



INDONESIAN JOURNAL ON GEOSCIENCE

Geological Agency
Ministry of Energy and Mineral Resources

Journal homepage: <http://ijog.geologi.esdm.go.id>
ISSN 2355-9314, e-ISSN 2355-9306



New Approach for Developing Correlation of NSPT and Shear-Wave Velocity (V_s): Bantul Case Study

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Manuscript received: November, 11, 2020; revised: March, 10, 2022;

approved: August, 9, 2022; available online: October, 31, 2022

Abstract - Predictions of ground motion levels that, under certain conditions, may cause liquefaction require a sufficient knowledge of the underlying soil characteristics. The utilization of the seismic refraction method applies measurements of the subsurface shear-wave velocities (V_s) as a representation of the properties of stiffness and soil amplification. This study, carried out in Bantul, Yogyakarta Province, Indonesia, is conducted to determine the relationship between Standard Penetration Test N values (NSPT) and V_s by using data from eighty-eight drill sites and twenty-nine seismic reflection investigations with the statistical method, namely the Statistical Gradation Approach. The new equations, developed from a power regression analysis, are applied to all soil and eight soil types: silty sand, sand, gravelly sand, clay, silt, sandy clay, clay sand, and sandy silt. The equations, proposed to predict V_s , show a strong relationship between NSPT and V_s values, which applied to other regions with the shear-wave velocity of <300 m/sec, shallow groundwater depth, and dominant sandy soil.

Keywords: soil type, shear-wave velocities, seismic reflection, power regression, gradation approach

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How to cite this article:

Muktaf, H. A., Wiyono., and Tampubolon, B.D., 2022. New Approach for Developing Correlation of NSPT and Shear Wave Velocity (V_s): Bantul Case Study. *Indonesian Journal on Geoscience*, 9 (3), p.395-413. DOI: [10.17014/ijog.9.3.395-413](https://doi.org/10.17014/ijog.9.3.395-413)

INTRODUCTION

Background

One of the essential parameters in the analysis of the seismic response of soil and the determination of soil classification concerning building design standards is the shear-wave velocity (V_s). Geotechnical investigations for determining V_s experience a significant degree of difficulty and expense, especially when obtaining undisturbed soil samples. Meanwhile, in situ studies (e.g. seismic measurements) are a more widely used

alternative than laboratory tests, particularly techniques involving measuring surface wave velocity by creating a shear-wave velocity profile without needing drilling or penetration tests (Kramer, 2005). The non-destructive and non-intrusive methods are a viable alternative to V_s -based approaches for characterizing the susceptibility of sandy soils to liquefaction (Andrus, 2004). The seismic in-situ tests are not always appropriate, especially in urban areas, due to space constraints and noise level limits. Therefore, it is necessary to determine V_s indirectly through methods such

as Standard Penetration Test (SPT) and Cone Penetration Test (CPT), Cross-Hole Analysis, Surface Wave Spectrum Analysis (SASW), Multi Analysis Spectral Wave (MASW), and seismic array analysis. Those applications are usually applied in geotechnical site investigations (Andrus, 2004; Shooshpasha *et al.*, 2014). On the other hand, such in-site investigations are not always available due to the considerations of costs and availability of personnel with particular expertise (Hanumantharao and Ramana, 2008).

For this reason, the linear statistical regression approach is often used as an alternative method to estimate V_s between V_s and the Standard Penetration Test (NSPT) without data acquisition or investigation, when V_s data is not available (Akin *et al.*, 2011; Fatehnia *et al.*, 2015). Previous research by Kanai (1966), amongst others, described the correlation between NSPT and V_s using a relationship developed between V_s and NSPT based on approximately seventy microtremor measurements performed in predominantly sandy soils. Imai and Tonouchi (1982) analyzed an extensive data set, containing 1654 data pairs from 386 borings at 250 sites throughout Japan. They developed V_s correlation equations based on NSPT, soil type, and geologic age. Hasancebi and Ulusay (2007) investigated the correlation between V_s and NSPT at a site within an alluvial basin, using seismic refraction measurement. The analysis evaluated the association between shear-wave velocity, NSPT, and soil properties as depth functions for the encountered geological units, consisting mainly of alluvial and Pliocene members (Akin *et al.* 2011). These relations were developed based on the geotechnical sounding approach and active and passive seismic experiments for sand soils, clayey silt, and silty clay, with the results showing that there is a better correlation in the estimation of V_s when the number of uncorrected blows is used (Dikmen, 2009). A statistical approach was used by employing the M5 model tree algorithm, which is a kind of machine-learning technique with the idea of splitting the parameter space into areas (subspaces) and building a linear regression model in each of

them, with the relationship between V_s and NSPT (Fatehnia *et al.* 2015).

V_s reflects the dynamic response of soil due to its relationship to the strain-shear modulus (G_{max}) (Ghazi *et al.*, 2015). The V_s and G_{max} values represent soil density, void ratio, and effective stress. These parameters explained the soil type, soil age, depositional environment, cementation, and history of soil stress (Hardin and Drnevich, 1972a; Wair *et al.*, 2012). Previous researchers have used a simplified procedure to determine the V_s values when assessing the effects of earthquakes on soil resistance that result in liquefaction (Andrus and Stokoe, 1997; Goda, 2011; Kayen, 2013; Robertson, 1990; Satyam, 2014; Tokimatsu, 1991). This study does not use the value of V_{s30} as the basis for determining soil classification based on the strength of earthquake vibrations due to local effects. Instead, the value of V_{s30} used is the average shear-wave velocity to a depth of 30 m. This value does not represent the effect of soil stress which has a different value at each depth of the soil layer.

This study aims to develop a new statistical approach for developing the new relationship between V_s and NSPT, which is implemented for the soil type classification. The proposed new empirical relationships show a correlation between NSPT and V_s applied to all soil types, such as silty sand, sand, gravelly sand, clay, silt, sandy clay, clayey sand, and sandy silt. The studied area is in the vicinity of Bantul, Yogyakarta Province, Indonesia, where the employed data covers areas where liquefaction events have occurred, such as following the May 26 Yogyakarta earthquakes in 2006. For this purpose, information on soil classification, V_s (derived from the reflection method), and NSPT is necessary. The new approach is the Statistical Gradation Approach (SGA), a repetitive operation in finding the optimum technical procedures to build mathematical models of dynamical systems from measured data. This method covers cleaning duplicate data sets, removing outliers by adjusting the database, filtering data with the equal width distance bin, and processing filtered data with power regres-

sion. Comparisons are then made with previously developed relationships from other studies to evaluate the results of this work.

METHODS AND MATERIALS

Geotechnical and Geophysical Investigations

A study to formulate the correlation between NSPT and Shear-wave Velocity (V_s) was conducted in Bantul Regency, Yogyakarta Province, as an area where the evidence of liquefaction exists (Figure 1). The study uses geotechnical data consisting of eighty eight boreholes (red triangle). The borehole depths prepared by Geological Agency of Indonesia were relatively uniform, ranging from 4 - 20 m, with the groundwater depth between 0.3 - 7 m, hence relatively shallow (TRS-PVMBG, 2012). NSPT analysis provides information on soil classification, index parameters, and some geotechnical applications through semi-empirical procedures, such as evaluating of a shallow foundation settlement, bearing capacity of piles, and assessing the potential for sandy soil liquefaction. SPT was carried out using a split tube dropped from a height of 75 cm, with a hammer weighing 63.5 kg to push the pipe to a total depth of 45 cm. The NSPT value was calculated at

15 cm steps, with the number of hammers blows not exceeding 50 every 15 cm (Akin, 2011).

The seismic refraction investigation result produced V_s data initially as the SH-wave profile (yellow star). The SH-wave seismic reflection was measured using a series of Geophone-SH actual wave receivers, OYO-DM 10 Hz, ground streamer system, at forty-eight points with 1 m space. Seismic vibration sources used the wheel barrier vibrators, Geosym-Elvis IV S8 (20 - 160 Hz), while seismic signals were recorded using Geode Exploration Seismograph (twenty-four channels). Seismic recording equipment retrieved data with a distance between sources of 2 m. It started from a range of 0 (zero), which was positioned 1 m before the first geophone, to the last place at 50 (3 m after the geophone 47). Seismic reflection records were analyzed based on the travel time of the waveform from the source to the geophone (Figure 2), enabling the velocity variations of the soil layers below the surface to be determined (Buana, 2013).

Subsurface information, such as geological profiles, NSPT, V_s , and CPT (see Figure 3a) were obtained from the borehole data and seismic reflection investigations. These data was compiled to develop a geotechnical subsurface model of the area. Because of the large amount of data,

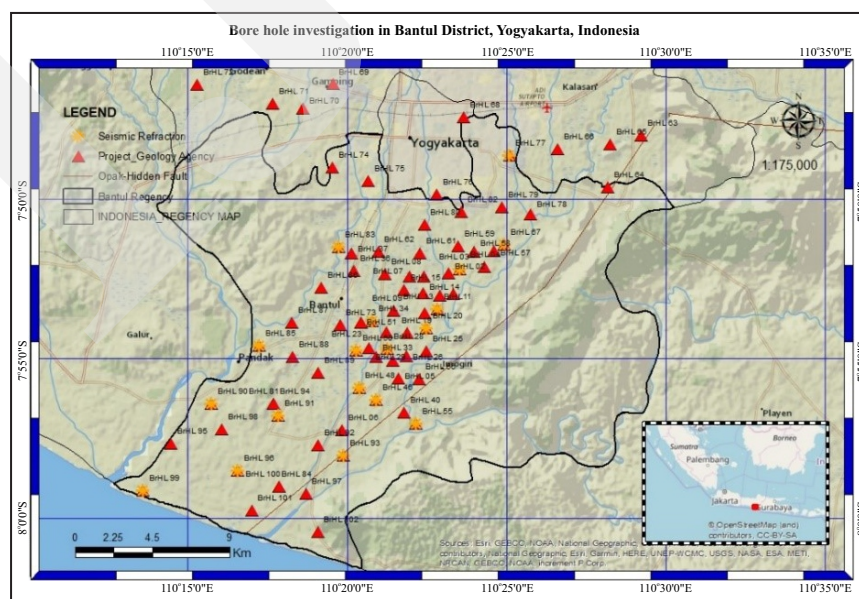


Figure 1. The locality map of the boreholes and seismic refraction sites in the studied area and its vicinity.



Figure 2. Land streamer geophone and seismic signal transmitter (vibrator).

these bore logs are considered the representative of the typical soil profiles. Based on the nature of the soils, they are classified into general groups referred to USCS for the identification of the soil layers. The total number of data pairs (NSPT and Vs) used in this research is 4791.

As with all methods, investigations using SPT have uncertainties that will affect the results of the analysis. Experts agree that there is a tolerance for NSPT ranging at best 1.4% and at worst 100% (Kulhawy and Mayne, 1990; Kulhawy and Trautmann, 1996; Schmertmann, 1975; Youd, 2001). The uncertainty is the representative of the outlier data, so the Statistical Gradation Approach must be used to minimize its influence on the accuracy of the analysis results. The sources of the control for NSPT data precision include:

- the nature of the soil encountered (*i.e.* vertical stress, mineralogy, rough gravel, horizontal stress, age of sand deposition, geology),
- the source of pore water pressure generation,
- the equipment and maintenance (hammer efficiency, borehole diameter, sampler, rod length),
- other factors (*i.e.* human factors, weather conditions, and topography) (Zekkos, 2004).

Bantul is located on a plain flanked by two mountains in the west and east, called Bantul Graben. The southern landscape is the coastal plain and to the north there is Mount Merapi, which lies 80 km from the researched area. Terban Bantul (Vessel and Davis, 1981) is included in the

distal volcanic category, volcanic material that has undergone transportation process of erosion and mechanical deposition from its original rock, including pyroclastic debris, which has not been consolidated (Fisher, 1961). The studied area referring to the general geological conditions in the area of research (Rahardjo *et al.*, 1985) is composed of rock formations, from young to old are the Alluvium (Qa) Unit, Volcanic Deposits of Mount Merapi (Qmi), Wonosari Formation (Tmwl), Sentolo Formation (Tmps), Nglanggran Formation (Tmn), and Semilir Formation (Tmse) (Figure 3). The description of borehole 20 shows that silty sand material from volcanic deposits dominates vertically the constituent of soil (Figure 4a).

The oldest rocks exposed are rocks from the Semilir Formation (Tmse), located in the northern hills of Wonosari. This Oligocene-Lower Miocene formation, comprises alternations between tuff breccia, pumice breccia, tuff, and tuff clay. These rocks vary from fresh condition to strongly weathered. Residual soil consists of silt and clay cohesive soils. The Nglanggran Formation (Tmn), Early Miocene -Middle Miocene age, lies conformably above the Semilir Formation (Tmse) in the part of the southern mountains. These formations are composed of uncoated agglomerates and incoherent conditions. Residual soil is generally in the form of clay and silt.

The Wonosari Formation (Tmwl) in the southern hills consists of reef limestone and bedded limestone with clay soil residue. This formation is from Late Miocene to Pliocene age. The Sentolo Formation (Tmps) is located in the western hills of the studied area, composed of limestone and tuffaceous sandstones of the Early Miocene -Pliocene age. The Tertiary age formations are overlain by the Young Volcanic Sediments (Qmi) and the Quaternary Alluvium (Qa) Deposits. The Young Volcanic Deposits of Mount Merapi (Qmi) are Quaternary (Pleistocene - Holocene) spread over the plains between the Bedog and Opak Rivers, coarse to fine tuff and ash. These rocks are generally noncohesive loose materials in sand and

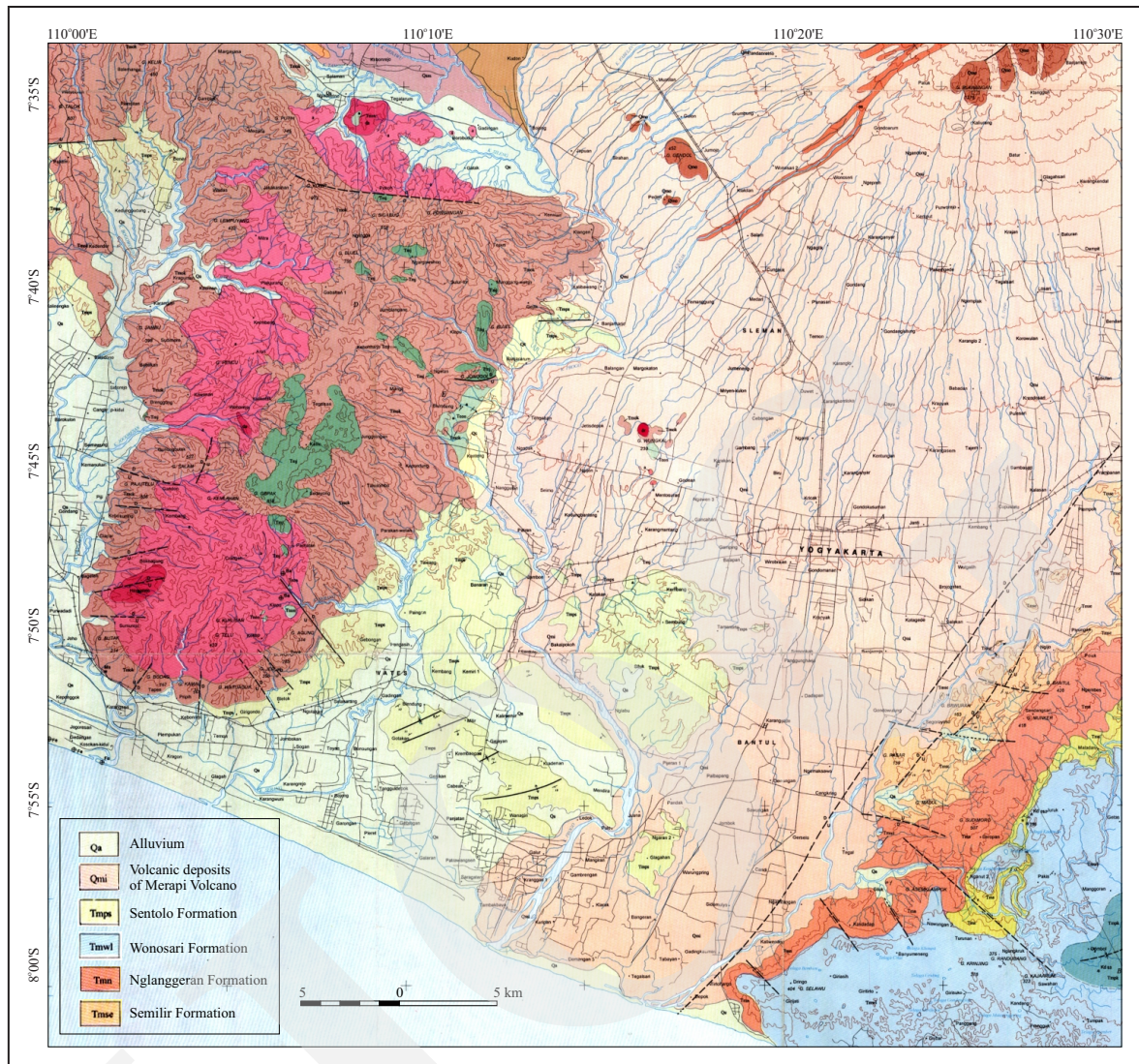


Figure 3. Geological map of studied area (part of Yogyakarta Special Province), modified from Rahardjo *et al.* (1995).

silt forms, easily exposed to liquefaction (Untung and Sugiyanto, 2007). The youngest deposits in the form of alluvium deposits (Qa) in the age of Holocene are found as the Opak River sediments, composed of sand, silt, clay, and fine to medium sand (Figure 4b).

Sandstone of the Quaternary Young Volcanics of Mount Merapi (Pleistocene - Holocene) of (Qa) spread in the plains between the Bedog River and Opak River over rough, fine sand, and ash. These lithologies are generally noncohesive materials in the forms of sand and silt that are susceptible to liquefaction. Holocene-rich Alluvium (Qa) formation is found in the Opak River sediment composed of sand, silt, and clay, and fine-grained

sand. Volcanic deposits in the Bantul area are derived from reworked pyroclastic (Rahardjo and Sukandarrumidi, 1985) with thicknesses reaching 80 m. This reworked pyroclastic material from volcanic eruptions has moved from the initial depositional position (Fisher, 1961). The study uses geological data composed of Young Merapi Volcanic Deposit in the Yogyakarta basin from (MacDonald and Partners, 1984). Based on the drilling data, it can be explained that the horizontal distribution of volcanic material for the Bantul area and its surroundings is dominated by sand, silt, and clay deposits. This phenomenon represents The Quaternary Young Volcanics of Mount Merapi (Figure 4c).

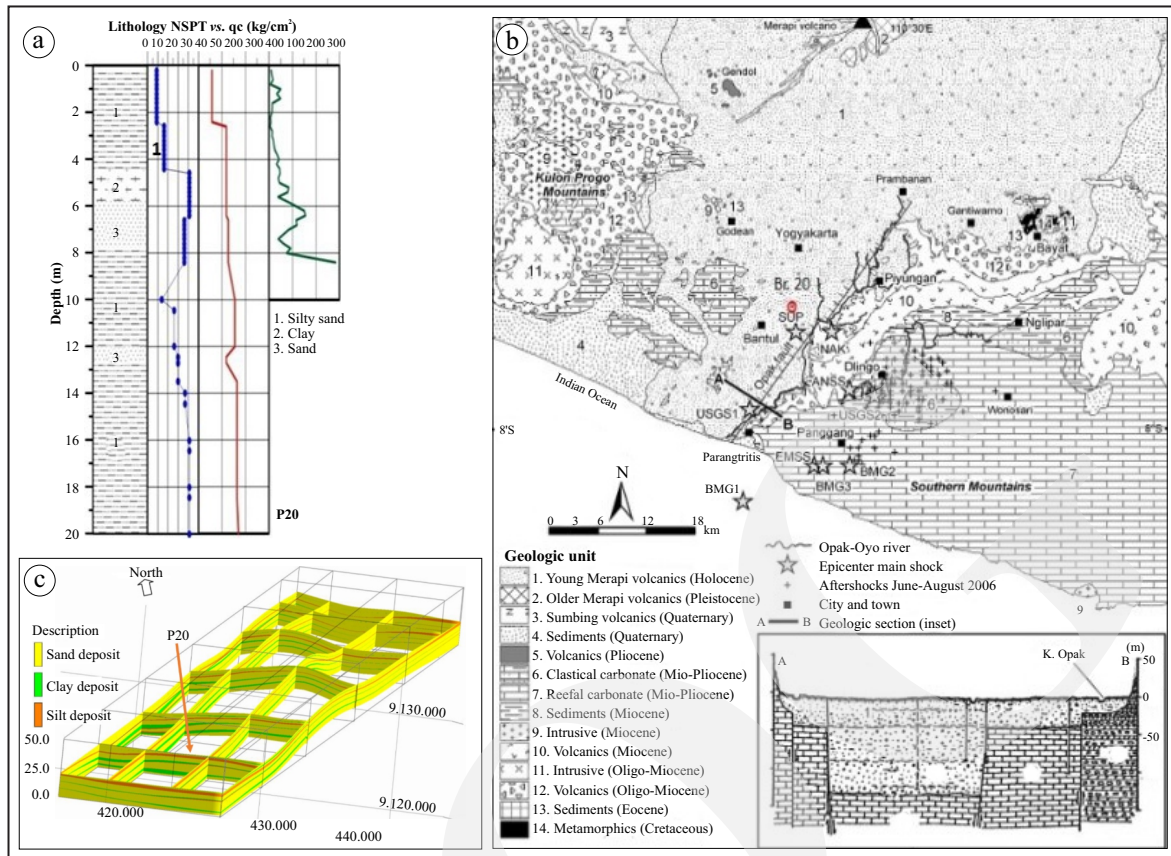


Figure 4. (a) Vertical section of borehole sample BH020, (b) Geological map of studied area, part Yogyakarta Special Province (Setijadji, 2006), (c) 3D landscape of the researched area representative of the Young Volcanic Deposit (Buana, 2013).

Forming the NSPT vs. Vs formulation, the study used nineteen Vs measurements and twenty-nine borehole data. Then, the borehole data is described based on the depth of land per 1 m which produces NSPT and Vs data pairs. The relationship that shows the distribution of Vs and NSPT values to borehole depth is presented in Figure 5. In general, the studied area is composed

of Vs values with a range of 120 - 300 m/s and a maximum of 400 m/s. The NSPT score consists of 2 - 60. This characteristic indicates that the researched area is composed of soil with class D -E or stiff - soft soil.

Previous researchers have proposed several correlations between Vs and NSPT, as presented in Table 1. There is a correlation that uses uncor-

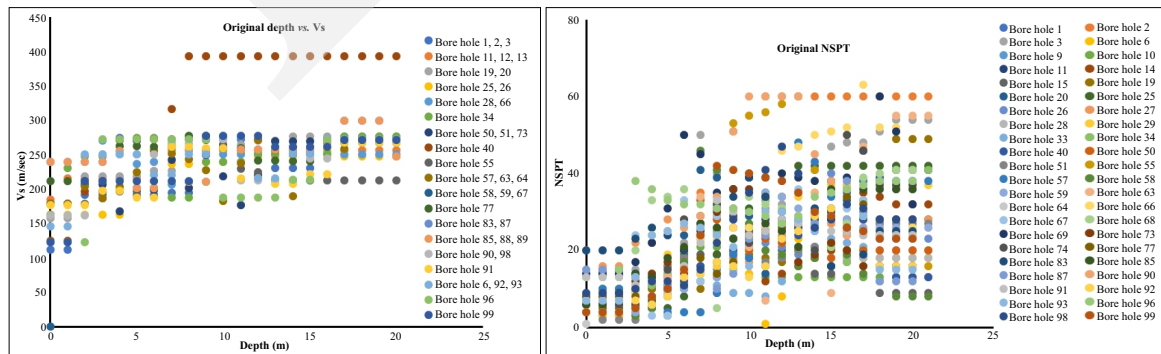


Figure 5. (a) Distribution Vs data in every soil depth, (b) Distribution NSPT in every soil depth.

Table 1. Existing Correlation between NSPT and Vs

No	Author(s)	All Soil	Sand	Clay
(Vs)				
1	Kanai (1966)	$19N^{0.6}$	-	-
2	Fujiwara (1972)	$92.1N^{0.337}$	-	-
3	Imai (1977)	$91N^{0.337}$	$80.6 N^{0.331}$	$80.2N^{0.292}$
4	Ohta and Goto (1978)	$85.35N^{0.348}$	-	-
5	Seed and Idriss (1971)	$61.4 N^{0.5}$	-	-
6	Imai and Tonouchi (1982)	$97 N^{0.314}$	-	-
7	Yokota (1991)	$121N^{0.27}$	-	-
8	Athanasopoulus (1995)	$107.6N^{0.36}$	-	-
9	Iyisan (1996)	$51.5N^{0.516}$	-	-
10	Kiku (2001)	$68.3N^{0.292}$	-	-
11	Jafari <i>et al.</i> (2002)	$22N^{0.85}$	-	$27 N^{0.73}$
12	Anbhazagan and Sitharam (2006)	$50N60^{0.41}$	-	-
13	Hasancebi and Ulusay, (2007)	$90N0.309$	$90.82 N^{0.319}$	$97.89 N^{0.269}$
14	Maheshwari <i>et al.</i> (2008)	$90.8N0.319$	$100.53 N^{0.265}$	$89.31 N^{0.358}$
15	Hanumantharao and Ramana (2008)	$90N0.309$	$90.8N^{0.319}$	$97.9N^{0.269}$
16	Dikmen (2009)	$58 N0.39$	$73 N^{0.33}$	$44 N^{0.48}$
17	Fatehnia <i>et al.</i> (2015)	-	$77.1N^{0.355}$	$77.1N^{0.355}$
18	Bablukirar (2016)	$99.5N0.345$	$100.3N^{0.338}$	$94.4N^{0.379}$

rected SPT (NSPT) as the basis of the relationship between parameters. Still, other researchers use corrected SPT (N60) as SPT blow count corrected for hammer efficiency of 60 %. The power regression equation relating to Vs and NSPT is shown as:

$$V_s = X \text{ NSPT}^Y \dots\dots\dots (1)$$

where X and Y are the regression coefficients for best fitting the formula to the data. In this case, when X increases, Y tends to decrease, as described in previous researches (Dikmen, 2009; Hasancebi and Ulusay, 2007; Imai, 1982; Ohsaki and Iwasaki, 1973; Ohta and Goto, 1978).

In general, soil types are classified into three categories: sand, clay, and silt based on the depth of rock layers, grain size, and corrected NSPT60 (Andrus, 1994; Lum, 1994; Piratheepan, 2002; Pitilakis *et al.*, 1999; Rollins, 1998; Seed *et al.*, 1986; Sykora and Stokoe, 1983). Those factors become significant variables in assessing the correlation between Vs and NSPT. Geological age is also often used as a parameter that can show a substantial effect on the relationship between the NSPT and Vs (Andrus, 1994; Imai, 1982; Ohta and Goto, 1978; Pitilakis *et al.*, 1999; Raptakis, 1994; Rollins, 1998).

The two data variables mainly used in this study are NSPT and Vs. The available field data is processed using the statistical gradation approach that covers detecting duplicate data sets, removing outliers, distance binning approach, and processing the formulation using power regression to formulate the correlation between NSPT and Vs. The computation was done using MATLAB.

Detecting Duplicate Data Sets

The first stage is removing data pairs (*i.e.* NSPT and Vs values), which are classified by type of soil and sorted by NSPT or Vs from the lowest value. Data sets with different values will retain; otherwise, they will be deleted. Compilation data from various sources, and therefore may be varying degrees of reliability, can affect the accuracy of the analysis, which leads to incorrect results compared to using only a single data source (Kawado *et al.*, 2003). The removing data process takes into account several factors such as loss of essential data that characterize the site, data errors due to human error, or malfunctions of equipment (causing significant problems with the reliability and validity of the results). Another reason for removing data is that duplicate data require a longer time to process. However, the data pair included in the report extends the pro-

cessing time needed for data input, but can also improve data accuracy (Cumming and Masten, 1994). Finally, removing data pairs used in an algorithm function detects inconsistent values and identifies desired parameters. If the data are similar, but there are not in the form of duplicate data, then the data should remain in the basis data (Atkinson, 1984).

Removing Outliers

The second step is adjusting the database to make standardized data before the regression process. This process is the first step in eliminating outliers using a Z-score or standard score approach (Shiffler, 1988). The Z-score refers to how far a value is from the mean (*i.e.* how many standard deviations), expressed as:

$$Z_{sc} = (x - \mu) / \sigma \dots\dots\dots (2)$$

where:

Z_{sc} is the Z-score,

x is the observation data,

μ is the data mean, and

σ is the standard deviation.

The Z-score value can be detrimental, which means that the data value is below the mean value, and if the Z-score is positive, it means that the value is higher than the mean (Seo, 2006; Kreyszig, 2008; Mare, 2017). Detecting the presence of outliers can be seen in the calculation of the normal standard distribution, where a data point is considered an outlier if the absolute Z value is higher than, for example 3 (Andrus *et al.*, 2004) or 2.5 (Santoso, 2010). Outliers are the observational data with an abnormal distance to other observation data set in a population (Aguinis *et al.*, 2013; Kwak and Kim, 2017). The frequency distribution displays the soil type obtained from the borehole in every soil layer, with the consideration for developing the correlation between NSPT and Vs used in this study (Figure 6). Sandy soil is the dominant type, making up around 52% of the total soil distribution.

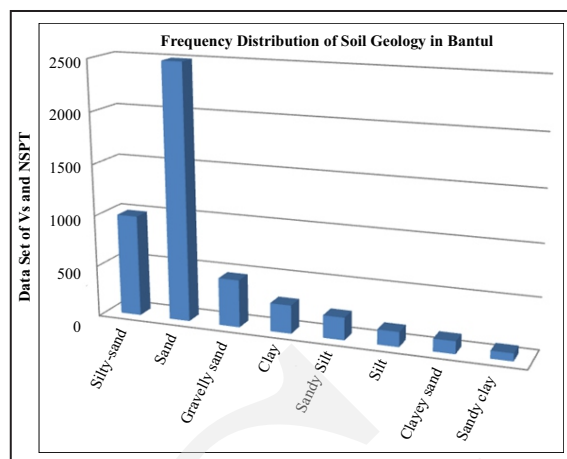


Figure 6. Frequency distribution of soil geology in Bantul.

Distance Binning Approach

The third step is to refine the filtered data. An adjustment was made when the detected data still contained outliers, and then the data was discarded. This process removes information that has a position far from neighbouring data by using the Equal Width Distance Binning Approach. At this step, the aim is to obtain a smooth evidence by considering compatibility with adjacent data. The data was then classified into three-bin classes: low, middle, and higher grades (Han *et al.*, 2011). In this case, Vs data are classified into three-bin categories, upper (283 m/sec), intermediate (229 m/sec), and lower (176 m/sec) as an example when developing correlations for All Soil, and then relationships between Vs and NSPT derived. The classification aims to eliminate the effect of outliers, where data can have abnormal distances from other values in a random population sample.

The analysis treats data by setting the lowest limit of class bin 1 (as the lowest value of data) and the highest limit of class bin 3 (as the highest value). This study determines the range of data values used as boundary values between data levels by defining the difference between the maximum NSPT and Vs against the minimum NSPT and Vs and the data range divided by the number of the class bin. For bin 1 SPT and Vs classes, data were taken by adding the minimum value of bin 1 level in the data range with one-

third of the data range. Class bin 2 was derived from the number of class bin 1 plus one-third of the data range, and class bin 3 was obtained from the number of class bin 2 plus one-third of the data range.

The filtering process places the data according to the data bin class value. Deleting bin Vs class data can be done by removing Vs data positioned above the Vs class bin 1 boundaries. This process is also applied to class Vs bin 2 and 3. Vs used in regression analysis must be smaller than the boundary minimum class Vs. The bin class system is also applied to delete SPT data, which considered an outlier using the same procedure. The process of removing outlier data will also apply to eight soil types.

Processing Power Regression

The fourth step is the power regression calculation. This method is a nonlinear regression model taking the natural log of both sides of the equation, which is employed to describe the data correlation between NSPT and Vs. This regression explains a function that leads to the best fit of a set of observational data. The validation process was carried out by calculating the RMSE. RMSE is a measure used to determine the values (sample or population values) predicted by the model or estimator and the values observed. RMSE represents the square root of the difference between the predicted value and the observed one or the average square of this difference. The smaller the RMSE value, the more it indicates that the proposed equation is valid and better fits the prediction versus measured data (Santoso, 2010).

Calculation of RMSE (Root Mean Square Error) was carried out for the prediction equations derived in this work and for the previous equations in Table 1. Comparisons are made for the RMSE values from this study and the previous studies. The RMSE value is calculated as the following:

$$RMSE = \frac{1}{N} \sqrt{\sum_i^N (x_i - x_a)^2} \dots\dots\dots (3)$$

where:

N is the amount of data,

x_i is the measured Vs value,

x_a is the calculated Vs value.

Figure 7 shows the entire process of the SGA with the impact of removing outlier data from the compilation data of eighty-eight boreholes in Yogyakarta Province until the power regression process. The first stage (Figure 7a) shows the entire observational data set. It is related to the relationship between the NSPT and Vs to generate the correlation between NSPT and Vs for All Soil that has done in the process of removing duplicate data, which means the pair data have the duplicate value have to be discarded. This process discarded 400 data pairs with the same value for both SPT and Vs. The second stage (Figure 7b) is the process of standardizing the data by discarding data that has a difference in the mean that exceeded the normal limits determined. At this stage, twenty-eight outliers were rejected. The third and fourth stages (Figures 7c and 7d) are the process of classifying data by using three bin classes, which successfully removed fifty-nine data sets that are assumed to be outlier data. The fifth stage (Figure 7e) is the power regression to obtain a correlation that shows a strong relationship between the NSPT and the value of Vs.

RESULTS, ANALYSIS, AND DISCUSSION

In this study, NSPT and Vs data pair grouping is based on a combination of all soil data without distinguishing classification called All Soil (can be used for various types of soil) and based on soil types classified into eight types, namely silty sand, sand, gravelly sand, clay, sandy silt, silt, clayey sand, and sandy clay. Based on Statistical Gradation Approach, the study derives the following relationships between Vs and NSPT for All Soil by Vs=116.27 m/s, where Equation (3) gives a coefficient R= 0.6701 for Vs < 300 m/s, and is valid for all soil types (Figure 7a).

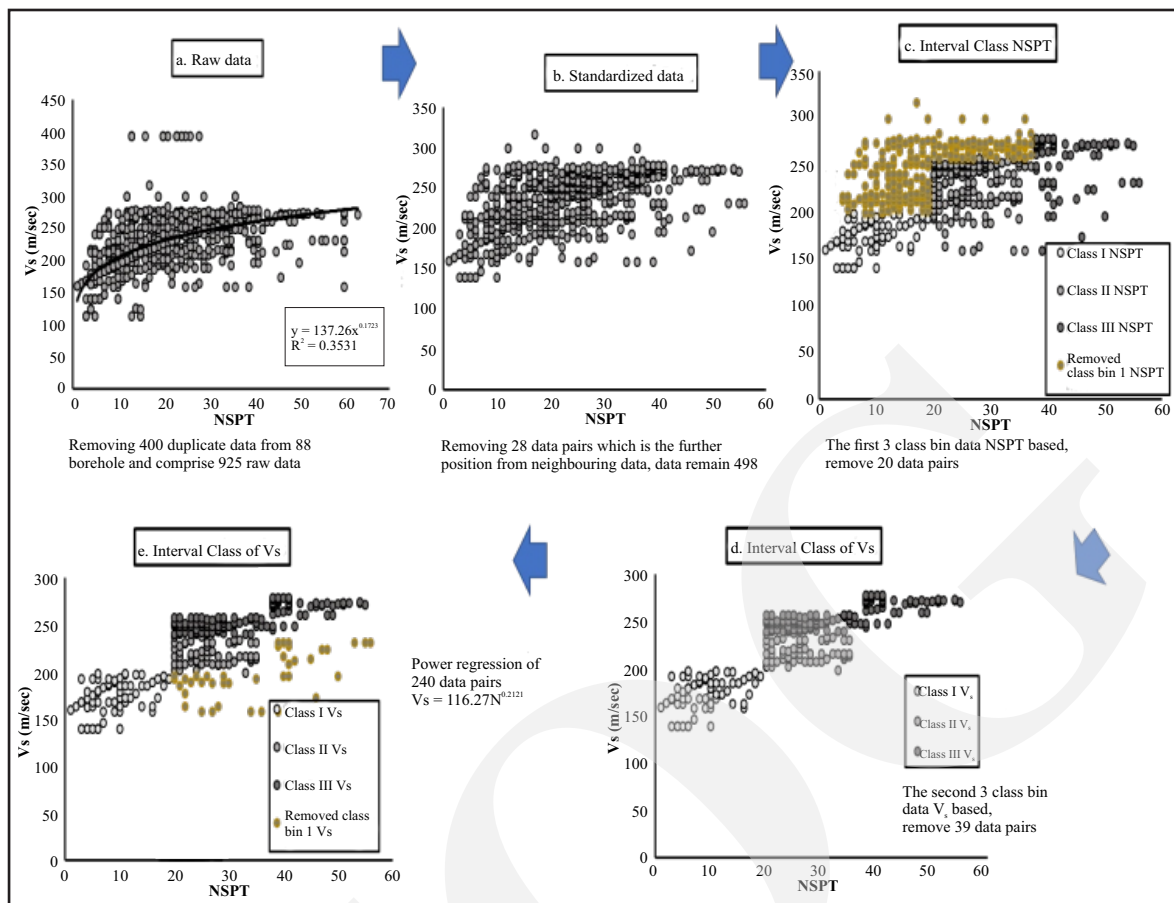


Figure 7. The sequence of the statistical approach followed to determine the correlation between NSPT and V_s .

$$V_s = 119NSPT^{0.2051} \dots\dots\dots (4)$$

This result shows that there is a strong relationship between NSPT and V_s which can produce a higher accuracy to determine the value of V_s from NSPT. Figure 8 shows the measured data of NSPT and V_s using 925 data pairs of NSPT and V_s measurements.

As presented in Table 2, the RMSE value is 38.43, generated from Equation (3). This value is less than the RMSE resulting from the equations listed in Table 1. As seen in Figure 8b, Equation (3) (brown rectangle) shows the bottom of the comparison with the previous equation. The proposed equation lies between the Hasancebi and Ulusay (1995) equation (pink circle) as the lower limit value and Kiku (2001) equation (dark grey circle) as the upper limit value. In the range of NSPT up to 20, V_s shows a sharp increase, and then stably increases until it reaches the

NSPT sixty-five value. This figure shows that the proposed equation shows the importance of V_s which is close to the actual condition of the field data. This proof is shown by the distribution pattern of the predicted value V_s (brown square) coincides with the trend line value of the measured V_s (dark purple triangle). The investigation suggests that the correlation of NSPT and V_s for All Soil indicates that the studied area categorized as class D (Stiff Soil) - E (soil profile with soft clay) with a V_s range between 112.748 - 393.333 m/sec (NEHRP, 1994).

The RMSE value obtained from the calculation results (Table 2) shows that the All Soil correlation produces the smallest error factor compared with the relationship of the equation proposed by the previous researcher, which is 38.161. This number indicates that the proposed correlation produces the lowest deviation, which means the proposed equation

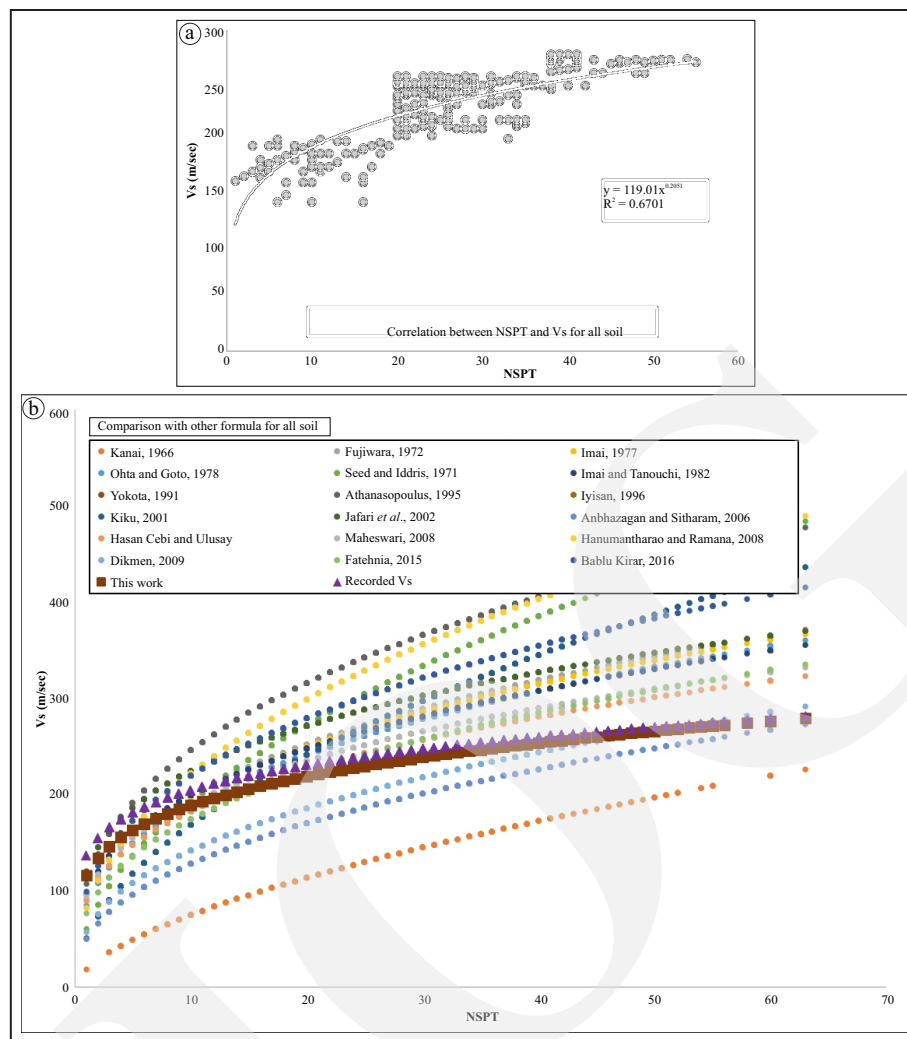


Figure 8. Correlation between Vs and NSPT for all soil.

Table 2. Comparison of RMSE Values Between The Equations

No	Formula	RMSE
1	This work	38.43
2	Kanai, 1966	120.07
3	Fujiwara, 1972	51.27
4	Imai, 1977	49.64
5	Ohta and Goto, 1978	47.23
6	Seed and Iddris, 1971	85.78
7	Imai and Tonouchi, 1982	46.71
8	Yokota, 1991	57.87
9	Athanasopoulos, 1995	105.82
10	Iyisan, 1996	66.60
11	Kiku, 2001	77.47
12	Jafari <i>et al.</i> , 2002	57.87
13	Anbhazagan and Sitharam, 2006	71.88
14	Hasancebi and Ulusay, 2006	41.04
15	Maheswari, 2008	41.28
16	Hanumantharao and Rumana, 2008	99.02
17	Dikmen, 2009	60.20
18	Fatehnia, 2015	44.37
19	Bablu Kirar, 2016	71.34

regression analysis between NSPT and Vs of individual soil types is explained and compared with other methods.

Silty Sand

For silty sand, the analysis used the 138 pairs of NSPT and Vs data. The equation of the regression results is comparable with the other two equations, namely Seed *et al.* (1983);

$$V_s = \frac{185\sqrt{\text{NSPT}}}{0.9} \dots\dots\dots (4)$$

and Lee (1992):

$$V_s = 105.64\text{NSPT}^{0.32} \dots\dots\dots (5)$$

can adequately model the observation data. In the following, the formula obtained from

The correlation between NSPT and Vs can be seen in Figure 9a yielded a regression coefficient value of 0.7493, again illustrating a strong relationship between NSPT and Vs, with the regression equation by:

$$V_s = 108.7 \text{NSPT}^{0.2334} \dots\dots\dots (6)$$

The calculations of Seed and Idriss (1983) are generally around the upper bound value of SPT of 60, and those of Lee (1990) has a distribution pattern almost parallel with Equations (4 and 5) (Figure 9b). The RMSE is again used to validate the result of the regression process, and as shown in Table 3, the equation displayed in Figure 8a shows the lowest error value of 34.509.

Sand

The correlation data used to form equations between NPST and Vs for sandy soil consisted of 518 pairs. Figure 10a shows the regression results on the sand samples, which yields a regression coefficient $R = 0.8851$.

As shown in Figure 9b, which compares the curve from the equation displayed in Figure 10a with the appropriate equations from Table 1, the formulation proposed by Hanumantharao and Ramana (2008) provides an upper limit, while the one of Kanai (1966) gives a lower limit. The proposed Equation (7) within the range of the other equations, where the noted NSPT between 5 and 20, the change in Vs is relatively steep, while for NSPT above 20, the increase in Vs is fairly flat.

Table 3. RMSE Calculations for Sand Comparing Equation (7)

No	Author	RMSE
1	This work	35.022
2	Kanai, 1966	116.545
3	Shibata, 1970	92.023
4	Imai, 1977	48.095
5	Imai and Tanouchi, 1982	41.268
6	Sykora and Stokoe, 1983	43.011
7	Hasancebi and Ulusay, 2007	75.626
8	Seed, 1983	51.692
9	Ohta and Goto, 1978	98.098
10	Hanumantharao and Ramana, 2008	40.0238
11	Maheswari, 2008	41.3698
12	Jafari, 2002	60.214
13	Lee, 1990	71.799
14	Pitilakis <i>et al.</i> , 1992	50.418
15	Raptakis, 1994	82.374
16	Fatehnia <i>et al.</i> , 2015	43.173
17	Bablukirar, 2016	71.858

$$V_s = 77.033 \text{NSPT}^{0.2313} \dots\dots\dots (7)$$

This implication confirms that sandy soil produces relatively low Vs up to 280m/sec. Table 3 shows the results of the validation process using the RMSE approach, where it is noted that Equation (7) produces the smallest value of 35.022.

Gravelly Sand

The regression result from eighty-four data pairs (Figure 11a) produces a regression coefficient (R) of 0.7551. The comparison of the field data investigation with the equations produced by the three previous researchers, namely Imai and Tonouchi (1982), Ohta and Goto (1978), and Andrus (1994), is displayed in Figure 10b. This figure shows that Imai and Tonouchi (1982) graph has a parallel form to Equation (8). At NSPT values larger than 60, both equations (Imai and this work) produce Vs values similar.

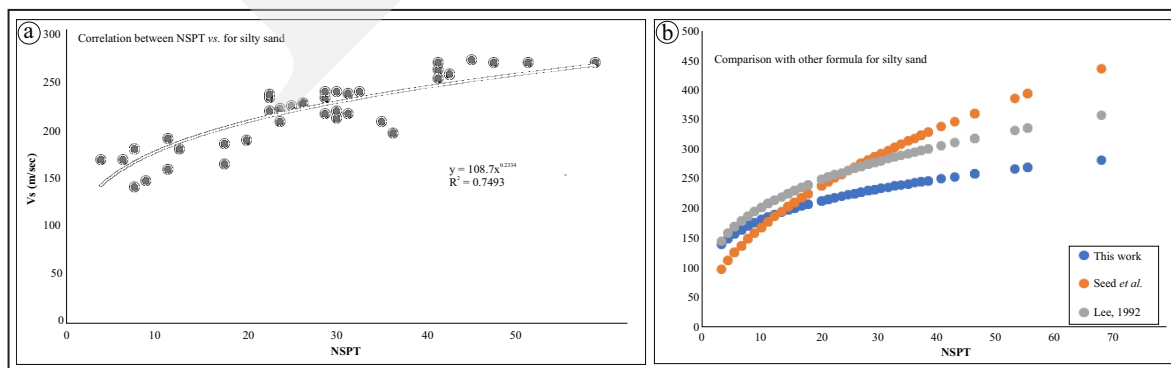


Figure 9. (a) Correlation between NSPT against Vs for silty sand and (b) comparison with three existing equations.

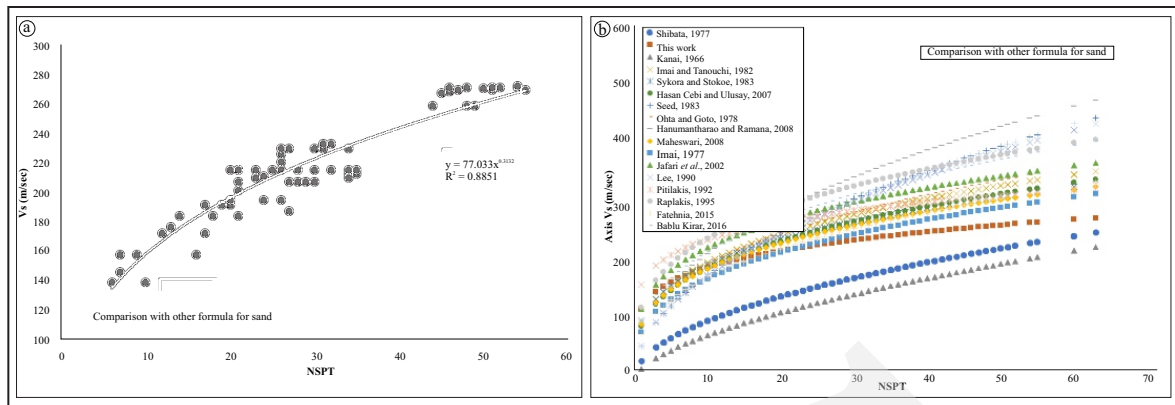


Figure 10. (a) NSPT correlation against V_s for sand type, and (b) Comparison with sixteen existing equations.

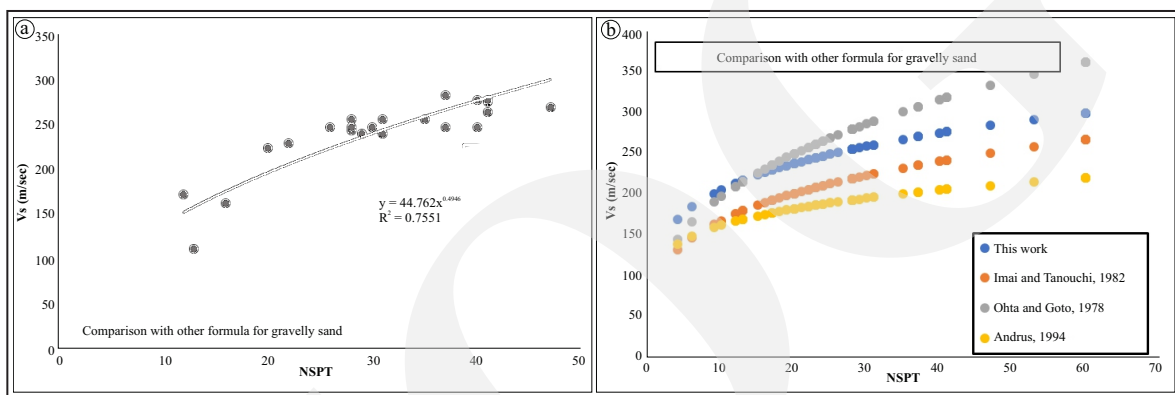


Figure 11. (a) NSPT correlation against V_s for gravelly sand type, (b) comparison with three existing equations.

$$V_s = 44.762NSPT^{0.495} \dots\dots\dots (8)$$

For all the equations, Ohta and Goto (1978) gave the highest limit, and Andrus (1994) the lowest one. The validation process of Equation (7) is presented in Table 4, and it shows the smallest RMSE value of 43.809 for the equation derived in this work.

Clay

The NSPT and V_s pair data used to make the regression equation for clay consist of sixty-five pairs. The resulting equation shows a reasonably good correlation $R = 0.735$, expressed in Equation (9).

$$V_s = 92.807NSPT^{0.275} \dots\dots\dots (9)$$

These results are compared with some previous examples listed in Table 1, with Raptakis

Table 4. Results of RMSE Calculations for Gravelly Sand Soil Comparing Equation (7)

No	Author	RMSE
1	This work	43.809
2	Imai and Tanouchi, 1982	56.652
3	Ohta and Goto, 1978	56.269
4	Andrus, 1994	73.192

(1992) as the upper limit and Imai (1977) as the lower one (Figures 12a and b). The result of the validation of Equation 9 and previous equations shows that the Equation 9 has the smallest RMSE of 40.733 (Table 5).

Silt

The analysis to derive the equation for silt soils involved twenty-six data sets, leading to a regression coefficient $R = 0.822$, with the equation given by:

$$V_s = 79.946NSPT^{0.3406} \dots\dots\dots (10)$$

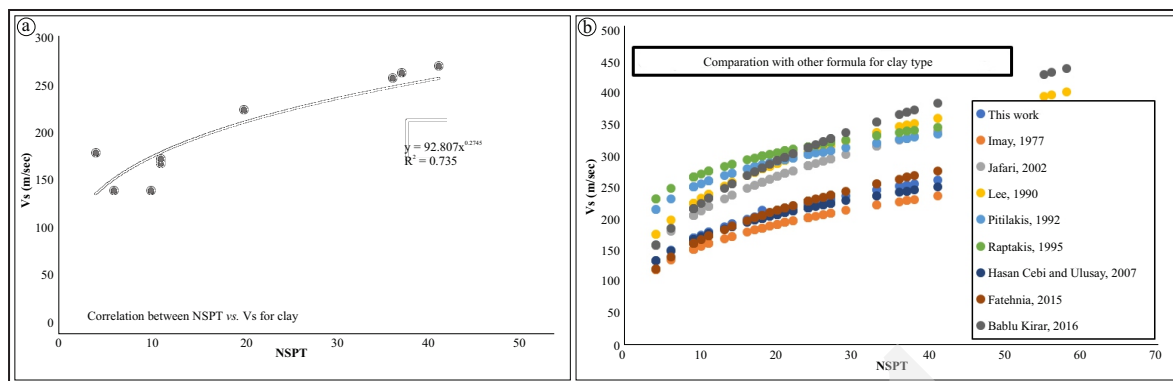


Figure 12. (a) NSPT correlation against Vs for Silt types, (b) comparison with nine existing equations.

Table 5. Results of RMSE Calculations for Clay Soil Comparing Equation (9)

No	Author	RMSE
1	This work	40.733
2	Imai, 1977	55.123
3	Jafari, 2002	51.722
4	Lee, 1990	66.945
5	Pitilakis 1992	65.157
6	Raptakis, 1994	77.138
7	Hasancebi and Ulusay, 2007	43.854
8	Fatehnia, 2015	42.138
9	Bablu Kirar, 2016	75.753

Table 6. Results of RMSE Calculations for Silt Soil Comparing Equation (10)

No	Author	RMSE
1	This work	68.896
2	Dikmen, 2009	97.926
3	Lee, 1990	72.307

The validation process was carried out by comparing the results of this work with the equations of Lee (1990) and Dikmen, (2009), and showed a close correlation between Equation (9) and displayed in Figure 13a and Dikmen (2009), leading to the smallest error value of 68.896 (Table 6).

Sandy Clay, Clayey Sand, and Sandy Silt

For sandy clay, clayey sand, and sandy silt soils, a power regression analysis derives the

correlation between the NSPT and Vs. However, this assessment will not implement a comparative RMSE analysis, because no other equations are suitable for these soils found in the literature. The formulation to show the correlation between Vs and NSPT values shows that for clayey sand soil types the highest R Square value is 0.955, meaning that there is 95% confidence that the NSPT value of the data is used to determine the value of Vs. Successively followed by sand 0.8851, silty sand 0.853, and silt 0.822 (Figure 14).

The summary of the comparison resulting from the regression analysis for all soil types is outlined in Table 7. This table presents several

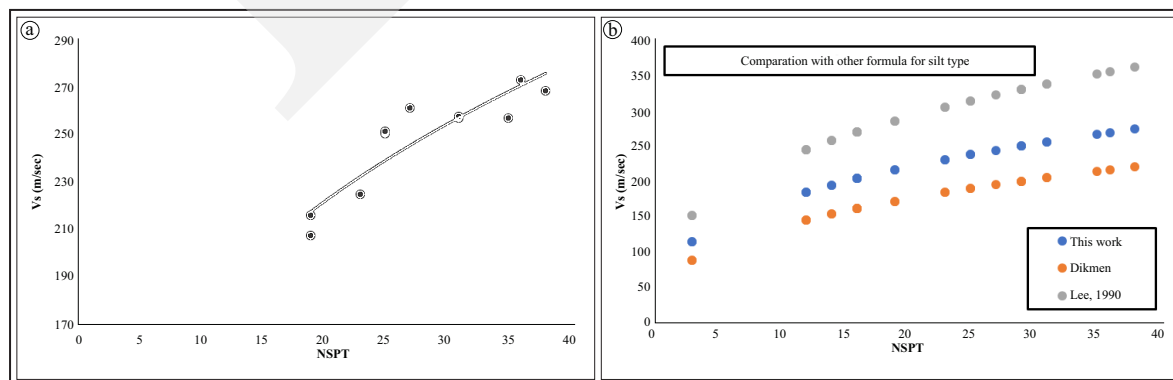


Figure 13. (a) NSPT correlation against Vs for silt types, (b) Comparison with three existing equations.

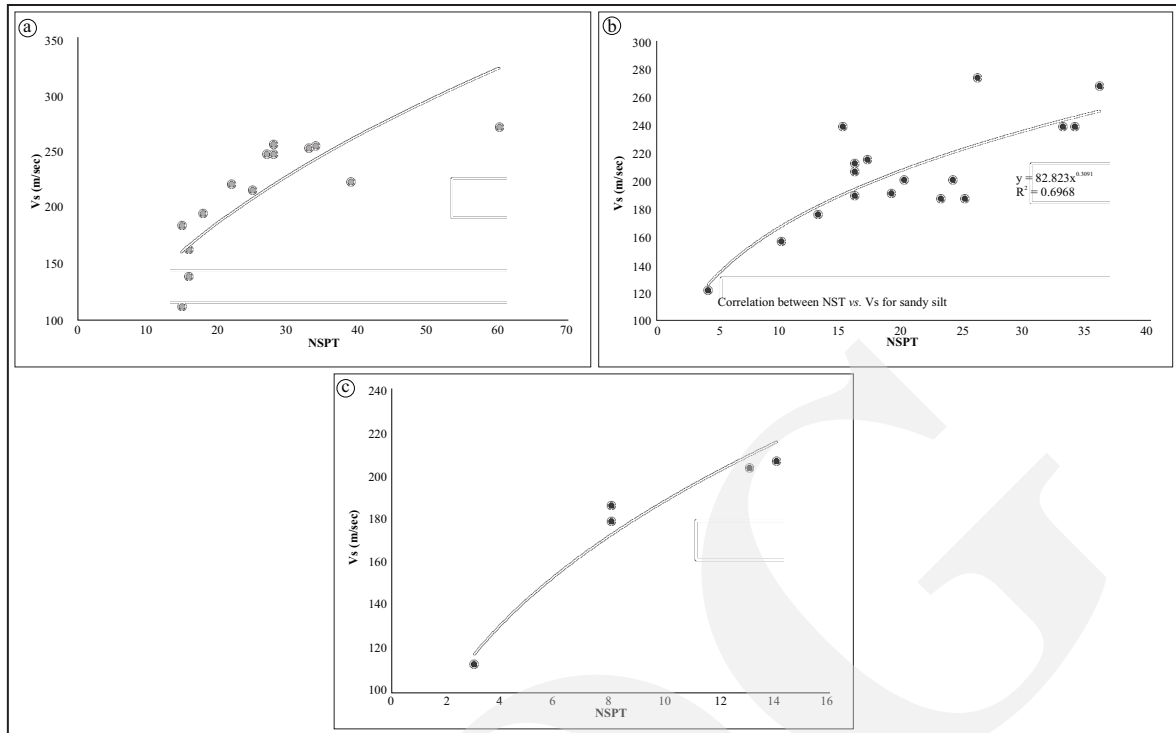


Figure 14. NSPT correlation against V_s in (a) sandy clay, (b) sandy silt, and (c) silt.

Table 7. Summary of the Power Regression Equations Derived for All of Soil Types Based on RMSE and R

No	Soil Type	Formula	RMSE	R
1.	All Soil $V_s < 350$ m/s	$V_s = 119 \text{ NSPT}^{0.2051}$	38,4302	0.6701
2.	Sand	$V_s = 77.033 \text{ NSPT}^{0.2313}$	35,0217	0.8851
3.	Gravelly Sand	$V_s = 44.762 \text{ NSPT}^{0.4946}$	43,8098	0.755
4.	Silty Sand	$V_s = 93.67 \text{ NSPT}^{0.282}$	34,5095	0.853
5.	Sandy Silt	$V_s = 82.823 \text{ NSPT}^{0.3091}$	36,7334	0.697
6.	Clayey Sand	$V_s = 75.51 \text{ NSPT}^{0.159}$	20,3498	0.955
7.	Sandy Clay	$V_s = 41.115 \text{ NSPT}^{0.5049}$	45,1801	0.638
8.	Silt	$V_s = 79.946 \text{ NSPT}^{0.3406}$	68,8959	0.822
9.	Clay	$V_s = 92.807 \text{ NSPT}^{0.2745}$	40,7334	0.735

equations resulting from the analysis using the statistical gradation approach. The combination of R and RMSE values show the clayey sand best fits the proposed equations.

CONCLUSIONS

The correlation between the NSPT and V_s developed for the study location, situated in the Bantul region, Yogyakarta Province, Indonesia. New equations generated using data from

eighty-eight boreholes and twenty shear-wave velocity profiles. Data is analyzed statistically using the bin class approach and compared with previous results in the literature. The SGA successfully formulated nine new equations to describe the relationships between NSPT and V_s for different soil types. This proposed method produces a proper formulation that can be indicated by a relatively high R coefficient and low RMSE values. The combination of R and RMSE show which clayey sand best fits the proposed equations.

Moreover, this work has a lower RMSE value than the previous work showing the proposed correlation that has a reasonably good predictive performance. The SGA method also introduces three new equations that have never been presented before, namely association for NSPT vs. Vs for sandy silt, sandy clay, and clayey sand. The relationship proposed in this paper applied to other areas provided that the shear-wave velocity is <300 m/sec, shallow groundwater depth, and dominant sand soil. The use of these equations can support seismic microzonation programmes, nothing that there are similarities in soil and conformity provisions for similar geotechnical and geological conditions.

ACKNOWLEDGMENT

This project has been conducted as part of doctoral research at Tü Berlin, Germany, sponsored by Riset-PRO batch III, Ministry of Research and Higher Education (KEMRISTEK-DIKTI) 2015, addressed to the first author. The authors thank BAPETEN for supporting this research. The authors also express their gratitude to Prof. Stefano Parolai for constructive inputs in this project and the anonymous reviewers for their valuable suggestions.

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