Mapping of Soil Bearing Capacity in Butuan City, Agusan Del Norte, Philippines using Geographic Information System

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Abstract

Soil bearing capacity is critical for the success of infrastructure projects and foundational design. This study utilizes Geographic Information System (GIS) software to generate soil bearing capacity maps for Butuan City, Agusan Del Norte, Philippines, based on Standard Penetration Test (SPT) borehole logs from various sectors. The study addresses the challenge of limited geotechnical data in urban areas by providing a reliable method for mapping soil bearing capacity using sparse data. Thematic maps were produced using interpolation techniques: Inverse Distance Weighted (IDW), Empirical Kriging, and Spline. Results indicated soil bearing capacity values ranging from 58.09 kPa to 87.40 kPa at 1.5 m and 165.53 kPa to 238.31 kPa at 3.0 m depth. IDW interpolation emerged as the most accurate method, confirmed by high Pearson's coefficient values and lower root mean square error (RMSE), mean absolute error (MAE), and Relative Mean Error (RME) metrics. The integration of GIS and IDW interpolation fills a significant knowledge gap, enabling the creation of detailed and dependable soil maps. These maps are crucial for geotechnical and civil engineers to perform preliminary assessments and make immediate decisions in urban planning. Regular updates are recommended as new Standard Penetration Test (SPT) data becomes available to ensure map accuracy and relevance.

***Keywords**:* bearing capacity, geotechnical engineering, interpolation, simulation, soil

1. Introduction

The geotechnical properties of soil play a vital role in the success of infrastructure and are considered prerequisites for a good foundation design. The primary sources of geotechnical information are the boreholes and wells. Boreholes are vertical holes drilled in the ground to obtain soil and rock samples in order to determine stratigraphy, groundwater conditions, and soil properties. Geotechnical information is useful for evaluating the effects of projects on the environment and natural resources. It may also help in constructing an advanced treatment against geotechnical risks in the case of building settlements in the future. On the other hand, without proper geotechnical investigation, it is impossible to design an appropriate foundation for the project. This may lead to costly, over-designed foundations, project delays, and even serious failures and destruction.

Today, there is great demand for accurate soil information over large areas from environmental modelers, land use planners (both urban and rural), and more traditional agricultural users of soil resource inventories. Soil properties or behavior directly relevant to their application (Ruiz *et al*., 2018). Geographic Information System (GIS) is a computer-based information system that has been used in many geotechnical applications, and it is capable of capturing, storing, analyzing, and displaying geographically referenced information. According to Azaronak (2015), GIS allows a geotechnical engineer to input field data displayed in CAD, spreadsheets, photos, or maps, and export it to a visual model to bring all relevant and available data together into a single, less complex database. By presenting all relevant data in an easy-to-view medium, geotechnical engineers can make better-quality decisions more efficiently. The Environmental Systems Research Institute [ESRI] (2012) stated the benefits of GIS, which generally fall into five basic categories: cost savings and increased efficiency, better decision making, improved communication, better record keeping and managing geographically. Various studies have demonstrated the application of GIS software to produce maps related to the geotechnical properties of soil. These include the study of the case study conducted by Pando *et al*. (2022), which concluded that GIS-based zonation maps offer a better overview of subsurface geology, bedrock elevations, and geotechnical properties of the various soil types. Another study by Ikara *et al*. (2022) conducted a geotechnical mapping using GIS at Abubakar Tafawa Balewa University (A.T.B.U) Gubi Campus in Nigeria. They further disclosed that the existing data stored in this software could be easily updated to reflect new changes/modifications to the initial conditions. The thematic maps provide valuable information about the soil properties, which is essential during planning and preliminary design work. Furthermore, Nkwunonwo and Okeke (2013) stated the benefits associated with the use of soil mapping technology; however, its proper application and implementation in many places remain unresolved. The gap between using existing hardcopy soil maps from various locations and providing suitable soil data for a range of human activities has increased. In the Philippines, studies on geotechnical mapping were published. These include the study of Caingles and Lorenzo (2022) on GIS-based mapping of geotechnical properties of residual soil in Kibawe, Bukidnon; Dungca *et al*. (2017) conducted a soil bearing capacity reference using GIS where a total of 486 borehole logs data were collected all over Metro Manila; Landingin *et al*. (2024) conducted a soil liquefaction hazard mapping for Daguan City in Pangasinan City based on regional geology, local geotechnical data, and cyclic stress ratio data and among others.

Thematic maps generated from the GIS may vary depending on the interpolation techniques/methods used. Various studies applied the inverse distance weighted spatial interpolation method in mapping the geotechnical properties, such as Tuncay *et al*. (2015), Li *et al*. (2018), Khatri and Suman (2019), Liu *et al*. (2021), and others. Some researchers used kriging interpolation techniques in their studies, including Awan *et al*. (2022) and Pham *et al*. (2019). Igaz *et al*. (2021) and Robinson and Metternicht (2006) used the spline method in generating soil property maps.

Butuan City is a highly urbanized city located in the northern part of Mindanao. The city serves as the capital of the Caraga Region and is the seat of regional administrative and higher-level social services, as well as urban amenities. With the vast economic progress the city is undergoing, low-rise to medium- and high-rise buildings are expected to be constructed in the area. Thus, a geotechnical study requires engineers to understand how soil interacts with the foundation (Dungca *et al*., 2017). Engineers must be aware of how soil affects foundations while designing them. However, because they are underground, engineers are unable to specifically design without performing any studies describing how the underground soil interacts. Engineers rely on prior investigations by their peers near the project site to provide an approximation of the value of the soil bearing capacity for the aforementioned since soil exploration is a highly expensive test. This study attempts to develop a solution to meet the urgent needs of engineers relative to expensive and timeconsuming soil investigation by providing various maps of the geotechnical properties of the soil.

2. Methodology

The chronological process of this study is outlined in Figure 1. First, borehole logs were gathered from previous soil exploration data obtained from the Department of Public Works and Highways (DPWH) Caraga Region, City Architects Office, and Practicing Structural Engineers. A total of 24 borehole logs were collected, as shown in Figure 2 and its corresponding location is presented in Table 1. Second, the collected data were organized into spreadsheets for better visualization, analysis, and further geotagging processes. Third, the sorted data were used as input parameters in the ArcGIS 10.4.1 version software performing interpolation to create geospatial representations of the data. Fourth, all the data and geospatial outputs were compiled to summarize the soil's data. Fifth, the accuracy and reliability of the interpreted data were verified against the selected validation points. Lastly, the consolidated information was analyzed to derive meaningful insights about the soil condition.

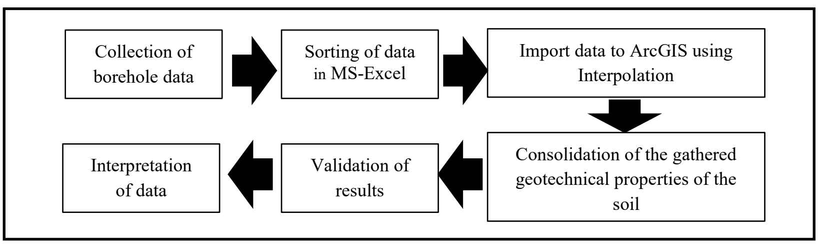

Figure 1. Process flow of the study

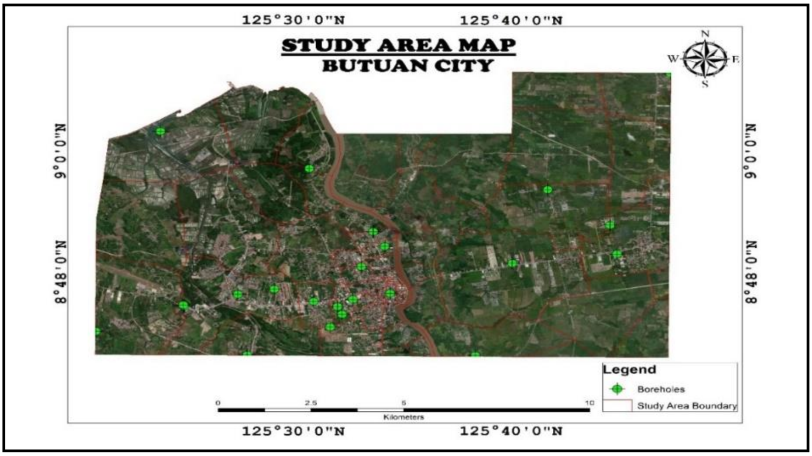

Figure 2. Location map of Butuan City

In this study, three interpolation methods were used to generate bearing capacity maps namely: Inverse Distance Weighting (IDW), Kriging Method, and Spline Function Method. A statistical technique was used to evaluate the accuracy of the generated maps. The IDW method is a commonly used interpolation technique in ArcGIS. It is used to predict values at unsampled locations based on known values at nearby sampling locations. The IDW method uses a weighted average of the values of the surrounding sampled points, with the weights being inversely proportional to the distance from the unsampled location. This means that the points closer to the unsampled location will have a greater influence on the predicted value than points further away. Kriging is a geostatistical interpolation method that is used to predict values at unsampled locations based on known values at sampled locations. It is similar to the Inverse Distance Weighted (IDW) method but uses a more sophisticated statistical model to calculate the weights for the surrounding points. Kriging accounts for the spatial autocorrelation in the data, which means that it considers the fact that nearby points are more likely to have similar values than points that are further away. In Spline function (SF) interpolation, a method in approximation theory for an unsampled location is based on the values of known points. It creates a smooth surface that passes through the input points, which is often used in environmental science, hydrology, and other fields where continuous surfaces are needed (ESRI, 2012).

Table 1. Location of the boreholes

Point	Description	No. of Borehole	Northing	Easting
1	Big Daddy Hotel	1	778214.69	989173.77
2	Camp Rafael	1	775429.45	989844.29
3	DSWD - Caraga	1	785333.00	992298.94
4	LMX Convention	1	773987.72	989428.82
5	ACLC College	1	777450.45	989610.97
6	Rose Lands Realty	1	774012.09	989420.13
7	Rose Lands Realty	1	778496.60	989687.87
8	LMX Convention (Ext)	1	773987.72	989428.82
9	TCA	1	779488.10	989904.74
10	CSU	1	785523.24	991304.90
11	Brgy Imadejas - Tower	1	987773.05	781771.39
12	Brgy Mahay - Tower	1	989434.86	778090.42
13	Brgy Los Angeles - Tower	1	997547.09	786903.60
14	Brgy Libertad - Tower	1	989313.98	776695.30
15	Brgy Limaha - Tower	1	990822.15	778716.46
16	Brgy Bonbon - Tower	1	987751.11	775693.47
17	Brgy Pagatpatan - Tower	1	994203.02	777306.25
18	Brgy Sintos - Tower	1	988730.05	777898.62
19	Brgy Port Poyohon - Tower	1	991526.47	779330.77
20	Brgy Libertad - Tower	1	990029.41	776402.12
21	Brgy R.Calo - Tower	1	992034.40	779022.47
22	Brgy Dumalagan - Tower	1	988543.89	771658.49
23	Brgy Tiniwisan - Tower	1	993514.36	783658.84
24	Brgy Masao - Tower	1	995458.22	773331.58

The Pearson Correlation Coefficient (R) was used to measure the linear correlation to assess both the strength and direction of the linear relationship between two variables (Taylor and Harris, 2023). Table 2 shows the key concepts in Pearson's correlation coefficient.

Table 2. Pearson's correlation coefficient

Concept	Explanation
Range	Values range from -1 to 1 1: Perfect Positive Linear Relationship 0: No linear relationship -1: Perfect Negative Linear Relationship
Strength of Correlation	Describes how closely the data points fit in a line 0.1 to 0.3 or (-0.1 to -0.3); Weak Correlation 0.3 to 0.5 or (-0.3 to -0.5): Moderate Correlation 0.5 to 1 or (-0.5 to -1): Strong Correlation

The evaluation of interpolation methods for soil property estimation involves various statistical measures, including the Pearson coefficient, RMSE (Root Mean Square Error), MAE (Mean Absolute Error), and MRE (Mean Relative Error). RMSE provides an indication of the average magnitude of the prediction errors, with lower values indicating more accurate predictions, while MAE represents the average absolute error, providing a straightforward measure of prediction accuracy (Karunasingha, 2022). MRE measures the average relative error between predicted and observed values, expressed as a proportion of the observed values (Jorgensen *et al.*, 2022). These metrics help in understanding the relative magnitude of the errors in relation to the actual data. The RMSE, MAE, and MRE were calculated using Equations 1-3, respectively:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_o - y_p)^2} \tag{1}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_o - y_p\right| \tag{2}$$

$$\text{MRE} = \frac{1}{n}\sum_{i=1}^{n}\frac{y_o - y_p}{y_o} \tag{3}$$

where y_o are the observed values, y_p are the predicted values, and n is the number of observations.

2.1 Consolidation of the created Geotechnical Properties of Soil Maps

Statistical properties of the sample data were examined. The required information is incorporated into three known interpolation methods. The generated geotechnical maps were consolidated to form soil bearing capacity maps at depths of 1.5 m, 3.0 m, 4.5 m, and 6.0 m.

2.2 Validation of the results

Data from previous soil explorations conducted by the Department of Public Works and Highways (DPWH) and the City Building and Maintenance Division (CBMD) were gathered and utilized to validate the geotechnical values generated from the thematic maps. These maps depicted essential soil properties, including unit weight, plasticity index, angle of internal friction, and cohesion, at various depths. To ensure reliable comparisons, ten (10) representative sampling points were strategically selected across the study area, taking into account variations in terrain and anticipated soil behavior.

The collected historical geotechnical data included a range of soil properties, with a particular focus on parameters such as plasticity index, which reflects soil consistency; angle of internal friction, indicative of shear strength; and cohesion, representing the adhesive force between soil particles. These properties were systematically analyzed to establish their spatial distribution and trends. Subsequently, a correlation analysis was performed to assess the consistency and reliability of the geotechnical values derived from the thematic maps against those obtained from the DPWH and CBMD exploration records. This process involved statistical comparison and evaluation of the relationships between the two data sets, aiming to identify any significant discrepancies or patterns. The correlation analysis not only validated the thematic maps but also provided insights into the accuracy and applicability of historical exploration data within the context of the current study.

3. Results and Discussion

3.1 Bearing Capacity Values

The soil bearing capacity analysis reveals a clear increase with depth, highlighting the relationship between soil strength and the depth at which it is located. At 1.5 m, the bearing capacity ranges from 46.01-61.91 kPa in the lower values to 189.2-205 kPa in the higher range. At a depth of 3 m, the capacity increases to between 142.1-173.7 kPa (lower range) and 426.5-458 kPa (higher range). At 4.5 m, the values rise further to between 212.2-276.8 kPa (lower) and 793.5-858 kPa (higher). Finally, at 6 m, the soil bearing capacity ranges from 232-378.2 kPa in the lower range to 1549-1694 kPa in the higher range. This progressive increase in soil strength plays a critical role in determining the appropriate foundation depth for various structures. Shallow foundations are more appropriate for lighter structures when the bearing capacity at shallow depths is relatively low, while deeper foundations, such as piles or caissons, are necessary for heavy structures due to the higher bearing capacity at greater depths. Understanding the soil bearing capacity at different depths is also essential for mitigating risks like differential settlement, which can occur when foundations are placed in areas with low bearing capacity at shallow depths. Moreover, this data aids in the selection of the most suitable foundation types and materials, ensuring a safe and efficient design. By conducting site-specific investigations, engineers can avoid both over-design and under-design, ensuring that the foundation supports the structure adequately while optimizing construction costs and enhancing long-term durability. The analysis of the map for soil bearing capacity revealed distinct ranges across various depths, reflecting the progressive increase in bearing capacity with depth. At a depth of 1.5 m, the soil bearing capacity ranged from 46.01 kPa to 61.91 kPa in the lower values and from 189.2 kPa to 205 kPa in the higher range. At 3 m depth, the bearing capacity increased, ranging from 142.1 kPa to 173.7 kPa in the lower range and from 426.5 kPa to 458 kPa in the higher range. At 4.5 m depth, the values ranged from 212.2 kPa to 276.8 kPa in the lower range and from 793.5 kPa to 858 kPa in the higher range. Lastly, at 6 m depth, the bearing capacity further increased, ranging from 232 kPa to 378.2 kPa in the lower range and from 1549 kPa to 1694 kPa in the higher range.

3.2 Generated Geotechnical Maps

The generation of soil bearing capacity (SBC) maps at depths of 1.5 m, 3 m, 4.5 m, and 6 m was conducted using three interpolation methods in ArcGIS: Inverse Distance Weighting (IDW), Kriging, and Spline. IDW assigned greater weight to nearer data points, providing localized accuracy in representing SBC variations. Kriging incorporated spatial autocorrelation, offering statistically robust predictions by accounting for the relationship between data points. Spline generated smooth and continuous surfaces, ensuring gradual transitions between values for a more visually intuitive representation. These methods facilitated a comprehensive spatial analysis of SBC, enabling a deeper understanding of subsurface conditions critical for engineering applications and design. Figures 3-14 show the generated geotechnical maps.

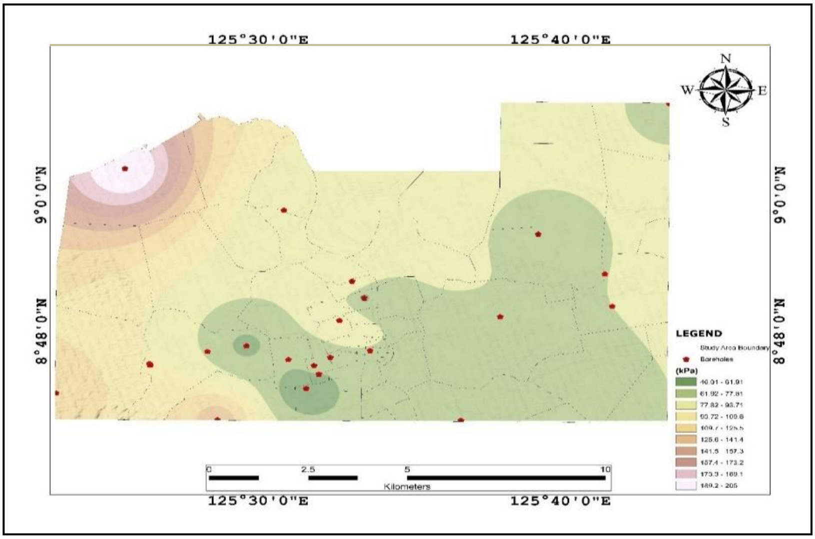

Figure 3. Soil bearing capacity map using IDW interpolation at 1.5 m depth

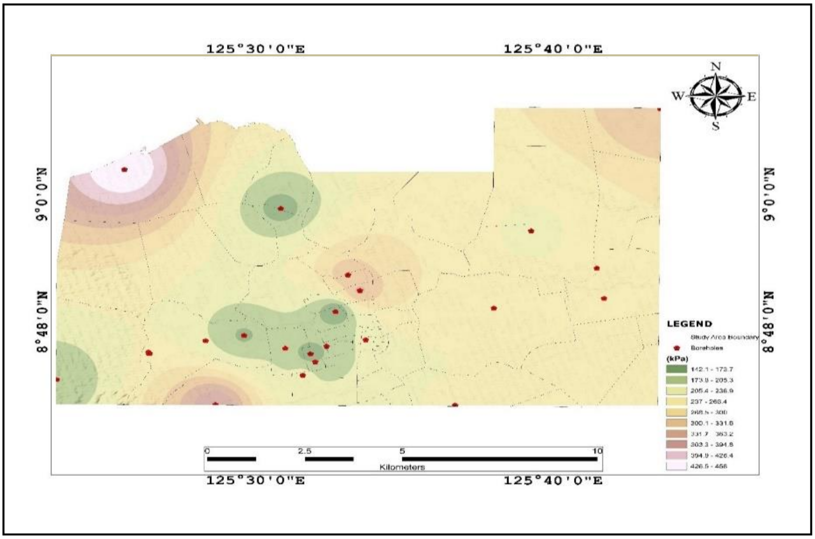

Figure 4. Soil bearing capacity map using IDW interpolation at 3.0 m depth

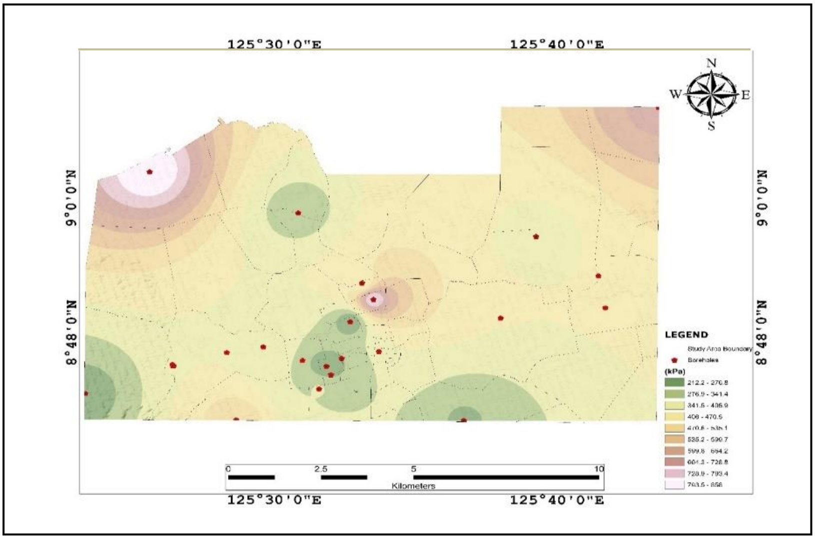

Figure 5. Soil bearing capacity map using IDW interpolation at 4.5 m depth

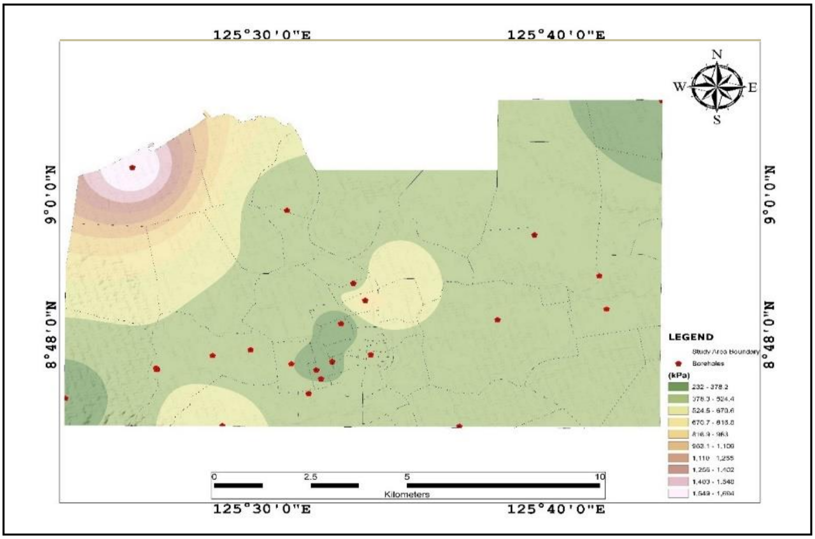

Figure 6. Soil bearing capacity map using IDW interpolation at 6.0 m depth

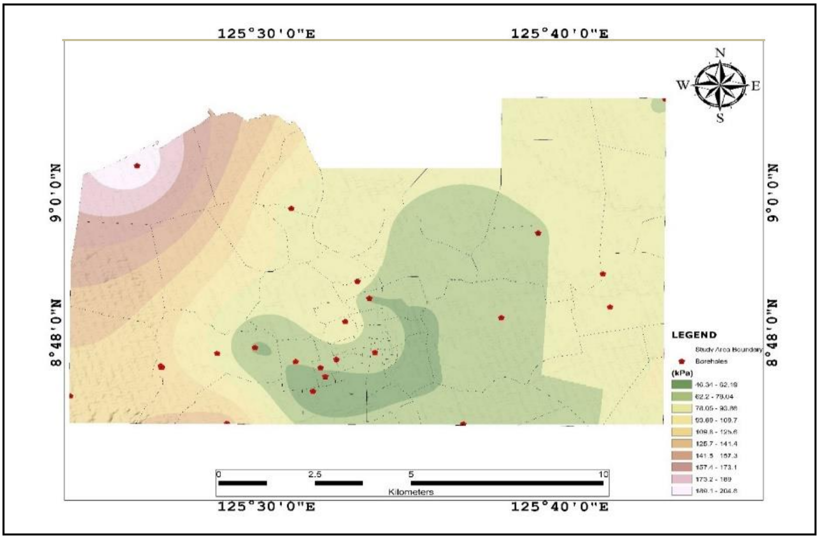

Figure 7. Soil bearing capacity map using kriging interpolation at 1.5 m depth

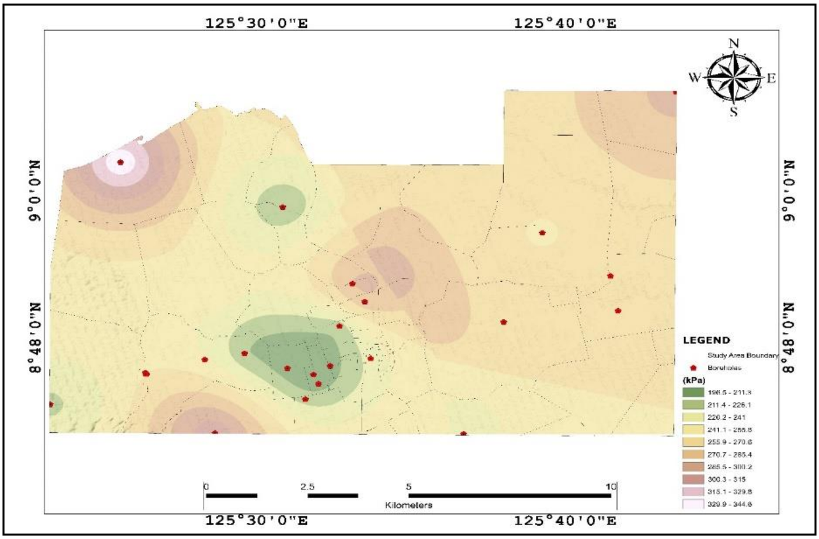

Figure 8. Soil bearing capacity map using kriging interpolation at 3.0 m depth

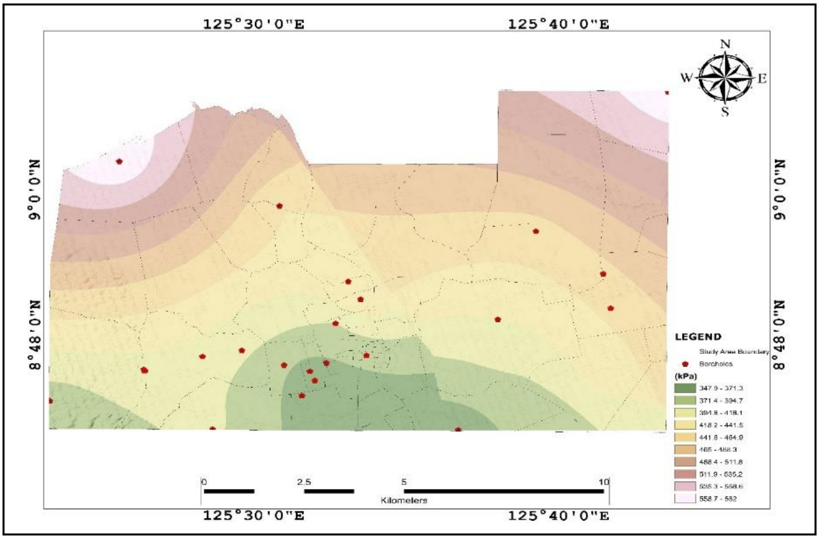

Figure 9. Soil bearing capacity map using Kriging Interpolation at 4.5 m depth

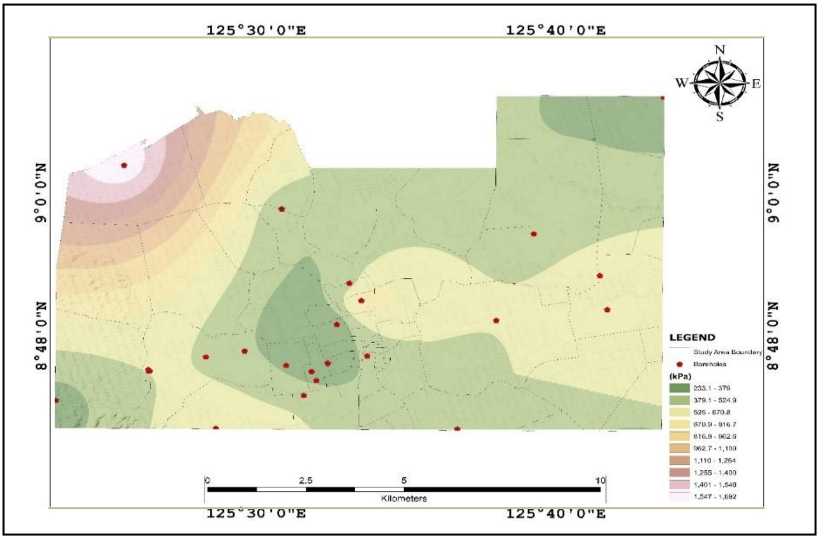

Figure 10. Soil bearing capacity map using kriging interpolation at 6.0 m depth

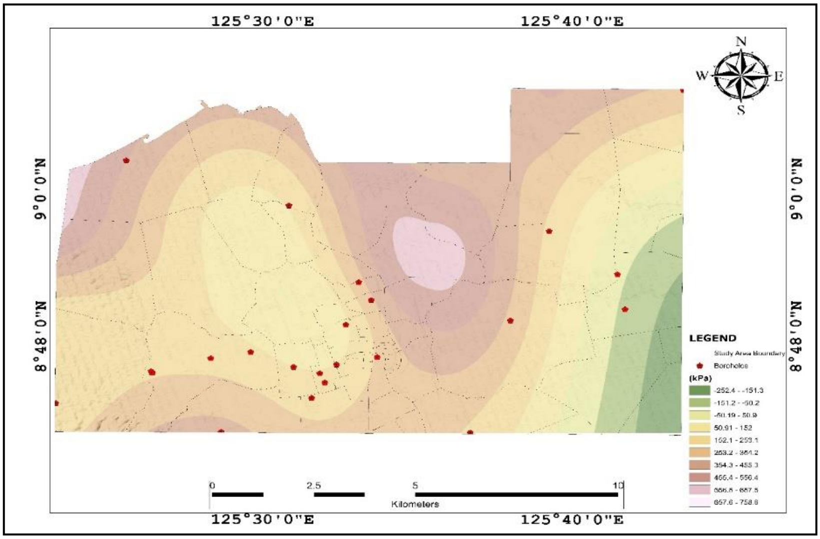

Figure 11. Soil bearing capacity map using Spline Interpolation at 1.5 m depth

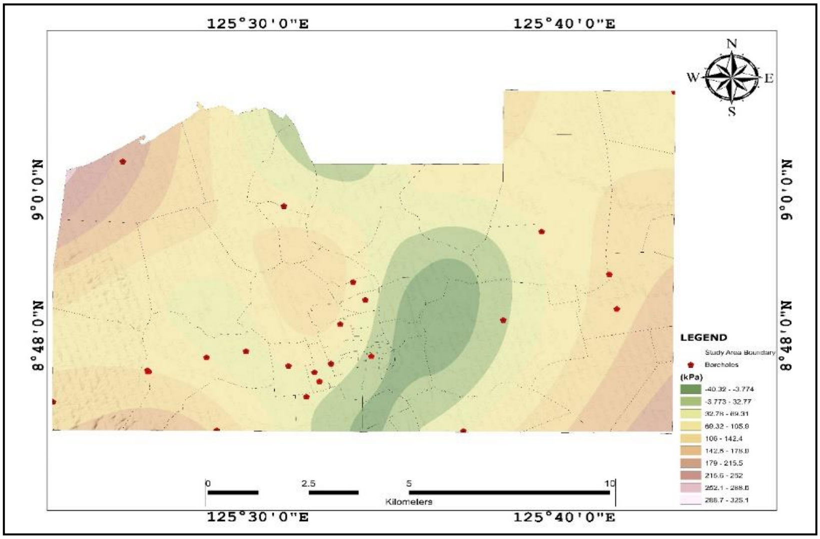

Figure 12. Soil bearing capacity map using Spline Interpolation at 3.0 m depth

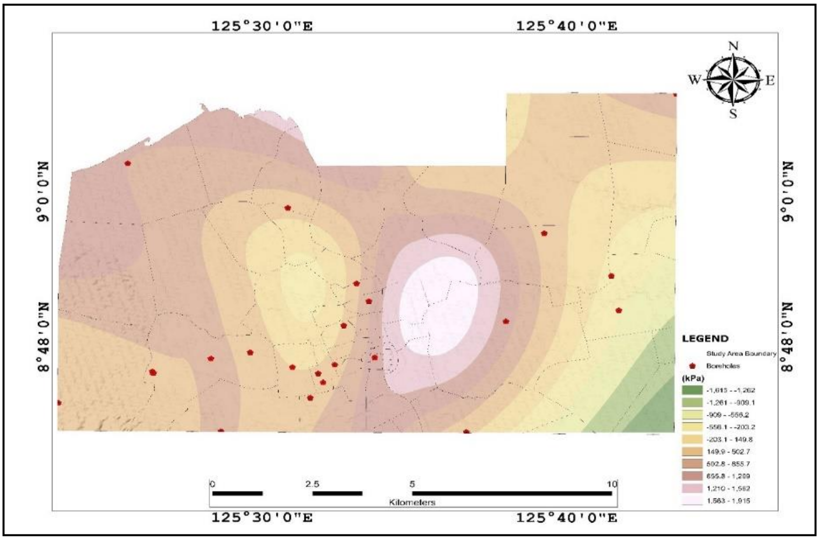

Figure 13. Soil bearing capacity map using Spline Interpolation at 4.5 m depth

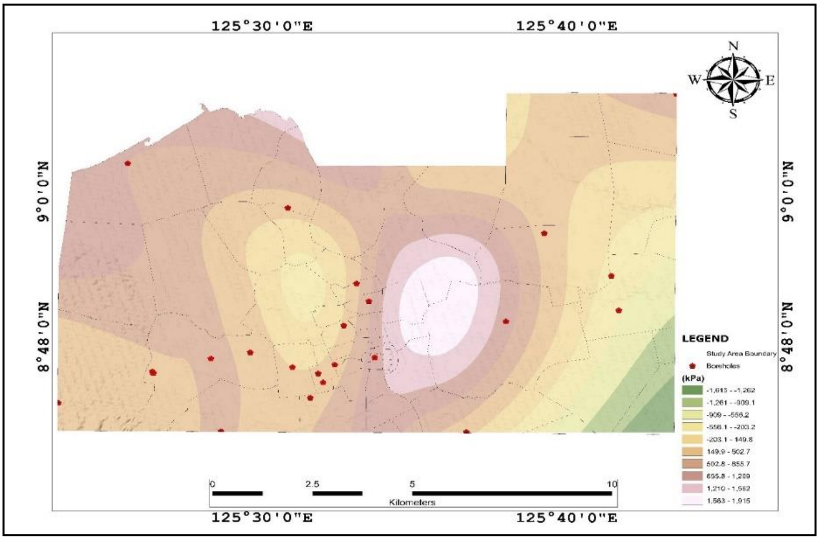

Figure 14. Soil bearing capacity map using Spline Interpolation at 6.0 m depth

3.3 Validation of values

Based on the interpolation performance metrics provided in the table, IDW (Inverse Distance Weighting) generally emerges as the most effective method across various depths. At 1.5 m depth, although Spline exhibits the lowest RMSE (1.91) and MAE (0.60), indicating high precision, IDW shows the highest R^2 (0.7032), suggesting a better overall fit of the predicted values. For 3.0 m depth, IDW again performs best with the highest R^2 (0.6675) and the lowest RMSE (364.94), despite its relatively high MAE. At 4.5 m depth, IDW continues to outperform the other methods, offering the lowest RMSE (755.24) and MAE (-238.83), which underscores its reliability in minimizing prediction errors. Finally, at 6.0m depth, IDW maintains its superior performance with the lowest RMSE (989.56) and MAE (-312.93), even though its R^2 is the lowest (0.2978). In contrast, Kriging and Spline methods demonstrate varying levels of efficiency, with Spline excelling at shallow depths due to its minimal error values. However, IDW's consistent performance across all depths, particularly in terms of minimizing RMSE and MAE, makes it the most suitable interpolation method for this dataset. The results confirm the study conducted by Li *et al*. (2018) that IDW provides accurate mapping results. On the other hand, in the study of Karwariya *et al*., among the IDW, Ordinary kriging, and spline, the IDW with the power of one was the best choice with low skewness while the kriging gave better results where the coefficient of skewness larger than one. Table 3 shows the comparison of the efficiencies of the interpolation methods, and Figures 15-17 display the regression charts.

Table 3. Comparison of the efficiencies and errors of the interpolation methods

Interpolation Method	Efficiency (R^2)	RMSE	MAE	MRE
1.5 m Depth				
IDW	0.7032	21.17	6.69	-0.03
Kriging	0.5571	7.72	-2.44	-0.17
Spline	0.4915	1.91	0.60	-0.12
3.0 m Depth				
IDW	0.6675	364.94	-115.40	-1.68
Kriging	0.4334	440.09	-139.17	-1.98
Spline	0.4334	412.92	-130.58	-1.88
4.5 m Depth				
IDW	0.3940	755.24	-238.83	-2.40
Kriging	0.5375	900.38	-284.73	-2.81
Spline	0.2881	1077.35	-340.69	-3.14
6.0 m Depth				
IDW	0.2978	989.56	-312.93	-3.24
Kriging	0.4354	1073.67	-339.53	-3.63
Spline	0.4845	1094.99	-346.27	28.65

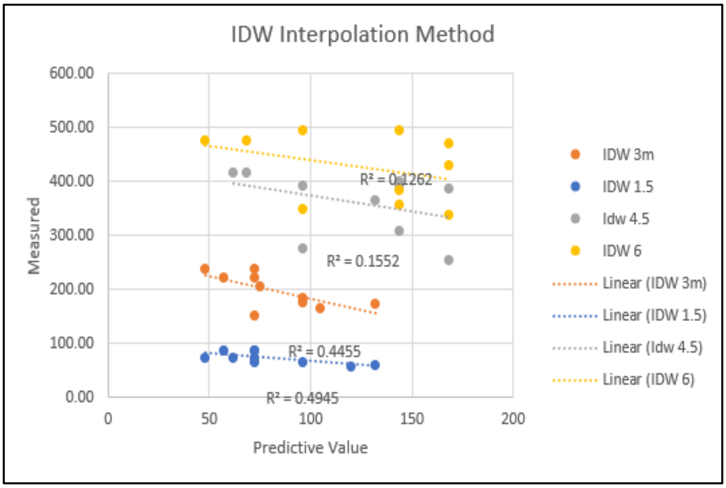

Figure 15. Regression chart using IDW method for 1.5 m, 3 m, 4.5 m, and 6 m depth

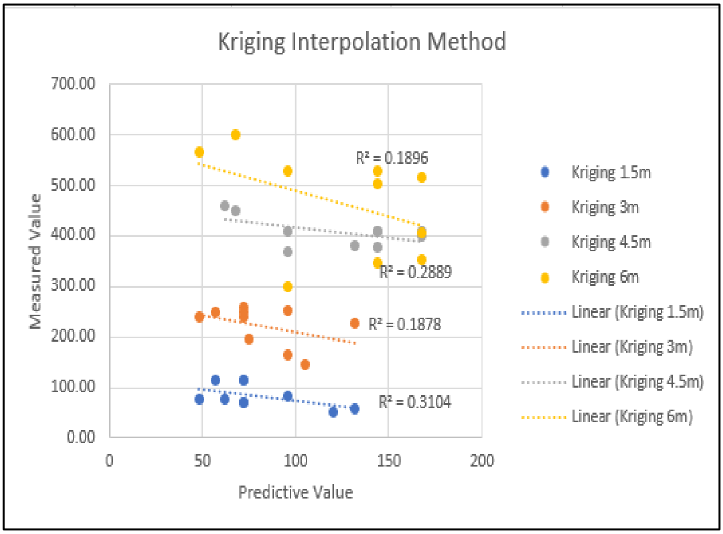

Figure 16. Regression chart using kriging method for 1.5 m, 3 m, 4.5 m, and 6 m depth

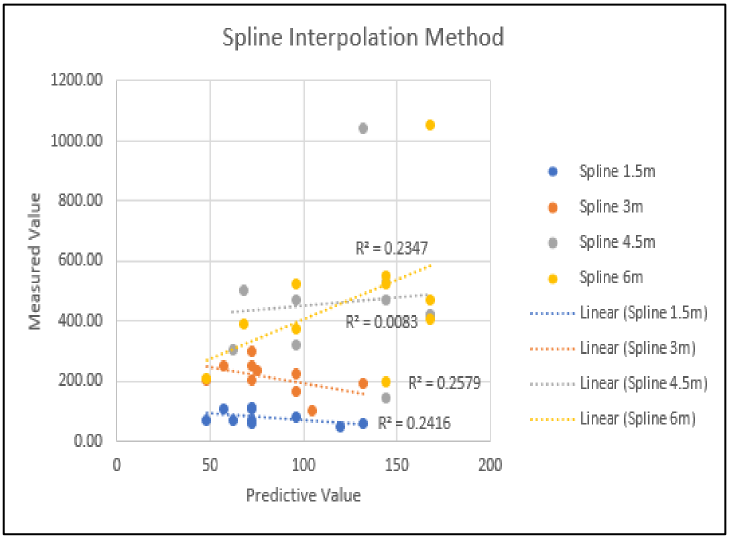

Figure 17. Regression chart using spline method for 1.5 m, 3 m, 4.5 m, and 6 m depth

The analysis of the three interpolation methods: IDW, Kriging, and Spline, revealed distinct patterns in predictive performance based on their respective R^2 values. For the Inverse Distance Weighting (IDW) method R^2values range from 0.0126 to 0.4945, with the highest value observed at 1.5 m (R^2=0.4945). This indicates that IDW performs best at shorter distances, as the predictive accuracy significantly declines with increasing distance, such as at 6 m ($R^2 = 0.0126$). In contrast, the Kriging method demonstrates a more consistent performance, with R^2values ranging from 0.1878 to 0.3104. Its highest predictive accuracy is observed at 6m (R^2=0.3104), suggesting that Kriging is more robust at longer distances compared to IDW. Meanwhile, the Spline method shows the weakest predictive performance among the three, with R^2 values ranging from 0.0083 to 0.2579. The highest R^2value is observed at 4.5 m (R^2=0.2579), but overall, Spline struggles to establish a strong relationship between measured and predictive values. While IDW proves to be the most effective for localized predictions at short distances, Kriging offers more stable results across varying distances. However, the Spline method appears less suitable for this dataset due to its generally low R^2 values, making it the least reliable of the three interpolation methods. Hence, the IDW method is more accurate for closer distances, while the Kriging and Spline method provides more reliable predictions over a broader range of distances, especially as the distance increases. The choice between these methods depends on the specific application requirements, particularly the distance over which predictions are made.

Table 4 illustrates the variation in soil bearing capacity at different depths. Figure 18 shows the relationship between soil bearing capacity at different depths, with the x-axis representing depth in meters and the y-axis showing bearing capacity in kilopascals (kPa). Two distinct lines are plotted: the blue line represents the average of the lower range of bearing capacity values, while the red line shows the average of the higher range. The lower range starts at approximately 54 kPa at a depth of 1.5 m and increases steadily to about 305 kPa at 6 m. Similarly, the higher range begins at around 197 kPa at 1.5 m and rises significantly to approximately 1621 kPa at 6 m. This progressive increase in bearing capacity with depth indicates that deeper soil layers can support heavier loads. For engineering design, this suggests that shallow foundations may be suitable for lighter structures at depths of 1.5 to 3 m, while deeper foundations like piles or caissons are necessary for heavier structures at depths of 4.5 to 6 m, where the soil's bearing capacity is much higher.

Table 4. Variation in soil bearing capacity at different depths

Depth (m)	Lower Range (kPa)	Higher Range (kPa)
1.5	46.01- 61.91	189.2 - 205
3.0	142.1 – 173.7	426.5 - 458
4.5	212.2 – 276.8	793.5 - 858
6.0	232 – 378.2	1549 - 1694

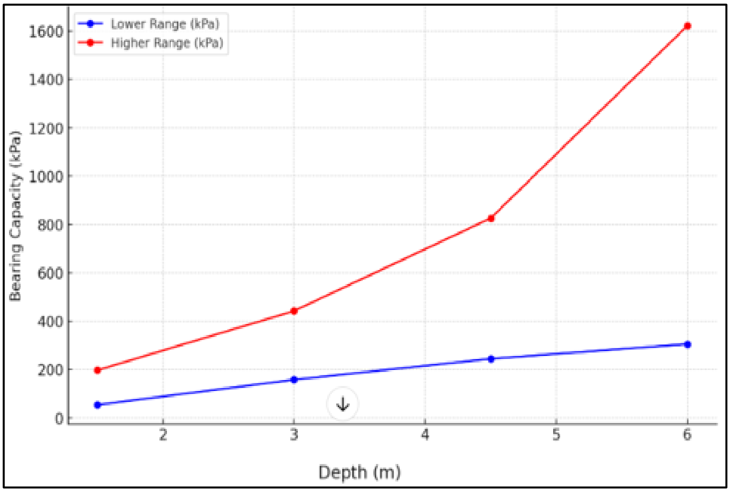

Figure 18: Range of soil bearing capacity for IDW Method

4. Conclusion and Recommendation

Soil bearing capacity values ranged from 46.01 kPa to 61.91 kPa in the lower values and from 189.2 kPa to 205 kPa in the higher range for shallow foundations, with variations reflecting differences in soil type and strength parameters. Higher bearing capacities were observed in areas with predominantly granular soils. The calculated values align with engineering standards and are suitable for construction purposes in the study area. Moreover, among the evaluated methods—Inverse Distance Weighted (IDW), Empirical Kriging, and Spline Function—Inverse Distance Weighted emerged as the most precise interpolation technique. This method's ability to account for spatial autocorrelation resulted in geotechnical maps with the lowest error metrics, ensuring better accuracy and reliability. Therefore, the Inverse Distance Weighting (IDW) method is the best-suited interpolation technique for this study, as it demonstrated the highest accuracy with a strong correlation, low RMSE and MAE values, and minimal RME, ensuring reliable and precise results. Regular updates are recommended as new Standard Penetration Test (SPT) data becomes available to ensure map accuracy and relevance.

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