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Multiple Regression Models for Predicting Stability of Reinforced Soil Slope

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Abstract

Slope failures are prevalent issue in the construction sector. Thus the engineers must use appropriate slope stabilization techniques to reduce the risk of human life and property. This work investigates the efficacy of multiple regression analysis in predicting slope stability, specifically focusing on the slopes in the Kullu district, Himachal Pradesh, India. A total of 160 cases with different parameters were analyzed by using the well-known Limit Equilibrium Method (LEM), Morgenstern and Price on PLAXIS LE. Numerical analysis was performed using different nail lengths (6 m, 8 m, 10 m, and 12 m) and nail inclinations (0°, 5°, 10°, 15°, 20°, 25°, 30°, and 35°), applied to a homogeneous soil slope with 45°, 50°, 60°, and 70° inclinations, respectively. The limit equilibrium analysis may not offer predictive capabilities for future scenarios directly. In contrast, Multiple Regressions (MR) can provide predictive insights based on the historical data, allowing for forecasting of stability under different conditions or design scenarios. The utilization of MR provides the coefficients that quantify the influence of each variable on slope stability, enabling a detailed understanding of how each factor contributes. To develop the prediction models using Multiple Regression Analysis (MRA), the factor of safety values obtained by the numerical method were used. The accuracy of this model was evaluated against the conventional LE methods. The results indicate that multiple regression provides a good predictive performance with an R2 value equal to 0.774, offering a more nuanced and accurate assessment of slope stability compared to the traditional LE techniques.

1. Introduction

Slope stability is a critical concern in geotechnical engineering, particularly in construction, mining, and infrastructure development. It refers to the ability of a slope, whether natural or man-made, to withstand the forces acting upon it without undergoing failure [1]. When a slope becomes unstable, it can lead to landslides, rockfalls, or other types of ground movements, posing significant risks to the human safety, infrastructure, and the environment. The stability of a slope is influenced by several factors including the type of soil or rock, the slope's geometry, water content, and the external forces such as seismic activity or human activities like excavation or construction [2]. Understanding these factors is essential for predicting the potential slope failures, and implementing effective stabilization measures [3]. The engineers use various methods to assess slope stability including analytical approaches like the limit equilibrium methods, numerical modeling, and empirical techniques [4]. The assessment of the Factor of Safety (FOS) of the slopes is of paramount importance in geotechnical engineering, as it directly relates to the stability and safety of the slopes in various environments [5]. The FS is a numerical value that quantifies the margin of stability of a slope by comparing the resisting forces (or moments) that prevent slope failure to the driving forces (or moments) that could cause it. An FS greater than 1.0 indicates that the resisting forces exceed the driving forces,

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suggesting stability. However, if the FS is close to or less than 1.0; it signals a potential risk of failure. By assessing the FS, the engineers can identify the slopes at risk, and take necessary precautions to prevent catastrophic failures such as landslides that could endanger lives, infrastructure, and the environment [6]. Various methods are used to calculate the FS such as the limit equilibrium methods, numerical methods, probabilistic methods, empirical methods, and advanced methods based on machine learning and artificial intelligence. The selection of a method for calculating the FS depends on the specific characteristics of the slope, the complexity of the soil conditions, the accuracy required, and the available computational resources. The engineers often use a combination of methods to cross-verify the results, and ensure the safety and stability of the slope. Limit equilibrium methods are among the most widely used approaches for calculating the FS of the slopes [7]. These methods assume that the slope is at the point of failure, and balance the forces or moments acting on a potential failure surface. LEM includes two methods, method of slices and Fellenius (Swedish) method. Method of slices is a popular approach, where the slope is divided into vertical slices. The forces acting on each slice including weight, shear resistance, and interslice forces are analyzed [8]. The common methods under this category are the Bishop's simplified method, Janbu's method, Spencer's method, and Morgenstern-Price method. While the Fellenius (Swedish) method is a simple method that assumes no interslice, the forces and uses moment equilibrium about the base of each slice to calculate FS. It is less accurate for complex or irregular failure surfaces in comparison to the method of slices [9]. In addition to it, the numerical methods provide a more detailed analysis by discretizing the slope and solving the governing equations using the computational techniques [10]. These are particularly useful for complex geometries and heterogeneous materials. The most common numerical methods are Finite Element Method (FEM), Finite Difference Method (FDM), and Strength Reduction Method (SRM). The probabilistic methods account for the inherent variability and uncertainty in the soil properties, loading conditions, and other factors. The probabilistic methods such as Monte Carlo simulation, First-Order Reliability Method (FORM), and Hasofer-Lind method provide a probability distribution of the FS rather than a single value [11]. The methos based on correlations and observations from the field data, and are often used for preliminary assessments are known as the empirical methods such as the infinite slope analysis and Taylor charts. The recent advancements have seen the application of the machine learning and AI techniques to predict the FS of the slopes, particularly when dealing with large datasets or complex and non-linear relationships. Each of these approaches has its own advantages and disadvantages [12]. For example, Limit Equilibrium Methods (LEMs) are widely used in slope stability analysis because they provide a straightforward way to estimate the factor of safety (FS) by considering the balance of forces or moments acting on a potential failure surface. Varied types of LEMs were used in the stability analysis with a historical background such as the Fellenius or Swedish method, which assumes no interslice forces (i.e. forces between adjacent slices are neglected), making the calculations straightforward [13]. The Bishop's simplified method improves on the Fellenius method by considering the vertical interslice forces, but still neglecting the horizontal interslice forces. The method uses moment equilibrium to calculate the FS for circular failure surfaces. In the Bishop's method, only vertical interslice forces are considered; horizontal forces are assumed to be negligible [14]. This method is more accurate than the Fellenius method, while still being relatively simple to apply. It is widely used for circular slip surfaces, but it is less accurate for non-circular failure surfaces or the cases, where the horizontal interslice forces are significant. The Janbu's method is more versatile, as it can be applied to both the circular and non-circular failure surfaces [15]. It uses force equilibrium rather than moment equilibrium, allowing for the analysis of more complex slope geometries. This method accounts for both the vertical and horizontal interslice forces, but it simplifies the moment equilibrium by focusing on force equilibrium, but It requires more complex calculations, and may be less intuitive than simpler methods like thr Bishop's. The Spencer's method is a rigorous LEM that ensures both force and moment equilibrium are satisfied for each slice [16]. It is applicable to both the circular and non-circular failure surfaces. This method assumes a constant ratio of interslice shear to normal forces, and it balances both the force and moment equilibrium. The Spencer's method provides highly accurate results, and can be applied to complex slope geometries and failure surfaces, but it is computationally intensive and requires iterative procedures, making it more challenging to implement manually [17]. The Morgenstern-Price method extends the Spencer's approach by allowing for a more general distribution of interslice forces. This method also satisfies both force and moment equilibrium and can be used for any shape of the failure surface. The method allows for a flexible distribution of interslice forces, making it adaptable to various slope conditions. It is one of the most accurate LEMs available, capable of handling complex failure surfaces and providing reliable results but similar to the Spencer's method; it is also computationally demanding, and often requires a specialized software for implementation.

Multiple regression analysis often surpasses the conventional methods in predicting slope stability due to its ability to handle multiple variables simultaneously and uncover complex relationships between them [18]. Unlike the traditional approaches, which might rely on single factor or simplistic models, multiple regression integrates various influencing factors—such as soil properties, moisture content, and slope angle—into a cohesive predictive framework [19]. This comprehensive approach allows for a more nuanced and accurate estimation of slope stability by accounting for the interplay of different variables. Additionally, the multiple regression models can be continuously refined and improved, as new data becomes available, enhancing their predictive power and reliability over time [20]. This adaptability and precision make multiple regression a superior choice for evaluating and forecasting slope stability compared to the more conventional, one-dimensional methods [21].The use of multiple regression analysis in the rock and slope stability assessment has been increasingly recognized for its effectiveness in handling multiple influencing factors. The researchers like Lee and Smith (1995) employed multiple linear regression to predict the FOS of soil slopes based on factors such as soil cohesion, angle of internal friction, and slope angle [22]. The regression model showed a moderate correlation with actual slope stability, highlighting the potential of regression analysis, but also identifying the need for more complex models to account for non-linear relationships, and interactions between the variables. Wright and Anderson (2002) focused on developing the empirical regression models to estimate the FOS of slopes in clayey soils. By analyzing a dataset of slope stability tests, the authors created the multiple regression models incorporating soil properties, slope geometry, and moisture content [23]. The study demonstrated that the empirical regression models could effectively predict slope stability, though they emphasized the importance of local calibration for different soil types. Patel and Kumar (2008) integrated groundwater conditions into the multiple regression models to predict the FOS of slopes; The variables such as water table depth, soil permeability, and effective stress were included. The study found that groundwater significantly affects the slope stability, and incorporating these factors improved the accuracy of the FOS predictions [24]. Khosla et al. (2018) demonstrated how the multiple regression models could integrate the geological conditions, soil properties, and slope geometry to improve the slope stability predictions. Lewis and Harris (2020) investigated how the regional geological conditions and climatic factors affect slope stability using the multiple regression models. By incorporating the data from various regions, the work aimed to account for the regional variability in the soil and slope characteristics [25]. The results highlighted the importance of considering the regional factors when applying regression models to slope stability. Similarly, Lee, and Cho (2020) applied the multiple regression techniques to analyze large datasets, and identify the critical predictors of slope failure, revealing complex interactions between the variables that traditional methods often overlook [26]. Furthermore, Singh and Kumar (2021) utilized multiple regression to develop a comprehensive stability assessment model, which enhanced risk evaluation by incorporating various factors such as moisture content and load conditions [27]. These studies collectively highlight how multiple regression not only provides a more nuanced understanding of slope stability, but also offers a robust alternative to the conventional methods, enhancing predictive accuracy and risk management in geotechnical engineering [28].

In the mountainous regions like Kullu district in Himachal Pradesh, India, the traditional methods such as the Limit Equilibrium method (LEM) are widely used for assessing slope stability, but they often fall short in accounting for the complex interactions between the multiple influencing factors. This work explores the application of multiple regression analysis as an advanced technique to enhance the accuracy of slope stability predictions.

2. Studied Area

This article focuses on a slope in the Kullu district of Himachal Pradesh (32°17’38.2” N 77°10’53.8” E), where the original landform is a somewhat low mountain. The material parameters of the slope that are tested in the laboratory are as follows: Unit weight (γ) = 17 KN/m^3, cohesion (c) = 5 KPa, angle of internal friction (φ) = 30°. Figure 1 shows the image of the studied slope. The parameters utilized in slope and nail modeling are summarized in the Tables 1 & 2.

Table 1. Parameters of nail layout.

Parameters	Values
Slope angles	45°, 50°, 60°, 70°
Nail lengths	6 m, 8 m, 10 m, 12 m
Nail Inclination	0°, 5°, 10°, 15°, 20°, 25°, 30°, 35°

Table 2. Properties of soil slope.

S.No	Parameters	Unit	Value
1	Cohesion (c)	kPa	5
2	Friction angle (°)	Degree	30
4	Plasticity index	-	22.32143
5	Unit weight (γ_{sat})	kN/m^3	17
6	Surcharge load	kN/m^2	0.425

Figure 1. Image of the studied slope.

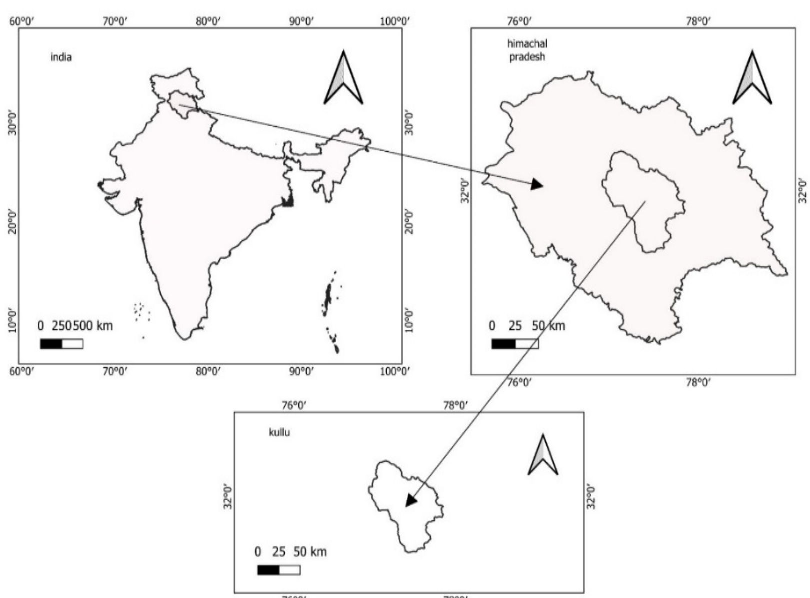


Figure 2. Map of the studied area.

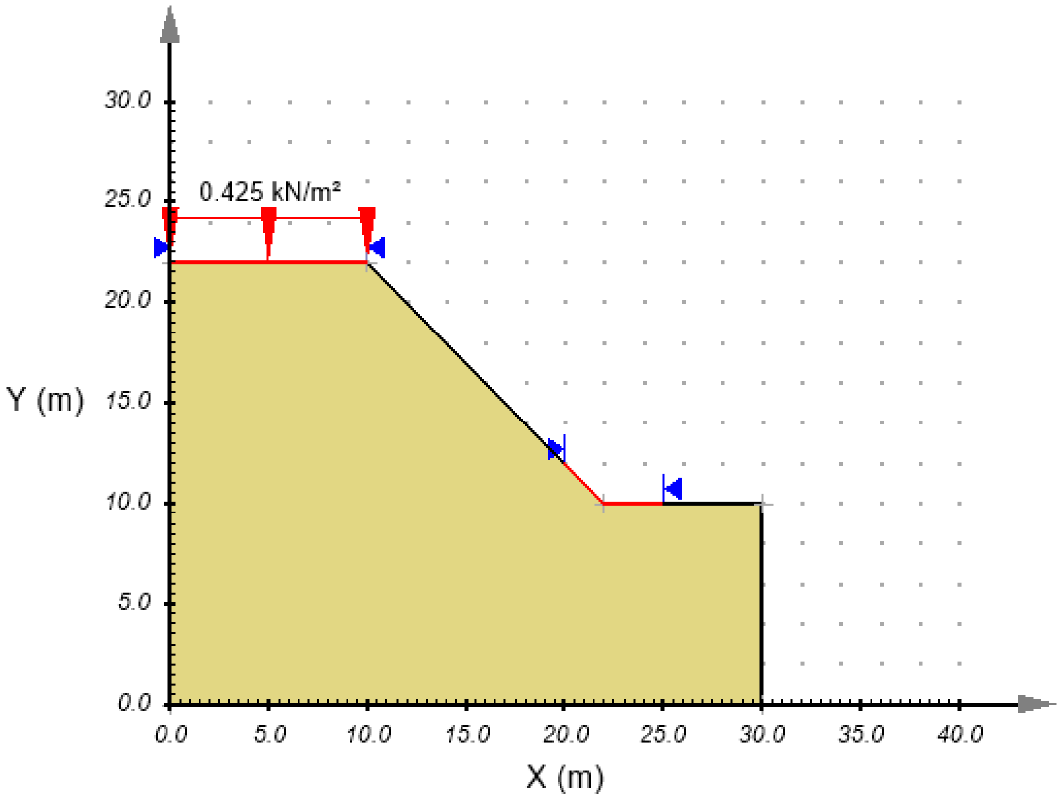


Figure 3. Geometry of the slope in PLAXIS.

Table 3. The soil nail parameters.

S. No.	Parameters	Values	Units
1	Bond strength	100	KN/m
2	Plate capacity	100	KN
3	Tensile capacity	160	KN
4	Out of plane spacing	1	m

2. Methodology

2.1. Data collection

We performed parametric variations on the selected slopes, applying the Morgenstern-Price LEM method, using the PLAXIS LE software to calculate the FS under varying conditions. This generated a dataset consisting of various FS values.

2.2. Verification of LEM with FEM

Comparative examination of the analysis's dependability was conducted with finite principle of the element approach for strength reduction factor. The deterministic and probabilistic Linear Equation Modeling (LEM) revealed a strong correlation with the Finite Element Method-based strength reduction factor (FEM). The results indicated that the stability of the studied slopes is mostly influenced by the total slope angle and steepness. The present work utilized PLAXIS 2D by the finite element method and PLAXIS LE of limit equilibrium method to analyze and compare the slope stability. Table 1 depicts the FS variation with the LEM and FEM methods.

Table 4. Factor of safety value from LEM and FEM.

Nail Inclination	5°	10°	15°	20°
Factor of safety from LEM	1.322	1.422	1.451	1.51
Critical FOS by FEM	1.299	1.385	1.424	1.48

The LEM results compared well with Finite Element-Model-based approach (FEM), as shown in Fig 1. The FEM yielded a minimum global safety factor (FS) compared to LEM, and it evaluates the slopes' stability condition better. The factor of safety based on LEM ranges from 1.322 (NI = 5°) to 1.51 (NI = 10°), and the critical strength reduction factor-based FEM ranges from 1.299 (NI = 5°) to 1.48 (NI = 10°), indicating that the slopes are critical to marginally stable. The factor of safety obtained by LEM showed a good correlation with the factor of safety based on FEM-SRF. The percentage difference between the factor of safety based on LEM and the factor of safety based on FEM-SRF is about 2.23%.

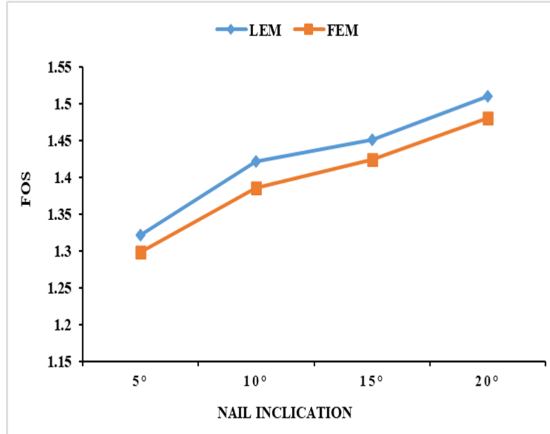


Figure 4. Comparison between factor of safety from LEM and FEM.

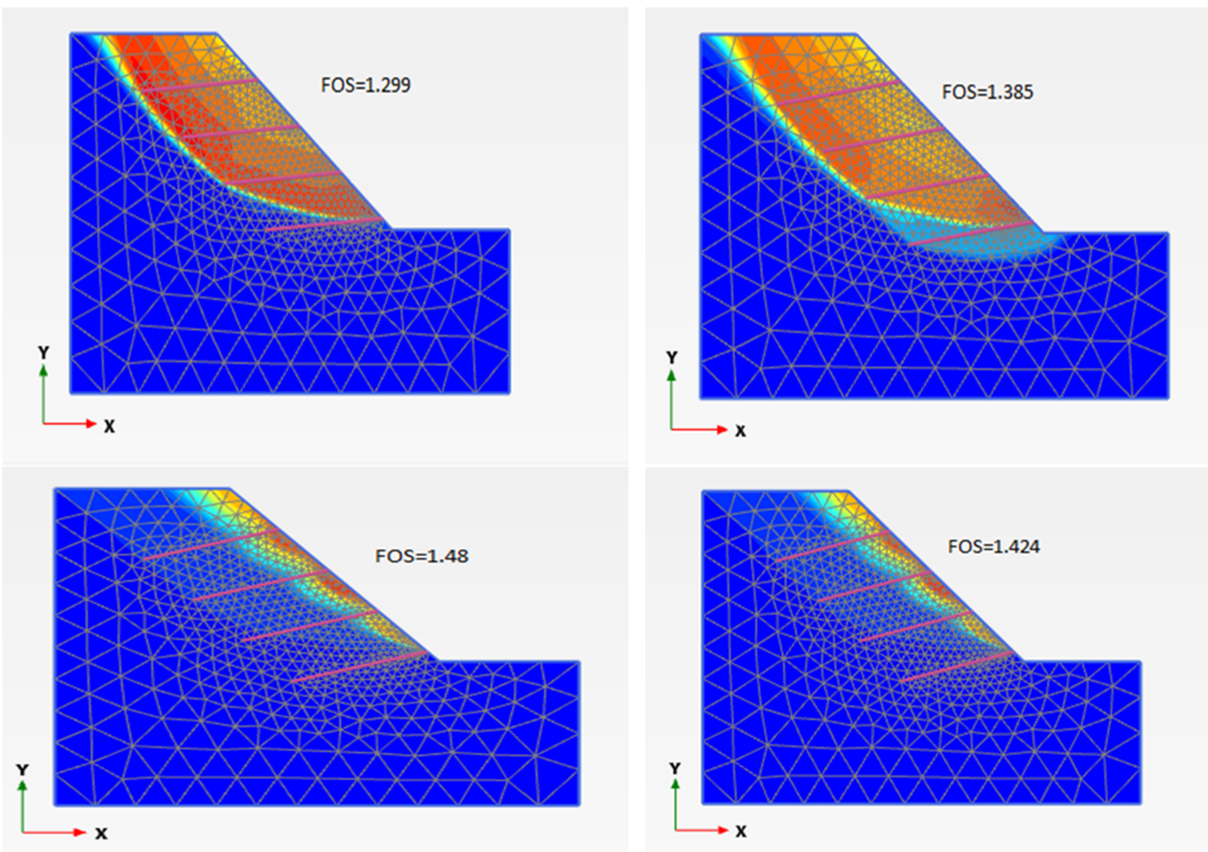


Figure 5. Strength Reduction Factors (SRFs) or FOS by finite element modelling of the studied slope inclination 5°, 10°,15°, and 20°.

2.2. Multiple regression analysis

Multiple regression analysis (MRA) is a statistical technique used to examine the relationship between one dependent variable and two or more independent variables. This method helps to understand how the multiple factors collectively influence an outcome, allowing for predictions and insights based on the historical data. It helps in predicting the dependent variable based on new values of the independent variables. The generalized multiple regression model is expressed through Equation (1):

$$Y = A + BX_1 + BX_2 + \cdots \dots \dots .... + BX_n + C \qquad (1)$$

where:

Y is a dependent variable.

X_1, X_2, X ……..., X_n are the independent variables.

A is the intercept, and C is the residual.

The prediction of value of Y can be done by using Equation 1 at any given time, provided that the values of independent variables are known.

In the present work, the collected data was used to develop a multiple regression model. Multiple regression analysis was employed to predict the factor of safety (FOS) by incorporating multiple variables such as angle of the slope (45°, 50°, 60°, 70°), nail inclination angle (0°, 5°, 10°, 15°, 20°, 25°, 30°, 35°) and nail length (6 m, 8 m, 10 m, 12 m). The multiple regression model is expressed through Equation (2):

$$FOS = f(\varphi, l, \theta) \qquad (2)$$

where, FOS is a dependent variable, and slope angle (Θ), nail inclination (φ), and nail length (l) are the independent variables.

Plots have been generated to validate the assumption of linearity between the independent and dependent variables. Figure 5 to 13 illustrate the linear connections between the independent and dependent variable. Figure 5 illustrates the graphs of nail inclination v/s the FOS values for various slope angles.

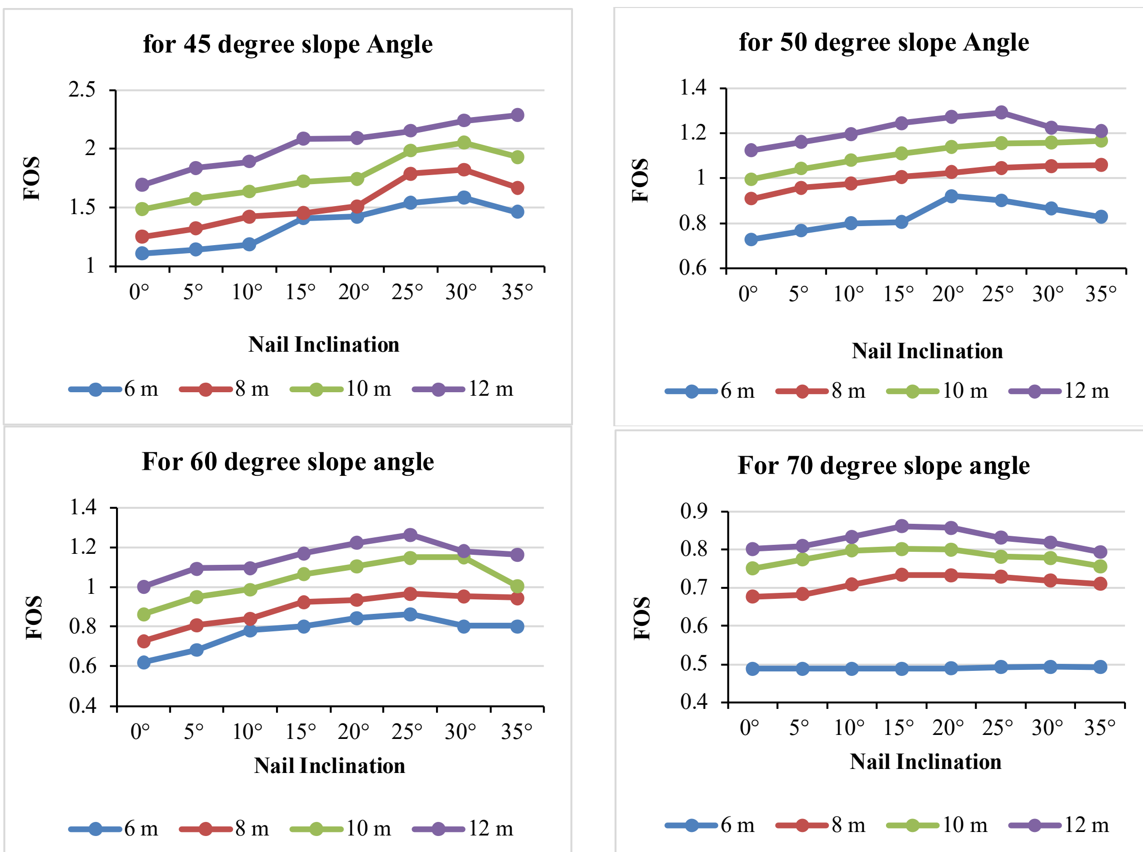


Figure 6. Graphs of nail inclination v/s FOS values for various slope angles.

Figure 5. shows that the FOS increases initially with increasing nail inclination up to a particular inclination, for which FOS is the greatest. For each increment in nail inclination decrease in FOS for all slope angles, the optimum nail inclination is defined as the nail inclination that yields the highest FOS. The percentage improvement is about 30% between 15° and 25° nail inclination for all slope angles. The ideal nail inclinations for slope angle 45°, 50°, 60°, and 70° is found between 15° and 25°. The results found from the numerical analyses in this work show the significance of the selection of the best nail orientation.

In a similar manner graphs of nail length v/s FOS values for different nail inclination are illustrated in Figures 6 to 13.

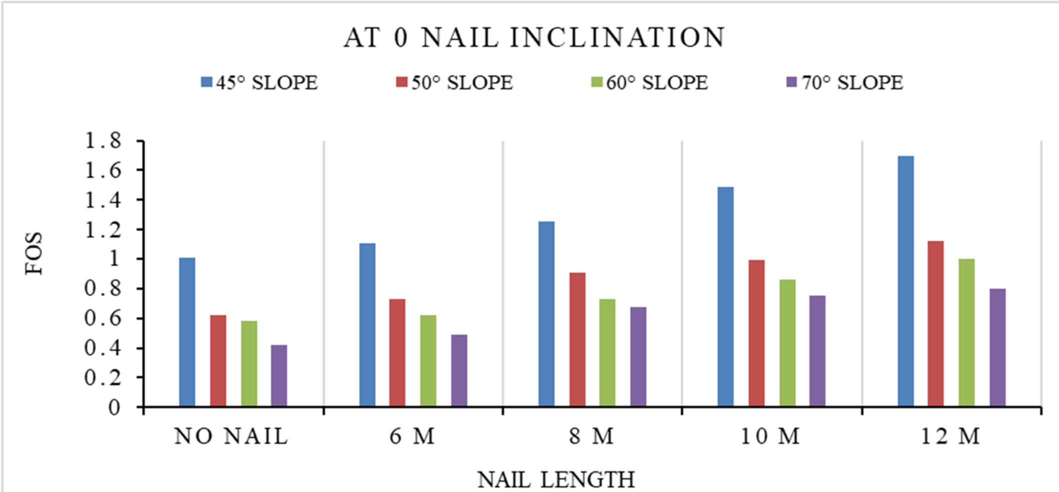


Figure 7. Graphs of nail length v/s FOS values for 0° nail inclination.

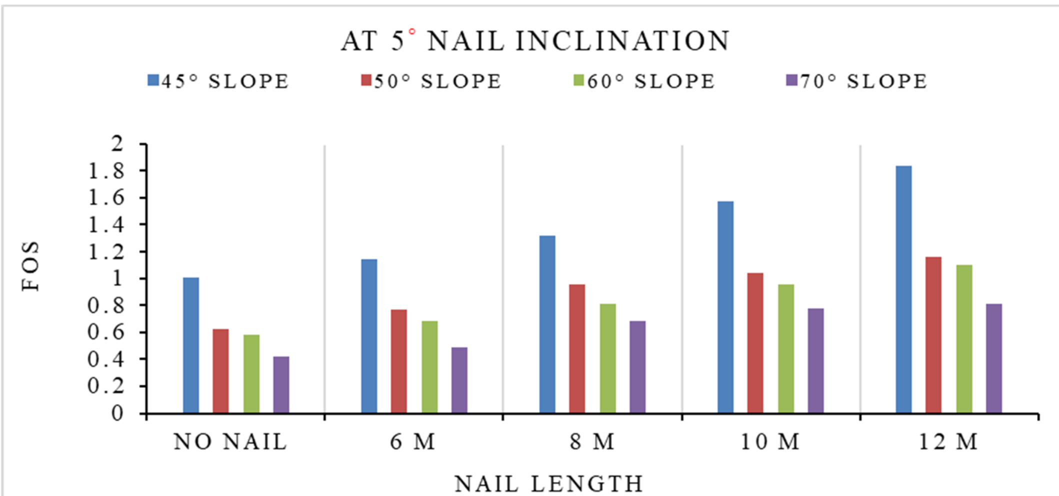


Figure 8. Graphs of nail length v/s FOS values for 5° nail inclination.

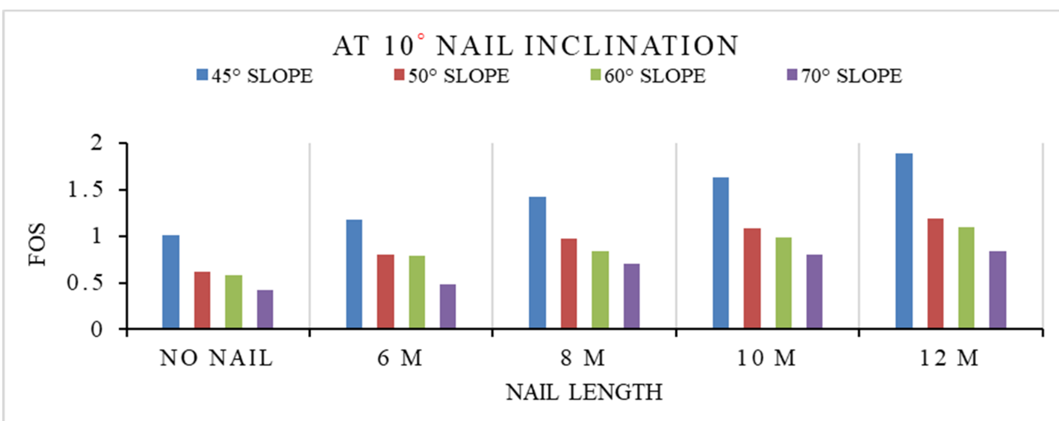


Figure 9. Graphs of nail length v/s FOS values for 10° nail inclination.

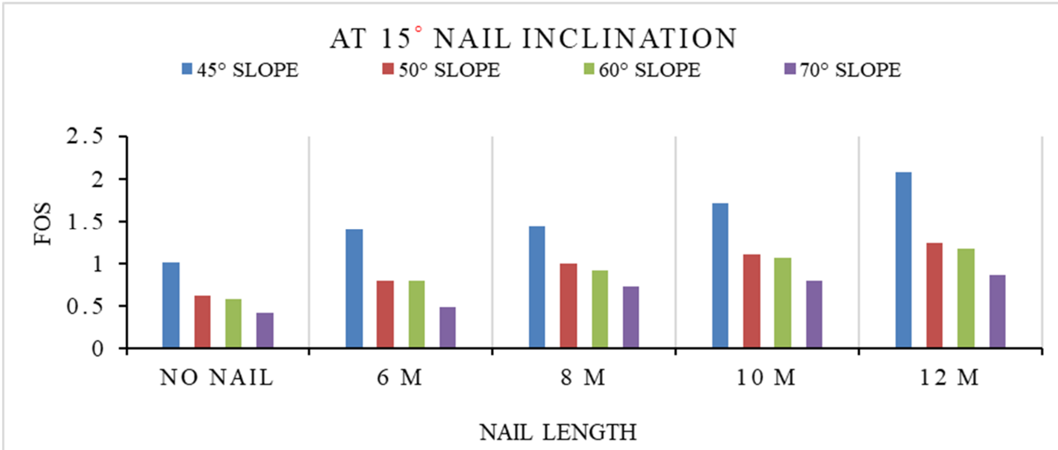


Figure 10. Graphs of nail length v/s FOS values for 15° nail inclination.

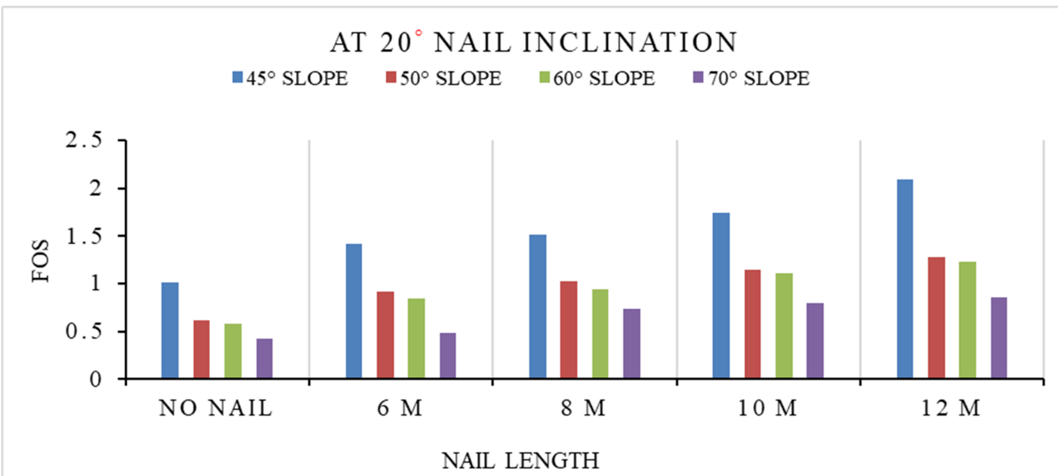


Figure 11. Graphs of nail length v/s FOS values for 20° nail inclination.

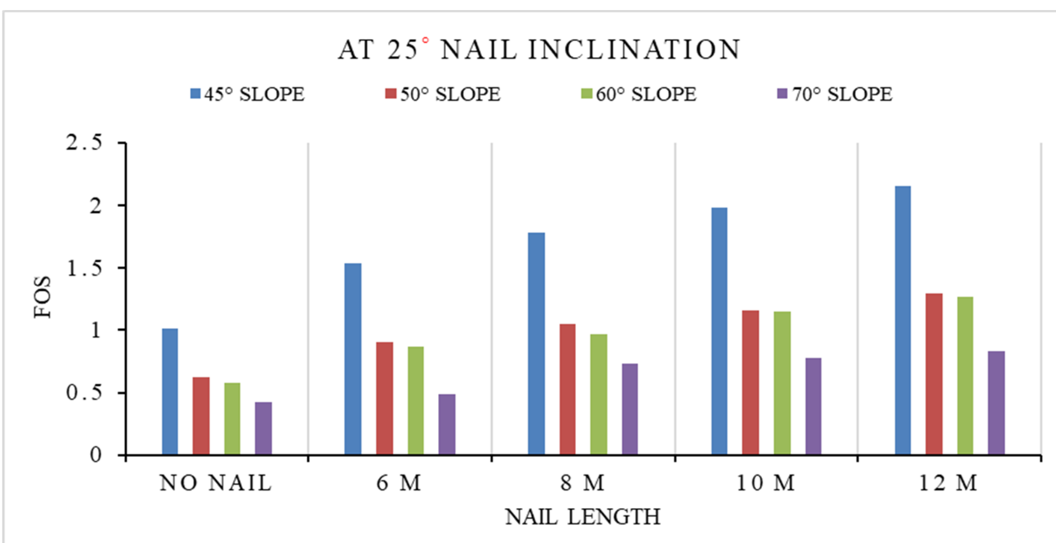


Figure 12. Graphs of nail length v/s FOS values for 25° nail inclination.

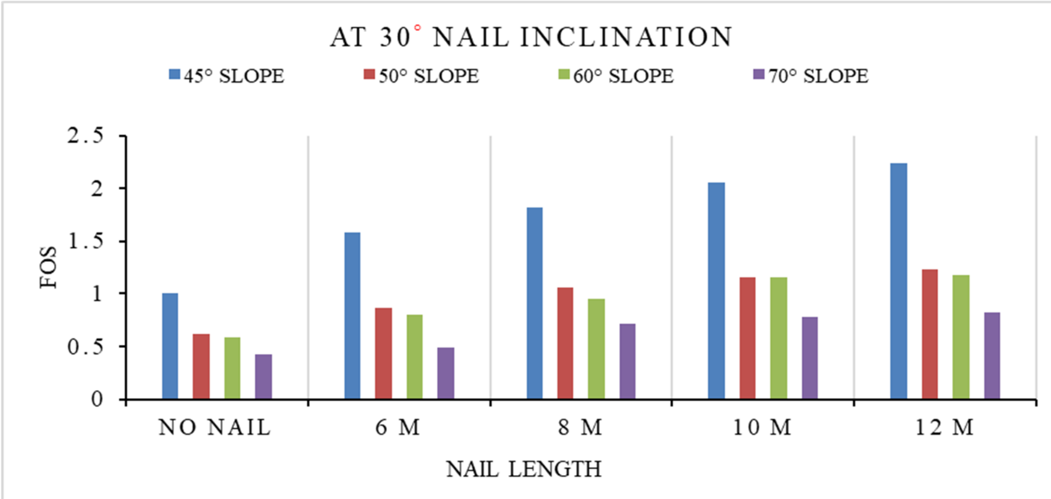


Figure 13. Graphs of nail length v/s FOS values for 30° nail inclination.

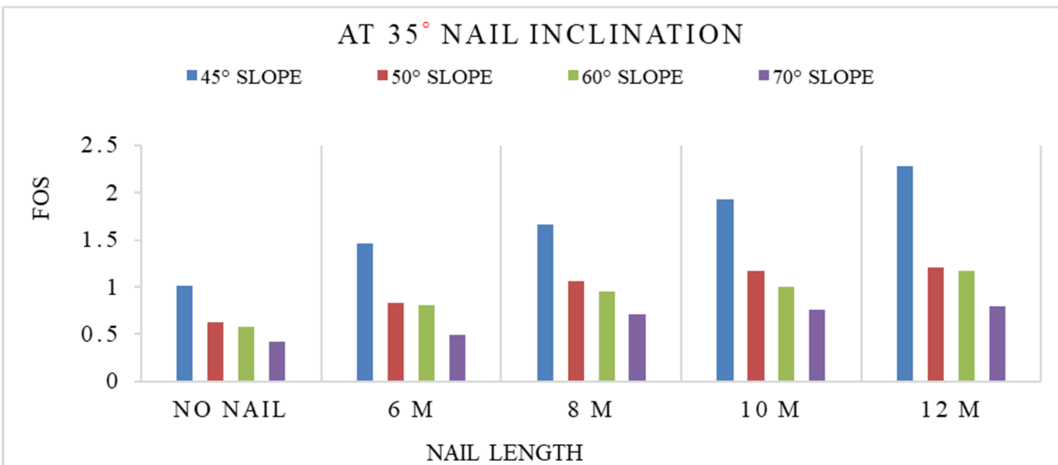


Figure 14. Graphs of nail length v/s FOS values for 35° nail inclination.

Figures 6 to 13 shows that as the length surpassing the slip surface, i.e the anchored length (la) increases the resistance developed between the soil and nail increases and hence FOS increases.

3. Results and Discussion

3.1. Model fitness

The fitness of the model can be checked using the value of R^2. An R^2 value close to 1 indicates that a large proportion of the variance is explained by the model, while a value close to 0 indicates that the model does not explain much of the variance. In this MRA model, the value of R^2 is 0.774, which means 77.4% independent variables (nail length, nail inclination and slope angle) have good strength of explaining the dependent variable (FOS). The model statics is given in Table 4.

Table 5. Regression of variable FOS.

Observations	160
Sum of weights	160
DF	156
R^2	0.774
Adjusted R^2	0.770
MSE	0.040
RMSE	0.201
MAPE	16.410
DW	0.262
Cp	4.000
AIC	-509.165
AICC	-508.907
SBC	-496.864
PC	0.237

The average squared difference between the actual and the predicted values is known as Mean Square Error (MSE). In the present work, the MSE value for the MRA model is about 0.04. Lower values of MSE indicate a better fit of the model to the data. Higher values indicate that the model's predictions are, on average, further from the actual values.

Here, the multiple regression model demonstrated a high degree of correlation with these values, as evidenced by a lower Mean Squared Error (MSE), and a higher coefficient of determination (R^2) compared to the traditional methods.

3.2. Significance of model

The significance can be used to test whether the overall regression model is a good fit for the data. The low p-value (typically < 0.05) indicates that the model is statistically significant, and that at least one of the predictors is significantly related to the Dependent Variable (DV). In the present model, the p-value of all the three Independent Variables (IDV) slope angle, nail length and nail inclination are < 0.0001, < 0.0001, and 0.003, respectively, which indicates that the all the three IDVs are significantly related to the DV.

Table 6. The summary of MLR for the 160 slope cases is given in the Table below.

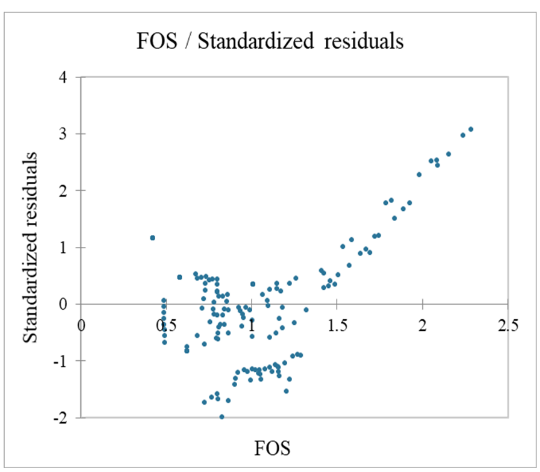
Variable	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
FOS	160	0	160	0.423	2.285	1.006	0.419
Slope angle	160	0	160	45.000	70.000	56.250	9.632
Nail length	160	0	160	0.000	12.000	7.200	4.131
Nail inclination	160	0	160	0.000	35.000	14.000	12.449

3.3. Prediction of FOS using MRA model

The equation of the MRA model is given by Equation 3. In Equation 3, the regression coefficients represent the independent contributions of each independent variable to the prediction of the dependent variable i.e. FOS. Hence, the regression line expresses the best prediction of the dependent variable (Y), given the independent variables (X).

$$FOS = 2.29 - 3.002 \times 10^{-2} \times \text{slope angle} + 4.7810^{-2} \times \text{nail length} + 4.4 \times 10^{-3} \times \text{nail inclination} \quad (3)$$

However, the nature is rarely perfectly predictable, and hence, there is always a substantial variation of the observed points around the fitted regression line. Hence, it can be stated that the prediction results obtained from the Morgenstern and Price method have a close relationship between the input variables, and prediction of FOS (DV) can be done using the above equation.



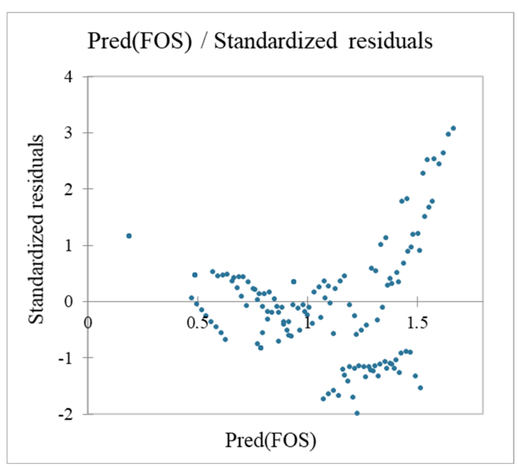


Figure 15. (a) Graph between standardized residuals v/s FOS, (b) Graph between standardized residuals v/s predicted FOS.

A graph plotting the Factor of Safety (FOS) against the standardized residuals provides insights into the relationship between the predicted FOS and the discrepancies between the observed and predicted values. This indicates that the residuals are randomly distributed, and that the model's predictions are unbiased across different levels of FOS.

In the Figure 15, the 45-degree line (or the line of equality), which represents the line where the predicted FOS equals the observed FOS. Points lying on this line indicate perfect predictions by the model. Points close to or on the 45-degree line suggest that the model's predictions are accurate. Points above the 45-degree line indicate that the model has under-predicted the FOS. Points below the line indicate that the model has over-predicted the FOS.

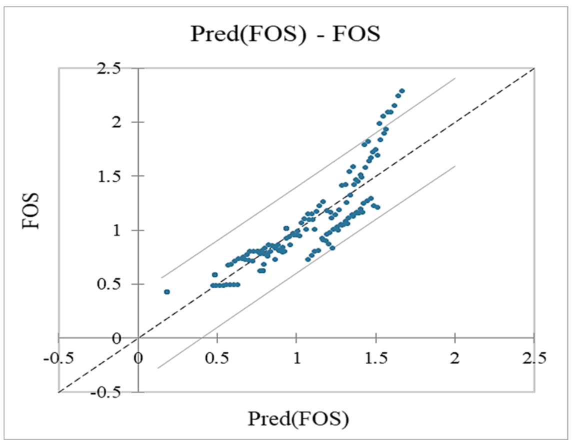


Figure 16. Graph between factor of safety (FOS) and predicted factor of safety.

3.4. Comparison with LEM method

The multiple regression model consistently outperformed the traditional LEM approach in predicting the slope stability. The model's ability to integrate and analyze multiple influencing factors simultaneously led to more accurate predictions. The results indicate that multiple regression analysis provides a more comprehensive assessment by considering complex interactions that the conventional methods may overlook.

4. Conclusions

This work demonstrates that multiple regression analysis offers significant advantages over the traditional slope stability assessment methods. By incorporating a range of influencing factors and providing a more accurate prediction of factors of safety, multiple regression enhances the reliability of slope stability analysis in the Kullu district. This approach not only improves understanding, but also supports better risk management and decision-making in geotechnical engineering.

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Conflict of Interest

The authors have no conflicts of interest to declare. All co-authors have seen, and agree with the contents of the manuscript, and there is no financial interest to report.

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مدل‌های رگرسیون چندگانه برای پیش‌بینی پایداری شیب خاک تقویت شده

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چکیده:

شکست شیب‌ها مسئله رایج در بخش ساخت و ساز است. بنابراین مهندسان باید از تکنیک‌های تثبیت شیب مناسب برای کاهش خطر جان و مال انسان استفاده کنند. این کار به بررسی اثربخشی تحلیل رگرسیون چندگانه در پیش‌بینی پایداری شیب می‌پردازد، به‌ویژه با تمرکز بر دامنه‌ها در ناحیه کولو، هیماچال پرادش، هند. در مجموع ۱۶۰ مورد با پارامترهای مختلف با استفاده از روش شناخته شده تعادل حد (LEM)، Morgenstern و Price on PLAXIS LE تجزیه و تحلیل شد. تجزیه و تحلیل عددی با استفاده از طول های مختلف میخ (۶ متر، ۸ متر، ۱۰ متر و ۱۲ متر) و شیب ناخن (۰ درجه، ۵ درجه، ۱۰ درجه، ۱۵ درجه، ۲۰ درجه، ۲۵ درجه، ۳۰ درجه و ۳۵ درجه انجام شد. در شیب خاکی همگن با شیب های ۴۵ درجه، ۵۰ درجه، ۶۰ درجه و ۷۰ درجه اعمال می شود. به ترتیب. تجزیه و تحلیل تعادل حد ممکن است قابلیت‌های پیش‌بینی را برای سناریوهای آینده به طور مستقیم ارائه ندهد. در مقابل، رگرسیون‌های چندگانه (MR) می‌تواند بینش‌های پیش‌بینی‌کننده‌ای را بر اساس داده‌های تاریخی ارائه دهد، که امکان پیش‌بینی ثبات را در شرایط مختلف یا سناریوهای طراحی فراهم می‌کند. استفاده از MR ضرایبی را فراهم می‌کند که تأثیر هر متغیر بر پایداری شیب را تعیین می‌کند و درک دقیقی از نحوه مشارکت هر عامل را ممکن می‌سازد. برای توسعه مدل‌های پیش‌بینی با استفاده از تحلیل رگرسیون چندگانه (MRA)، از ضریب مقادیر ایمنی به‌دست‌آمده به روش عددی استفاده شد. دقت این مدل در برابر روش‌های LE مرسوم ارزیابی شد. نتایج نشان می‌دهد که رگرسیون چندگانه عملکرد پیش‌بینی‌کننده خوبی با مقدار R2 برابر با ۰.۷۷۴ ارائه می‌دهد و ارزیابی دقیق‌تر و دقیق‌تری از پایداری شیب را در مقایسه با تکنیک‌های LE سنتی ارائه می‌دهد.

کلمات کلیدی: PLAXIS LE، روش تعادل حدی، ضریب ایمنی، تحلیل رگرسیون چندگانه.