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Development of Soil Cohesion and Friction Angle Models Using Multiple Linear Regression (MLR) Statistical Techniques

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Abstract - The multiple linear regression (MLR) soil strength models developed from electrical resistivity tomography and seismic refraction tomography are presented in this paper. The multiple linear regression method was used to estimate two dependent values, namely soil cohesion and friction angle, based on the values of two independent variables, namely resistivity and velocity. These parameters were regressed using regression statistics to create a multiple linear regression model using SPSS software. At the first stage, the MLR model results were needed to be evaluated to avoid bias. In this stage, the MLR for both soil cohesion and friction angle were checked for the coefficient of multiple determination, significance level (*p*-value), and multicolinearity. The next is the second stage, where the accuracy assessment of the MLR models was validated using root mean squared error (*RMSE*) and mean absolute percentage error (*MAPE*) for the statistical analysis. Based on the results of these analyses, the newly soil strength models from the geophysical data set for the near-surface study were successfully created. The soil strength models developed using MLR are reliable for imaging the subsurface in two-dimensional form, covering a larger area than the traditional method rather than laboratory tests, especially a large number of samples for site investigation.

Keywords: Multiple linear regression, soil strength, accuracy assessment, site investigation

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Introduction

Background

In geotechnical and geophysical studies, near-surface imaging is a problematic technique. As previously stated (Smethurst *et al*., 2006; Nordiana *et al*., 2013; Balarabe *et al*., 2021; De and Rout, 2022; Sedara and Alabi, 2022), understanding that ground subsurface behaviour was important as it plays a significant role in effectively optimizing space and developing response strategies. Furthermore, internal factors are essential and required for a compelling slope monitoring study. Many other types of research have investigated the contribution of vegetation (Greenwood *et al*., 2004), subsurface behaviour using design of slope geometry (Alejano *et al*., 2007), infiltration of rainfall (Zhan *et al*., 2007), the effect of groundwater table (Rahardjo *et al*., 2010), and measurements of pore pressure profile (Huang *et al*., 2012). Meanwhile, the landslide prediction and slide motion analysis methods in Japan were suggested by Suwa *et al*. (2010). These previous studies showed that various methods could be used to study the condition of the subsurface.

Before beginning any construction work, it is becoming more common to hire geoscientists who specialize in slopes made of soil or rock. Because mass movement events like landslides and rockfall are linked to human and building safety, they are also concerned about the importance of studying the slope area. Slope stability assessment currently relies on sensor points, which are difficult to interpret, expensive to study, and do not cover a large portion of the terrain. The near-surface monitoring technique of electrical resistivity tomography (ERT) is well-known (Balarabe and Bery, 2021). Data from the landslide-slope resistivity monitoring inversion was used by Suzuki and Higashi (2001) and Bery (2016). Groundwater flow following heavy rain is the subject of this study. An experiment was conducted in a laboratory to determine the differences in geological features. Since borehole records can only provide subsurface information from a limited perspective, this geophysical method of ERT is used because it can provide more information than borehole records (Bery and Ismail, 2018). The aquifer beneath Sungai Kelambu, Banting, Selangor, was mapped using this geophysical technique by Hamzah *et al*. (2006a). A meteorite impact study used the ERT method to characterize the ground subsurface (Kiu *et al*., 2012). In the meantime, geo-electrical and geochemical surveys were used by Hamzah *et al*. (2006b) to examine soil and groundwater characteristics in the coastal plain.

Soil properties can be predicted using statistical methods. Based on soil and tractor properties, Elaoud *et al*. (2017) demonstrated how the statistical method of multiple linear regression could be used to estimate the soil penetration resistance. According to their research, a variety of predictors are used in the statistical method they employ. An artificial neural network (ANN) is used for the estimation of rock parameters as suggested by Yilmaz and Yuksek (2008).

The objective of this study is to use a multiple linear regression (MLR) statistical technique to develop shear strength parameters of soil from two geophysical methods. To ensure that the regression model is accurate, it was tested and validated. The multiple linear regression (MLR) models were used to model soil strength by combining geophysical and geotechnical methods. Previous statistical approaches (Egbe *et al*., 2017; Jung *et al*., 2017) used the MLR model in their study, but did not include MLR model prediction in their study. Although geo-electrical parameters were included in the models of Chand *et al*. (2004) and Israil *et al*. (2006), the importance of multiple factors was overlooked. As a result, as previously stated, it distinguishes this work from previous works. In the first stage, the MLR model is tested for significance level (*p*-value, and free from multicollinearity) in this study. The proposed multiple regression model was based on ERT and seismic velocity parameters as two main predictors (known as parameters). For determining soil cohesion, a multiple regression model developed by the researchers is more accurate than the traditional method. Additionally, the MLR model prediction accuracy and actual value were evaluated. It has been demonstrated that the MLR model, which incorporates multiple soil property parameters, can provide accurate soil strength model estimates in a manner similar to the laboratory method. The model developed here can be applied to any other location with a similar geological setting.

Geological Settings

In Malaysia, on the island of Penang, these studies are being carried out. Penang State is in charge of the area around Penang Island. As part of Malaysia's north-west peninsula, this state is one of the fastest-growing places in the country (Kong, 1994). Equatorial climates are common in Malaysia, including Penang Island. When compared to the mainland, its average daytime temperature ranges from 29° to 35°C. This area is made up of Penang Granitic rocks (Kong, 1994), divided into two types: Type I, known as Bukit Bendera, and Type II, known as Sungai Ara (Kong, 1994). Type II Penang Granitic rock was discovered in Minden, Gelugor, for the purpose of this investigation (Figure 1). Figure 1 depicts the studied area as a red triangle. The biotite granites of Minden are well-known for their medium- to

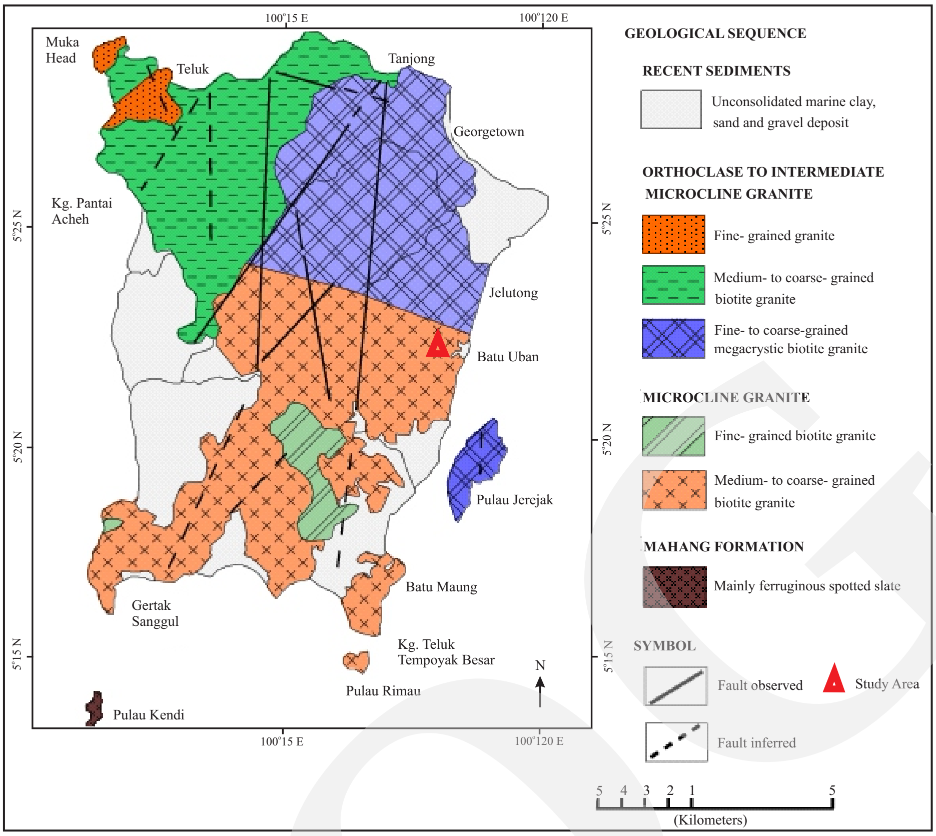

Figure 1. Geological map of Penang, Island, Malaysia (after; ong, 1933).

coarse-grained size. Due to the weathering of granitic rocks, the soil in the studied area consists primarily of clayey sand.

Methods and Materials

2-D Resistivity and Seismic Refraction Methods

ABEM SAS4000 equipment was used to collect two-dimensional resistivity data in Minden, Penang. For 2-D resistivity surveys, this multi-electrode resistivity system is ideal. The Wenner-Schlumberger array was used as an electrode array because of its ability to resolve vertical and horizontal subsurface changes (Bery *et al*., 2014). The total survey length is 40 m, and the minimum electrode distance used is 1.0 m. Horizontal resolution can be improved by using smaller electrode spacing rather than larger electrode spacing, as demonstrated by Bery and Saad (2013) and Okpoli (2013). Data collection was done in the morning, because the subsurface is suitable for electrode planting. In the afternoon and evening, dry subsurface conditions can lead to data set errors.

Electrode Selector (ES10-64) equipment was used to gather the data in an automated manner. The number of data stacking is set to two for the field survey. Automatic recording of the apparent resistivity data and a profile at each of the vertically-planted electrode positions took place. RES2DINV software was used to convert the data before inversion and data filtering. Loke and Barker (1996) created the RES2DINV software for inversion. Following the inversion resistivity data set, the model resistivity was obtained. The data set was then filtered to remove bad data that could lead to incorrect interpretation of the resistivity model. Calculated resistivity data was compared to actual measurements. During the iteration process, the programme adjusted the apparent resistivity model until it matched the measured apparent resistivity model. The iteration concluded when the resistivity inversion process converged. In other words, the iteration ended when the percentage difference between Root Mean Squares (RMS) errors for consecutive iterations became negligible or the percentage RMS error fell to acceptable levels.

Geophysical exploration methods that use seismic refraction tomography (SRT) are among the oldest. This method is controlled by the arrival time of refracted waves at the time of the seismic wave generation. In order to detect the recorded waves, a system of geophones was positioned on the ground. This study employed the SRT method, which included eleven shot points and twenty-four geophones spaced apart by one metre. A survey line of 40 m can be covered using the roll-along method, which is like the ERT method. SeisOpt velocity optimization software was used next to finish processing the seismic data set, followed by Surfer software for contouring.

Direct Shear Test (BS1377)

The direct shear test was used in a geotechnical laboratory to collect soil samples. A soil sample is subjected to a constant load while being forced to fail along a plane. The shear resistance developed along a known sample section area within the sliding plane was used to define the obtained shear stress. Cohesion (*C*') and friction angle (ϕ') parameters could be determined by using this technique along the survey line at a known location (distance and depth). On the resistivity survey line, soil samples were taken at depths of up to 1.2 m along the survey line. The simple regression models can be developed with the soil strength parameters as a reliable source of laboratory data. The shear strength regression derived from the laboratory test was represented by Equations 1 and 2. These equations (derived from laboratory results) were then treated as real shear strength parameters integrated with resistivity parameters.

$$c' = 3.156 + 0.014(\rho) \quad \text{..............................(1)}$$

$$\phi' = 53.80 - 0.041(\rho) \quad \text{..............................(2)}$$

where

c' in kN/m^2; ϕ' in degree and ρ in ohm.m.

Soil Strength Prameters and Geophysical Data Correlations

The ERT (unit in ohm.m) and SRT (unit in m/s) were generated by the two-dimensional imaging scheme. True resistivity and seismic velocity values were correlated with the actual soil strength parameters (cohesion and friction angle) measured in the laboratory test at the exact location (X), elevation (Y). This method is based on sound science and is intended to provide accurate data about the subsurface. The electrical resistivity values were set in log10 ($Log_{10}\rho$), while seismic velocity (Log_{10}Vp) values were set in metre per second (m/s). Because of the non-linear nature of the earth subsurface complexity, a non-linear equation for these two geophysical parameters was required, as explained by Loke (2014). Subsurface imaging data such as true resistivity and seismic velocity were transformed into non-linear forms as a result.

Multiple Linear Regression (MLR) Model

Indicator variables were used in regression models to represent qualitative parameters. When analyzing geophysical parameters from in-field studies using indicator variables, understanding variance analysis (also known as ANOVA) is essential. A more generic MLR model is depicted in the following manner:

$$Y = \beta_0 + \beta_1(x_1) + \beta_2(x_2) + \ldots.. + \beta_n(x_n) + \varepsilon_i \quad \text{....(3)}$$

where:

β_0 is the intercept;

β_1 and β_2 are the slopes of the regression line with independent variables or predictors (x_1 and x_2), respectively;

ε_i is the error term; and lastly

Y is the dependent variable or response explained in Koutsoyiannis (2001) and Balarabe *et al*. (2021).

Based on two geophysical parameters, the MLR model developed in this study was used to build a novel model of soil cohesion. These two geophysical parameters were designated as predictors, which were independent variables. In this study, ANOVA statistical analysis and the MLR model use of two factorial independent variables were considered as suggested by Balarabe *et al*. (2021). Meanwhile, the dependent variable is defined as the soil strength parameters. The significance level was set to 0.05 (5%). In other words, the level of confidence was 95%. Balarabe *et al*. (2021) suggested that the multiple linear regression model in the present was expressed as

$$C^{'} = \beta_0 + \beta_1(Log_{10}\rho) + \beta_2(Log_{10}\mathrm{Vp}) \quad ....(4)$$

$$\phi^{'} = \beta_0 + \beta_1(Log_{10}\rho) + \beta_2(Log_{10}\mathrm{Vp}) \quad ....(5)$$

Result And Analysis

The ERT modeling results of Lines 1 and 2 are shown in Figure 2. Clayey sand soil subsurface characteristics were predicted by the ERT model. Low resistivity values (50–450 ohm.m) were used to determine the saturation zone in clayey sand soils. Unsaturated clayey sand soil was identified by medium resistivity values, ranging from 700 to 4700 ohm.m (Nordiana *et al*., 2013; Balarabe *et al*., 2021). Lines 1 and 2 of the resistivity inversion have an RMS error value of 10.6% and 8.8%, respectively (Figure 2). It is clear from this low RMS value that the model is accurate, and that the resistivity distribution varies slightly across the model results. According to the results of the SRT modeling results, the researched area can also be divided into two areas (Figure 3). Loose clayey sand soil with speeds ranging from 1 to 300 m/s is found in the first region. Dry to compacted clayey sand soil makes up the second region, with velocities ranging from 300 to 1100 m/s (Bery, 2016; Balarabe *et al*., 2021).

Multiple Linear Regression (MLR) of Soil Strength Models

The qualitative statistical analysis performed on the developed soil strength models in Microsoft Excel enabled parameter significance evaluation. The developed models are examined for verification using the two-way ANOVA scheme. The *p*-value of predictors were always looked at for each independent variable. Any predictors with *p*-values equal to or greater than 0.05 must be excluded. When the *p*-value is 0.05 or higher, it indicates that the predictor values of the independent variables are insignificant in predicting the outcome as explained by Balarabe and Bery (2021). As a result, it is insignificant.

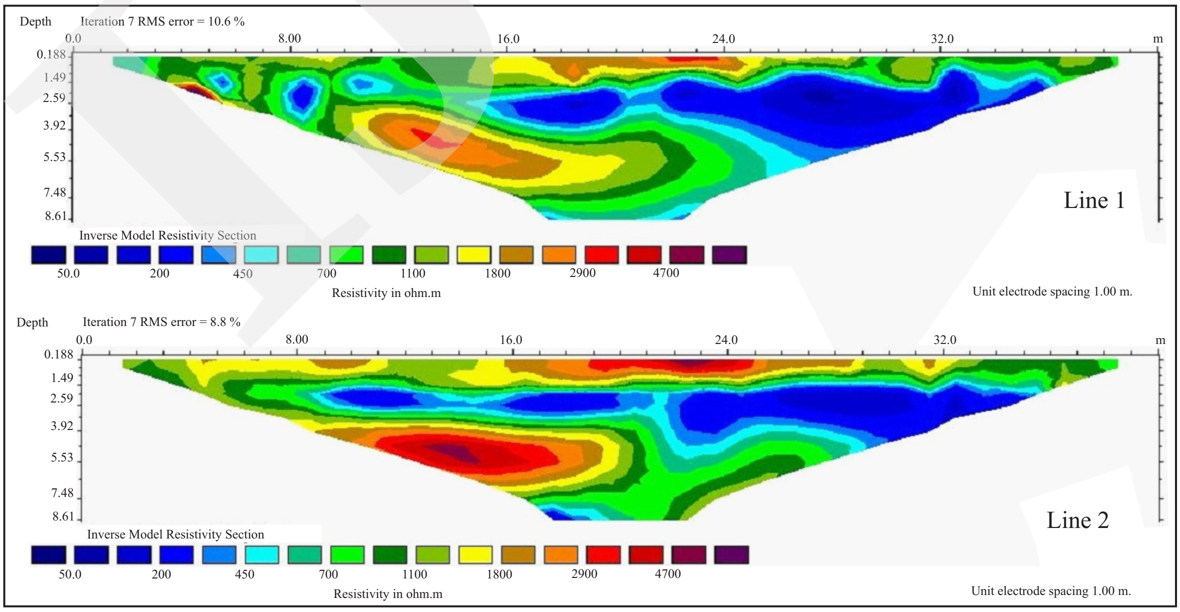

Figure 2. ERT modelling results for Lines 1 and 2.

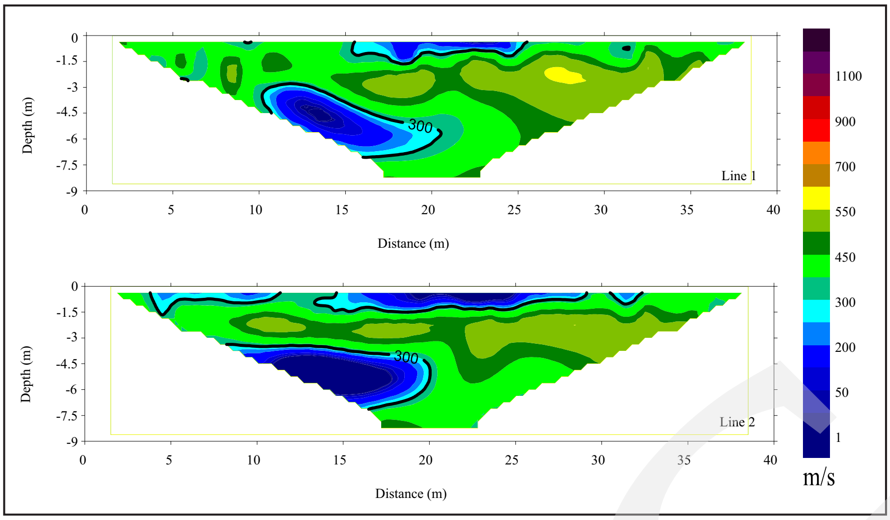

Figure 3. SRT modelling results for Lines 1 and 2.

According to the summary results for Tables 1 and 2, the evaluated resistivity and velocity parameters have a significant relationship with the responses or outcomes. The *p*-value for each predictor that supports this significant relationship is less than 0.05. (5%). This means that at a 95% confidence level, the significance of both selected predictors (resistivity and velocity parameters) can explain the cohesion model (Equation 4) and the friction angle model (Equation 5). Tables 1 and 2 show that Equations (4) and (5) for these soil strength parameters have a significant relationship to the response. Based on the cohesion model, the first predictor variable of resistivity has a *p*-value of 0.00 and the second predictor variable of velocity has a *p*-value of 0.03. Whereas the friction angle model gives a *p*-value of 0.00 for the first predictor variable of resistivity and a *p*-value of 0.03 for the second predictor variable of velocity. The MLR statistical technique showed that they were statistically significant, because the calculated *p*-values for both predictors were less than 0.05 as explained by Balarabe and Bery (2021). As a result, it is concluded that the model obtained using the MLR method is correct and acceptable. The next stage of this research will be to compare the prediction and actual values of the soil strength models.

Table 1. Multiple Linear Regression Results for Cohesion Parameter with Geophysical Data

	Coefficients	*p*-value	*VIF*
Constant	-7.50	0.01	
$Log_{10}\rho$	9.56	0.00	1.04
Log_{10}Vp	-1.96	0.03	1.04

R-Square = 0.826

Table 2. Multiple Linear Regression Results for Friction Angle Parameter with Geophysical Data

	Coefficients	*p*-value	*VIF*
Constant	83.65	0.00	
$Log_{10}\rho$	-26.75	0.00	1.04
Log_{10}Vp	5.50	0.03	1.04

R-Square = 0.826

The coefficient for β_0, β_1, and β_2 were determined through regression analysis using the ANOVA scheme for data set. From the multiple linear regression analysis, it gives β_0 = -7.50, β_1 = 9.56, and β_2 = -1.96 for Equation (4). Meanwhile the multi linear regression analysis, it gives β_0 = 83.650, β_1 = -26.754, and β_2 = -5.497 for Equation (5). By substituting all the coefficients into Equation (4) and Equation (5), the new cohesion (C') and friction angle (ϕ') models become Equation (6) and Equation (7) respectively.

$$C' = -7.50 + 9.56(Log_{10}\rho) - 1.96(Log_{10}\mathrm{Vp}) \quad C' \text{ in kN/m}^2 \quad ....(6)$$

$$\phi' = 83.65 - 26.75(Log_{10}\rho) + 5.50(Log_{10}\mathrm{Vp}) \quad \phi' \text{ in degree} \quad ....(7)$$

Both coefficients of multiple determination found are 82.6% for both models (Equations 3 and 4). In addition, the variance inflation factor (*VIF*) value is less than 10, thus it indicates that there is no multicollinearity issue as explained by Balarabe and Bery (2021). Equations (4) and (5) are new MLR equations with cohesion and friction angle as dependent variables or outcomes and resistivity and seismic velocity parameters as independent variables or predictors. Therefore, the shear strength models, according to Balarabe *et al*. (2021) is presented by Equation (4) and Equation (5). As a result, Equations (4) and (5) are considered the new model of soil strength parameters for this specific studied area only, with resistivity and seismic velocity as predictor parameters.

Estimation Accuracy Assessment

The estimation accuracy of cohesion and friction angle models was assessed using Equations 8 and 9. The first statistical method is the root mean squared error (*RMSE*), and the second one is the mean absolute percentage error (*MAPE*). The *RMSE* statistic provides information about the differences between predicted and actual values, whereas the *MAPE* statistic provides information about the accuracy of the estimation or prediction as explained by Balarabe and Bery (2021).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{N}} \quad \text{..........................(8)}$$

$$MAPE = \frac{100\%}{N}\sum_{i=1}^{N}\left|\frac{x_i - \hat{x}_i}{x_i}\right| \quad \text{..........................(9)}$$

There are two statistical analyses: *RMSE* and *MAPE* (refer Tables 3 and 4). The analysis results show that the RMSE for cohesion is 2.051 kN/m^2, and for friction angle is 1.742 degree. The MAPE for cohesion is found 9.383 %, and friction angle is 8.119 %. The RMSE and MAPE values obtained from mathematical analyses indicate that they are deemed very well. The results of the statistical analyses show that the multiple linear

Table 3. Accuracy Assessment for Soil Cohesion Data

Actual Cohesion (kN/m^2)	Predicted Cohesion (kN/m^2)	Square Error	Absolute % error
11.7012	11.5632	0.019	1.179
11.647	11.4007	0.061	2.115
17.6124	18.5712	0.919	5.444
21.7376	21.2227	0.265	2.369
21.0802	20.832	0.062	1.177
18.052	17.7809	0.073	1.502
17.2602	19.7805	6.352	14.602
22.6958	21.5609	1.288	5.000
25.946	22.0136	15.464	15.156
19.2658	19.7841	0.269	2.690
12.3888	16.4399	16.411	32.700
12.5162	16.5805	16.519	32.472
13.1756	15.2023	4.108	15.382
16.8228	17.8878	1.134	6.331
15.7354	16.1487	0.171	2.627

RMSE = 2.051 kN/m²

MAPE = 9.383 %

Table 4. Accuracy Assessment for Soil Friction Angle Data

Actual Friction Angle (degree)	Predicted Friction Angle (degree)	Square error	Absolute % Error
28.7748	29.0162	0.058	0.839
28.9335	29.2574	0.105	1.119
11.4634	10.2846	1.390	10.283
5.2396	5.2436	0.000	0.076
10.176	9.4407	0.541	7.226
6.6377	6.482	0.024	2.346
6.6213	6.4698	0.023	2.288
12.7426	11.3701	1.884	10.771
13.7758	12.2734	2.257	10.906
15.1505	16.9194	3.129	11.676
17.1382	16.9561	0.033	1.063
18.726	15.2473	12.101	18.577
14.447	19.0815	21.479	32.079
16.2142	16.7302	0.266	3.182
15.9937	14.497	2.240	9.358

RMSE = 1.742 deg.

MAPE = 8.119 %

regression models using the MLR method can be used to develop new soil strength models, which for the studied area.

Discussion

Near-surface Investigation Using the MLR Models

The predicted soil strength parameters are acceptable for the MLR model using both geophysical parameters, according to the accuracy assessment results (Tables 3 and 4). The MLR cohesion and friction angle models were used to estimate or predict the soil cohesion and friction angle parameters of the chosen studied area. Along the same survey line, the ERT and SRT methods were used, after the data set for both geophysical data. The obtained two files should have contained three parameters, namely distance (x), depth (y), and resistivity (ρ) or velocity (Vp) records. The MLR model was used to generate the new files for cohesion and friction angle parameters, indicating the same distance and depth as geophysical data. The predicted cohesion and friction angle values from each geophysical parameter were obtained using Equations (6) and (7) (resistivity and velocity).

The predicted cohesion and friction angle parameters using the multiple linear regression (MLR) models are shown in Figures 4 and 5. It was discovered from the final predicted models of cohesion and friction angle that the selected geophysical methods were capable of covering the earth subsurface. The interpretation of the visualization shows that low cohesion zones are interpreted with values ranging from 13.0 to 15.0kN/m^2. These low cohesion zones are found in the upper and nearly middle portions of pseudo-sections (Lines 1 and 2). Meanwhile, a high cohesion zone is defined by values ranging from 15.0 to 17.0kN/m^2 (Balarabe and Bery, 2021). This high cohesion soil is found in the centre of pseudo-sections. For the soil friction angle model, the same pattern is successfully visualized and interpreted. The subsurface for Lines 1 and 2 is divided into two regions. The first region was analyzed as soil with a low friction angle varying from 26 to 30 degrees. Meanwhile, the second region is interpreted as soil with a high friction angle varying from 30 to 34 degrees (Balarabe and Bery, 2021). At the studied area, these two regions are clearly imaged and visualized from both Lines 1 and 2. The soil shear strength parameters calculated using the MLR technique provide useful information about the shear strength of interparticle friction-free soil. A zone with a high soil cohesion parameter contains a greater proportion of clay components than zones with a low soil cohesion parameter (lesser clay quantity). In other

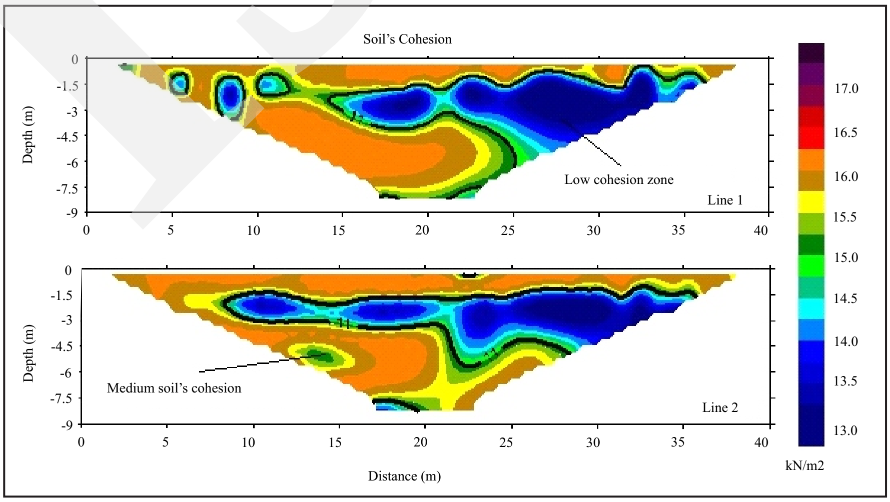

Figure 4. Cohesion models for Lines 1 and 2 using the MLR method.

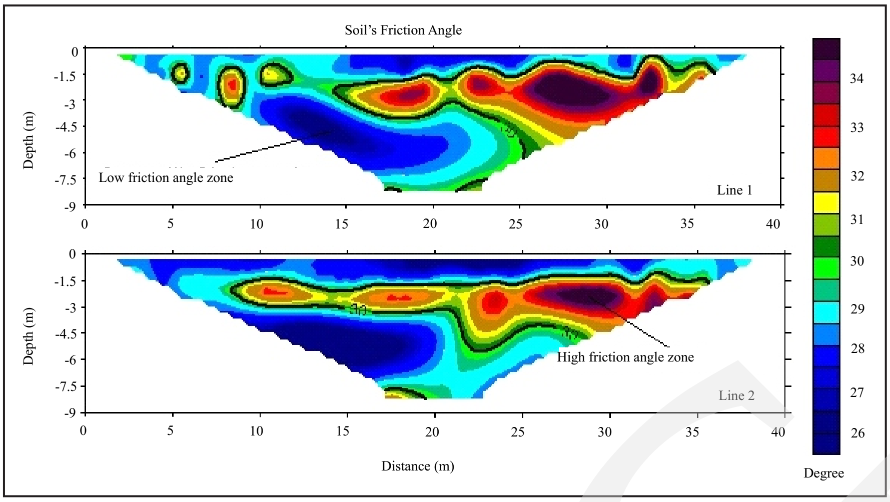

Figure 5. Friction angle models for Lines 1 and 2 using the MLR method.

words, high cohesion indicates a more cohesive soil (particles of soil adhere to one another). Thus, an increase in cohesion indicates an increase in the amount of clay and a decrease in the amount of sand. An increase in the friction angle, on the other hand, indicates an increase in sand content and a decrease in clay content as explained by Balarabe and Bery (2021).

As a result, the developed shear strength parameter of the soil model is a reliable tool for near-surface investigation using two geophysical methods (ERT and SRT). The new MLR soil strength models are appropriate for predicting or estimating the subsurface geotechnical parameters with more coverage (in 2-D form) in the studied area.

Conclusions

In this study, the subsurface of the chosen studied area was imaged and visualized using soil strength models. Multiple linear regression (MLR) models are used to develop these soil strength models. Geophysical parameters, such as resistivity and seismic velocity, were used to generate the newly proposed soil strength models. Furthermore, before generating predicted soil strength (cohesion and friction angle) models, the prediction accuracy of the proposed soil strength models was assessed using *RMSE* and *MAPE* statistics. Throughout the survey lines, the MLR method was used to predict or estimate the cohesion and friction angle parameters of the soil. The method used in this study can provide a quick and cost-effective prediction of soil strength parameters based on geophysical infield measurements. The limitation of this work is that a new MLR model for different geology areas must be developed. This is due to the fact that the nature of the soil type varies from one area to the next (sedimentary-igneous-metamorphic).

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