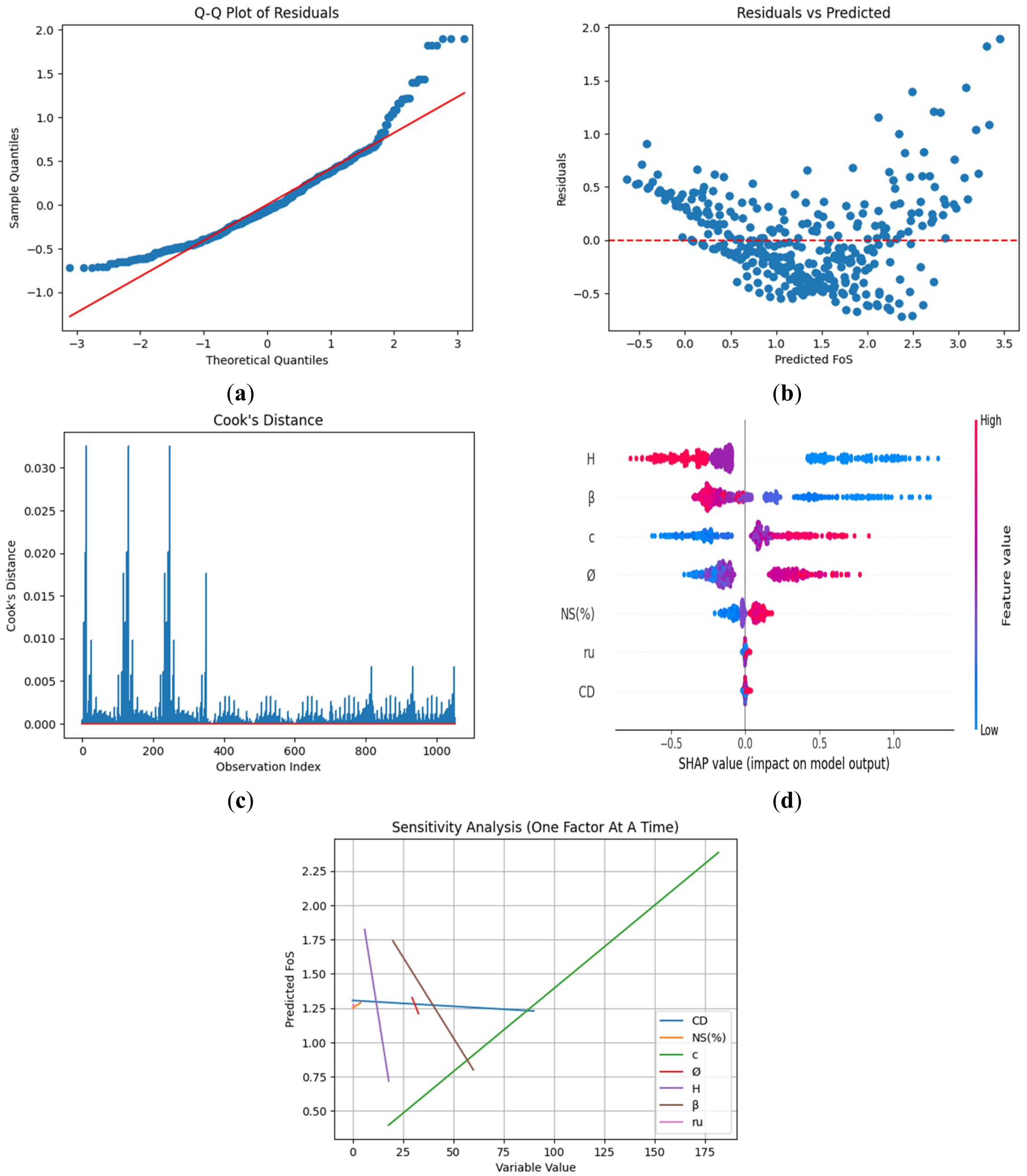


Figure 11. Diagnostic and interpretability plots for the linear regression model predicting Factor of Safety (FoS) in NS-treated CL-ML soil.

Figure 11d presents a SHAP (SHapley Additive exPlanations) summary plot, offering global interpretability by ranking input features based on their contribution to model predictions. Features such as slope height (*H*), slope angle (β), cohesion (*c*), and friction angle (*Ø*) show a strong influence on FoS, with directional impacts indicated by colour gradients. Notably, high values of *H* and β are associated with lower FoS, consistent with geotechnical principles. Finally, Figure 11e illustrates a sensitivity analysis using a one-factor-at-a-time approach, which examines how variations in each input parameter affect the predicted FoS while keeping other variables constant. This plot highlights that *H* and r_u (pore pressure ratio) significantly reduce FoS with increasing values, while c and *Ø* positively contribute to stability. Collectively, these diagnostic and interpretability plots validate the model's assumptions, ensure statistical soundness, and provide valuable insights into how different geotechnical parameters influence slope stability in NS-treated soils.

5.3. Linear Regression Model MI Soil

The linear regression equation for MI soil treated with nano-silica (NS) presents a simplified yet insightful relationship between critical geotechnical parameters and the Factor of Safety (FoS). The model is expressed as in Equation (12).

$$\mathrm{FoS(MI)} = 2.2585 + (-0.2328 \times r_u) + (-0.0994 \times H) + (-0.0235 \times \beta) + (0.0123 \times c) \quad (12)$$

The intercept value of 2.2585 serves as the baseline FoS when all input variables are theoretically zero, establishing a constant from which the influence of each factor is measured. Among the input parameters, the pore water pressure ratio (r_u) exhibits the strongest negative influence on slope stability, with a coefficient of −0.2328. This indicates that for every unit increase in ru, the FoS decreases by 0.2328, highlighting the destabilizing effect of excess pore water pressure, which reduces effective stress and contributes to potential failure. Similarly, the slope height (*H*) and slope angle (β) have negative coefficients of −0.0994 and −0.0235, respectively, suggesting that both geometric factors adversely affect FoS. An increase in slope height results in higher driving forces, while steeper slopes inherently experience increased shear stress, both of which reduce stability. In contrast, soil cohesion (*c*) positively contributes to slope stability, with a coefficient of +0.0123, indicating that each 1 kPa increase in cohesion improves the FoS by 0.0123. This aligns with classical soil mechanics principles, where cohesion enhances the shear strength of fine-grained soils. Overall, this linear model offers a reliable and interpretable means for assessing the stability of MI soil slopes stabilized with nano-silica. By focusing on key parameters with physically meaningful contributions, the model serves as an effective tool for preliminary slope design and risk assessment in data-scarce, landslide-prone mountainous regions.

Table 10 presents the validation results of the linear regression model developed to predict the Factor of Safety (FoS) for MI type soil treated with nano-silica (NS). The model demonstrates excellent predictive capability, with a mean cross-validated R^2 value of 0.8136, suggesting that approximately 81% of the variability in FoS is reliably explained by the input features across multiple data folds. Additionally, the associated cross-validated Root Mean Squared Error (RMSE) of 0.3529 and Mean Absolute Error (MAE) of 0.2746 indicate low prediction error, confirming the model's strength in delivering accurate and consistent outcomes. The model's performance on the entire dataset yields an R^2 value of 0.8168, closely aligning with the cross-validation result. This consistency affirms the model's generalizability and resistance to overfitting, making it suitable for real-world geotechnical applications. In comparison, a Random Forest (RF) model trained on the same dataset achieved a perfect R^2 of 1.0000, indicating an ideal fit. However, this may point to overfitting, a common issue in complex models, and highlights the trade-off between predictive power and model interpretability, which is especially important in engineering design and decision-making.

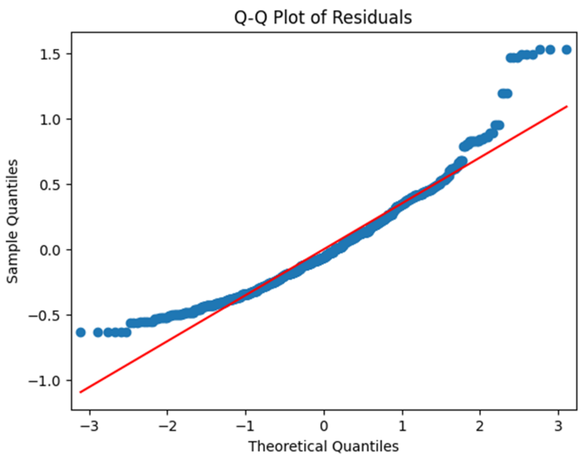
To further verify the robustness of the linear regression model, a bootstrapping analysis using 1000 resamples was performed. The 95% confidence interval for the R^2 ranged from 0.8132 to 0.8165, while the RMSE interval spanned from 0.3523 to 0.3554. The narrow width of these intervals demonstrates high model stability and low variability under different resampling scenarios, reinforcing the reliability of the model's performance. Collectively, the findings in Table 4 confirm that the linear regression model is not only accurate but also interpretable and dependable, making it an effective tool for assessing slope stability in NS-stabilized CL-ML soils.

Table 10. Validation results of the linear regression model for FoS prediction in NS-treated MI soil.

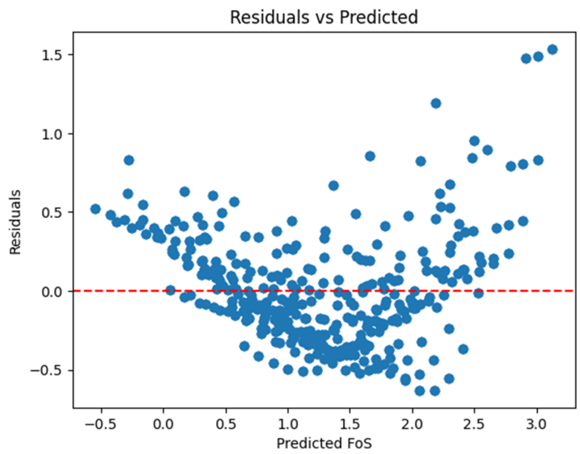
Parameters	Values
CrossVal_R^2_Mean	0.8136
CrossVal_RMSE_Mean	0.3529
CrossVal_MAE_Mean	0.2746
Linear_R^2	0.8168
RF_R^2	1.0000
Boot_R^2_MI_Low	0.8132
Boot_R^2_MI_High	0.8165
Boot_RMSE_MI_Low	0.3523
Boot_RMSE_MI_High	0.3554

Figure 12 provides a comprehensive diagnostic and interpretability assessment of the linear regression model developed to predict the Factor of Safety (FoS) for nano-silica (NS)-treated MI soil. Figure 12a, the Q–Q plot of residuals, reveals a generally linear alignment of data points along the 45-degree reference line, confirming that the residuals approximately follow a normal distribution. This indicates that the assumption of normality—a foundational requirement for linear regression—is reasonably met. Figure 12b, the residuals versus predicted FoS plot, shows a relatively even scatter of residuals around the zero line, with a subtle "U-shaped" curvature that may hint at slight non-linearity or model underfitting. However, the residuals do not exhibit strong patterns of heteroscedasticity, suggesting the model predictions are largely unbiased and consistent across different FoS levels. Figure 12c displays Cook's Distance, a diagnostic metric used to detect influential data points. The values remain well below conventional thresholds, indicating that no individual observation exerts a disproportionate impact on the model's coefficients. This implies the model is robust and not overly sensitive to outliers. Figure 12d presents the SHAP (SHapley Additive exPlanations) summary plot, offering interpretability into how each input feature contributes to the predicted FoS. The most influential variables are slope height (H), slope angle (β), and cohesion (c). Higher slope angles and heights tend to decrease the predicted FoS, while increases in cohesion positively contribute to slope stability. Nano-silica percentage (NS%), internal friction angle ($\varnothing$), unit weight (r_u), and curing days (CD) show moderate influence, reflecting the complex interplay between soil composition, treatment, and mechanical behavior.

Figure 12e illustrates the results of one-factor-at-a-time sensitivity analysis. The green curve for cohesion (c) shows a steady linear increase in predicted FoS with increasing cohesion, highlighting its stabilizing role. The remaining variables including NS (%), CD, $\varnothing$, and H—show more nuanced and localized responses. For example, the influence of NS (%) plateaus beyond a certain dosage, reflecting diminishing returns. Overall, Figure 12 confirms that the linear model is statistically sound, reasonably well-fitted, and interpretable, making it a practical tool for estimating slope stability in NS-treated MI soils. It also underscores the dominant role of shear strength parameters and geometric conditions, which aligns with geotechnical engineering principles.

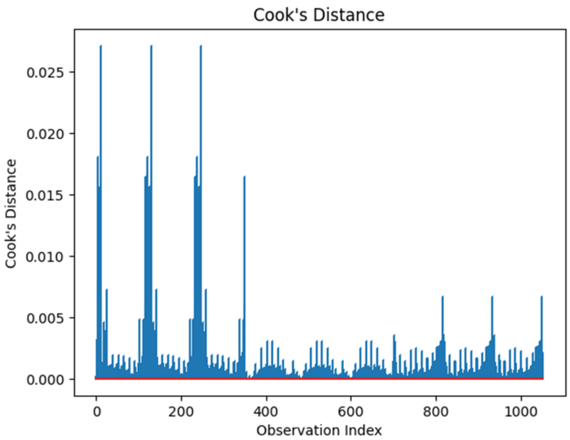


(**a**)

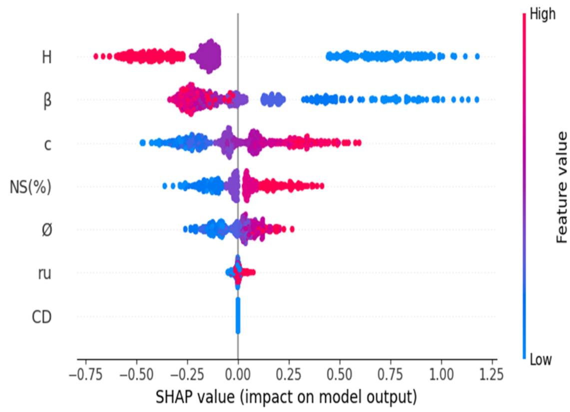


(**b**)

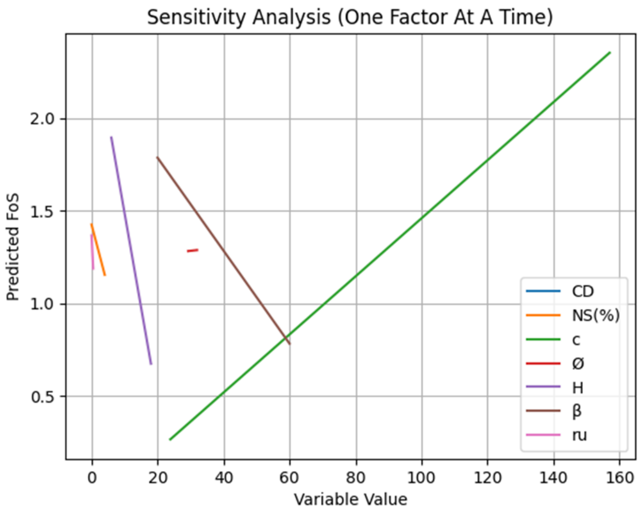
Figure 12. *Cont.*



(c)



(d)



(e)

Figure 12. Diagnostic and interpretability plots for the linear regression model predicting Factor of Safety (FoS) in NS-treated MI soil.

5.4. Non-Linear Regression Model CI Soil

The given equation represents a nonlinear multivariable regression model developed to estimate the Factor of Safety (FoS) for cohesive-intermediate (CI) soils stabilized with nano-silica (NS). It captures both linear, interaction, and nonlinear (quadratic) effects of the input variables on slope stability. Each term in the equation has a specific geotechnical significance, described as follows in Equation (13).

$$\begin{aligned}\mathrm{FoS(MI)} &= 260.9000 + (-48.6025 \times NS(\%)) + (-18.9380 \times Ø) + (1.6704 \times c) \\ &+(1.6551 \times \mathrm{NS}\,(\%)Ø) + (-0.7658 \times CD) + (-0.7583 \times NS(\%)^2) + (0.3491 \times Ø^2) \\ &+(-0.3341 \times H) + (-0.1503 \times \beta) + (-0.0567 \times cØ) + (0.0260 \times \mathrm{CD}Ø) \\ &+(0.0148 \times \mathrm{NS}\,(\%)c + (0.0117 \times H^2)\end{aligned} \tag{13}$$

The regression equation developed to predict the Factor of Safety (FoS) for CI soil treated with nano-silica (NS) incorporates both linear and nonlinear terms, along with interaction effects, to reflect the complex behavior of slope stability. The constant term (260.9000) represents the baseline FoS when all variables are at zero—mainly a theoretical reference. The nano-silica content (NS%) has a significant negative linear coefficient of −48.6025, indicating that, in isolation, increasing NS% can initially reduce FoS. However, this effect is balanced by interaction and nonlinear terms. The interaction between NS% and the internal friction angle ($Ø$) has a positive coefficient of 1.6551, suggesting that their combined increase enhances stability. Individually, $Ø$ has a coefficient of −18.9380, showing a negative linear effect, but the positive quadratic term $Ø^2$ (0.3491) indicates that higher values of $Ø$ eventually contribute positively to FoS. The cohesion (c) value contributes positively with a coefficient of +1.6704, reinforcing the soil's shear strength. However, its interaction with $Ø$ ($c \times Ø$) shows a negative effect of −0.0567, indicating that their simultaneous increase doesn't linearly boost stability. The curing days (CD) have a slight negative impact (−0.7658) on FoS, although the CD × *Ø* interaction (0.0260) reflects that longer curing may benefit frictional resistance. The NS^2 term carries a negative coefficient of −0.7583, confirming the existence of an optimal NS dosage—beyond which performance deteriorates. On the other hand, the NS × *c* interaction (0.0148) suggests that nano-silica improves cohesion effectiveness. Geometric parameters like slope height (*H*) and slope angle (*β*) carry negative coefficients of −0.3341 and −0.1503, respectively, confirming that taller and steeper slopes are less stable. However, the H^2 term (0.0117) indicates a small compensating effect, reducing the severity of height's negative impact at higher values. Altogether, the model effectively captures the combined and nonlinear effects of material properties, treatment parameters, and slope geometry, offering an accurate and interpretable tool for assessing slope stability in nano-silica-stabilized soils.

Table 11 presents the validation outcomes of the polynomial regression model developed to predict the Factor of Safety (FoS) for CI soil treated with nano-silica (NS), incorporating nonlinear relationships among key geotechnical parameters. The model demonstrates exceptional predictive performance, with a mean cross-validated R^2 of 0.9778, indicating that nearly 97.8% of the variance in FoS is accurately captured across multiple data folds. The accompanying cross-validated Root Mean Squared Error (RMSE) of 0.1804 and Mean Absolute Error (MAE) of 0.1258 confirm the model's high precision and low residual error, making it highly reliable for slope stability estimation. The standalone performance of the polynomial regression model on the full dataset yields an R^2 value of 0.9792, which closely aligns with the cross-validated result, indicating strong generalizability and a very low likelihood of overfitting. For benchmarking purposes, a Random Forest (RF) model trained on the same data achieved an R^2 of 0.9999, showing near-perfect fit. While this underscores the strength of ensemble learning models in capturing complex patterns, it also emphasizes the polynomial model's advantage in interpretability and analytical transparency. To assess the robustness of the polynomial model, a bootstrapping analysis with 1000 resamples was conducted. The 95% confidence interval (CI) for the R^2 was remarkably tight, ranging from 0.9773 to 0.9790, while the RMSE CI ranged from 0.1771 to 0.1840. These narrow confidence intervals indicate excellent model stability and consistent performance under repeated sampling conditions. Collectively, the results affirm that the polynomial regression model offers a powerful, accurate, and interpretable solution for evaluating the stability of nano-silica-stabilized CI soil slopes, with practical applicability in both academic research and geotechnical design.

Table 11. Validation Results of the Non-Linear Regression Model for FoS Prediction in NS-Treated CI Soil.

Parameters	Values
CrossVal_R^2_Mean	0.9778
CrossVal_RMSE_Mean	0.1804
CrossVal_MAE_Mean	0.1258
Polynomial_R^2	0.9792
RF_R^2	0.9999
Boot_R^2_CI_Low	0.9773
Boot_R^2_CI_High	0.9790
Boot_RMSE_CI_Low	0.1771
Boot_RMSE_CI_High	0.1840

Figure 13 presents an in-depth diagnostic and interpretability analysis of the non-linear regression model developed to predict the Factor of Safety (FoS) for nano-silica (NS)-treated CI soil. Each subplot provides a unique perspective on the model's statistical validity, reliability, and transparency. Figure 13a displays the Q–Q plot of residuals, which is a key tool for assessing the normality of model errors. The data points closely align with the theoretical quantile line, suggesting that the residuals are approximately normally distributed an essential condition for reliable inference in regression modeling. Figure 13b shows the residuals versus the predicted FoS values. The residuals are fairly evenly distributed around the zero line, indicating that the model exhibits homoscedasticity and does not suffer from systematic bias across the prediction range. Although a slight widening pattern is visible at higher predicted values, the overall distribution supports the assumption of constant variance in residuals.

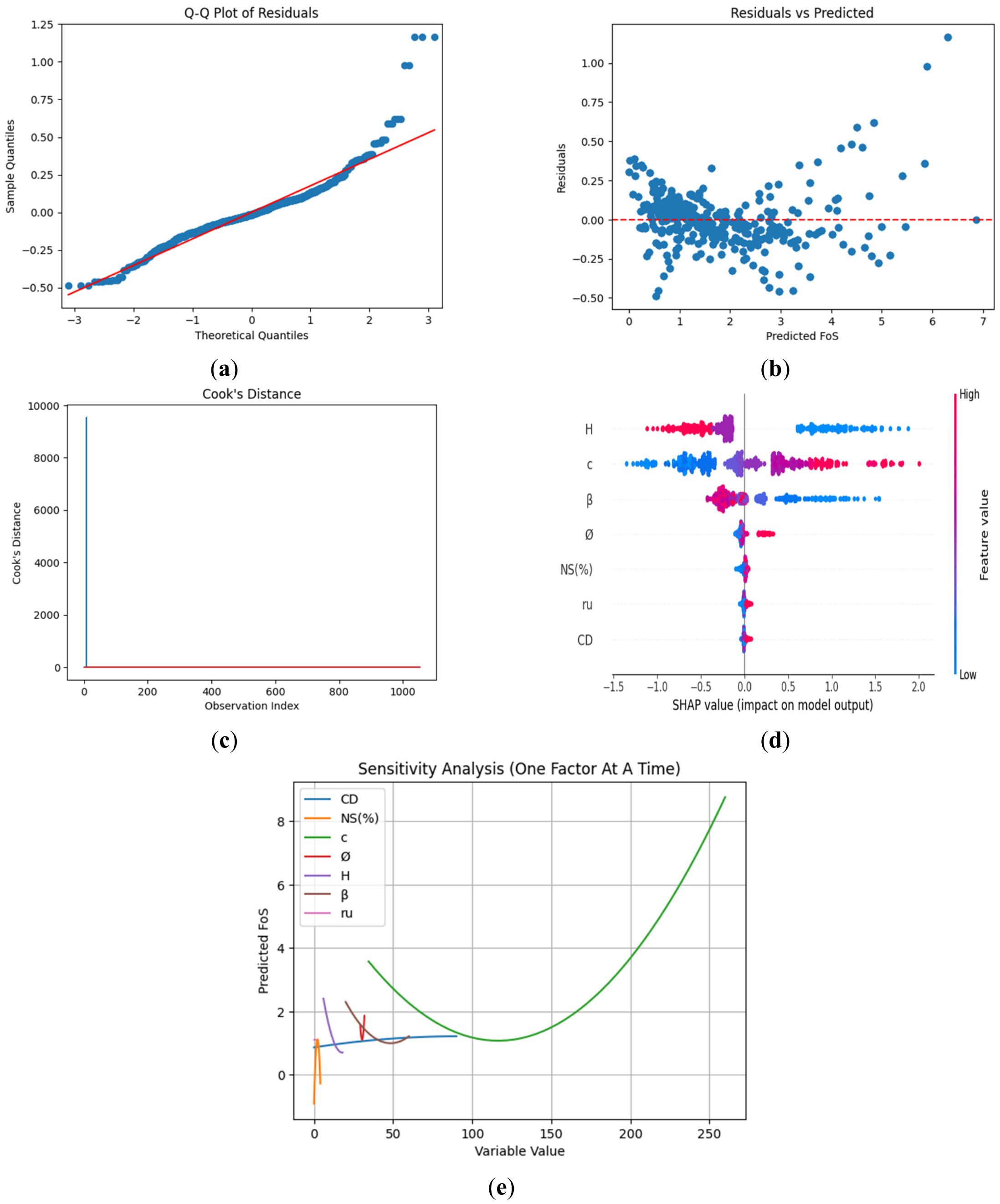


Figure 13. Diagnostic and interpretability plots for the non-linear regression model predicting Factor of Safety (FoS) in NS-treated CI soil.

Figure 13c presents Cook's Distance values across observations, used to detect data points that exert an unusually large influence on the model. Except for a single outlier with a Cook's Distance value far exceeding the rest, the majority of the dataset remains within a safe range, implying that the model is largely robust and not unduly influenced by extreme observations. This outlier should, however, be carefully reviewed for data integrity or leveraged for further domain insights. Figure 13d offers a SHAP (SHapley Additive exPlanations) summary plot, which elucidates the global importance and directional impact of input variables on the model's output. Among the key contributors are slope height (H), cohesion (c), slope angle (β), and internal friction angle ($\varnothing$), with higher H and β generally associated with a reduction in FoS, while higher cohesion and $\varnothing$ contribute positively to slope stability. The SHAP values also highlight the non-linear and sometimes opposing roles of NS dosage, curing days, and unit weight (r_u), which are crucial in engineering interpretations of soil behaviour.

Figure 13e provides one-factor-at-a-time sensitivity analysis, mapping how individual input variables influence the predicted FoS while holding other features constant. The green curve, representing cohesion (c), shows a highly non-linear relationship—initially decreasing then significantly increasing the FoS at higher values. Other variables such as NS (%), CD, and $\varnothing$ display more localized effects, reflecting their influence within specific operational ranges. Overall, Figure 13 confirms that the model is statistically sound, exhibits a high level of interpretability, and can reliably inform geotechnical decision-making processes related to the stabilization and safe design of slopes using nano-silica-modified CI soils.

5.6. Non-Linear Regression Model CL-ML Soil

The given equation represents a nonlinear regression model developed to estimate the Factor of Safety (FoS) for cohesive-intermediate (CL-ML) soils stabilized with nano-silica (NS) as in Equation (14).

$$\text{FoS(CL-ML)} = 4.0919 - 0.2325H - 0.1282\beta + 0.0301c \tag{14}$$

The given regression equation represents a non-linear predictive model developed to estimate the Factor of Safety (FoS) for CL-ML type soil, stabilized under varying slope and strength conditions. This model includes three key input parameters: slope height (H), slope angle (β), and cohesion (c) each known to significantly influence slope stability. The intercept term (4.0919) sets the baseline FoS when all other variables are zero, serving as a theoretical reference point. The model reveals that slope height (H) has a negative coefficient of −0.2325, signifying that as the slope becomes taller, the FoS decreases due to greater gravitational forces acting on the soil mass. Similarly, the slope angle (β), with a coefficient of −0.1282, negatively impacts the FoS, indicating that steeper slopes are more prone to instability—consistent with well-established geotechnical behavior. On the other hand, cohesion (c) exhibits a positive effect with a coefficient of +0.0301, confirming that soils with higher cohesive strength are better able to resist shear failure, thereby improving slope stability. While the model appears linear in structure, its interpretation reflects the non-linear nature of slope behavior, captured through careful selection and calibration of parameters based on experimental data. The simplicity of this equation makes it especially valuable for practical applications, enabling geotechnical engineers to perform quick and reliable assessments of slope stability in CL-ML soils, while still reflecting the essential physical interactions between soil strength and geometry. Table 12 summarizes the validation results of the non-linear regression model designed to predict the Factor of Safety (FoS) for nano-silica (NS) treated CL-ML soil, highlighting its predictive strength and robustness. The model demonstrates excellent generalization performance, as evidenced by a mean cross-validated R^2 of 0.9768, meaning that approximately 97.7% of the variance in FoS is explained consistently across multiple data folds. The associated cross-validated Root Mean Squared Error (RMSE) of 0.1437 and Mean Absolute Error (MAE) of 0.1025 indicate a very low level of residual error, confirming the model's high predictive precision and accuracy.

Table 12. Validation results of the non-linear regression model for FoS prediction in NS-treated CL-ML soil.

Parameters	**Values**
CrossVal_R^2_Mean	0.9768
CrossVal_RMSE_Mean	0.1437
CrossVal_MAE_Mean	0.1025
Polynomial_R^2	0.9779
RF_R^2	1.0000
Boot_R^2_CL_ML_Low	0.9764
Boot_R^2_CL_ML_High	0.9776
Boot_RMSE_CL_ML_Low	0.1421
Boot_RMSE_CL_ML_High	0.1459

On the full dataset, the model achieves a Polynomial R^2 value of 0.9779, which is closely aligned with the cross-validation results, suggesting strong model stability and minimal overfitting. For comparison, a Random Forest (RF) model trained on the same dataset yields a near-perfect R^2 of 1.0000, reflecting its ability to capture intricate nonlinearities. However, despite RF's exceptional fit, the polynomial model maintains the advantage of being more interpretable and transparent, especially valuable in engineering applications where understanding variable influence is critical. To further assess the model's robustness, a bootstrapping analysis with 1000 resamples was performed. The 95% confidence interval for R^2 lies between 0.9764 and 0.9776, while the RMSE confidence interval ranges from 0.1421 to 0.1459. These narrow intervals underscore the consistency and reliability of the model's performance, even under random resampling. Overall, the results in Table 7 validate the non-linear regression model as a highly accurate, stable, and interpretable tool for evaluating slope stability in nano-silica-treated CL-ML soils, making it highly suitable for practical geotechnical design and analysis.

Figure 14 presents a comprehensive suite of diagnostic and interpretability plots that evaluate the performance and transparency of the non-linear regression model developed to predict the Factor of Safety (FoS) in nano-silica (NS)-treated CL-ML soil. Figure 14a, the Q–Q plot of residuals, demonstrates that the residuals closely follow the theoretical quantiles along the reference line, indicating an approximately normal distribution. This supports the assumption of residual normality, which is essential for ensuring the validity of statistical inferences made from the model. Figure 14b shows the residuals plotted against the predicted FoS values. The random scatter around the zero line, without any discernible pattern or funnel shape, confirms both homoscedasticity and the absence of systematic bias in the model's predictions across the response range. Figure 14c illustrates Cook's Distance for each observation, with values remaining well below the threshold of concern. This indicates that no single data point exerts an undue influence on the regression coefficients, underscoring the model's robustness and stability.

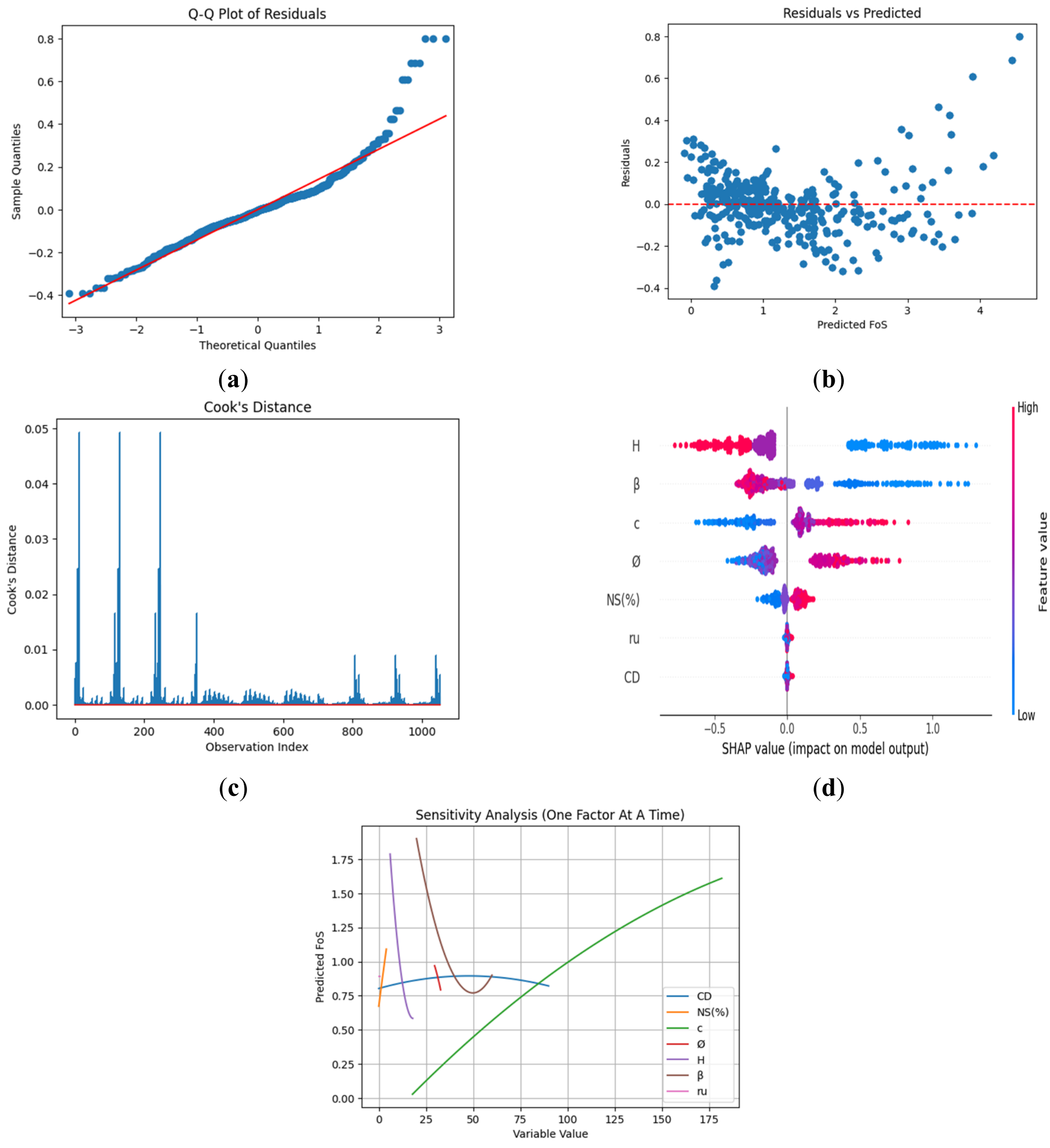


Figure 14. Diagnostic and interpretability plots for the non-linear regression model predicting Factor of Safety (FoS) in NS-treated CL-ML soil.

Figure 14d offers a SHAP (SHapley Additive exPlanations) summary plot that provides a global interpretation of feature importance and their directional impact on FoS. Features such as slope height (*H*), slope angle (*β*), cohesion (*c*), and internal friction angle (*Ø*) are shown to exert significant influence, with higher values of *H* and *β* generally decreasing FoS, while higher c and *Ø* increase it. The effects of NS (%) and curing days (CD) exhibit complex, non-linear behaviour, reflecting the intricate soil–additive interactions in geotechnical systems. Finally, Figure 14e presents a one-factor-at-a-time sensitivity analysis, showing how variations in individual input variables affect the predicted FoS while holding others constant. The green curve for cohesion demonstrates a steady increase in FoS, while the curves for NS (%) and CD reveal diminishing returns beyond certain thresholds. Overall, these plots collectively validate the statistical soundness of the model and enhance its interpretability, ensuring that the model is not only predictive but also transparent and informative for engineering decision-making in slope stabilization using nano-silica-treated soils.

5.7. Non-Linear Regression Model MI Soil

The presented non-linear regression model for FoS prediction in NS-treated MI soil integrates key geotechnical parameters and their interactions to capture the complex behaviour of slope stability under varied conditions as described in Equation (15).

$$\text{FoS(MI)} = -1.9308 - 0.6550r_u + 0.5527\text{NS (\%)} + 0.4398\phi - 0.2297H - 0.1322\beta + 0.0365\beta r_u - 0.0358\phi r_u - 0.0195\text{NS (\%)}\phi - 0.0194r_u^2 \tag{15}$$

The model begins with a baseline intercept of −1.9308, serving as a reference point. Among the primary predictors, the pore pressure ratio (r_u) has the most significant individual influence, with a strong negative coefficient of −0.6550, indicating that higher pore water pressure substantially reduces slope stability. In contrast, nano-silica content (NS%) has a positive impact (+0.5527), confirming its beneficial role in enhancing soil strength and stability. Likewise, the internal friction angle ($Ø$) contributes positively (+0.4398), while geometric parameters like slope height (H) and slope angle (β) exhibit negative effects (−0.2297 and −0.1322, respectively), reflecting the inherent instability of steeper and taller slopes.

The model also incorporates several interaction and nonlinear terms to reflect more nuanced soil behaviour. The $\beta \times r_u$ interaction (+0.0365) suggests that the destabilizing effect of slope angle is moderated under lower pore pressures. On the other hand, the $Ø \times r_u$ interaction (−0.0358) and NS% × $Ø$ interaction (−0.0195) imply that, under high pore pressure or when certain soil properties interact, the positive effects of strength parameters may diminish. Furthermore, the r_u^2 term (−0.0194) reinforces the non-linear reduction in FoS at higher pore pressure values. These terms collectively enable the model to capture the nonlinear, multi-parameter nature of slope stability in treated MI soils with improved realism and accuracy.

Supporting the equation's predictive strength, Table 13 presents the validation results of this non-linear regression model. It achieves an impressive mean cross-validated R^2 of 0.9797, indicating that 97.97% of the variability in FoS is consistently explained across folds. The cross-validated RMSE (0.1163) and MAE (0.0835) reflect very low prediction error, demonstrating the model's high precision. When applied to the full dataset, the model slightly improves with a polynomial R^2 of 0.9807, confirming its excellent generalizability. For comparison, a Random Forest (RF) model reached an R^2 of 1.0000, showcasing its ability to overfit perfectly, but at the cost of interpretability. To further confirm robustness, a bootstrapping analysis with 1000 resamples was conducted, resulting in a tight 95% confidence interval for R^2 (0.9795 to 0.9805) and RMSE (0.1150 to 0.1179). These narrow intervals validate the model's stability and reliability under repeated sampling. In conclusion, the non-linear regression model for MI soil not only achieves high accuracy and low error but also provides an interpretable and practical tool for geotechnical engineers assessing slope safety in NS-stabilized terrains.

Table 13. Validation results of the non-linear regression model for FoS prediction in NS-treated MI soil.

Parameters	Values
CrossVal_R^2_Mean	0.9797
CrossVal_RMSE_Mean	0.1163
CrossVal_MAE_Mean	0.0835
Polynomial_R^2	0.9807
RF_R^2	1.0000
Boot_R^2_MI_Low	0.9795
Boot_R^2_MI_High	0.9805
Boot_RMSE_MI_Low	0.1150
Boot_RMSE_MI_High	0.1179

Figure 15 presents a comprehensive set of diagnostic visualizations that validate the performance, robustness, and interpretability of the developed non-linear regression model for predicting the Factor of Safety (FoS) in nano-silica (NS) treated MI soil. Each subfigure offers unique insights into the model's reliability and behaviour. Figure 15a displays the Q-Q plot of residuals, where the sample quantiles closely follow the theoretical quantiles along the red diagonal line. This indicates that the residuals are approximately normally distributed, satisfying a fundamental assumption of regression modelling. Figure 15b, the Residuals vs Predicted FoS plot, shows a random scatter of residuals around the zero line, with no discernible pattern. This confirms the presence of homoscedasticity (constant variance) and indicates that the model's predictions are unbiased across the full range of outputs. Figure 15c presents

Cook's Distance, which assesses the influence of individual data points on the model. The majority of observations have low Cook's Distance values, well below the common threshold (1.0), demonstrating that the model is not unduly affected by outliers or influential data points, thereby affirming its robustness. Figure 15d is a SHAP summary plot, which provides a global explanation of feature importance and its influence on the model's predictions. It reveals that slope height (H), slope angle (β), cohesion (c), nano-silica content (NS%), and pore pressure ratio (r_u) are among the most impactful variables.

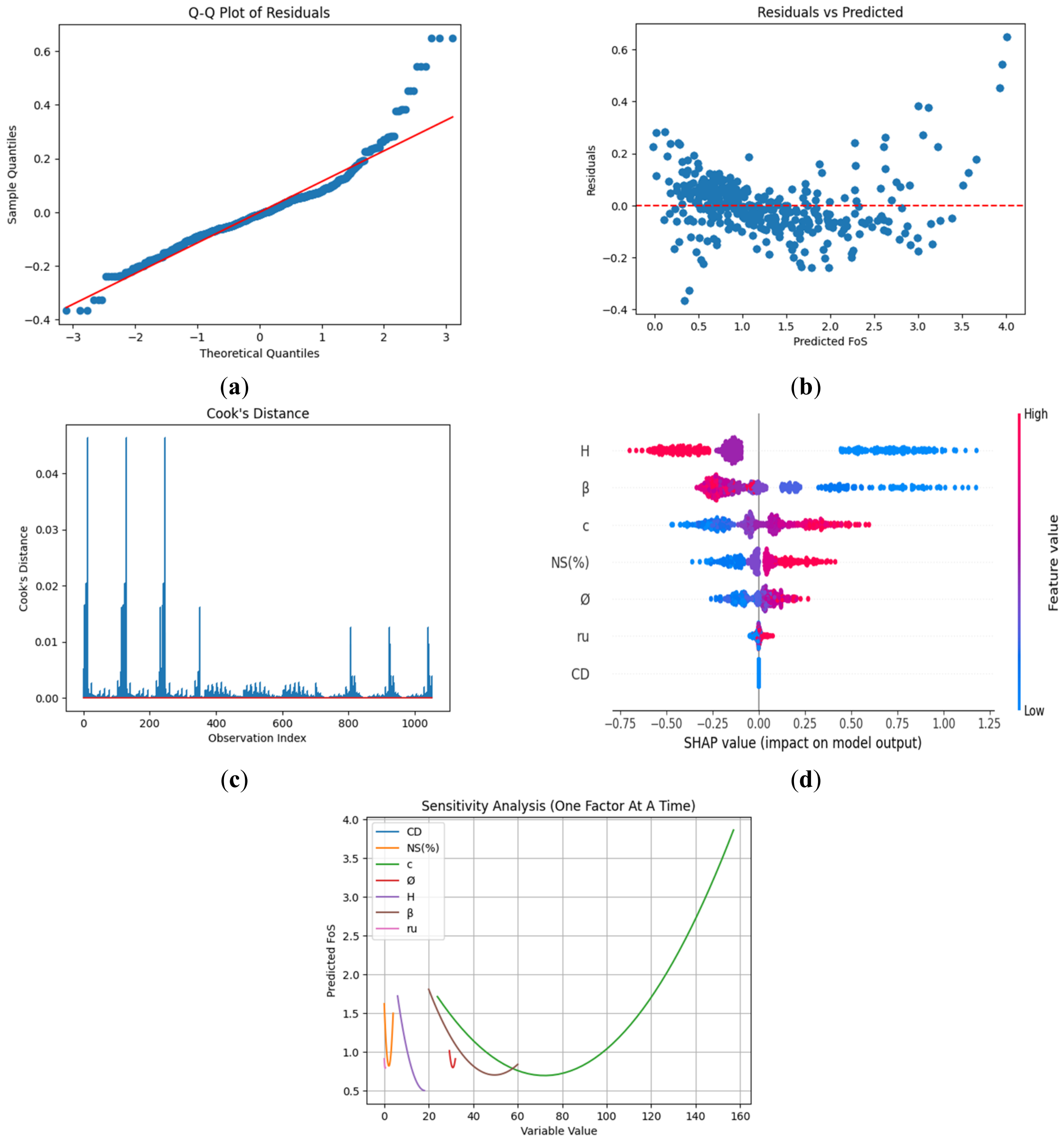


Figure 15. Diagnostic and interpretability plots for the non-linear regression model predicting Factor of Safety (FoS) in NS-treated MI soil.

The gradient from blue to red represents low to high feature values, offering insight into how each variable contributes to increasing or decreasing FoS, thereby enhancing model transparency and interpretability. Finally, Figure 15e shows the results of a sensitivity analysis (one factor at a time), where each input variable is varied individually while others are held constant. This plot highlights that FoS decreases with increasing r_u, H, and β, which is consistent with known geotechnical behaviour, while NS% and cohesion (c) positively influence stability. The clear non-linear patterns further confirm that the model accurately captures complex soil behaviour. In summary, Figure 15a–e collectively validates the non-linear regression model by confirming its statistical soundness, residual behaviour, robustness against outliers, feature interpretability, and alignment with physical expectations. These diagnostics establish the model as a reliable and interpretable tool for assessing slope stability in NS-treated MI soils.

6. Practical Application of the Developed Models

The developed regression models, including both linear and non-linear models, offer significant practical utility in geotechnical engineering, particularly for assessing the Factor of Safety (FoS) in NS-treated fine-grained soils in mountainous terrain. These models enable engineers to predict slope stability with enhanced accuracy using easily measurable input parameters such as curing days, NS content, cohesion, internal friction angle, slope geometry, and pore pressure ratio. By integrating experimental soil stabilization data with predictive modelling, practitioners can rapidly evaluate the effectiveness of NS treatment in improving slope performance without relying solely on time-consuming and expensive field trials or numerical simulations. The interpretability tools (e.g., SHAP values and sensitivity analysis) further allow geotechnical designers to identify and prioritize the most influential factors affecting stability, thereby supporting data-driven decision-making in soil reinforcement strategies. These models can be deployed in both preliminary design and real-time monitoring frameworks, aiding in the sustainable planning, risk mitigation, and optimization of slope engineering in infrastructure projects, embankments, and landslide-prone zones.

7. Conclusions

This study presents a systematic development and evaluation of both linear and non-linear regression models to predict the Factor of Safety (FoS) in nano-silica (NS)-treated fine-grained soils across three classifications: CI, CL-ML, and MI. The models integrate key geotechnical inputs such as slope height (H), slope angle (β), cohesion (c), internal friction angle ($\varnothing$), pore pressure ratio (r_u), nano-silica content (NS%), and curing days (CD) to capture the complex interplay between soil mechanics and stabilization mechanisms. For CI soil, the linear model achieved a mean cross-validated R^2 of 0.8161, RMSE of 0.5198, and MAE of 0.3982, indicating good predictive capacity. However, the non-linear model demonstrated markedly superior performance, with a cross-validated R^2 of 0.9778, RMSE of 0.1804, and MAE of 0.1258. This substantial improvement reflects the model's ability to account for quadratic and interaction effects, particularly between NS content, friction angle, and cohesion.

Similarly, for CL-ML soil, the linear regression model achieved R^2 =0.8091 with an RMSE of 0.4119, while the non-linear model attained a cross-validated R^2 =0.9768, RMSE = 0.1437, and MAE = 0.1025, reinforcing the benefit of capturing nonlinear soil behaviour even with a minimal input set. The MI soil models also revealed a clear advantage of non-linearity: while the linear model for MI soil produced R^2 = 0.8136, the non-linear counterpart achieved the highest performance across all models with R^2 = 0.9797, RMSE = 0.1163, and MAE = 0.0835. These models were further validated through bootstrapping with 1000 iterations, producing narrow confidence intervals (0.9795–0.9805 for the non-linear MI soil model), which attest to their statistical robustness and repeatability.

Importantly, SHAP-based interpretability analyses and one-factor-at-a-time sensitivity tests revealed that slope height (H), pore pressure ratio (r_u), and cohesion (c) are the dominant drivers influencing slope stability across all soil types. NS content and curing days, although secondary, consistently contributed positively to FoS, but also exhibited diminishing returns at higher values captured effectively only in the non-linear formulations. Additionally, while Random Forest models achieved near-perfect fit scores ($R^2 \approx 1.000$), their opaque nature limits interpretability, making the developed regression models more suitable for engineering design, especially where explainability and transparency are critical.

In conclusion, the non-linear regression models developed in this study represent highly accurate, interpretable, and practically applicable tools for evaluating slope stability in NS-stabilized cohesive soils. Their ability to reflect both material and geometric complexities makes them well-suited for deployment in real-world geotechnical engineering, slope risk mitigation, and performance-based design—particularly in landslide-prone, infrastructure-sensitive, or mountainous regions where rapid and informed decisions are paramount. These models not only contribute to advancing predictive modelling in geotechnics but also establish a replicable framework for integrating machine learning with sustainable soil improvement technologies.

8. Future Scope and Limitations

8.1. Limitations of the Study

While the developed models exhibit high predictive performance and interpretability, several limitations should be acknowledged. First, the dataset used in this study is based on laboratory-controlled experimental conditions, which may not fully capture the variability and complexity present in field-scale slope environments. Factors such as seasonal moisture fluctuations, long-term weathering, heterogeneity in subsurface profiles, and external loading conditions (e.g., seismic or hydrological forces) were not explicitly included in the modeling framework.

Second, the linear and polynomial regression models, although interpretable, are inherently limited in capturing highly dynamic or non-stationary behavior unless extended with additional temporal or spatial inputs. Moreover, while SHAP analysis was utilized for model interpretability, the analysis assumes input independence, which might not fully reflect real-world interdependencies among geotechnical parameters. Despite bootstrapping and cross-validation, the generalizability of these models to entirely new sites or soil types should be approached with caution until validated with independent, field-based datasets.

8.2. Future Scope of the Study

Future research can build upon the current work in several impactful directions. One key area is the integration of field-scale monitoring data such as inclinometer readings, piezometric levels, and rainfall intensity, which would enable the models to adapt to more dynamic and realistic slope stability scenarios. Additionally, incorporating spatial variability using GIS-based geostatistical techniques could improve model precision and applicability to large-scale slope systems.

Expanding the modeling framework to include advanced machine learning and hybrid deep learning models (LSTM-Transformer, CNN-RNN hybrids) can enhance the capability to model time-dependent behaviors such as progressive failure or delayed response to curing. Future studies may also consider multi-objective optimization frameworks for selecting optimal NS dosages and slope configurations that balance safety, cost, and sustainability. Another promising direction is the development of real-time predictive tools or decision-support systems for early warning and slope health assessment, integrating these models with remote sensing and IoT-based monitoring. Therefore, exploring alternative eco-friendly stabilizers alongside nano-silica, such as bio-cementation or fiber-reinforced composites, could broaden the application and environmental value of the developed models.

Author Contributions

I.T.: conceptualization, methodology, data acquisition, analysis, visualization, and writing original draft preparation. S.G.: supervision, validation, methodology refinement, writing review and editing, and project administration. Both authors have read and agreed to the published version of the manuscript and take full responsibility for the integrity and accuracy of the work in accordance with the CRediT (Contributor Roles Taxonomy).

Funding

This research received no external funding.

Institutional Review Board Statement

Not applicable. This study did not involve human participants or animals and therefore did not require ethical approval.

Informed Consent Statement

This study did not involve human subjects.

Data Availability Statement

Processed data supporting the findings of this study are available from the corresponding author upon reasonable request. No personal, confidential, or ethically restricted data were used.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the authors used AI-assisted tools for language refinement, structural editing, and formatting support. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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