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Determination and Mapping of the Bearing Capacity of Subsurface Soil: A Case Study of Moi University, Eldoret Kenya

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Abstract
Ground investigation is a prerequisite for any construction work that ultimately transfers its loads to the earth. Geotechnical investigation eliminates the uncertainties of ground conditions and can be planned for and considered accordingly during actual design and construction. In Kenya, ground investigation is not given the weight it deserves since most players in the sector use their experience and physical inspection to judge on the soil conditions. This is however very risky especially for high-rise buildings. Moi University, the case study, is one of the institutions that has in its plan, a series of construction developments. This study aimed at investigating, determining and mapping of index properties and bearing capacity of subsurface soil. Direct shear box and tri-axial tests results were used to map soil bearing capacity by geospatial interpolation within geographical information system platform (GIS). 9 trial pits mapped by triangulation and visual inspection were excavated and soil samples obtained at a depth of up to 3 m. The soil samples were tested for soil index and engineering properties and classified using the USCS approach. A relationship between tri-axial and direct shear box test results was developed by correlating soil bearing capacity results from the two tests. This paper provides a thematic map of the bearing capacity for the study area derived from spatial interpolation. Four geospatial interpolation methods namely; Ordinary Kriging (OK), spline, Natural Neighbour (NN) and Inverse Distance Weighting (IDW) were used. In this paper, the most suitable method for interpolating the soil bearing capacity of the four methods is provided. Six of nine sample test results were used for interpolation and the other three used for validation and error correction. Ordinary Kriging generated satisfactory results for soil bearing capacity for the study area with a relative error of 2.23 % and R^2 of 0.9993. From the safe bearing capacity map, the ground conditions of the study area varied gradually with the bearing capacity ranging from $73\ kN/m^2$ to $1965\ kN/m^2$. Generally, the amount of clay in the soil within the area affected to a large extent, the soil bearing capacity.
Keywords: Soil bearing capacity, Geospatial interpolation, Deterministic interpolation, correlation.
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1. Introduction

Uncertainties of the subsurface soil within an area or region earmarked for construction development can vary remarkably. In some cases, soils strength has been physically determined based on the historical structures that have been built on it or existing structures. However, the heterogeneity of soil conditions necessitates ground investigations. This depends mainly on the magnitude of the structure to be built.

Geotechnical investigation brings into clarity the uncertainties underlying the ground surface before construction. Where inadequate ground investigation is carried out, unforeseen construction challenges are always stumbled upon at the excavation stage and during foundation construction or in the worst case, it can lead to total failure of the structure. If the uncertainty is so significant, it can affect the project scope and cost (Fenton et al., 2003). This study aims at improving ground investigation by applying geospatial interpolation within Geographical Information System (GIS) platform in an expansive remote area of Moi University where structures and construction developments are planned with particular interest in mapping of index properties and bearing capacity of subsurface soil.

GIS can be applied widely in geotechnical engineering fields. It provides powerful techniques of inputting data in a systematic and representation of data in simple and clear format. Spatial and non-spatial data can be easily analysed and retrieved when needed. In their study, Sumedh and Deepankar (2009) developed a method for mapping the index properties of soil using GIS and Global Positioning System (GPS). They observed that, with geostatistical analysis, it was evident that practicing geotechnical engineers and interested parties can rely on the soil properties determined using GIS and GPS in executing engineering works. The study further concluded that maps can be generated in vector analysis module and the database updated. In the same year, this approach was used to determine substrate bearing strength from Hyperspectral Imagery during the Virginia Coast Reserve (VCR'07) Multi-Sensor Campaign (Bachmann, 2008). Bachmann used remote sensing to delineate soil index properties like moisture content and grain size which greatly determine the bearing strength of soil.

Spatial interpolation is one of GIS functionality. Spatial interpolation has been adopted widely for data analysis in such fields as hydrology, surveying, disaster management, environmental studies and planning, navigation and general mapping. For this numerical estimation many techniques of spatial interpolation are available. The methods are in two categories, namely deterministic and probabilistic interpolation methods. Deterministic methods include Inverse Distance Weighting (IDW), Global polynomial interpolation, Local interpolation, Natural Neighbour (NN) and Spline while Ordinary Kriging (OK) is a geostatistical model.

The choice on the technique to employ depends largely on the nature and quality of original data, the degree of accuracy desired, and the amount of computational effort affordable (Sajid et al., 2013). However, no conventional standards are available to establish the appropriateness of a spatial interpolation technique for a particular phenomenon like soil properties but the level of accuracy of the interpolation results should be confirmed by cross-validation (Swatantra et al., 2014). The performance of spatial interpolation methods is of interest and this varies depending on the phenomenon under study as established by Metternicht and Robinson (2006). Soil properties are associated with low skewness and such interpolation techniques like IDW should have their power varied in order to establish the most suitable interpolation power that gives more accurate results (Metternicht & Robinson, 2006). The study also indicated that the power of two or three resulted to more accurate results for the case of spline and lognormal kriging.

In the study of Sajid et al., 2013 on the suitability of using Kriging and IDW to determine the spatial values of the bulk density of soil, IDW proved to provide superior results than Kriging when optimal power value is used for bulk density. However, both Kriging and IDW had almost the same accuracy, precision and consistency with a difference of less than 1.0%, 0.5% and 2.0%, respectively. However, no significant relation was established in the variation and skewness.

A slightly similar study on mapping of agricultural topsoil properties by Karydas et al (2009) established that Ordinary Kriging, IDW and Natural Neighbour gave similar results in terms of accuracy without any of them being clearly better than the other. This is true where datasets are in abundant hence closely distributed. This does not hold for sparsely distributed datasets. When Kriging and IDW are used to interpolate variation of soil bulk density, the reliability of the results depends on the distribution of data points. Sajid et al (2013) in their widely reported study on spatial analysis of bulk density recommended both Kriging and IDW are suitable as suitable methods.

For each method, it is necessary to analyze its applicability, algorithm, efficiency and advantage before adopting the best approach (Kravchenko & Bullock, 1999). Optimal choice of method can only be made under the circumstances in which the study is being carried out (Yang et al., 2015). The study by Yang et al indicates that Kriging had better results compared to all other methods. Many researchers agree that Kriging produces better results than IDW in most of the phenomena (Setiento, 2013). Other interpolation techniques like thin plate smoothing splines have limited computational efficiency hence their applicability output optimization is achieved by double iteration (Hancock & Hutchinson, 2006). All these methods adopt the geographic principle ‘things that are closer together tend to be more alike than those far apart’ (Tobler, 1970).

2. Study area

The study area covers the entire Moi University acreage, situated 32 km south east of Eldoret town, in Uasin Gishu County (UGC), Kenya. The study concentrates on the developed and proposed sites for construction as shown in figure 1.

The study area is about 6.2 km^2, its average location is latitude 0^o 17’ 19’’ N and longitude 35^o 17’ 18’’ E with an average elevation of 2221 m above sea level at the top of the surrounding plateau (Kimotho, 1996). The area is relatively flat towards Eldoret with undulating terrain towards Nandi hills. The area within Kesses a sub-county of UGC, is further classified as LH3 – Lower Highland and wheat is the main crop grown with scarce maize farms (Akenga, 2014). The mean annual rainfall is 1188mm with April to September as the main rainy season with August recording the highest rainfall (Kimotho, 1996). The study by Kimotho further indicates that the area experiences mean annual, maximum and minimum temperatures of 16 ^{0}C, 23 ^{0}C and 10 ^{0}C respectively. The resulting annual potential evaporation is 1658 mm. The area is therefore classified in agro climatic zone II – 6 which has a high potential for plant growth (Sombroek, 1982).

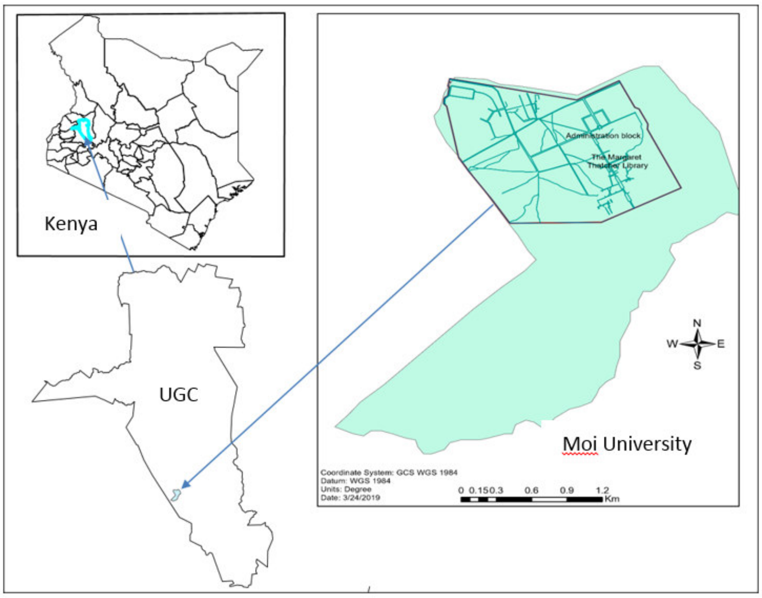

Figure 1: Study site

3. Methods

Triangulation method was adopted to establish the sampling points on the study area shape file this was followed by subdivision of the area using gridlines into triangles and the nodes taken as initial data points. The grid system resulted in points approximately 1.5 km apart. It is worth noting that the distribution of data points affects surface interpolation significantly but with the application of triangulation a representative sample of the population is obtained which enhances accuracy during geospatial interpolation.

However, 1.5 km is seemingly large enough and possibilities of different soils existing within this radial distance are eminent. Geostatistical approach of interpolation significantly arrests this possibility since the soil property has more strength on the point of analysis and its strength reduces in a radial distance. This infers that two points adjacent to each other will actually share the 1.5 km and each will have an influence of 0.75km.

Visits were made to the site to carry out ground survey and GPS locations to establish feasibility and accessibility of trial pit location and excavation. The survey was conducted in the entire area of study to obtain the general topography and notable land forms guiding the types of soils in the study area. The variability of surface soil validated the hypothesis that the study area is covered with a variety of soils ranging from stiff to weak soils.

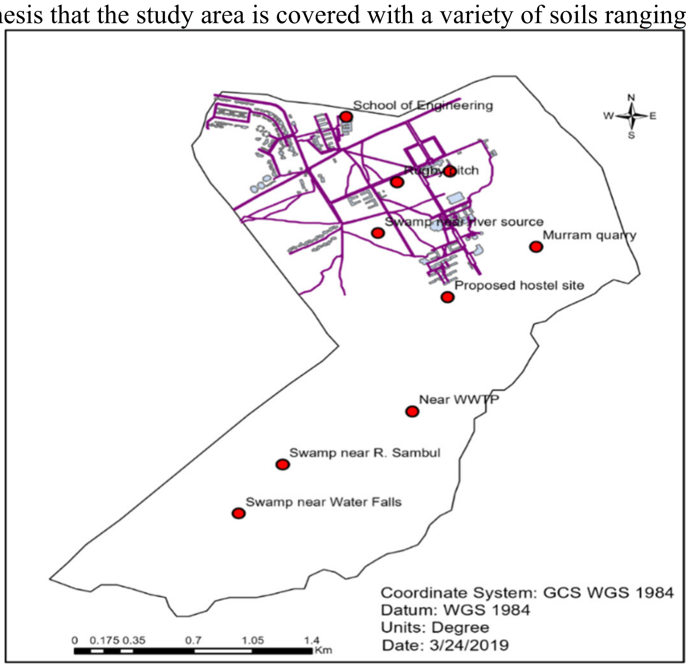

Figure 2: Sampling points.

The points were distributed as shown in figure 2. The northern part of the study area is a built-up area hence has more data points than the southern part which is mainly composed of extensive weak clayey soils with some sections covered in marsh. With the total area of about 6.2 km^2, the largest radial area for the sampling points was 2.0108 km^2 which is 31. 97 % while the smallest was 0.3849 km^2, representing 6.1% of the total area. There is no standard method of determining the optimum number of data points and its distribution for a given area (Gouri et al., 2018), however, careful selection of sampling points which adequately represented the study area so as to improve on the accuracy was carried out.

3.1 Soil sampling and testing

Nine trial pits of 3 m depths were excavated, their final locations shown in figure 2. Disturbed samples were collected from these sites and tested to establish the Liquid Limit (LL), Plastic Limit (PL), Plasticity Index (PI), moisture content (MC), specific gravity, and shear strength parameters (cohesion and internal angle of friction). In determination of soil bearing capacity, two approaches were used; direct shear box and tri-axial test.
The bearing capacity results obtained by direct shear test and tri-axial test were compared for all the nine samples and the method that produced the lowest bearing capacity value was taken as the critical method. A graph of direct shear test against tri-axial test results was plotted and a linear equation of $\boldsymbol{y = mx + c}$ derived.

3.2 Spatial interpolation of bearing capacity

Out of the nine datasets obtained from trial pits, six were used for spatial interpolation while the remaining three were used to correct and validated the interpolated results for OK, IDW, Spline and NN. The estimated results from the map is compared with the actual results obtained from the tests. The mapped results were checked for errors and compared to find out which method has minimum errors during interpolation of surface bearing capacity.

4. Results and Analysis

4.1 Soil classification and particle size distribution

To achieve soil classification using the Unified Soil Classification System (USCS) method, the following inputs are required; Liquid limit, Plastic limit, Plasticity index and Particle distribution (% fines). These tests were carried out on the disturbed soil samples from each trial pit. Tables 1 and 2 show the Atterberg limits and soil classification respectively.

Table 1: Atterberg limits and percentage fines

TP ID	SITE	LL (%)	PL (%)	PI (%)	% fines	PLASTICITY
1	Proposed site for an amphi-theatre	32	18	14	34	Medium
2	School of engineering	42	23	19	58	Medium
3	Rugby pitch	31	17	14	26	Medium
4	Swamp near river source	44	29	15	8	Medium
5	Near WWTP	47	31	16	6	Medium
6	Proposed hostel site	21	11	10	5	Low
7	Swamp near River Sambul	19	15	4	48	Non-plastic
8	Swamp near Water Falls	22	16	6	24	Non- plastic
9	Murram quarry	22	9	13	41	Medium

Table 2: Soil Classification

TP ID	C_u	C_c	Gravel (%)	Sand (%)	Fine (%)	Soil classification (USCS)	
						Soil Group	Soil classification
1	15.0	0.6	28	38	34	GP	Poorly Graded Gravel
2	8.0	1.1	14	28	58	GW	Well graded gravel
3	31.0	0.1	26	48	26	SM	Silty sand with gravel
4	4.8	5.2	64	28	8	GP	Poorly graded gravel with sand
5	3.7	15.6	69	25	6	SM	Clayey silt
6	3.9	12.7	57	38	5	GP	Silty, clayey sand with gravel
7	6.0	0.1	20	32	48	SP-SM	Poorly graded sand with silt and gravel
8	18.5	0.1	24	52	24	SW	Poorly graded sand with gravel
9	10.0	0.1	10	49	41	SW	Poorly graded sand with gravel

From table 1, it is clear that the level of plasticity of different soil samples within the study area has a slight varying plasticity. Sample 5 has the highest plastic and liquid limits and is classified as clayey silt as shown in table 2. This is attributed to the high clay content in the sample. Clay has a high ability to take and retain a new shape when compressed or molded because of their flakiness. Worth noting is the fact that sample 5 showed swelling since it had a high moisture content (28%) at the time of sampling. Clay also contains montmorillonite clays whose swelling potential is very high (Whitlow, 1995). Montmorillonite has a structure with layers held together by weak van der Waal forces. Additional water breaks the bond hence causing swelling. The level of swelling reduces with reduction of plasticity and amount of clay content. Sample 6 has low plasticity index and low clay content than sample 5. Some of the proportion of clay is taken up by silt and gravel.

Particle size distribution significantly affects the strength, permeability and compaction behavior of granular soils (Ming-liang, 2018). From table 2, sample 4 and 7 have uniformity coefficients of between 4 and 6. This infers that the soils are uniformly graded or poorly graded. These soils had nearly identical size of particles and such soils are difficult to compact. The two types of soils have a high clay content and are generally fine grained.

On the other hand, samples 1, 3, 8 and 9 had a relatively high value of coefficient of uniformity. This indicates that the soils have a wide range of particle sizes and such soils are suitable for construction activities where compaction is necessary.

4.2 Soil bearing capacity

A typical graph of normal stress against shear stress was plotted for the determination of the shear parameters namely internal angle of friction and cohesion strength as shown in figure 3. Soaked samples produced lower shear stresses compared to dry samples. Water particles lubricate the soil particles hence lowering the internal angle of friction. It further loosens the soil conglomerations which makes them disintegrate and easily collapsible. All the other samples were tested and their respective graphs of normal stress against shear stresses plotted. The shear parameters were explicated for direct shear test (DST) and tri-axial test (TAT) as shown in table 3.

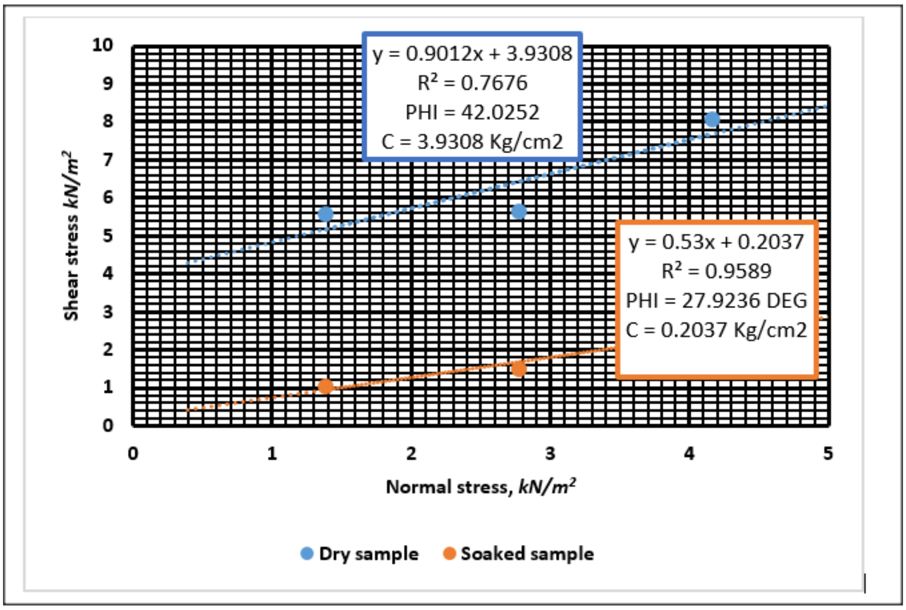

Figure 3: Normal stress vs shear stress (combined)

Table 3: Safe bearing capacity for DST and TAT

TP ID	Safe Bearing Capacity (kN/m^2)			
	Direct Shear Test (DST)	Tri-axial test (TAT)	Critical SBC	Critical Method
1	640.873	551.42	551.42	Tri-axial Test
2	511.03	483.51	483.51	Tri-axial Test
3	713.05	694.53	694.53	Tri-axial Test
4	73.14	92.55	73.14	Direct Shear box
5	338.88	295.23	295.23	Tri-axial Test
6	1891.06	1862.68	1862.68	Tri-axial Test
7	469.95	432.02	432.02	Tri-axial Test
8	336.87	409.94	336.87	Direct Shear box
9	1963.49	2437.13	1963.49	Direct Shear box

From table 3, it can be deduced that there is a slight variability of the bearing capacity obtained from the direct shear box and the tri-axial tests. Direct shear box produced slightly lower values in samples 4 and 8. This samples are both sand gravel soils as shown from the classification results in table 2. Similarly, sample 9 has the highest soil bearing capacity with the direct shear box result being critical. Other sandy soils with gravel are samples 6 and 7 which have no significant variations in bearing capacity test results from the two methods. On the other hand, tri-axial test results were critical in fine grained soils i.e. samples 1, 2 and 5. These results suggests that direct shear box test is reliable for coarse grained soils while on the other hand tri-axial test is reliable for fine grained soils.

Soil samples from trial pits 6 and 9 have the highest bearing capacities. Sample 6 is silt clayey soil with gravel while sample 9 is poorly graded. The presence of high bearing capacity soils in this region can be attributed to the presence of thick vegetation cover, low water table and numerous rock outcrops. Vegetation roots hold together the soil particles into an extensive and firm soil mass compacted on large rock outcrops.

A graph of tri-axial test against direct shear test results from trial pits 1 to 6 was plotted as shown in figure 4 with a trend forming a linear equation in the form of $y = mx + c$.

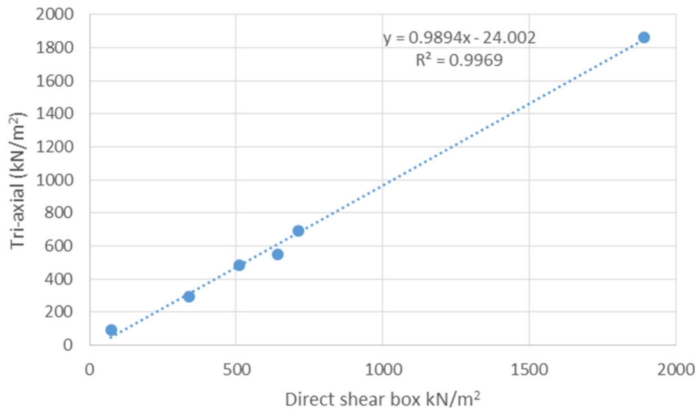

Figure 4: A graph of tri-axial test results against direct shear test results

The equation y = 0.9894x - 24.002 can be used to predict the bearing capacity of one of the methods using the measured results of the other tests. Table 4 elaborates this further where given direct shear box test results, Tri-axial test bearing capacity results can be derived.

Where:

y = Calculated bearing capacity for tri-axial test.

x = Measured bearing capacity for direct shear box.

In this approach, it is assumed that the presence of clay greatly determines the type of suitable method and hence the bearing capacity. Tri-axial test bearing capacity from trial pits 7, 8 and 9 were predicted using the model given their direct shear box results. Given that the data fits well in the model with R squared of 0.9969, the relative errors of 2% for predicted results of trial pits 7 and 9, and 11.36% for trial pit 8 are well within acceptable limits.

Table 4: Prediction of Tri-axial test bearing capacity

TP ID	**Safe Bearing Capacity (kN/m^2)**				
	Direct Shear box	Clay content	Tri- axial test (Measured)	Tri- axial test (Predicted)	Relative error (%)
7	469.95	Present	432.02	440.97	2.07
8	336.87	Present	348.92	309.30	11.36
9	1963.49	Absent	2437.13	2387.29	2.05

4.3 Geospacial interpolation of Soil Bearing Capacity (SBC) results

To obtain the surface interpolation we sampled and tested results from six of the nine trial pits. The other three points were used to validate the interpolated results. The results of surface interpolation of bearing capacity applying the four methods namely Ordinary Krigging, IDW, Spline and NN are shown in figure 5. The Digital Elevation Model (DEM) in figure 6 helps in locating bearing capacity results at different heights above mean sea levels of the study area. Similarly, table 5 shows the interpolated results with their corresponding measured values including associated errors for each method of interpolation.

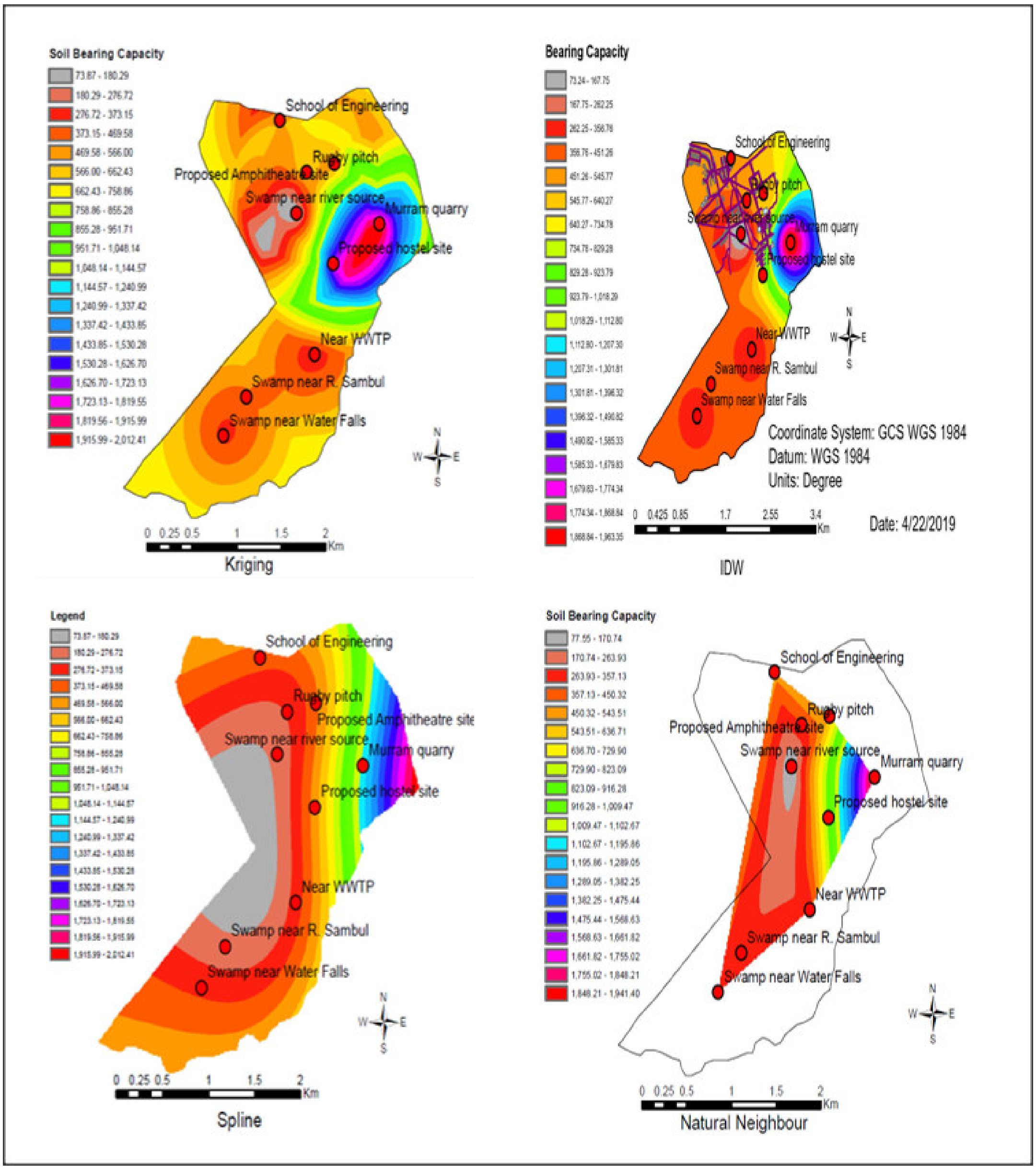

Figure 5: Safe bearing capacity distribution within study area for the four methods

With a relative error of less than 5%, Ordinary Kriging tends to offer relatively reliable results than IDW. Ordinary Kriging resulted to a relatively smaller error margin of 2.23% compared to the other three methods as indicated in table 5. The results also indicated that OK has its R^2 almost equal to one and is the highest compared to other methods. With R^2 of 0.9993, it implies that the data had a good correlation hence generated reliable results for geospatial interpolation. It was also deduced that NN had the highest error of the four methods hence produces unsatisfactory interpolated results. Its R^2 is however greater than that of IDW and Spline. This can be attribute to its property of estimating variables towards the middle point of the entire area unlike IDW and spline which considers a radial distance from a data point.

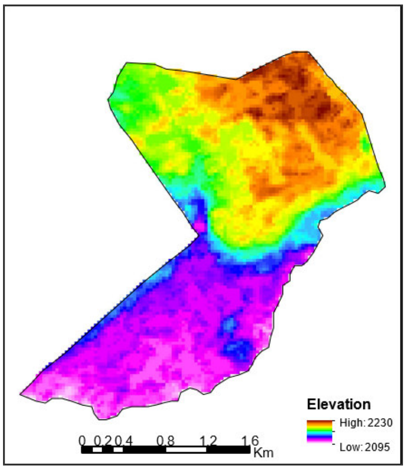

Figure 6: Hydrologically conditioned DEM of the study area

Table 5: Comparison between actual (measured) and predicted (interpolated) bearing capacity

TP ID	Actual SBC (*kN/m²*)	Predicted SBC (*kN/m²*)			
		Kriging (OK)	IDW	Spline	NN
3	694.53	710.00	593.02	421.37	403.73
6	1712.07	1674.50	1065.55	614.22	1056.07
7	432.02	421.00	404.01	228.51	310.58
Relative Mean Error (%)		2.23	14.62	39.33	41.87
R-Squared (R^2)		0.9993	0.9927	0.8961	0.9935

Data normality and distribution affects the performance of the interpolation methods (Yao et. al, 2013). It was observed that each interpolation technique had a prediction error for the nine data points sampled and the three points used for validation. This infers that the bearing capacity pattern significantly affects the performance of the interpolation estimators. Ordinary kriging assumes that the data point variables have an autocorrelation function which is a function of the distance between two particular sampling points (Zimmerman et. al, 1999). The correction of error in ordinary kriging by the automatic algorithm explains why ordinary kriging provided better results.

Unlike Kriging which corrects any errors by adjusting the variogram, IDW relies on the distance of neighboring points and whether the change of the variable (soil bearing capacity) within this stretch is gradual or not. Ordinary kriging was preferable to universal kriging because the variable did not show any trend and the covariance models (variogram) was observed to be stationary local. Also, variance kriging is not dependent on the data used to make the estimate like in the case of IDW, spline and NN (Yamamoto, 2005).

IDW is best suited in representing rainfall data since it is the most representative for rainfall distribution characterization as reported in the study by Mehdi et al (2012). The variability of soil bearing capacity within a small distance is the main reason as to why spline and NN produced unreliable results.

The soil in the southern part of the study area where there is no swamp, is also characterized by stiff clay overlain by gravel. This soil is generally weak and cannot be subjected to constant loading like carrying a structure without stabilization. Worth noting is that gravel in this region cannot be used as a subgrade unless stabilization is carried out. It was also observed that water table in this southern part is high. Such soil conditions have a high tendency for settlement and collapsing.

In this study, the level of clay minerals determines the soil strength and therefore gives a guide of whether to use the direct shear box or tri-axial test machine in measuring the bearing capacity. For all the four spatial interpolation methods used, it stood out that all of them indicated errors whenever there was distinct changes of soil bearing capacity. Sampling evenly within the study area is therefore not necessarily an ingredient for high accuracy since a completely regular network can be biased if it coincides with a 'regular pattern in the landscape' (Karydas, 2009).

5. Conclusion

The main aim of this study was to investigate, determine and map the index properties and soil bearing capacity of the sub-surface soil for Moi University, Kenya, for the purposes of guiding the design of foundations of structures planned to be constructed in future. From the study, the following conclusions are drawn:

a) The level of clay minerals determines the soil strength and therefore gives a guide of whether to use the direct shear box or tri-axial test machine in measuring the bearing capacity.

b) The four spatial interpolation methods used (Ordinary Kriging, Spline, Natural Neighbor and Inverse Distance Weighting) indicated errors whenever there were distinct changes of soil bearing capacity. Ordinary Kriging generated satisfactory results for soil bearing capacity for the study area with a relative error of 2.23 % and R^2 of 0.9993. For the purpose of engineering construction, the results obtained using ordinary kriging interpolation method can be used with the adopted value taken as 97% of the estimated soil bearing capacity.
c) From the safe bearing capacity map, the ground conditions of the study area varied gradually with the bearing capacity ranging from $73\ kN/m^2$ to $1965\ kN/m^2$.
d) The variability of soil bearing capacity within a small distance is the main reason as to why spline and NN produced unreliable results. It can, therefore be concluded that the accuracy of NN and spline can be improved by increasing the density of sample points while having other samples on the boundaries of the study area.

The results from this study will help in proper planning and design of structures envisaged within the study area.

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