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DEVELOPMENT OF SOIL TYPE REFERENCE OF METROPOLITAN MANILA USING GENETIC ALGORITHM

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ABSTRACT: A soil type reference of Metropolitan Manila was developed using an optimization algorithm called Genetic Algorithm (GA). In this study, a program was created to perform a Genetic Algorithm on each meter soil layer ranging from 40 meters below mean sea level up to 100 meters above means sea level for specified points with 2km grid intervals. The program utilized the Unified Soil Classification System (USCS) and a borehole database of the study area and surrounding provinces to predict the soil types. Two variables were chosen to assess the fitness of the prediction: the likeness of the soil type with surrounding boreholes, and the distance of the boreholes from a specified grid point. A total of 216 points were used in the study each containing 40 to 130 soil layers. The results were then compiled and plotted to create a total of 38 soil profiles of the study area for the longitudinal and transverse directions. The profiles followed the expected soil types based on the geologic zones of the study area: sands and clays for the coastal lowlands, rocks and sands for the central plateau, and clays and silts for Marikina Valley. Validation of the profiles suggests the Genetic Algorithm as a suitable tool for the development of soil type reference of the study area.

Keywords: Genetic algorithm, USCS, Soil types, Metropolitan Manila

1. INTRODUCTION

Metropolitan Manila, or more locally known as Metro Manila, is the capital region of the Philippines. It has about 13% of the total population of the country and it is where the majority of government offices along with important business and commercial infrastructures are located. It has a land area of 619.54 square kilometers bordered by the Manila Bay at the west and the Laguna de Bay at the east.

Due to its unique location and the shifts in tectonic plates in its geologic past, a fault system was formed leading to the frequent earth movements up until the present [1, 2] As such, there is a need for proper planning and design for all infrastructure. Furthermore, policymakers and disaster response teams need to know these hazards to create a robust disaster reduction and management plan. Currently, there were a lot of studies [3-10] that tried to evaluate the geotechnical properties of the study area. However, even being a major component of these studies, there was no available soil type reference for Metropolitan Manila except for the city of Quezon [11] The discussion on the effect of soil type on their respective studies was only discussed concerning the different geologic zones of the study area. Usually, researchers would divide Metro Manila into several zones with the Central Plateau, Marikina Valley, and the Coastal lowlands as the most prominent zones [5]. The problem with this, however, is that a detailed soil profile is absent along with the thicknesses of each soil layer. Thus, this study focuses on creating a soil type reference to map the locations and boundaries of the different soil layers present in the study area.

Mapping of geotechnical parameters is not uncommon as there were several studies already making use of Graphic Information System (GIS) to create maps and projections of the different soil characteristics [3-13]. However, current GIS software has no functions fit for mapping the profiles needed for this study, as such, the soil type reference was patterned to the soil profiles presented by Galupino and Dungca [11] in their study on the Quezon City soil profile reference

To create the soil profile reference of Metro Manila, an algorithm was used to predict the existing soil type in specified locations. The use of machine learning and other algorithms is becoming common in the field of Geotechnical Engineering [15-17]. One of the fast and easy algorithms is the Genetic Algorithm (GA). GA follows the idea of survival of the fittest wherein fitter individuals have a higher chance to survive and pass on their genes to the next generation. Several studies [15, 18-21] have already applied GA to geotechnical engineering and the results are very promising. The application of GA, however, is unique for each problem. With this, a fitness function was created for this specific application of GA to the prediction of soil types.

This study aims to create a soil type reference for Metropolitan Manila that will aid engineers, policymakers, and other stakeholders in knowing the expected soil type in their respective project sites.

2. RESEARCH SIGNIFICANCE

Currently, there is a lack of soil type reference for Metropolitan Manila, even though there had been a lot of studies and mapping of the different geotechnical parameters of the study area. With the results of this study, the created soil type can provide support for future studies on the geotechnical characteristics of the study area. Furthermore, the program developed can be deployed in other provinces to create their own soil type reference maps. Lastly, local government units and other private individuals can use the maps to know the expected soil characteristics of a specific location.

3. METHODOLOGY

Borehole logs located in Metropolitan Manila and other surrounding provinces were collected. Erroneous borehole logs were removed and a representative borehole was determined for sites with multiple borehole logs. A grid system with 2km intervals was also placed in the study area. the grid intersections will be the location where the Genetic Algorithm will be deployed. The grid was labeled alphabetically from west to east and numerically from north to south. The borehole locations and the grid system were presented in Fig. 1.

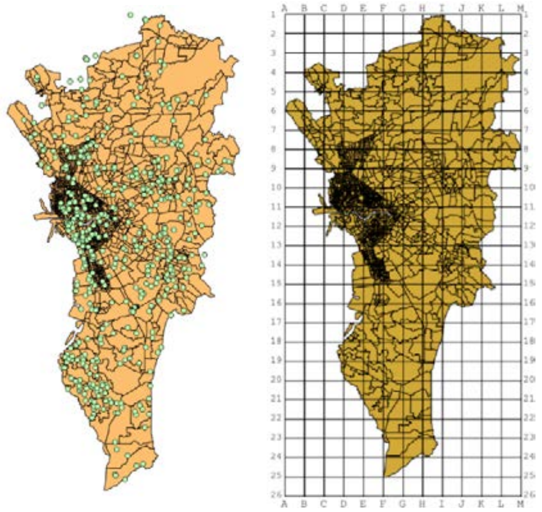

Fig. 1. Borehole locations and grid system of Metropolitan Manila.

The elevations of the borehole logs and the grid intersections were plotted to create a 3D Elevation map shown in Fig. 2. This was crucial as each borehole was adjusted to its correct meter elevations with the mean sea level as the reference elevation.

The soil types were grouped into classes based on the Unified Soil Classification System. The classes were adjusted to cover the different soil type reporting given by the borehole logs. A total of 24 soil types were used in this study, including the 15 original soil types from USCS, unspecified or general Gravel, Sand, Clay, and Silt, and 5 classifications for Rock. The summary of the soil types with their short description was shown in Table 1.

Fig. 2. 3D elevation Map of Metropolitan Manila.

Table 1. Summary of soil types.

General Soil Type	Specific Soil Type	Description
G Gravel	GW	Well-graded gravel
	GP	Poorly-graded gravel
	GC	Clayey gravel
	GM	Silty gravel
	G	Unspecified gravel
S Sand	SW	Well-graded sand
	SP	Poorly-graded sand
	SC	Clayey sand
	SM	Silty sand
	S	Unspecified sand
C Clay	CH	High-plasticity clay
	CL	Low-plasticity clay
	C	Unspecified clay
M Silt	MH	High-plasticity silt
	ML	Low-plasticity silt
	M	Unspecified silt
R Rock	GR	Boulders and large-sized gravel
	SR	Sandstone
	CR	Mudstone
	MR	Siltstone
	R	Tuff and other unspecified rock
PT Peat	PT	Peat
O Organic Fines	OH	High-plasticity organic fines
	OL	Low-plasticity organic fines

The process of a Genetic Algorithm (GA) starts with the creation of a random initial population followed by the fitness evaluation then the crossover and mutation operations to create the next generation population. The new generation replaces the initial population and the process is repeated until a given set of generations or if a convergence criterion is attained [17]. The method is shown in Fig. 3.

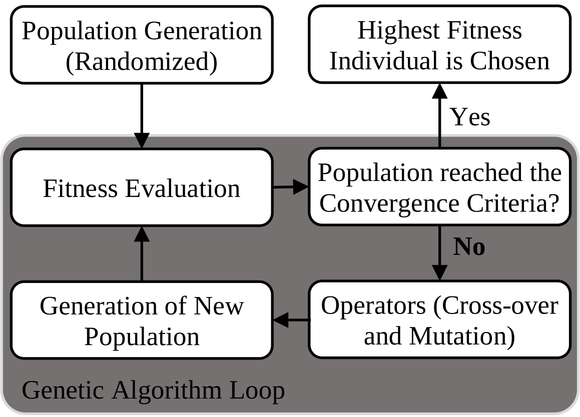

Fig. 3. Genetic Algorithm Flowchart

The GA used in the creation of the program was deployed in the grid intersection. GA was used as its process is a fast and easy way for the program to converge into a prediction of the soil type. The program scores the prediction based on their accuracy to surrounding borehole logs. The maximum distance of the referenced borehole logs was set at 2.5km from the respective grid intersections. Furthermore, the influence of the borehole logs in the scoring of the predictions was adjusted in relation to their distance to a specific grid point. Usually, Euclidean distance is used in these applications [11], however, due to the size of the study area, the great-circle distance was used. The calculation for this distance follows the Haversine formula defined in Eq. (1).

$$\sin^2\left(\frac{d}{2R}\right) = \sin^2\left(\frac{\phi_2 - \phi_1}{2}\right) + \cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right) \quad (1)$$

Where: d is the great circle distance between two points, R as the radius of the Earth (6371km), ϕ_1 and ϕ_2 as the latitudes of the two points, and λ_1 and λ_2 as the longitudes of the two points.

For GA to function, it required a set of variables to optimize, its mutation rates, and the fitness function to quantify the accuracy of the prediction. The created program used two variables: the soil type and the maximum distance of boreholes to be considered. The range of this distance was set from 500 meters to 2500 meters from the grid intersection points. This was implemented to lessen the irrelevant data points for the comparison of the prediction. The soil type variable was set as categorical data following the specific soil type presented in Table 1. The mutation rates for these variables are set to be 0.10 and 0.30 for the soil type and the maximum distance considered. Lastly, the fitness function incorporated the weights used in k-Nearest Neighbor by Galupino and Dungca [11], and a 'likeness' function. The fitness formula was shown in Eq. (2).

$$F = L_{ij}W_{ij} = \frac{\sum L_{ij}e^{-D_{ij}}}{\sum e^{-D_{ij}}} \quad (2)$$

Where: L_{ij} is the 'likeness' function of the specific soil layer of grid intersection point i to the j^{th} borehole under the training data set. L_{ij} has a value of 1 if the specific soil layer has the same soil type as the j^{th} borehole, otherwise, the value is 0. Meanwhile, D^{ij} is the great-circle distance between grid intersection point i to the j^{th} borehole

The genetic algorithm was deployed in each grid intersection point for each meter soil layer. The extents of the elevations were set at 40 meters below sea level up to 100 meters above sea level. The program skips those grid intersections without surrounding boreholes under a 2.5km radius. These grid intersections were usually present in protected areas in the study area, or bodies of water. Once all elevation points were completed for all grid intersections, the results were compiled and soil profiles were plotted in CAD.

4. RESULTS

Metropolitan Manila is composed of different geologic zones due to its locations. The study area can be divided into 4 main areas: Central Plateau composed of mainly Guadalupe Tuff, Marikina Valley composed of delta deposits from the Marikina River, the coastal lowlands composed of delta deposits from Pasig River, and the Coastal swamp/wetlands on the north-west [5, 7]. It is surrounded by Manila Bay on the west, and Laguna de Bay on the east. It is bordered by the province of Bulacan in the north, the province of Rizal to the north-east, and the provinces of Cavite and Laguna in the south.

Metro Manila was also submerged in its geologic past. Volcanic and tectonic activities then deposit volcanic materials, more specifically "Adobe", resulting in this rock being prominent in the underlying layers in the central plateau area [7, 11]. These activities are then followed by the erosion brought by the different river systems in the study area such as the Marikina River and the Pasig River.

For this specific study, the highest ground elevation from the borehole logs inside the study area was determined to be 88 meters above sea level, however, there were borehole logs in the neighboring province of Rizal that exceeded 100 meters above sea level. These excess soil layers were disregarded as they were beyond the set extents of the study area.

The resulting soil profiles followed the expected soil types based on the geologic zones. The prediction of the soil in the central plateau showed prevalent rock layers with sand and silt top layers. Furthermore, on the western side near the area of Manila, clays were predicted to be overlain by sands and some mixtures of silts and organic fines. As for the eastern side in the cities of Pasig and Marikina, clays were predicted to be the top layer with silts and sand for the lower layers.

For the plot of the soil profiles in CAD, the soil layers were grouped and color-coded based on their general soil types following Table 1. Gravels were shaded with dark green, sands were shaded in light blue, clays with orange, silts with light green, rocks with brown, and organic fines as pink. There was no predicted soil type for peat. The generalization of the soil types was done for the simplicity of the plotting as well as to easily observe the trend and movement of the soil types throughout the study area.

4.1. Longitudinal Sections

Due to the Guadalupe Tuff formation, different rock classes were observed to be prevalent in the study area with the only exception for this being on the western and eastern sides near the bodies of water. Samples of the soil profile in the longitudinal direction were shown in Fig. 4 and Fig. 5.

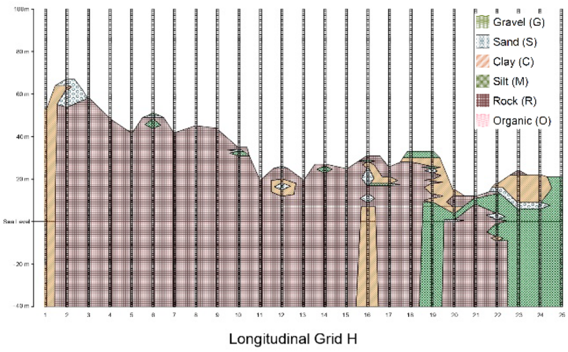

Fig. 4. The soil profile of longitudinal grid H.

Longitudinal grid H, shown in Fig. 4, passed through the entire length of the central plateau area along with the cities of Quezon, Mandaluyong, San Juan, Makati, Taguig, and some parts of Muntinlupa. It was also the longest grid present in the area. In the area of Quezon City, it was observed to be composed of different rock types, which was expected based on past studies [5, 11]. The topsoil, however, did not conform with the predictions of Galupino and Dungca [11] as a different technique was used in their study.

Looking at a grid nearer the western coast, longitudinal grid E, presented in Fig. 5, showed a prevalent sand top layer, especially in the central area in grid E10 to E15. These grid points were located in the cities of Manila and Pasay where the mouth of the Pasig River was located. Furthermore, some parts of these locations were also reclamation areas. Traveling further south, revealed a transition from clay to a mixture of rocks and silts as the soil type underneath the sand topsoil.

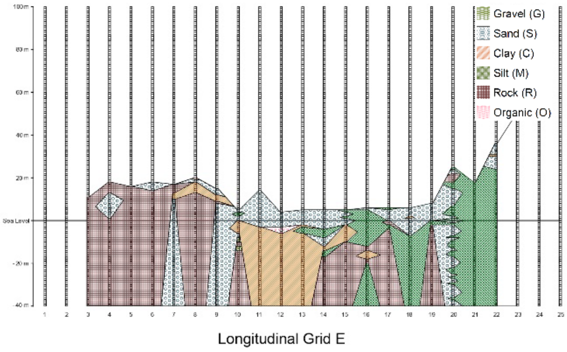

Fig. 5. The soil profile of longitudinal grid E.

The different parts of the study area followed the expected soil types based on the geologic zones. Other parts of the central plateau not shown by Fig. 4 and Fig. 5 were mainly composed of rock types with a 5-meter topsoil depth composed of mixtures of sand, clays, and silts. Furthermore, the Marikina Valley showed prevalent clay and silt layers. The topsoil for this area was a mix of clay, silt, and sands.

4.2. Transverse Sections

The transverse soil profiles gave the perspective of the different geologic zones of the study area. The central plateau was easily seen together with the coastal lowlands on the west and the Marikina Valley in the east. Shown in Fig. 6 and Fig. 7 were two adjacent grids, namely, Grid 11 and Grid 12.

As mentioned before, the three areas of coastal lowlands, the central plateau, and the Marikina Valley were visible in this soil profile. The differences in the soil composition of these three main areas were observed in Fig. 6. The western coast has clay and rock layers overlain by sands and silts, meanwhile, the eastern coast has silt and sand layers overlain by clays. Gravels were also present in the lower layers of Grid G5. The soil types in the western coast were expected from the Pasig River Delta deposits draining to Manila Bay. Additionally, tide changes and ocean movement in Manila bay may have contributed to the soil types present on the western coast. As for the soil types in the Marikina Valley, it was as expected from the Marikina River Delta deposits. Surrounding areas of the Marikina Valley were also composed of the central plateau and the Antipolo Plateau of the province of Rizal. These surrounding areas were previously identified to be mostly composed of Tuff formations [11].

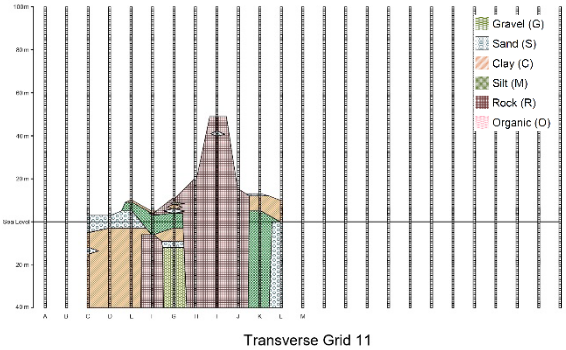

Fig. 6. The soil profile of transverse grid 11.

The adjacent transverse grid 12, shown in Fig. 7, has an almost identical profile with grid 11. The difference was observed to be the changes in the topsoil of grid E11 and F11. Sands replace the silt top layers, however, silts were still present in the lower layers. Additionally, the central plateau was also lower in elevation. This trend continued on the succeeding transverse grids. A translation from the grid I to grid H of the peak of the central plateau was also observed as the profiles travel southward. Minimal changes were observed for the soil profile in the eastern coast as it opens up to the Laguna de Bay.

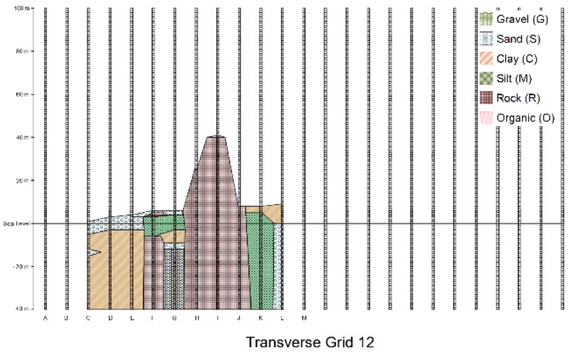

Fig. 7. The soil profile of transverse grid 12.

4.3. Genetic Algorithm Analysis and Validation

A total of 551 borehole logs were used in the program to predict the soil profile. 56 borehole logs were put aside for the validation of the results of the GA program. The results of the profile were compared to this validation subset. Since there were varying depths of boreholes, it was better to compare the accuracy of prediction on each meter depth. From these 56 borehole logs, a total of 1113 soil layers were obtained.

These soil layers were compared to the closest grid intersection point about their respective elevations. The number of correct soil layers was tallied and grouped per city. The summary of the accuracy of the prediction was shown in Table 2. Overall, the accuracy of the prediction is 52.83% and 74.75% for the specific and general soil types respectively. As observed in the summary, the cities of Malabon and Marikina had 100% accuracy. This, however, was due to the low number of boreholes present in their respective areas. The same reason was also observed for the 0% accuracy for the city of Navotas. Additional boreholes in these areas were needed to confirm the accuracy of the prediction.

Table 2. Percentages of correct predictions from the validation subset of the borehole logs

City	Percent of Correct Layers (Specific)	Percent of Correct Layers (General)
Caloocan	70.00%	82.86%
Las Pinas	7.77%	38.83%
Makati	80.00%	80.00%
Malabon	100.00%	100.00%
Mandaluyong	16.67%	38.89%
Manila	45.99%	76.56%
Marikina	100.00%	100.00%
Muntinlupa	87.50%	87.50%
Navotas	0.00%	46.67%
Paranaque	69.09%	70.91%
Pasay	47.69%	76.92%
Pasig	93.59%	93.59%
Pateros	26.67%	46.67%
Quezon	43.20%	78.40%
San Juan	80.00%	90.00%
Taguig	58.00%	78.00%
Valenzuela	72.73%	77.27%
Total	52.83%	74.75%

The higher accuracy of the general soil types was expected as there were multiple soil types under a single general soil type. Confusion matrices, shown in Fig. 8 and Fig. 9, were created to visualize these inaccuracies. These matrices show the distribution of the predictions across each soil type category. The distribution was then shaded to highlight the concentration of the prediction. A good prediction model would have a darker main diagonal and a bad prediction model would have high distributions deviating from the main diagonal.

In Fig. 8, the confusion matrix for the general soil types was shown. The main diagonal had a higher value than other parts and was reflective of the overall 74.75% accuracy of the prediction. Only organic fines had a lower value for the main diagonal. Most of the organic fines were predicted as clays or sands. This prediction error can be attributed to their location as organic fines were commonly found in the western coastal lowlands surrounded by sands and clays. This prediction error can be attributed to their location as organic fines were commonly found in the western coastal lowlands surrounded by sands and clays. Furthermore, there were a reasonably large amount of rock layers wrongly predicted as sands, clays, or silts.

	PREDICTED						
ACTUAL	G	S	C	M	R	PT	O
G	3	1	1	0	0	0	0
S	5	145	34	11	24	0	3
C	1	24	213	5	9	0	0
M	0	19	11	34	14	0	2
R	5	42	26	26	436	0	0
PT	0	0	0	0	0	0	0
O	0	8	10	0	0	0	1

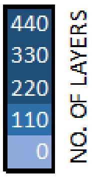

Fig. 8. Confusion matrix for the general soil types.

Looking at Fig. 9, this confusion matrix shows the detailed distribution of the prediction for the specific soil types. The low accuracy of the prediction was observed in this matrix as there was a prediction distribution that deviates from the main diagonal. Some of these wrong predictions, however, were not as severe such as high-plasticity clays being predicted as low-plasticity clays and vice versa. There were predictions as well wherein sandstones were predicted as silty sand. Clayey sand was determined to have more errors in the prediction as the majority of clayey sands were predicted as silty sands. Although both are sand, there might be differences in their behaviors. As such, it is still necessary for engineers to perform additional tests to determine the different geotechnical parameters to properly design a safe and economical foundation.

5. CONCLUSION

This study was able to create a soil type reference of Metropolitan Manila using a Genetic Algorithm and a compilation of borehole logs collected from the study area and surrounding provinces. This soil profile hopes to serve as a reference for engineers, policymakers, and other stakeholders.

A program was created to perform a Genetic Algorithm to predict the soil type. The soil type was classified using a revised Unified Soil Classification System (USCS). This program was deployed at specific points with 2km grid intervals from 40 meters below mean sea level up to 100 meters above mean sea level. The genetic algorithm was programed to predict the soil type based on the soil types of surrounding boreholes and the distance of these boreholes to the grid intersection points. A fitness function was presented which incorporates the weights used on k-Nearest Neighbor by Galupino and Dungca [11] and a 'likeness' function. The results were then compiled and the soil profiles were plotted in CAD.

	PREDICTED																							
ACTUAL	GW	GP	GC	GM	SW	SP	SC	SM	CH	MH	OH	CL	ML	OL	PT	G	S	C	M	GR	SR	CR	MR	R
GW	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GP	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GM	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SW	0	0	0	0	0	0	0	9	2	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0
SP	3	0	0	0	0	7	0	5	2	0	0	0	2	0	0	0	0	1	0	0	0	0	0	0
SC	0	0	0	0	0	0	4	25	14	0	3	2	0	0	0	0	0	0	0	0	0	1	0	2
SM	2	0	0	0	3	0	4	87	8	2	0	3	6	0	0	0	1	1	0	0	0	4	1	14
CH	1	0	0	0	0	0	5	3	117	0	0	34	4	0	0	0	0	0	0	0	1	4	0	0
MH	0	0	0	0	0	0	0	5	6	17	0	1	1	0	0	0	0	0	0	3	2	1	1	3
OH	0	0	0	0	0	0	4	3	10	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
CL	0	0	0	0	2	0	3	8	31	0	0	23	0	0	0	0	0	0	0	0	1	0	0	0
ML	0	0	0	0	0	0	0	9	0	0	2	2	15	0	0	0	1	0	0	0	0	0	0	2
OL	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0
C	0	0	0	0	0	0	1	2	7	0	0	0	1	0	0	0	0	1	0	0	1	2	0	0
M	0	0	0	0	0	0	2	2	2	0	0	0	1	0	0	0	0	0	0	0	0	0	0	2
GR	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
SR	3	2	0	0	1	0	1	18	13	2	0	0	3	0	0	0	0	0	0	0	56	30	9	34
CR	0	0	0	0	1	0	3	8	3	10	0	0	0	0	0	0	0	0	0	0	16	33	0	11
MR	0	0	0	0	0	0	0	0	0	3	0	3	0	0	0	0	0	0	0	0	8	2	16	2
R	0	0	0	0	0	0	0	9	7	6	0	0	2	0	0	0	0	0	0	1	0	9	0	208

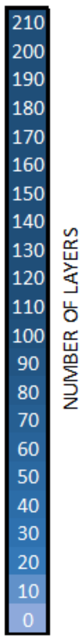

Fig. 9. Confusion matrix for the specific soil types

The soil profiles followed the expected soil types based on the geologic zones of the study area. Rocks were prevalent in the Central Plateau, Clays overlain by sands and silts were observed in the western coastal lowlands, and silts overlain by clays were found in the Marikina Valley. Validation of the results was done by comparing a subset of the borehole database to the closest grid intersection point of the soil profiles. It was determined that the predictions were 74.75% and 52.83% accurate for general and specific soil types. Confusion matrices were also created to show the distribution of the prediction across the soil types. This accuracy was satisfactory considering the size of the Metropolitan Manila and the distribution of borehole logs throughout the study area

This soil type reference, however, should not replace the in-situ and laboratory tests performed at the site. The results are still predictions and deviations are to be expected.

6. ACKNOWLEDGEMENTS

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