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Session 3 – B

Analysis of Subsurface Strata of Colombo and Gampaha Districts of Sri Lanka, Based on Geotechnical Investigation Data

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Abstract

The subsurface exploration for geotechnical engineering applications in Sri Lanka is mainly based on borehole investigations. Several leading geotechnical engineering companies in the country have already done more than a couple of thousands of subsurface investigations for small- and large-scale civil engineering projects.

Even though project-wise subsurface information is available, integration of available subsurface data in proximity, and development of subsurface three-dimensional (3D) models can hardly be seen in the country. This has been a significant disadvantage in the cost and planning of large-scale new investigation projects. Due to lack of information, most of the projects start even without knowing the tentative bedrock level of the area. Hence, in investigation cost estimations, pricing for most of the items is recorded as “rate-only”, hence the total cost could immensely be higher than the available budget with the client. However, if 3D modelling of subsurface strata can be done area-wise, based on already available borehole data, such uncertainties could be minimized.

In this research, more than a thousand subsurface investigation reports were reviewed; data were recorded and analysed targeting to interpret the subsurface of the western province of Sri Lanka, and to develop a 3D subsurface model for the same. However, scattered data had to be excluded in data analysis, and eventually, the study was confined to Colombo and Gampaha districts, in which more than sufficient data could be found. By using interpolation methods, surface strata were interpreted in between borehole locations by matching similar geological features. In addition, artificial neural networks were used to forecast borehole data in exceptional cases for a few locations. This helped to improve the spatial coverage and accuracy of the 3D model developed by means of “Surfer” software.

The 3D model developed for the study area well demonstrates the subsurface strata and facilitates taking of cross sections in any direction within minutes. Hence, the findings of this research will enhance the outcome of general geotechnical investigation practice in Sri Lanka. This will also be immensely beneficial in planning and budgeting of future large-scale geotechnical investigation projects, more accurately than in the past, saving energy and time.

Keywords: Boreholes; Geotechnical investigation; Modelling; Subsurface strata

1 Introduction

Subsurface exploration is an essential requirement related to Civil Engineering constructions, as the durability of foundations of structures depend on the quality of data gathered from geotechnical investigations. Several factors need to be considered in selecting the land for construction purposes such as suitability of the land, capital cost for the investment, available infrastructure, total consumable area, and subsurface conditions. Among them, subsurface condition plays a huge part in the planning stage, and site preparation [1].

Subsurface exploration can broadly be classified into two as indirect methods of exploration and direct methods of exploration. Indirect methods are geophysical techniques that are less labor-intensive and efficient. However, these methods give tentative information, and exact detailed information can only be gathered by borehole investigations by drilling into the earth and collecting of soil, rock, and water samples. Soil and rock samples are initially analyzed by means of borehole logging, and subsequently subjecting them to laboratory testing to understand the physical properties of them. For instance, out of the physical properties of soils and rocks; cohesion(c), friction angle(φ), and bulk density(γ) are taken as engineering design parameters in foundation engineering.

In Sri Lanka, insufficient research has been conducted to develop subsurface 3D models by analysing subsurface data, and sharing of such information is also limited. This means that every large-scale construction project needs a comprehensive investigation, without letting the project planning optimize the number of boreholes needed due to lack of former sub-surface information. Hence, it is identified the importance of having systematically developed sub-surface information models in the 3D format.

In this research, “Surfer” software which is a product of Golden Software Inc, USA has been used for data analysis. This software is widely used in mining and civil engineering applications. Surfer software offers capabilities for contouring, gridding, and 3D surface mapping, volume calculation for material available above a given datum level. In terms of 3D mapping, it allows users to create accurate terrain models and geological surfaces from scattered XYZ data points or grid files [2].

Firms that are doing geotechnical investigations need to give quotations before starting investigations. Before providing quotations, such companies can refer to the existing 3D subsurface models, which immensely help in visualizing sub-surface information. Availability of tentative 3D sub-surface models in the proposed investigation area is crucial in decision-making for cost optimization without sacrificing the quality of the investigation. By integrating 3D subsurface modeling, geotechnical engineering companies can improve cost control, project planning, and risk assessment leading to informed and financially viable investigations [3], [4].

2 Materials and Methods

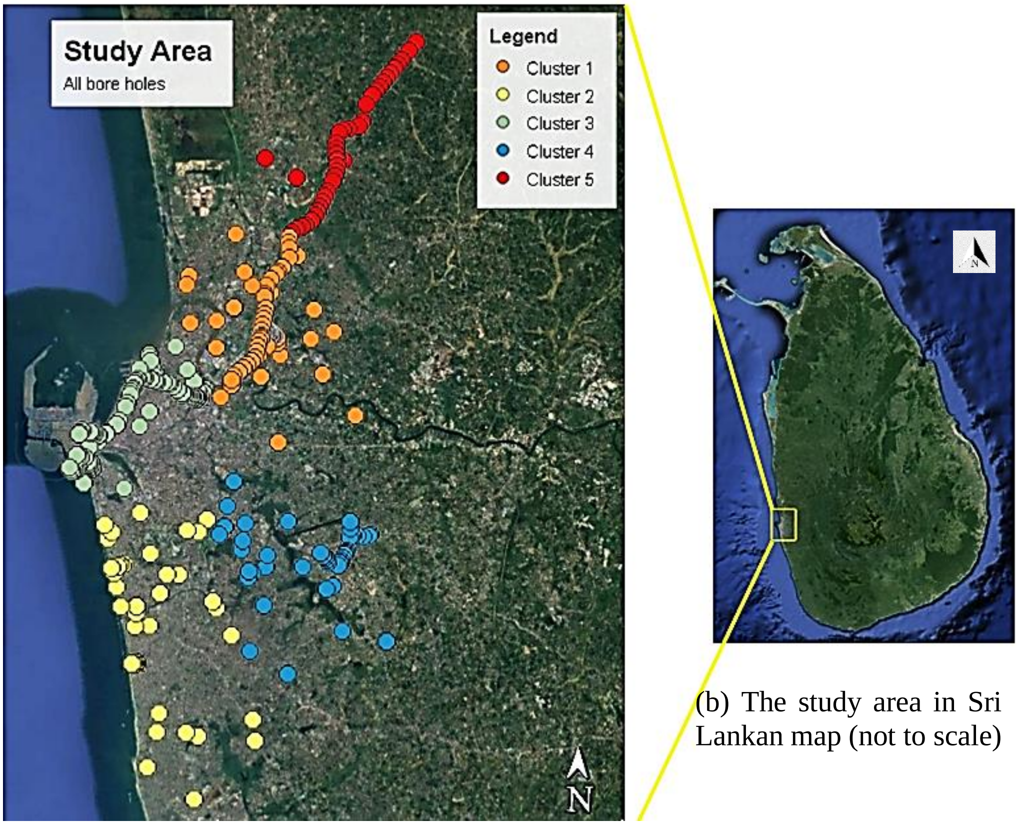
2.1 Study Area

The study area of this research was confined to Colombo and Gampaha districts in the Western Province of Sri Lanka, based on the available investigation borehole density of 702 in the database made available for this study (Figure 1). All the boreholes were divided into five clusters, as illustrated in Figure 1(a).

2.1.1 Geology

Sri Lanka's basement geology consists of four distinct tectonic provinces: the Highland, Wanni, Vijayan, and Kadugannawa complexes. Hornblende-biotite gneiss Hornblende gneiss and Biotite gneiss are included in granulite facies rocks of the Highland Complex. It occupies the base rock of the City of Colombo area. “Malwana” and “Ranala Gravel” can be identified along the “Kelani” River which is the fourth longest river in Sri Lanka offering insights into past geological events. Lower reaches of the “Kelani” River quarts emerge within laterite formations. It hints at the area’s geological complexity. Near Slave Island and Ratmalana in

Colombo, Western Province of Sri Lanka quartz-rich white sands can be identified adding a layer of fascination to the terrain. In Colombo's recent geological history, Holocene deposits could be identified including alluvial and estuarine compositions [5], [6].



(b) The study area in Sri Lankan map (not to scale)

(a) Drillhole locations in the study area

Figure 26 Study Area

2.1.2 Geomorphology

The study area falls into the lowest peneplain of Sri Lanka. The main geomorphological features in the study area are the Kelani River in Gampaha district, Torrington tunnel in Colombo district, Dehiwala canal in Colombo district, Dematagoda- Kirilipone canal system in Colombo district, Colombo harbour, Port City in Colombo district, and from the west side: Indian ocean. In Colombo, the landscape is mostly made up of gently undulating plains and low-lying flatland areas close to the ground. There are lots of streams and rivers crisscrossing the land, creating a mix of both dry ground and watery areas [1].

2.1.3 Methodology

The ELS: Engineering & Laboratory Services (Pvt)Ltd. was initially established in 1991 as an investigation company dedicated to drilling and helping with geotechnical investigations, across the country. Even though by now the company has a well-established number of sister companies, the original drilling unit is still there and has completed more than a couple of thousand boreholes over the past thirty-three years.

Most of the geotechnical investigation reports are available as hard copies, and available in a steel container at ELS-Yard in Colombo. These drillhole locations are spread across various locations throughout Sri Lanka. Initially, it was focused on filtering out reports that had been conducted within Colombo and Gampaha districts in Sri Lanka, as these areas had a higher availability of reports compared to other areas of the island. These data were used to develop 3D sub-surface models which will be immensely beneficial for future large-scale geotechnical investigations of the country which will fall within these two districts.

The methodology was adopted at a few stages in this study, including data collection, data standardization, geospatial clustering, model development, and model validation. The flowchart (Figure 2) illustrates this sequential process of methodology adopted in this study.

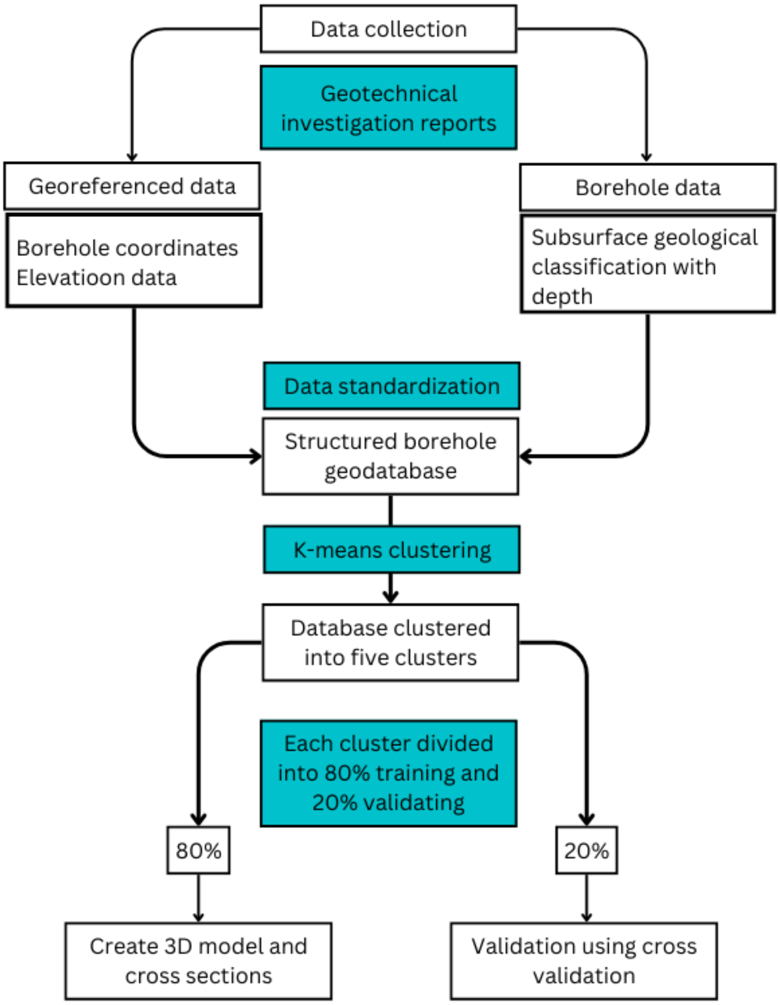


Figure 27 Research methodology sequential steps adopted

2.1.4 Data collection

Bore holes are holes drilled into the earth and borehole logs show soil stratification, soil types, depth of the borehole, groundwater level, and SPT (standard penetration test) values [1]. The data collection process had several uses that supported the objectives of this study. Georeferenced data and borehole data are the two main types of gathered data. Engineering & Laboratory Services (Pvt) Ltd. made available the entire borehole data set available with the company for this study. Out of the entire data set, 702 numbers of boreholes were selected based on the sufficient density of data available for comprehensive sub-surface analysis to develop 3D models.

Georeferencing of borehole locations was crucial for spatial analysis and 3D model development. Therefore, borehole locations were georeferenced according to the coordinates and elevation information. However, certain boreholes in the study area had no georeferenced data in the reports. In such cases, the Google Earth Engine was used to find the georeferenced data of the boreholes with the help of indirect information such as the address and the location map.

2.1.5 Data Standardization

Data standardization plays a huge role in geo-data management projects, ensuring consistency and compatibility across datasets [7]. The borehole data extracted from geotechnical investigation reports were structured into a systematic spreadsheet database, and a sample of the standardized spreadsheet is given in Table 1. Each borehole was identified by a unique identifier (Hole-ID), facilitating easy reference to the corresponding geotechnical report.

Table 1 A sample of the standardized spreadsheet

Hole-ID	Easting (m)	Northing (m)	RL (m)	From (m)	To (m)	Soil type
BH8	377338.4	771634.7	5.3	0	6	SAND
BH8	377338.4	771634.7	5.3	6	7.5	CLAY
BH8	377338.4	771634.7	5.3	7.5	9	PEAT
BH8	377338.4	771634.7	5.3	9	22.95	CLAY
BH9	377567.8	769355.6	6.9	0	5	CLAY
BH9	377567.8	769355.6	6.9	5	6	SAND
BH9	377567.8	769355.6	6.9	6	12	CLAY
BH9	377567.8	769355.6	6.9	12	27	SAND

Subsurface layers were classified into eight categories, as sand, clay, peat, silt, gravel, fill, weathered rock, and bedrock level. Elevation values relative to MSL (RL) (m) were calculated using Digital Elevation Model (DEM).

However, not every borehole in the dataset were drilled up to the bedrock level. To address this variability and smoothen the layer properties, a machine-learning model was used. For cluster 1, the model achieved a RMSE (Root Mean Square Error) of 1.26 m and an R^2 value of 0.78 which indicates a reasonable accuracy. However, due to poorer performance in other clusters, this step was skipped for those borehole clusters.

2.1.6 Geospatial clustering

Geospatial clustering is an important step in organizing the borehole data set, based on their coordinates. The cluster-based system has a strong control over the ability of the model to predict the 3D subsurface [1]. In this study, the K-means clustering algorithm was applied to group boreholes into clusters. The aim was to identify spatially coherent groups that exhibit similar geotechnical characteristics.

To determine the optimal number of clusters (k) for dataset selected for this analysis, the “Elbow” method was employed. This technique involves plotting the sum of squared distances (inertia) between data points and their respective cluster centroids for a range of k values. For this analysis, k values ranging from 1 to 15 were used. The curve's "Elbow" point represents the optimal k value, after which more clusters reduce inertia with decreasing effects

[8]. An elbow curve analysis using a k-means clustering algorithm to determine optimal k for the dataset selected for thus analysis is shown in Figure 3.

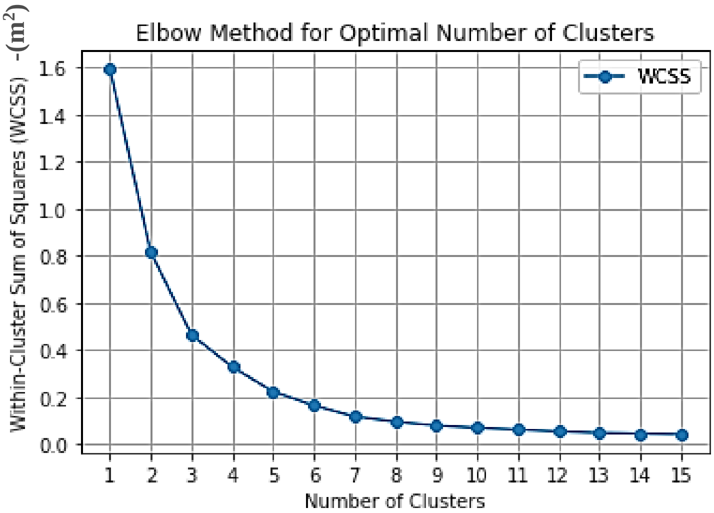


Figure 3 Elbow curve analysis based on borehole location coordinates.

After conducting the elbow method analysis, a k value of 5 was identified as optimal for this dataset. This value was selected because it represented a balance between optimizing cluster homogeneity and minimizing the number of clusters. Clustering analysis results using the k-means clustering algorithm is given in Figure 4.

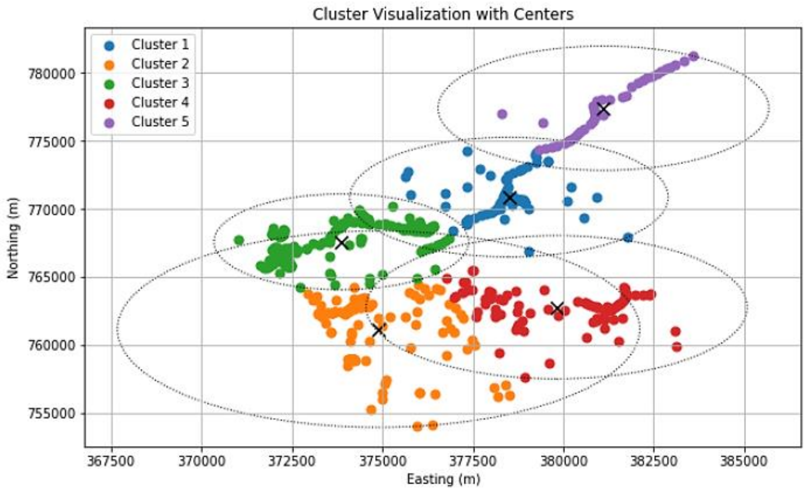


Figure 4 Clustering of borehole data based on borehole location.

Borehole location coordinates (Easting and Northing) are considered as the input parameter for the k-means clustering. The algorithm grouped the boreholes into five clusters by minimizing the distance between each borehole and the centre of its cluster. This process continued until the clusters were stable. To maintain the accuracy and quality of the clustering results, boreholes that deviated significantly from their cluster centers were excluded during the cluster development process.

It can be observed that borehole samples are grouped into five distinct clusters. The summery statistics related to each of investigation borehole cluster is given in Table 2.

Table 2 Summary statistics for clusters

Cluster Name	No. of Boreholes	Average Elevation (m)	Average distance between boreholes (km)	Geographic Area (km^2)
Cluster 1	174	3.26	1.16	26.22
Cluster 2	106	9.97	3.34	30.99
Cluster 3	225	5.76	2.56	18.74
Cluster 4	88	6.68	2.72	17.60
Cluster 5	42	6.54	2.77	12.02

2.1.7 3D model development and validation

Developing a new database from the existing dataset was the first stage in creating a 3D model. Each cluster's soil layers were carefully identified using the available dataset. For each cluster, a spreadsheet with the soil layers and their associated depths for every borehole was carefully created.

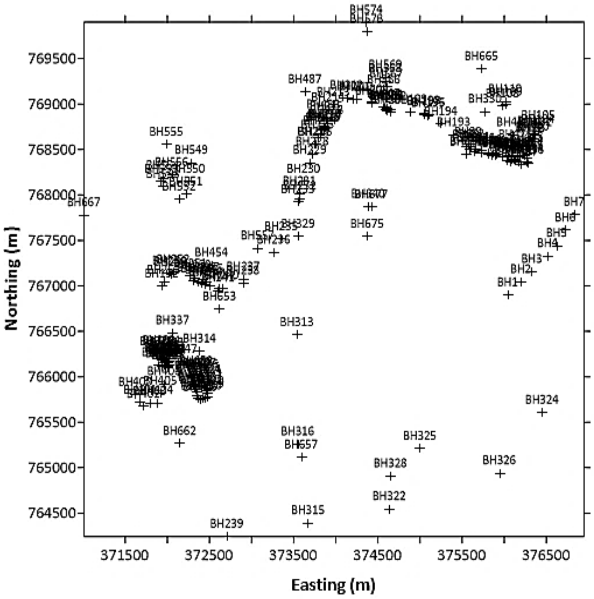
Table 3 A sample of the spreadsheet for 3D model development

HoleID	Easting (m)	Northing (m)	Layer1_RL (m)	Layer2_Fill (m)	Layer4_Sand (m)	Layer5_Clay (m)	Layer6_Peat (m)
BH8	377338.4	771634.7	5.3	5.3	-0.7	-2.2	-3.7
BH9	377567.8	769355.6	6.9	6.9	0.9	-5.1	-5.1
BH10	377384.7	769209.6	4.6	4.6	4.6	-5.9	-7.4
BH11	377732.5	769493.7	2.6	2.6	0.6	-0.4	-3.4
BH12	377320.1	769065	5.2	5.2	5.2	0.2	-3.3
BH13	377872.7	769617.6	8.6	8.6	6.6	-7.9	-7.9
BH14	378016.7	769743.4	6.1	6.1	6.1	-1.4	-4.4

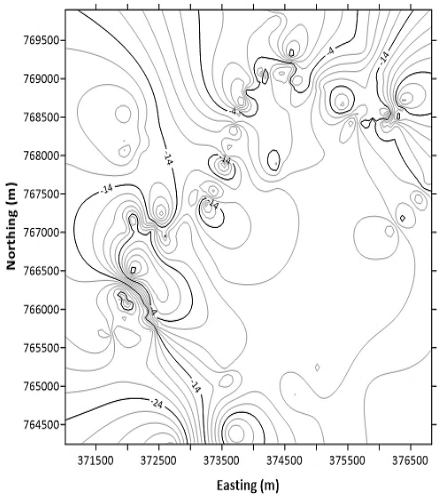
The first step involved in importing of a prepared database into the “Surfer” software platform. Then, the “Kriging” interpolation method was applied to create 3D profiles of soil layers at different depth intervals. Kriging has significantly enhanced the prediction accuracy for generating subsurface strata using borehole data [9]. To enhance the relationship between the interpolated surfaces and the observed borehole data, interpolation parameters were changed as needed. Additionally, to further enhance the accuracy, a digitized map was created to eliminate areas without borehole data (Figure 5 and Figure 6). The interpolated soil layer profiles at different depth intervals are stacked to create a composite 3D profile, representing the subsurface soil structure (Figure 7).

Cross-sections, contour maps, and 3D renderings of the soil strata were produced from this composite profile, providing detailed visualizations for analysis and interpretation of data.

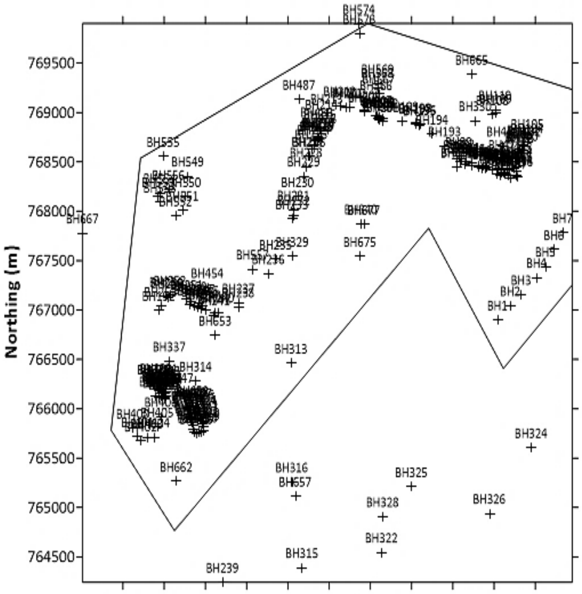
Cross-validation was performed for each layer within every cluster to validate the model's performance. All boreholes within a cluster were randomly divided into two subsets such that 80% for training (to create a 3D model) and 20% for validation. During the validation process, outliers were identified and removed to enhance the fit and performance of the model. To quantify the performance of the model, RMSE was calculated for each layer within the cluster. For each cluster, the average of RMSE value was determined.



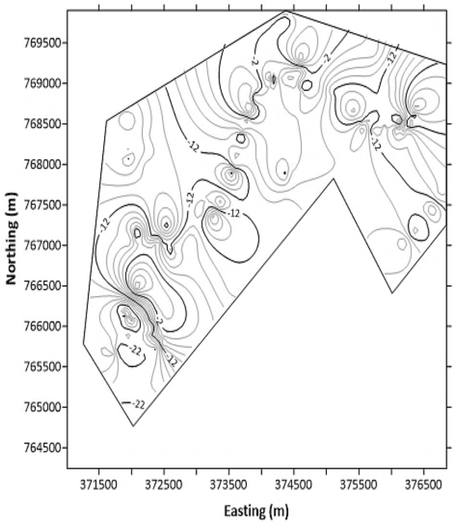
a). Post map of cluster 3



a). Contour map for bedrock depth in cluster 3.



b). Digitized post map of cluster 3



b). Digitized contour map for bedrock depth in cluster 3.

Figure 5 Post map and Digitized post map of cluster 3.

Figure 6 Contour map and digitized contour map for bedrock depth in cluster 3.

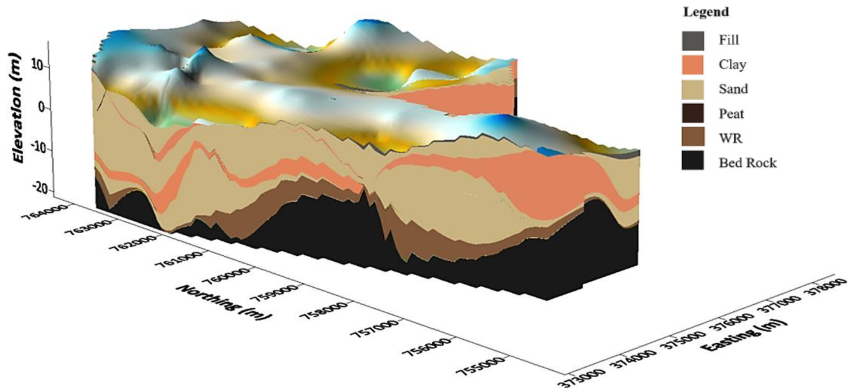


Figure 7 Subsurface 3D model of cluster 2

3. Results and discussion

3.1 Subsurface Composition

Analysis of the collected borehole data related to Colombo and Gampaha districts gives significant insights into the subsurface of the study area. The primary soil types encountered include sand, clay, gravel, peat, and silt.

Sand layers were normally found at shallower depths, particularly in coastal areas. Significant changes in the thickness of the sand layer were observed, with some places showing variations of up to 10 m (Figure 8(b)). Conversely, clay layers were observed as the most prevalent soil type encountered with significant variations in depth and thickness. In many locations, clay layers extend from near the surface to depths exceeding 15 meters (Figure 9(b)).

While less prominent compared to sand and clay layers, considerable deposits of peat, silt, and gravel were also identified. In areas near Muthurajawela and beyond the coastal line of the country, there were substantial peat layers (Figure 9. c). Around the new Kelaniya Bridge area, there was a significant amount of silt (Figure 10. b). Additionally, gravel layers with sand were prevalent near the Port City of Colombo (Figure 10. c).

The depth to bedrock varies significantly across the study areas. In some regions, bedrock was encountered at shallow depths, less than 10 m, while in others, it was found even at deeper levels than 30 m. In some cases, the thickness of the weathered rock layer was less than 1m and some cases its thickness was under 1m but in some cases, its thickness was above 10m. This variability highlights the diverse geological characteristics of the study area.

a). Orthographic projection of 3D model for Cluster 4

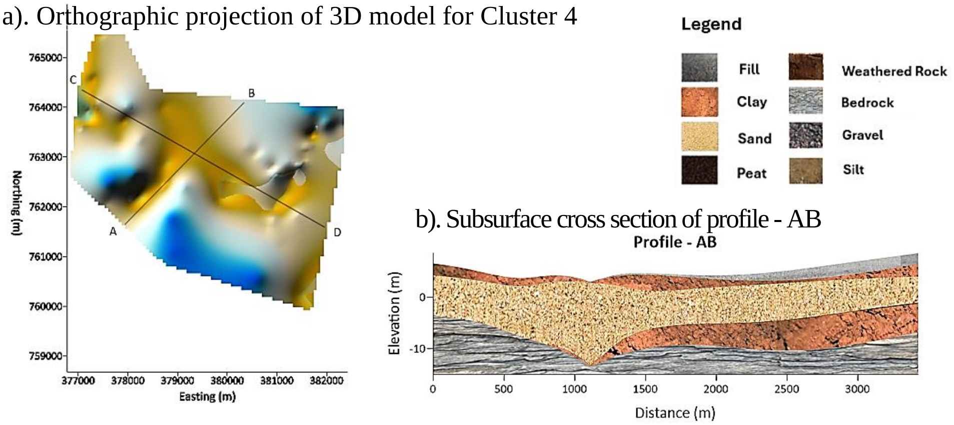
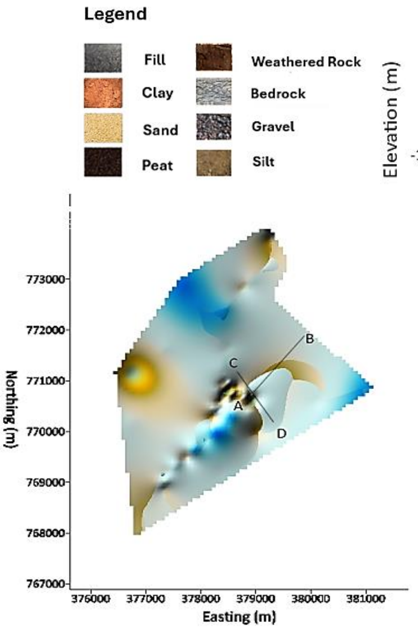
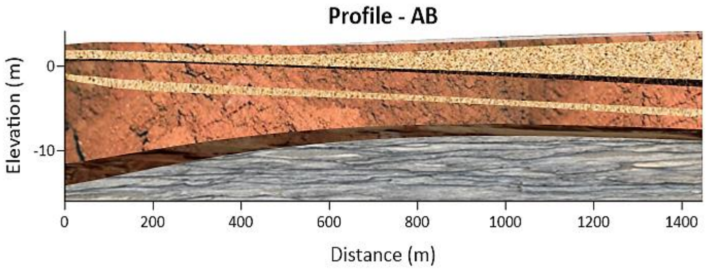
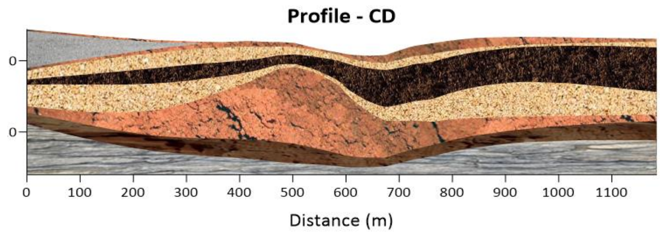


Figure 8 Orthographic projection and cross section for cluster 4





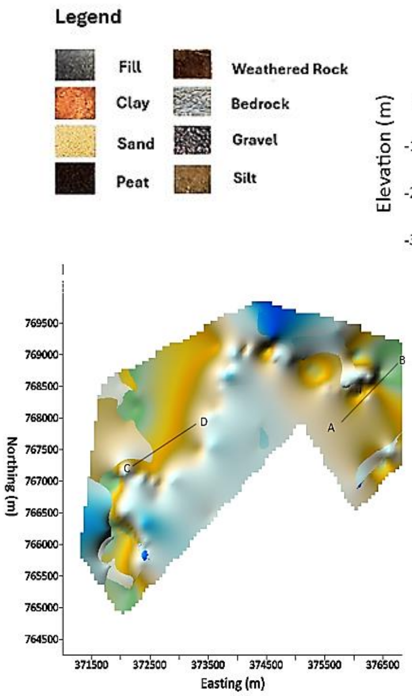
b). Subsurface cross section of profile - AB

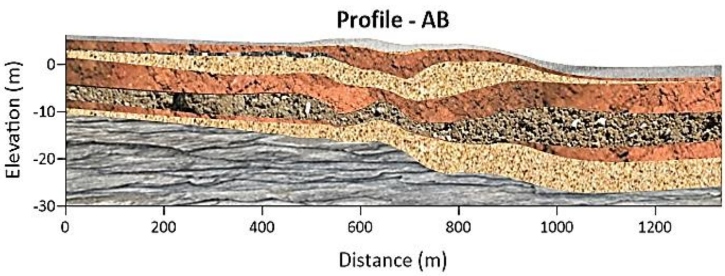


c). Subsurface cross section of profile - CD

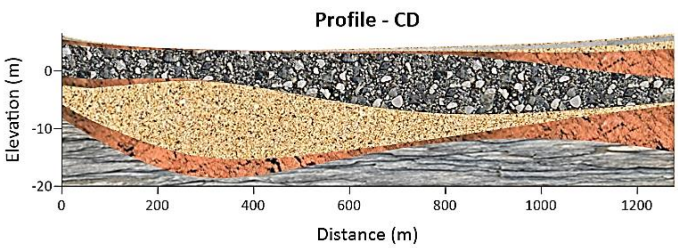
a). Orthographic projection of 3D model for Cluster 1

Figure 9 Orthographic projection and cross sections for cluster 1





b). Subsurface cross section of profile - AB



c). Subsurface cross section of profile - CD

a). Orthographic projection of 3D model for Cluster 3

Figure 10 Orthographic projection and cross sections for cluster 3

3.2 Model Validation

To evaluate the overall accuracy of our subsurface 3D model, the average RMSE was calculated across different clusters. The average RMSE offers a consolidated measure of model performance, facilitating easier comparison and interpretation. The average RMSE was computed by taking the meaning of the RMSE values from individual clusters. This approach is widely adopted in spatial statistics and predictive modeling, aligning with established practices [10]. This method ensures a comprehensive understanding of the model's predictive accuracy [11].

Table 4 Subsurface Layers and Average RMSE Values of Clusters

Cluster name	**Layers**	**Average RMSE (m)**
Cluster 1	RL, fill, clay, sand, peat, clay, sand, clay, weathered rock	3
Cluster 2	RL, fill, Sand, clay, sand, clay, sand, weathered rock	4.23
Cluster 3	RL, sand, fill, sand, clay, gravel, sand, clay, peat, silt, sand, clay, sand, weathered rock	3.27
Cluster 4	RL, fill, clay, sand, clay, sand, clay, weathered rock	3.04
Cluster 5	RL, fill, sand, clay, peat, clay, sand, clay, weathered rock	2.84

Apart from cluster 2, in all other clusters average RMSE value was below 3.3. This level of precision gives the model's efficacy in capturing the complex geological stratigraphy of the region. The 3D subsurface model's accuracy, with an RMSE below 3.3 m, is ideal for precise cost estimation for future geotechnical investigation projects. By accurately predicting soil conditions and geological structures, the model tells stakeholders to confidently allocate resources and mitigate budget risks from the outset. Model visualization capabilities enable engineers to do project planning more accurately than earlier, ensuring financially sound project execution.

4. Conclusions

Based on the results of this research, the following conclusions can be made:

- By selecting the densely distributed existing borehole investigation data, it is possible to develop 3D subsurface models to reflect tentative variation of important sub-surface strata like bedrock level.
- The 3D subsurface model developed for Colombo and Gampaha districts of Sri Lanka where major Civil Engineering constructions take place, based on densely spread borehole investigation data with statistically proven accuracy will be a valuable reference for project planning engineers for them to optimize the future large scale geotechnical investigations within these two districts.
- By conducting similar research in the future by integration of data from the geotechnical investigations carried out by major geotechnical engineering firms could help to develop tentative sub-surface major strata variations of the country within a reasonably limited time, for the benefit of future large-scale geotechnical investigation projects of the country.

Acknowledgment

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