Geotechnical Zonation of Cone Penetration Test -Based Bearing Capacity Using GIS Interpolation and Pile Driving Analyzer Validation

Dedy Hamdani
Civil Engineering Department, Universitas Islam Sultan Agung, Semarang, Indonesia | Public Works and Public Housing Agency, Banjarmasin, Indonesia
dedy.hamdani1993@gmail.com (corresponding author)

Pratikso Pratikso
Civil Engineering Department, Universitas Islam Sultan Agung, Semarang, Indonesia
pratikso@unissula.ac.id

Yulian Firmana Arifin
Civil Engineering Department, University of Lambung Mangkurat, Banjarmasin, Indonesia
y.arifin@ulm.ac.id

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ABSTRACT

This study develops geotechnical zonation maps of soil bearing capacity (Q) in Banjarmasin, Indonesia, an area characterized by soft soils. A total of 333 Cone Penetration Test (CPT) data points and five Pile Driving Analyzer (PDA) test locations were analyzed. Bearing capacity was estimated using the Meyerhof, Schmertmann, LCPC, and Begemann empirical methods. Comparison with PDA results indicated that the Schmertmann method had the closest alignment, making it the basis for further analysis. Using this method, Q-values were predicted at depths of 5, 10, and 25 m. Spatial interpolation using Inverse Distance Weighting (IDW) and Ordinary Kriging was applied to produce continuous bearing capacity maps. Cross-validation showed Kriging performed better at greater depths, while IDW had slightly better accuracy at shallow levels. These findings highlight the influence of soil depth on interpolation performance and confirm that CPT-based mapping, validated by PDA data, is a reliable and cost-effective approach for preliminary foundation planning in soft soil regions.

Keywords-CPT; PDA; GIS interpolation; bearing capacity; geotechnical zonation

I. INTRODUCTION

Accurate spatial prediction of soil bearing capacity is fundamental for safe and cost-effective foundation design, especially in regions with heterogeneous and challenging subsurface conditions. By enabling more precise estimations of load-bearing potential, such assessments support optimized foundation geometry and materials selection while reducing the risks of structural failure. Traditional analytical equations, though widely used, often fall short under complex site-specific conditions, prompting the need for more advanced and localized geotechnical approaches [1].

Banjarmasin, Indonesia, presents a uniquely demanding geotechnical environment due to its swampy landscape and tidal effects, which result in widespread soft soil conditions. The subsurface layers are typically saturated and highly compressible, with firm ground often lying as deep as 28 to 42 m below the surface [2]. These conditions require tailored foundation solutions, most commonly full-friction piles that depend on skin friction through the soft layers rather than tip resistance [3]. While mapping soil bearing capacity is essential, it is equally important to address the challenges of soft soil behavior. This calls for integrated approaches that not only predict spatial variability but also support ground improvement measures suited to such complex conditions [4, 5].

Among available in-situ methods, the Cone Penetration Test (CPT) has gained widespread application due to its efficiency and ability to generate continuous subsurface resistance profiles, including cone tip resistance (q_c) and sleeve friction (f_s) [6, 7]. CPT offers distinct advantages over methods such as the

Standard Penetration Test (SPT), including higher data resolution, lower disturbance, and faster acquisition [8]. CPT parameters are widely used in geotechnical modeling, and recent studies have emphasized their compatibility with SPT data. For instance, authors in [9] highlighted that integrating CPT and SPT data improves the prediction of ultimate pile bearing capacity, while authors in [10] demonstrated strong correlations between the two methods for enhanced soil characterization. However, CPT produces point-based data, which must be interpolated to develop site-wide assessments. Interpolation techniques, including Inverse Distance Weighting (IDW) and Kriging, are thus essential for creating spatially continuous zonation maps that inform large-scale foundation planning [11, 12].

Validating the predictions derived from CPT data is essential for ensuring their reliability in practice. For this purpose, Pile Driving Analyzer (PDA) tests, capable of capturing dynamic and static responses of piles during installation, serve as a valuable benchmark. PDA testing offers real-time measurements of pile capacity, enabling direct comparison with CPT-based estimates [13]. By aligning CPT-derived capacities with PDA outcomes, empirical methods can be critically assessed for suitability in local conditions.

Despite the widespread use of CPT data and GIS interpolation for geotechnical mapping, limited studies have systematically validated such maps using field-based load test data such as PDA, particularly in soft soil environments like Banjarmasin. This gap underscores the need for studies that integrate empirical modeling, spatial interpolation, and in-situ validation to improve zonation accuracy. The ultimate goal is to generate geotechnical zonation maps that support preliminary foundation design in soft-soil environments like Banjarmasin, offering enhanced reliability, spatial coverage, and engineering value. In this study, four widely recognized empirical approaches, Meyerhof, Schmertmann, LCPC, and Begemann are applied to a dataset comprising 333 CPT points in Banjarmasin. The most representative method is identified through the comparison of five PDA test results. The selected method is then used to interpolate bearing capacity values at various depths. materials and methods

A. *Study Area*

The study area is located in Banjarmasin City, South Kalimantan, Indonesia, situated in a low-lying deltaic region on the island of Kalimantan. The city covers an area of approximately 98.46 km^2, providing the spatial extent for this investigation. This area is characterized by predominantly soft clay deposits, often exceeding depths of 20 m, resulting from centuries of fluvial and marine sedimentation. These deposits are further influenced by tidal inundation and high groundwater tables, leading to persistent soil saturation throughout much of the year. Such hydrogeological conditions exacerbate compressibility and reduce shear strength, intensifying the challenges of foundation design. These soft soil conditions pose serious challenges to construction, including low bearing capacity, high compressibility, and differential settlement. Consequently, detailed subsurface mapping is essential to support safe and cost-effective foundation design. To address these issues, this study utilizes CPT data combined with spatial interpolation techniques to develop geotechnical zonation maps that represent the spatial variability of soil strength across the urban landscape.

B. *CPT Data and Bearing Capacity Calculation*

A total of 333 CPT soundings were conducted across the study area, covering the four sub-districts of Banjarmasin with diverse subsurface conditions. Each sounding penetrated to depths ranging from 20 to 25 m, recording two primary parameters: cone tip resistance (q_c) and sleeve friction (f_s). These measurements provide continuous vertical profiles essential for assessing the mechanical behavior of soft soils. The spatial distribution of the CPT locations is shown in Figure 1, where each yellow dot represents an individual sounding point. The data were obtained from the Office of Public Works and Public Housing (PUPR) of Banjarmasin City, and reflect a comprehensive investigation of soft clay deposits across the city. This dataset forms the foundational input for geotechnical mapping and spatial interpolation analysis.

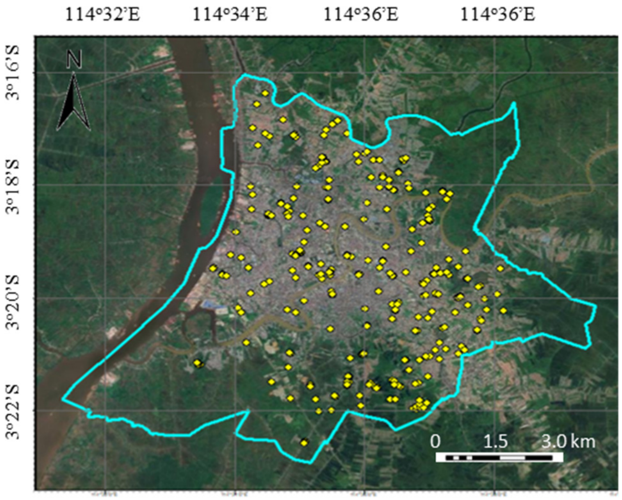

Fig. 1. Distribution of CPT sounding locations in Banjarmasin city.

The analytical procedures applied in this study for estimating pile bearing capacity, namely Meyerhof, Schmertmann, LCPC (Bustamante-Gianeselli), and Begemann methods, are grounded in established frameworks widely acknowledged in geotechnical engineering literature. The Meyerhof method incorporates both end bearing and shaft resistance, particularly effective in clayey soils, and remains relevant through continued validation and refinements [14, 15]. Similarly, the Schmertmann method has been consistently applied for interpreting CPT data and benchmarking pile capacity predictions against field performance [16]. The LCPC method is also adopted in this study for its proven accuracy in converting CPT results into reliable pile capacity estimates [17]. Together with the Begemann method, these approaches have been validated in recent studies through comparative analyses involving PDA testing, reinforcing their applicability and credibility [18, 19].

C. *PDA Test Locations and Data Utilization*

PDA tests were conducted at three strategic urban locations in Banjarmasin to provide control data for validating bearing capacity estimations derived from CPT-based empirical methods. A total of five PDA points were recorded, selected to represent variations in subsurface conditions across infrastructure, institutional, and residential zones of the city.

PDA tests were conducted at three strategic locations in Banjarmasin. Location 1 (PDA1) at Ahmad Yani Bridge (114.607514, -3.327157) represents a transport corridor near riverbanks, likely characterized by mixed granular and cohesive soils. Location 2 (PDA2 and PDA3) at Sultan Suriansyah Regional Hospital (114.585409, -3.332858 and 114.584462, -3.332848) included two nearby test points. Their values were averaged to represent intra-site conditions. Location 3 (PDA4 and PDA5) at the Mayor's Official Residence (114.592277, -3.313215 and 114.592252, -3.313206) also used averaged PDA data of two test points, reflecting typical urban subsoil influenced by long-term development.

In all locations with multiple PDA or CPT data points within proximity, average values were utilized in the analysis to ensure consistency and reduce the impact of local anomalies. PDA tests were performed either during or directly after pile driving, capturing dynamic responses used to compute ultimate bearing capacity (Q) through wave equation analysis. For comparison with CPT-based empirical methods, a safety factor of 2 was applied to PDA-derived Q values, while a factor of 3 was used for CPT-based estimations. All test locations employed the same foundation type, consisting of driven piles with a uniform diameter of 0.4 m.

D. Interpolation Techniques

To generate continuous geotechnical zonation maps from point-based CPT data, two spatial interpolation methods were employed: IDW and Ordinary Kriging. These methods were chosen for their widespread application in geotechnical and geostatistical analysis. The IDW method estimates unknown values by assigning greater weight to closer known points, based on the assumption that similarity decreases with distance. In this study, the power parameter was set to 2, a common default that balances local influence and smoothness. At the same time, the search radius was defined using a fixed number of nearest neighbors. IDW is deterministic and does not account for spatial autocorrelation, but it provides a simple and computationally efficient approach for preliminary mapping. In contrast, Ordinary Kriging is a geostatistical method that explicitly incorporates spatial autocorrelation through semi variogram modeling. A spherical model was used in this study, with key parameters including the nugget (micro-scale variation), sill (variance limit), and range (correlation distance) determined through empirical variogram fitting. Kriging offers improved accuracy over IDW by minimizing prediction variance and estimating interpolation uncertainty. Both interpolation techniques were implemented using ArcGIS 10.8, which provides integrated tools for geostatistical analysis and spatial data visualization. The resulting surfaces were used to develop bearing capacity maps and evaluate spatial patterns of subsurface strength.

E. Validation Methodology

To assess the accuracy of the interpolation results, a validation process was conducted using 10 independent CPT control points that were not included in the interpolation phase. These control points were strategically distributed across different zones of the study area to account for spatial variability in soil properties and provide an unbiased assessment of prediction performance.

Two standard error metrics were employed for validation: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). RMSE quantifies the square root of the average squared differences between predicted and observed values, making it highly sensitive to large deviations and useful for identifying interpolation methods that may over- or underperform in specific zones. In contrast, MAE measures the average magnitude of prediction errors in the same units as the observed data, providing a more interpretable and balanced estimate of general accuracy. Interpretation of these metrics was guided by general geotechnical practices, in which relative errors below 15% are typically considered acceptable for preliminary design purposes. Errors exceeding 25% may indicate the need for further sampling or method adjustment. The results of this validation process serve as the basis for selecting the most reliable interpolation method for geotechnical mapping in the study area.

II. RESULTS AND DISCUSSION

A. Subsurface Soil Classification Based on CPT Data

Figure 2 presents the classification of soil behavior types in Banjarmasin at depths of 5, 10, and 25 m, interpreted CPT data using the Robertson [20] method. Each image visualizes the distribution of soil zones across these depths, where the data points, represented by red, blue, and green dots, correspond to individual CPT measurements. At shallower depths (5–10 m), the majority of data points cluster within fine-grained zones such as clay, silty clay, and sensitive soils. As depth increases to 15, 20, and 25 m, the distribution gradually shifts, with a growing proportion of points occupying zones characterized by sandier or denser materials. This transition reflects the natural vertical stratification in Banjarmasin's subsurface profile. These classifications are critical in geotechnical engineering because the identified soil behavior types directly influence the selection of bearing capacity equations and soil strength parameters. Accurate identification of soil zones informs the estimation of bearing capacity, ensuring appropriate foundation design and safe structural performance. Consequently, the data shown in Figure 1 play a key role in determining soil types used for bearing capacity calculations in spatial geotechnical modeling.

B. Estimating the Bearing Capacity from In-Situ CPT Measurements

The three graphs in Figure 3 present bearing capacity profiles calculated from different methods across the three test locations. Each graph compares the results of static formula-based methods, namely Meyerhof, LCPC, Begemann, and Schmertmann, with field results obtained from PDA tests. To ensure consistent interpretation, a safety factor of 2 was applied to PDA results and a factor of 3 was applied to the CPT-based methods.

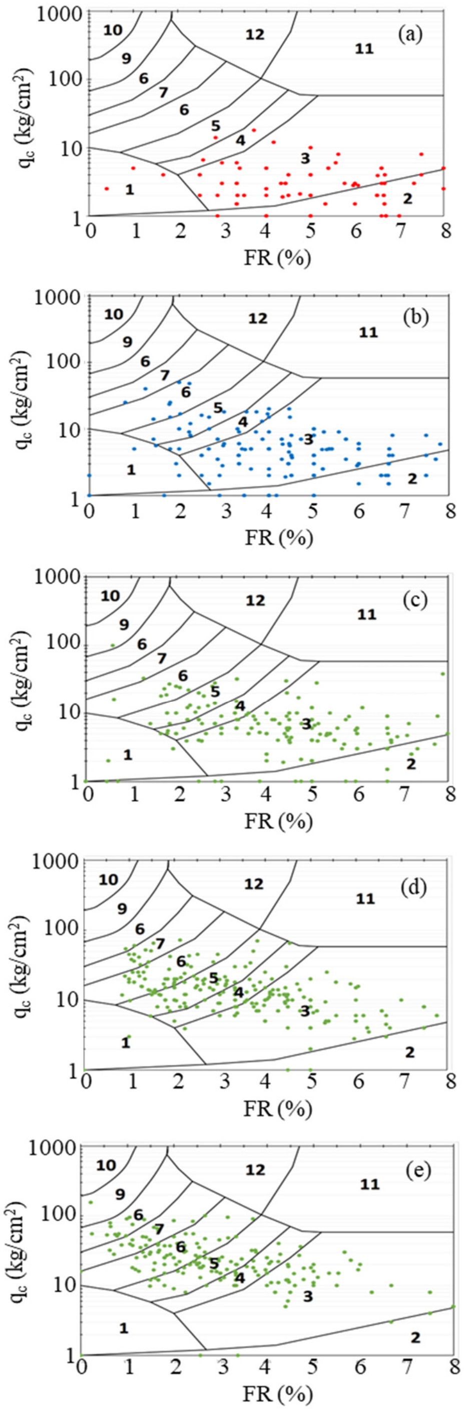

Fig. 2. Distribution of soil behavior types at various depths based on CPT data in Banjarmasin: (a) 5 m, (b) 10 m, (c) 15 m, (d) 20 m, and (e) 25 m. Note: (1) Sensitive fine grained, (2) Organic material, (3) Clay, (4) Silty Clay to clay, (5) Clayey silt to silty clay, (6) Sandy silt to clayey silt, (7) Silty sand to sandy silt, (8) Sand to silty sand, (9) Sand, (10) Gravelly sand to sand, (11) Very stiff fine grained, (12) Sand to clayey sand.

In general, across all locations, the Schmertmann method shows the closest agreement with the PDA results, as illustrated by its curve consistently aligning near the PDA-based bearing capacity line. Meyerhof results tend to overestimate capacity, especially at greater depths, whereas LCPC and Begemann show moderate deviations depending on the subsurface condition at each site. The consistent proximity of Schmertmann's predictions to PDA values suggests that it may provide the most realistic estimate of in-situ bearing capacity when validated against dynamic testing data, making it a more reliable method in practical foundation design scenarios for the studied sites.

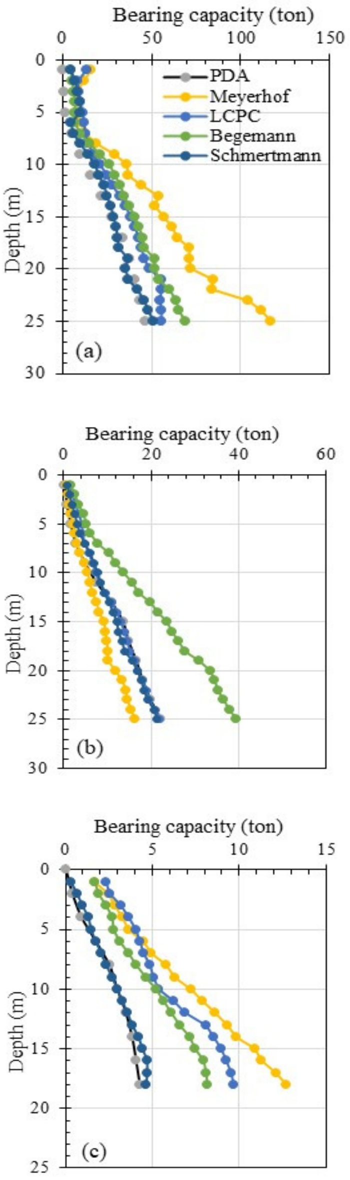

Fig. 3. Comparison of bearing capacity profiles from CPT-based methods and PDA test results at three locations

This result supports earlier findings [20, 21], which highlight that while CPT methods offer cost-efficient assessments, their predictive reliability depends on soil type and profile consistency. The Schmertmann method, grounded in empirical correlations, shows robustness in various soil conditions when compared to other CPT-based approaches [17, 22].

Although PDA tests provide real-time dynamic assessment, discrepancies with CPT-based estimates often arise due to differing interpretations of shaft and base resistance, especially in cohesive soils [2]. In this study, the comparative plots further underline the utility of Schmertmann's method as a practical tool in predicting pile behavior, particularly when site-specific calibrations are considered. Therefore, the subsequent analyses in this study utilize the Schmertmann method, as it demonstrated the closest agreement with PDA test results and offers a reliable basis for bearing capacity estimation.

C. Bearing Capacity Mapping Using Inverse Distance Weighting (IDW) Interpolation

Figure 4 illustrates typical bearing capacity maps generated using the IDW interpolation method at depths of 5 m, 10 m, and 25 m.

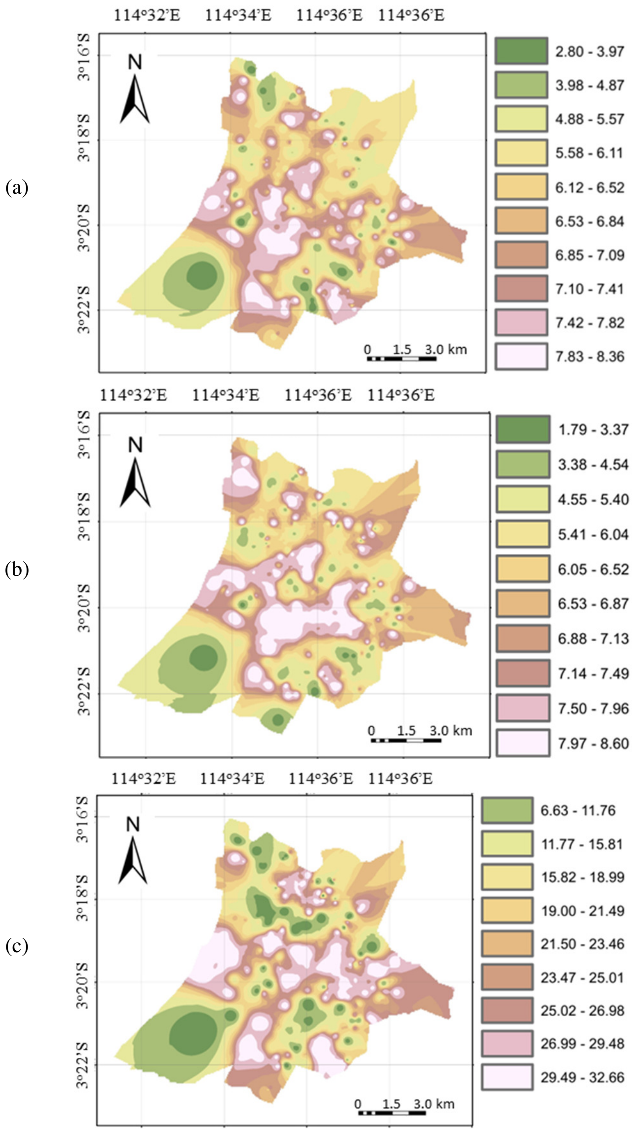

Fig. 4. Typical bearing capacity maps generated using GIS-based IDW interpolation at depths of (a) 5 m, (b) 10 m, and (c) 25 m.

At 5 m depth (Figure 4(a)), the estimated bearing capacity (Q) ranges from 2.80–8.36 tons, with most central urban zones displaying values between 5.58–6.11 tons. Higher capacities exceeding 1.63 tons appear sporadically in the southern and southwestern parts of Banjarmasin. As depth increases to 10 m (Figure 4(b)), the bearing capacity range expands to 1.79–8.60 tons. The map reveals a more developed pattern, with the majority of areas falling within 4.55 to 5.40 tons and high-strength zones (> 4.13 tons) emerging more prominently in the west and south. At 25 m depth (Figure 4(c)), the spatial variation becomes more pronounced, and the capacity increases significantly to a range of 6.63–32.66 tons. High-capacity zones (> 26.99 tons) dominate the southwestern and eastern regions, while the central areas show moderate to high values between 19 and 21.49 tons. These maps reflect the increasing strength of subsurface layers with depth and demonstrate the effectiveness of IDW in visualizing spatial trends in geotechnical capacity.

The application of IDW in geotechnical mapping is supported by numerous studies highlighting its simplicity, accuracy, and practicality. Authors in [24] successfully used IDW to map allowable bearing capacities in An-Najaf and Kufa using data from 464 boreholes, demonstrating its effectiveness in shallow-depth analysis. Authors in [25] also recognized IDW as a suitable method for subsurface mapping at Moi University, citing its consistency and ease of use. Authors in [26] further confirmed IDW's reliability through comparative GIS analyses for bearing capacity estimation, while authors in [27] used it to build a geotechnical property database in Kano, enhancing localized soil understanding. Author in [28] similarly produced IDW-based bearing capacity maps for Quezon City, facilitating safer structural design. These examples reinforce IDW's utility, particularly in areas with heterogeneous soil profiles. Its core principle, assigning higher weight to closer points, makes it particularly effective in reflecting localized geotechnical conditions [29].

D. Spatial Estimation of Soil Bearing Capacity Using Kriging

Figure 5 illustrates the spatial distribution of bearing capacity derived using the Ordinary Kriging method at depths of 5 m, 10 m, and 25 m.

At a depth of 5 m (Figure 5(a)), the predicted Q ranges from approximately 4.68 to 7.55 tons, with the higher values concentrated in the central and southern areas of the map. As the depth increases to 10 m (Figure 5(b)), Q ranges between 4.22 to 8.09 tons, showing a wider and more intense spatial spread of higher bearing capacity, particularly in the southwestern region. At 25 m (Figure 5(c)), Q values escalate significantly, ranging from 5.73 to 31.94 tons, indicating deeper layers tend to exhibit stronger soil resistance suitable for heavier structural foundations. These results demonstrate the strength of kriging in modeling spatial variability of subsurface conditions. Kriging's reliability lies in its capacity to produce high-resolution geotechnical maps, even when available data are sparse [30]. This is particularly useful in urban development planning, where understanding soil heterogeneity is crucial for design optimization. The method's integration with GIS further enhances spatial analysis, supporting complex investigations such as liquefaction risk and shear wave velocity estimation [31, 32].

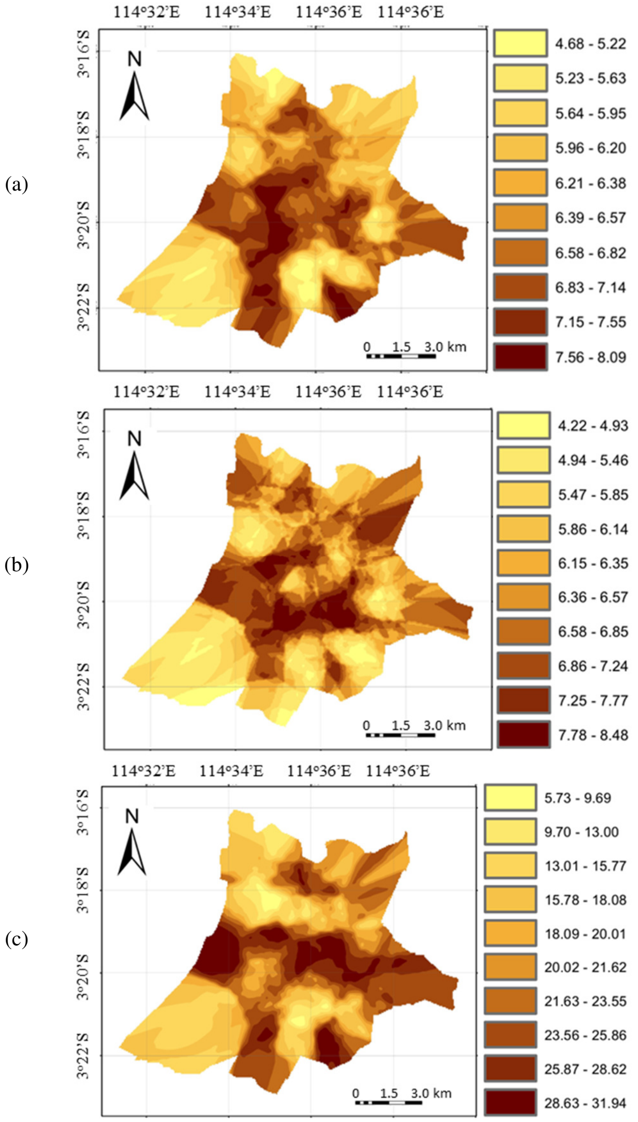

Fig. 5. Typical bearing capacity maps generated using GIS-based Kriging interpolation at depths of (a) 5 m, (b) 10 m, and (c) 25 m.

Moreover, applications like those in Ranya City [33] validate kriging's ability to deliver accurate average bearing capacities across depths using borehole data, an approach also mirrored in this study. The adaptability of kriging across regions, as confirmed in [34], enables its use for contouring multiple geotechnical parameters, not just Q_{ult}. However, authors in [35] remind us that while kriging is powerful, interpolation method selection should consider context, as IDW may sometimes outperform kriging in areas with sharply localized soil features.

E. Cross-Validation Performance of Interpolation Methods

Representative results of the Cross-Validation Comparison (CVC) at depths of 5 m and 10 m are shown in Figures 6 and 7 for both IDW and Kriging methods. Each figure presents a scatter plot of predicted versus measured values, where each point represents a validation location obtained through leave-one-out testing. The proximity of these points to the 1:1 reference line indicates the accuracy of each prediction. Summary metrics, such as RMSE, mean error, and standardized error, are also provided. At 5 m depth, Kriging demonstrates better accuracy (RMSE = 0.0964) compared to IDW (RMSE = 0.1225), while at 10 m, IDW slightly outperforms Kriging (RMSE = 0.0843 vs. 0.0902). These figures illustrate how the spatial structure of data affects interpolation performance and confirm the overall trends in Table I, where Kriging is generally more reliable at greater depths.

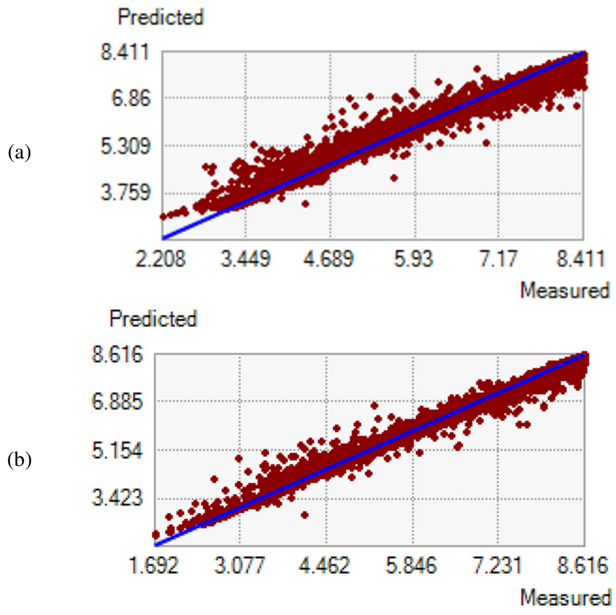

Fig. 6. Typical result of Cross-Validation Comparison (CVC) analysis using the IDW (a) at 5m and (b) at 10m.

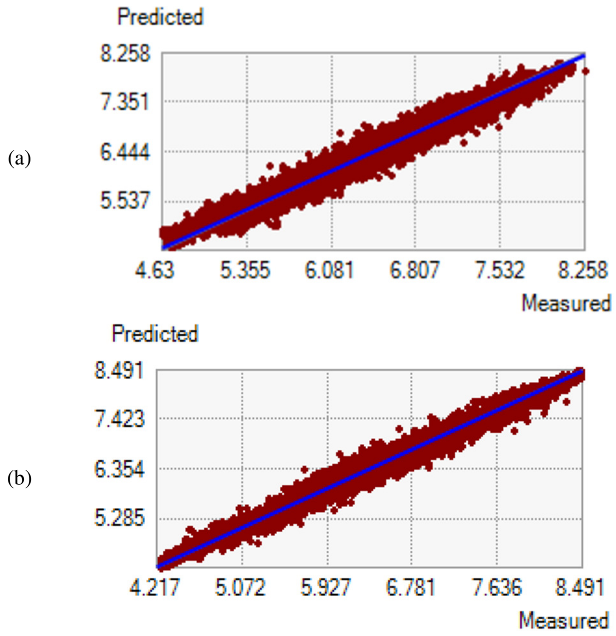

Fig. 7. Typical result of Cross-Validation Comparison (CVC) analysis using the Kriging (a) at 5m and (b) at 10m.

TABLE I. RMSE COMPARISON OF IDW AND KRIGING BY DEPTH

Depth (m)	**IDW RMSE**	**Kriging RMSE**	**Best Method**
5	0.1225	**0.0964**	Kriging
10	**0.0843**	0.0902	IDW
15	0.2274	**0.198**	Kriging
20	0.3759	**0.2225**	Kriging
25	0.7948	**0.5348**	Kriging

The results of the Cross Validation Comparison (CVC) using ArcGIS 10.8 for both IDW and Ordinary Kriging methods across five depth intervals (5 m, 10 m, 15 m, 20 m, and 25 m) demonstrate important insights into spatial interpolation accuracy for geotechnical data (Table I). At the 5 m depth, Kriging outperformed IDW with a lower RMSE of 0.0964 compared to 0.1225. However, at the 10 m depth, IDW produced slightly better performance (RMSE = 0.0843) than Kriging (RMSE = 0.0902), indicating that for relatively shallow depths with more uniform data distribution, IDW remains a reliable option. As the depth increases, Kriging consistently shows superior performance over IDW. At 15 m, Kriging recorded a lower RMSE (0.1980) than IDW (0.2274), and the difference becomes more significant at 20 m and 25 m, where Kriging achieved RMSE values of 0.2225 and 0.5348, compared to IDW's 0.3759 and 0.7948, respectively. Moreover, the standard errors of Kriging also increased with depth, from 0.6603 at 5 m to 1.3447 at 25 m, reflecting increasing uncertainty in deeper interpolations but still outperforming IDW in prediction reliability. This pattern suggests that Kriging's incorporation of spatial autocorrelation becomes increasingly beneficial in deeper, more complex subsurface conditions where variability is higher and linear distance-based assumptions (as in IDW) are insufficient.

Importantly, these insights are reinforced by rigorous cross-validation, a foundational technique in geostatistics to assess model robustness. Cross-validation involves withholding sample points and predicting their values using the remaining dataset, allowing quantification of predictive accuracy [36, 37]. Specifically, Leave-One-Out Cross-Validation (LOOCV) helps refine variogram models used in Kriging, ensuring minimal prediction error across the domain [38]. In geotechnical contexts where data sparsity and heterogeneity are common, such validation is essential not only for choosing between IDW and Kriging but also for fine-tuning model parameters to represent spatial variability accurately [39, 40]. Thus, the integration of CVC metrics validates Kriging's stronger adaptability to depth-related complexity in subsoil conditions, reinforcing its suitability for constructing reliable geotechnical zoning maps. Moreover, the value of spatial data accuracy has been echoed in recent studies outside of geotechnics, such as in the vertical evaluation of Google Earth DEMs for elevation modeling [41] and the integration of satellite altimetry in renewable energy potential mapping [42], underscoring the broader significance of reliable geospatial interpolation methods across environmental and engineering disciplines.

III. CONCLUSION

This study successfully developed geotechnical zonation maps of soil bearing capacity (Q) for the Banjarmasin area by integrating Cone Penetration Test (CPT) data with spatial interpolation techniques. Among the four empirical methods evaluated, the Schmertmann method showed the closest agreement with the Pile Driving Analyzer (PDA) test results, validating its suitability as the primary model for estimating bearing capacity in this context.

Interpolation results revealed distinct trends in performance across depths. Based on Root Mean Square Error (RMSE) values from cross-validation, Ordinary Kriging outperformed IDW at greater depths (≥15 m), while IDW slightly surpassed Kriging at 10 m depth. Specifically, the best interpolation method varied with depth: Kriging yielded lower RMSE at 5, 15, 20, and 25 m, while IDW performed better at 10 m. These findings suggest that Kriging is generally more robust in deeper, more variable soil layers, whereas IDW may suffice for shallower zones with more homogenous conditions.

Overall, the integration of CPT-derived data, empirical modeling, and geostatistical interpolation offers a reliable approach for generating bearing capacity maps. These maps provide valuable insights for preliminary foundation design, especially in soft soil environments like Banjarmasin where subsurface conditions are highly stratified and construction risk is elevated.

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