Pedotransference functions for prediction of density in soils of Piauí, Brazil

Funções de pedotransferência para predição da densidade em solos do Piauí, Brasil

DOI:10.34117/bjdv8n7-142

Recebimento dos originais: 23/05/2022
Aceitação para publicação: 30/06/2022

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ABSTRACT
The determination of the density of the horizons of a soil profile allows to evaluate certain properties, such as: porosity, hydraulic conductivity and water storage. However, measured data is not always available or easy to obtain. Thus, it was objective with the work to build and evaluate models of pedotransference function based on multiparameters of the soil as alternatives for the estimation of soil density in areas with agricultural potential of the state of Piauí. Thus, soil samples were collected from 42 soil profiles in the state of Piauí at depths of 0.0-0.20; 0.20-0.40; and 0.40-0.60 m e, characterized in terms of chemical and physical attributes. Through multiple regression analysis, two pedotransfer function models were generated: i) including all determined attributes and, ii) only the particle size analysis and total organic carbon. For both models, all classes (generalized character) were considered, as well as each individual soil class Latossolo (Ferralsol), Argissolo (Acrisol), Plintossolo (Plinthosol) and Neossolo (Arenosol). The generated pedotransference functions are alternative to estimate bulk density of soil, obtaining "excellent" performance in model I for the "Latossolos" (Ferralsols) and "Argissolos" (Acrisols), which included a greater number of variables in the construction of the predictive model of bulk density.

Keywords: pedometer, modeling physical attributes, multiple linear regression.

RESUMO
A determinação da densidade dos horizontes de um perfil de solo permite avaliar certas propriedades, como: porosidade, condutividade hidráulica, armazenamento de água. Entretanto, dados medidos nem sempre estão disponíveis ou fácil obtenção. Assim, objetivou-se com o trabalho construir e avaliar modelos de função de pedotransferência baseados em multiparâmetros do solo como alternativas para a estimação da densidade do solo em áreas com potencial agrícola do estado do Piauí. Assim, amostras de solo foram coletadas em 42 perfis de solo no estado do Piauí nas profundidades de 0,0-0,20; 0,20-0,40; e 0,40-0,60 m e, caracterizadas quantos aos atributos químicos e físicos. Por meio de análise de regressão múltipla, dois modelos de função de pedotransferência foram gerados: i) incluindo todos os atributos determinados e, ii) apenas a análise granulométrica e carbono orgânico total. Para ambos os modelos foram consideradas todas as classes (caráter generalizado), bem como para as classe de solo individualizada (Argissolo, Latossolo, Plintossolo e Neossolo). As funções de pedotransferência geradas são alternativas para estimativa da densidade do solo, obtendo "excelente" desempenho o modelo I para os Latossolos e Argissolos, que incluiu um maior número de variáveis na construção do modelo preditivo da densidade do solos.

Palavras-chave: pedometria, modelagem, atributos físicos, regressão.

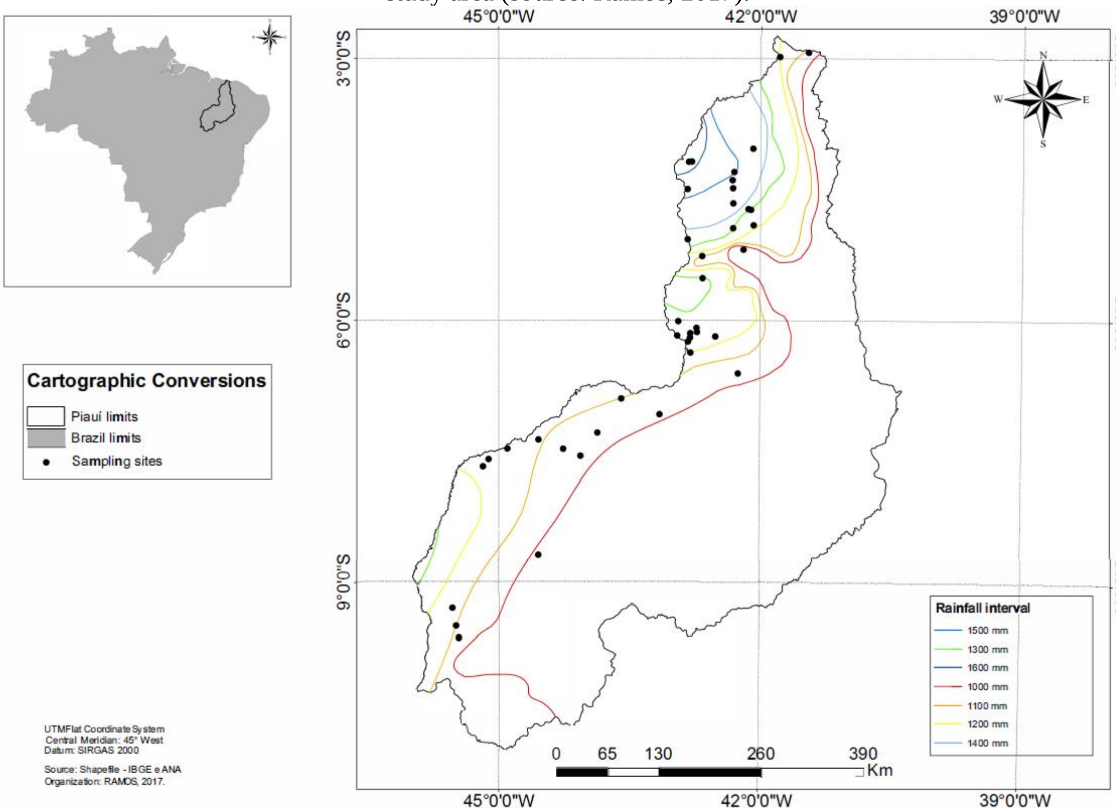
1 INTRODUCTION

The bulk density of soil (BD) is a essential physical attribute, which characterizes the level of soil compression and controls the flow and transport of fluids and solutes (Katuwal et al., 2020). It is also important for converting soil properties (such as moisture and soil carbon content) from gravimetric content to volumetric (Xu et al., 2016). In addition, in view of the growing interest in the evaluation of ecosystem services, soil density is considered one of the main attributes for soil functions (Rabot et al., 2018). Soil density is affected by the various environmental processes and agronomic practices, inducing a large space-temporal variation (Makovníková et al., 2017). In fact, effective samplings require numerous non-disturbed soil samples and as a result, fieldwork soon becomes quite expensive and labor, even for work to be carried out in small areas (Nasta et al., 2020). For Mulder et al. (2011), the lack of this information can lead to the adoption of inadequate and unsustainable practices, increasing the risk of soil degradation. In search of by circumventing this limitation, which can become an obstacle by making sampling in large areas, indirect estimates of soil density should be used (NASTA et al., 2020). Pedotransference functions (PTFs) allow you to estimate a certain ground property (for example, DS) from other variables, routinely obtained through laboratory measurements (Patil; Singh, 2016). Several pedotransference functions, in which they use organic matter, clay, clay added to silt and sand determine bulk density (Haddad et al., 2018; Beutler et al., 2017; Souza et al., 2016; Carvalho Junior et al., 2016; Barros; Fearnside, 2015; Boschi et al., 2015; Padua et al., 2015). However, according to Chen et al. (2018), published PTFs show large performance differences when applied in other environments other than those in which they were adjusted. Thus, it is suggested to use an PTF developed for data from the application area or for an area with similar genesis soils. The State of Piauí has adequate conditions for agricultural development (water, soils and climate) (Medeiros, 2017), is the expansion of the agricultural border in the country, especially for inner areas, as is the case of the current productive region of the agribusiness of Matopiba , acronym that represents the states of Maranhão, Tocantins, Piauí and Bahia (Elias, 2017). However, the pedotransference references, which may be alternative to the measurement and great lack of information on the bulk density of soils of the State of Piauí, which is essential in the adequate management of soil and water and, used in irrigated agriculture, example. In this sense, it was aimed to build and evaluate PTF models based on multiparameters of the soil as alternatives for the estimation of soil density in areas with agricultural potential of the State of Piauí.

2 MATERIAL AND METHODS

The study area is the western range of the State of Piauí, limiting itself with the State of Maranhão (Figure 1). The climate classification of the area, according to Köppen, is type AW (hot submitted tropical) (Almeida et al., 2019) with annual precipitation between 1000 to 1600 mm according to the map of Isoietas of annual average precipitation of Brazil (CPRM, 2011). Soil formation reflects the large extension of the study area and spatial variability of source materials. The soils were classified, according to the Brazilian System of Soil Classification (and with IUSS, 2015) as: "Latossolo" (Ferralsol), "Argissolo" (Acrisol), "Plintossolo" (Plinthosol), "Cambissolo" (Cambisol), "Chernossolo" (Phaeozems), "Planossolos" (Planosol) and "Neossolo" (Arenosol) dominate Area of study (Figure 1).

Figure 1. Study area, location of open minitrincheillas profiles for soil sampling and rainy isoietes of the study area (source: Ramos, 2017).

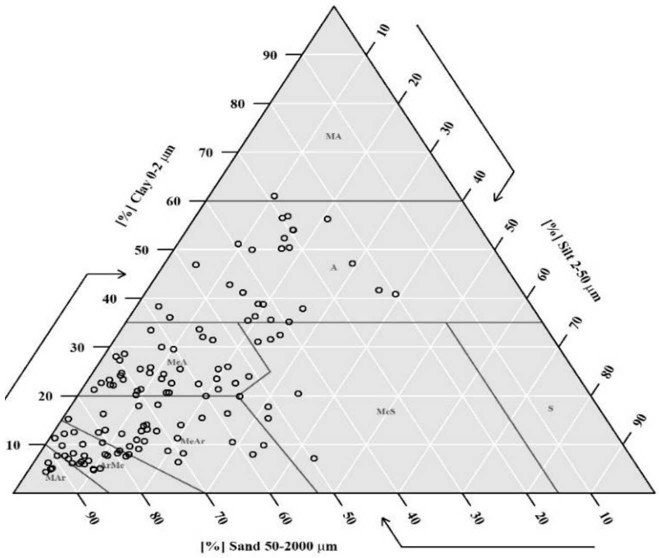


Based on the survey of the study area, soil samples were collected in 42 profiles (n = 3) located in the western range of the state of Piauí. In each area, minitrincheys were opened and soil samples, with deformed and indefined structure, collected in the depths of: 0.0 to 0.20; 0.20 to 0.40; and 0.40 to 0.60 m.

The bulk density of soil (BD), the total organic carbon content (TOC), pH (H_2O), phosphorus (P), calcium (Ca^{2+}), magnesium (Mg^{2+}), sodium (Na^{+}), potassium (K^{+}) were determined, aluminum (Al^{3+}), potential acidity (H + Al), total nitrogen (N), sum of bases (SB), effective cations exchange capacity (Effective CEC), capacity of exchange of cations (CEC at pH 7.0) and base saturation (V%), according to Teixeira et al. (2017). The particle size analysiswere performed, according to Teixeira et al. (2017).

The soil texture classes were outlined according to the Brazilian System of Soil Classification (Santos et al., 2018). Solo samples were concentrated in the sandy and clayey zones of the textural triangle (Figure 2).

Figure 2. Textures of soil samples in the textural triangle of the Brazilian Soil Classification System (Santos et al., 2018) for the 42 profiles located to the East of the State of Piauí



The first step of the PTFs generation consisted of the random division of the data in two subassemblies: (i) 80% of the data for the development of the model; and (ii) 20% for validation of the data set.

In order to assess the existence of anomalous data (outliers), the normalities of the data were observed by the analyzes of the asymmetry and curtosis coefficient, where the values closer to zero, for asymmetry, and smaller than three for curtosis tend to normal distribution. Then the data were submitted to descriptive statistical analysis, with mean, minimum and maximum analysis, standard deviation and coefficient of variation (Budiman et al., 2003).

To assess the relationship between the variables Pearson's correlation analysis and principal component analysis (PCA) were performed.

The explanatory analysis was performed considering two possibilities: a) Development of the generalized PTF to estimate bulk density, considering all determined soil classes; b) Development of specific PTFs for the classes of Ferralsol, Acrisol, Plinthosol and Arenosols. For the other classes (Phaeozems, Cambisol and Planosol) the data number was very low for validation.

To obtain the PTFs, multiple linear regression analysis was used. The "forward stepwise" procedure was used for exploratory analysis relating bulk density to the physical and chemical attributes of the soil for selection of predictive variables. This option makes the selection of the main variables among a set of independent variables to a level of pre-fixed significance, generating a coefficient for each of the selected independent variables (Budiman et al., 2003).

Two PTF models were generated for estimation of bulk density. In Model I used, as independent variables, all determined soil attributes (clay content, silt, thin sand, thick sand, total sand, total organic carbon, pH, phosphorus contents, calcium, magnesium, sodium Potassium, aluminum, potential acidity, capacity of exchange of cations at pH 7.0) for predictive variables selection. In model II, as independent variables, only the clay content, silt, thin sand, thick sand, total sand and the total organic carbon content, for predictive variables selection.

The evaluation of the performance of the regression models was performed graphically 1: 1 of the values estimated with the measured values and, applying statistical indicators such as the determination coefficient (R^2), the average error (EM) and the root of the error square (RMSE) obtained by Eq. 1, 2, and 3, respectively (Budiman et al., 2003). The confidence index (IC) was further carried out by the Eq. 6, obtained by the product of the Willmott Index (eq. 4) and the Pearson Correlation Coefficient (eq. 5).

$$R^2 = \frac{\sum_{i=1}^{n} (Ei - \bar{E})(Mi - \bar{M})}{\sum_{i=1}^{n} (Ei - \bar{E})^2 \sum_{i=1}^{n} (Mi - \bar{M})^{0,5}} \qquad \text{Eq. 1}$$

$$EM = \frac{1}{n} \sum_{i=1}^{n} (Mi - Ei) \qquad \text{Eq. 2}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (Mi - Ei)^2} \qquad \text{Eq. 3}$$

$$d = 1 - \frac{\sum_{i=1}^{n} (Ei - \overline{Mi})^2}{[\sum_{i=1}^{n} (| Ei - \overline{Ei} |) + \sum_{i=1}^{n} (| Mi - \overline{Mi} |)]^2} \qquad \text{Eq. 4}$$

$$r = \frac{\sum_{i=1}^{n} (Ei - \overline{E})\ (Mi - \overline{M})}{[\sum_{i=1}^{n} (Ei - \overline{E})^2\ \sum_{i=1}^{n} (Mi - \overline{M})^{0,5}]} \qquad \text{Eq. 5}$$

$$IC = r.\ d \qquad \text{Eq. 6}$$

Where:

Ei = The estimated value, MI = measured value, $\overline{E}$ e $\overline{M}$ = are the mean values estimated and measured respectively, n = total number of data and IC = reliable index that jointly integrates accuracy (r) and accuracy (d).

The in is an indicator of the accuracy of the estimate, revealing the trend of PTF to overestimate the values (when positive) or to underestimate (when negative). The closer to zero is the larger the accuracy of the model. The RMSE quantifies the dispersion of measured and estimated values around line 1: 1. When the RMSE value is equal to zero indicates that there was perfect adjustment between the estimated and measured data (Budiman et al., 2003). O IC foi classificado de acordo com Camargo e Sentelhas (1987) Table 1.

Table 1. Classification of performance indexes according to Camargo and senteth (1997)

Values of "IC"	performance
> 0,90	Excellent
0,81 a 0,90	Very good
0,71 a 0,80	Good
0,51 a 0,70	Median
0,41 a 0,50	Suffering
0,31 a 0,40	Bad
< 0,30	Terrible

IC = Confidence Index (Camargo; Fudes, 1997).

3 RESULTS AND DISCUSSION

Descriptive statistics for soil attributes Considering all soil classes with medium values, minimum value, maximum value, standard deviation, variation coefficient, asymmetry and curtosis coefficient, of the variables used in the generation of PTFs are presented in the table 2.

Table 2. Descriptive statistics of the variables used for the development of pedotransference functions considering all soil classes.

Variable	Average	Min.	Max.	SD	CV	Ass	Curt
TOC (dag kg^{-1})	1,1	0,0	4,0	4,0	62	1,0	1,9
pH	5,3	4,0	8,4	0,9	17	1,4	1,9
Phosphorus (mg kg^{-1})	9,3	5,9	41,4	5,2	57	3,9	17,1
Ca^{2+} ($cmol_c$ dm^{-3})	1,7	0,0	17,1	3,9	233	2,6	5,8
Mg^{2+} ($cmol_c$ dm^{-3})	1,5	0,0	18,3	3,2	208	3,6	13,5
Na^{+} ($cmol_c$ dm^{-3})	0,3	0,0	2,7	0,5	155	3,5	13,2
K^{+} ($cmol_c$ dm^{-3})	0,2	0,0	0,7	0,2	84	1,7	2,6
Al^{3+} ($cmol_c$ dm^{-3})	0,6	0,0	2,0	0,5	77	0,8	0,2
(H e Al) ($cmol_c$ dm^{-3})	3,3	0,0	11,7	2,2	68	1,5	2,7
Total nitrogen (dag kg^{-1})	0,3	0,1	1,4	0,2	72	2,1	6,3
Base sum ($cmol_c$ dm^{-3})	3,7	0,1	35,3	7,1	192	3,0	8,4
CEC effective ($cmol_c$ dm^{-3})	4,3	0,5	35,4	6,9	162	3,0	8,5
CEC a pH 7 ($cmol_c$ dm^{-3})	7,0	1,2	35,3	7,1	102	2,6	6,6
Base saturation (%)	35,9	1,9	100	27,8	77	1,0	-0,1
Clay (g kg^{-1})	224	44	610	145	65	0,8	-0,2
Silt (g kg^{-1})	137	8	433	90	65	0,9	0,5
Coarse sand (g kg^{-1})	240	44	715	165	69	1,0	0,1
Fine sand (g kg^{-1})	399	100	761	153	38	0,4	-0,3
Total Sand (g kg^{-1})	639	200	927	184	29	-0,5	-0,6
Bulk density (Mg m^{-3})	1,40	1,10	1,90	0,20	13	0,2	-0,4

Mín = minimum; Max. = maximum; SD = standard deviation; CV = coefficient of variation (%); Ass = asymmetry; Curt. = curtosis; TOC = total organic carbon content; pH = hydrogen potential; CEC= Cations exchange capacity; (H e Al) = Potential acidity and BD = bulk density.

The bulk density ranged from 1.10 and 1.90 mg .$^{m-3}$ with an average of 1.40 mg .m^{-3} with a variation coefficient of 13.0%, a standard deviation of 0.2 and a deviation asymmetry and curtosis of 0.2 and -0.4, respectively, being considered normal, in relation to the referential of the normal distribution (asymmetry 0 and curtosis 3).

The results showed that most variables presented positive symmetry (> 0), indicating left-inclined distribution (to the left of the median value). These results were similar to those obtained by Beutler et al. (2017), developing new PTFs to predict soil density in organic horizons of Brazilian soils and observed positive symmetry in explanatory variables for modeling.

The coefficient of variation, for most variables, were high (> 50%) with the exception of pH, total sand and soil density. Beutler et al. (2017), also observed high variation coefficients for the explanatory variables (independent variables) with the exception of pH.

According to Padua et al. (2015), bulk density is a naturally variable attribute, varying between different soil classes depending on their texture, organic matter content, structure and mineralogy. Table 3 are presented the soil density values by soil classes, maximum values 1.90 Mg.m^{-3} were observed for Arenosols and Plinthosols, and minimum 1.10 and 1.20 Mg·m^{-3} were observed for Ferralsols and Acrisols, respectively. The standard deviations and coefficients of variation were low, the deviation of asymmetry and short are considered normal, in relation to the reference of the normal distribution (asymmetry 0 and short 3).

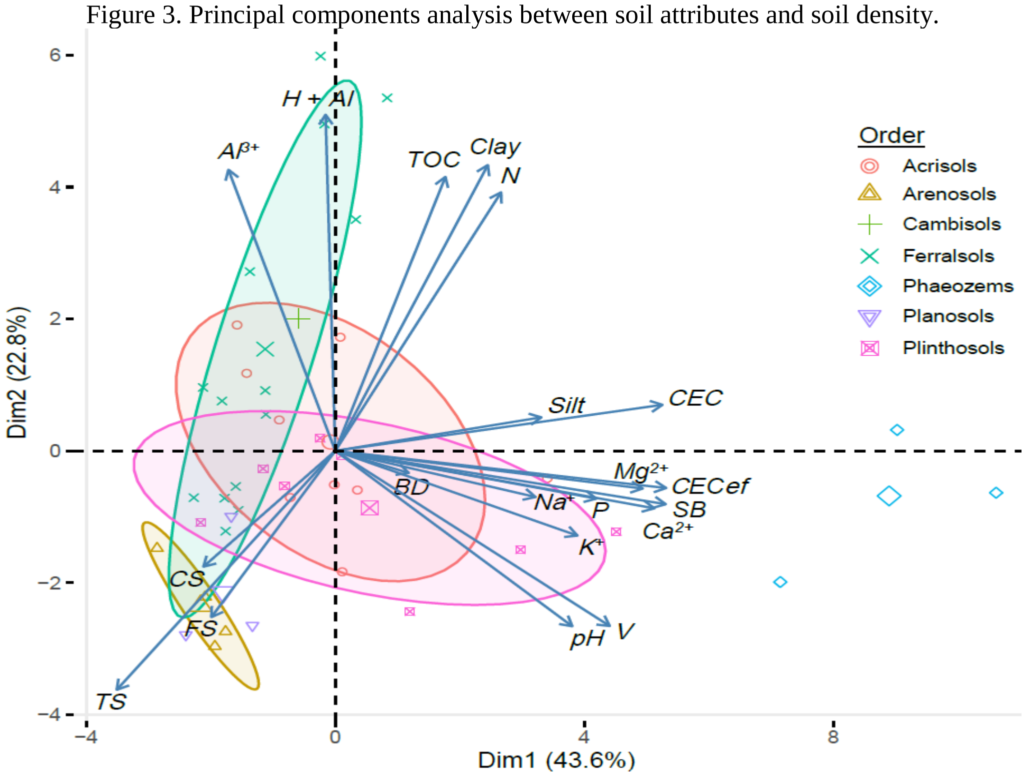
Table 3. Descriptive statistics soil density values used for the development of pedotransference functions for the group classes studied.

Soil classes	Soil density (Mg .m^{-3})						
	Average	Mín.	Max.	SD	CV	Ass.	Curt.
Acrisol	1,60	1,20	1,80	0,10	9,2	-0,2	0,2
Ferralsol	1,40	1,10	1,70	0,20	11,5	-1,0	0,0
Arenosol	1,70	1,50	1,90	0,10	7,0	-0,4	-0,6
Plinthosol	1,70	1,50	1,90	0,10	7,0	0,2	-0,2

Mín = Minimum; Max. = maximum; SD = standard deviation; CV = coefficient of variation (%); Ass = asymmetry; Curt. = curtosis;

The relationships between soil density and soil attributes are explained in the main component analysis. Data variability was explained in 43.60% on axis 1 and 22.80% on axis 2, totaling 66.40% of the data explained in the main component analysis (PCA) (Figure 3).

Figure 3. Principal components analysis between soil attributes and soil density.



BD = bulk density, TOC= total organic carbon, H^{+}+Al^{3+} = potential acidity, Al^{3+} = aluminum, N = total nitrogen, Na^{+} = sodium, CEC = cation exchange capacity effective , CEC = cation exchange capacity a pH 7,0, Mg^{2+} = magnesium, Na^{+} = sodium, P = phosphor, Ca^{2+} = calcium, K^{+} = potassium CS = coarse sand, V = Base saturation (%), pH = hydrogen potential, FS = fine sand and TS = total sand.

As for the coefficient of the Pearson correlation, between bulk density and physical and chemical attributes, in general, were low (R<0.5) (Tables 4). The largest correlations are observed with clay content (r = -0.66), potential acidity (r = -0.58), total sand, (r = 0.57) and the aluminum content (r = -0 ,51).

Table 4. coefficient of the Pearson correlation between soil attributes and bulk density

Soil attributes	Correlation coefficient Bulk density	Soil attributes	Correlation coefficient Bulk density
Bulk density	1,00	Sodium	0,18*
Coarse sand	0,35*	Potassium	0,07 ^{ns}
Fine sand	-0,32*	Aluminum	-0,51*
Total Sand	0,57*	Potential acidity	-0,58*
Clay	-0,66 *	Total nitrogen	-0,40*
Silt	-0,09 ^{ns}	Total organic carbon	-0,36*
pH	0,29*	Sum of bases	-0,12 ^{ns}
Phosphorus	0,15 ^{ns}	CEC effective	0,03 ^{ns}
Calcium	0,03 ^{ns}	CEC a pH	0,00 ^{ns}
Magnesium	0,01 ^{ns}	Base saturation	0,17 ^{ns}

* Significant correlations at 5% probability and ^{ns} significant correlations; CEC Effective = effective cations exchange capacity, CEC at pH 7.0 = capacity of exchange of cations at pH 7.0.

The total sand showed a positive correlation and the clay content presented a strong negative correlation. Such trends corroborate with the proposition that granulometric fractions have a significant role in the control of bulk density.

The fine sand content has a negative effect which is explained by the fact that thinner textured soils have higher micropority in contrast to those richer in thick sand that has a positive effect.

Corroborate with these Marcolin and Klein (2011) results, estimating the relative soil density from a pedotransference function for maximum bulk density in the state of Rio Grande do Sul. These authors observed that the clay content and organic matter of the soil influenced bulk density.

According to Padua et al. (2015), the negative effect of clay content is explained by the fact that more clayers have greater microporosity and the highest organic carbon retention of soil in soils with higher clay content.

As for the correlations between chemical attributes and soil density, a possible explanation, is that higher organic carbon contents induce the lower mass of dry soil mass by total volume of soils. The concentrations of H^+ and Al^{3+} are related to the formation of aggregates, where flocculant cations approach the particles allowing good aggregation and, consequently, larger total porosity, which implies reduction of bulk density values.

Agreement Padua et al. (2015), with H + Al contents and CEC at pH 7.0, in turn, are indirectly related to bulk density, since they depend on the TOC content, since the carboxyl and phenolic groups of organic matter release H^+ protonated in the determination of H + Al. Therefore, correlations between H + Al, CEC at pH 7.0 and soil density showed the same negative trend that TOC.

The exploratory analysis procedure of the data showed the predictive variables that significantly influenced ($p < 0.01$) the bulk density allowing, with this, to obtain a pedotransference function capable of describing, satisfactorily, this soil attribute. The equations of the I and II models with the predictors and their respective regresses, for all soil classes and by soil class are presented in Table 5.

Table 5. Pedotransfer functions and their respective regression indices of generalized and soil class

Model	Equations
	GENERALIZED
M I	BD = 1,670 – 0,0006*Clay – 0,0202*H^++Al^{3+} + 0,1649*Na^+ – 0,0168*Mg^{2+} + 0,0002*CS + 0,0067*P – 0.0115*CEC
M II	BD = 1,875 – 0,0009*Clay – 0,0002*FS – 0,0622*TOC
	"LATOSSOLOS" (*Ferralsols*)
M I	BD = 2,076 – 0,0014*Clay + 0,2604*Mg^{2+} – 0,1247*CEC – 0,0080*V + 0,3531*Na^+
M II	BD = 1,128 – 0,0006*TS – 0,0629*TOC
	"ARGISSOLOS" (*Acrisols*)
M I	BD = 2,015 – 0,1428*Al^{3+} – 0,7727*K^+ – 0,0008*FS – 0,0375*H^++Al^{3+} + 0,0004*TS
M II	BD = 1,807 – 0,0008*FS + 0,0973*TOC
	"NEOSSOLOS" (*Arenosols*)
M I	BD = 1,754 - 1,2720*K^+ + 0,0032*Silt
M II	BD = 1,563 + 0,0003*TS
	"PLINTOSSOLOS" (*Plinthosol*)
M I	BD = 1,734 - 0,7487*K^+ + 0,1338*Na^+ + 0,4477*N – 0,0829*TOC
M II	BD = 1,642 + 0,0003*TS – 0,1131*TOC + 0,0003*Silt

BD = bulk density, Mip = micropores, Al^{3+} = aluminum, Na^+ = sodium, TOC= total organic carbon, CEC = cation exchange capacity a pH 7,0 of Clay, Clay= clay, P = phosphor, Ca^{2+} = calcium, H^++Al^{3+} = potential acidity CS = coarse sand, V = Base saturation (%), FS = fine sand and TS = total sand.

The variables selected in the equations for all soil classes in model I were: clay content, potential acidity, sodium content, magnesium content, coarse sand, phosphorus content and clay CEC. In model II, they were: o clay content, fine sand content and total organic carbon.

In the models generated for the Ferralsols, the variables selected in the equations were: clay content, magnesium content, clay CEC, base saturation and sodium content for model I and total sand for model II. For Acrisols, aluminum content, potassium content, fine sand content, potential acidity and total sand for model I and fine sand content and total organic carbon for model II.

As for Neosols, the variables were: potassium content and silt content for model I and coarse sand content for model II and for Plinthosols were: potassium content, sodium content, total nitrogen and organic carbon total for model I and model II the coarse sand content, total organic carbon and silt content.

In general, particle size and total organic carbon were more influential in estimating bulk density, with clay content being identified in three models and total organic carbon in four models.

These results were similar to those observed by Padua et al. (2015), for these authors, the variables included in the function were: organic carbon, CEC at pH 7, total sand, exchangeable aluminum and clay. Also according to the same authors, among the selected predictor variables in the development of PTF, those that are directly related to bulk density are total organic carbon and soil texture.

Organic matter (total organic carbon) influences several soil characteristics, mainly those related to the formation of aggregates and the checking of negative charges, increasing the soil's cation exchange capacity. Regarding the formation of aggregates, organic matter acts as a cementing agent, uniting and stabilizing both unitary and secondary soil particles.

Table 6 shows the evaluation of the performance of the regression models, the statistical indicators and the confidence index. When grouping data by soil class, there is a small increase in R^2 values, evidencing better adjustments in the predictive capacity.

Table 6. Evaluation of regression models, statistical indicators and confidence index for all soils (general) and by soil class to estimate bulk density.

Model	R^2	EM	RMSPE	D	r	IC	Performance
			GENERALIZED				
M I	0,62	0,00016	0,1140	0,99	0,79	0,78	Very good
M II	0,47	0,00024	0,1341	0,99	0,68	0,68	Good
			"LATOSSOLOS" (*Ferralsols*)				
M I	0,87	0,00024	0,0587	0,99	0,93	0,93	Excellent
M II	0,64	0,00071	0,0989	0,99	0,80	0,79	Very good
			"ARGISSOLOS" (*Acrisols)*				
M I	0,78	-0,00242	0,0657	0,98	0,89	0,87	Excellent
M II	0,33	-0,00037	0,1153	0,98	0,58	0,57	bearable
			"NEOSSOLOS" (*Arenosols*)				
M I	0,46	-0,00067	0,0857	0,98	0,68	0,66	Good
M II	0,15	-0,00133	0,1075	0,97	0,36	0,35	Terrible
			"PLINTOSSOLOS" (*Plintosols*)				
M I	0,66	-0,00125	0,0673	0,98	0,81	0,80	Very good
M II	0,19	-0,00000008	0,1045	0,97	0,43	0,42	Bad

R^2 = determination coefficients, EM = average error, RMSE = root of square mean error, d = willmott index e IC = confidence index.

The M I and M II models of Ferrlasols were considered the most suitable for estimating bulk density, with determination coefficients of 0.87 and 0.64, respectively, showing a good agreement between the estimates. The models for the classes (generalized), Acrisols and Plinthosols only M I showed a good fit with the coefficients of determination of 0.62, 0.78 and 0.65 respectively. As for the coefficients of determination of Arenosols 0.46 and 0.15 for models M I and M II, they did not present a good adjustment of the equations.

These results were similar to those obtained by Padua et al. (2015), developing mathematical functions capable of describing bulk density up to 1 m deep in areas of native vegetation in the central and southern regions of Minas Gerais, these authors observed coefficients of determination for Ferralsols and Acrisols of 0.85 and 0. 51, respectively, higher than that obtained for the complete database, which was 0.50.

The average error for general and Ferralsols models, indicating that the generated models tend to overestimate, while the models for Acrisols, Arenosols and Plinthosols tend to underestimate the soil density values.

The roots of the mean square error, for most models, were low, the exceptions were for models MI and M II of Neosols, M II of Acrisols and M II of generalized, this means that there was a high dispersion of data for these models.

Similar results were observed by Padua et al. (2015), these observed roots of the mean square error of 0.0516 and adjusted R^2 of 0.90 of Latosols for a depth of 0-20 m in the native cerrado in the central and southern regions of Minas Gerais.

In general, the confidence indices were predominantly between good and great. It is also verified that the models using all the determined soil attributes as independent variables were superior to those using the particle size and total organic carbon content as independent variables.

The relationship between the bulk density values observed and predicted by the pedotransfer function models for all classes (generalized) and per soil class are presented in figures 3, 4, 5, 6 and 7.

Figure 3. Scatterplots of measured values vs. estimates of BD by models I and II for all soil classes (generalized), (A) dataset used in the construction of the model; (B) dataset used for model validation.

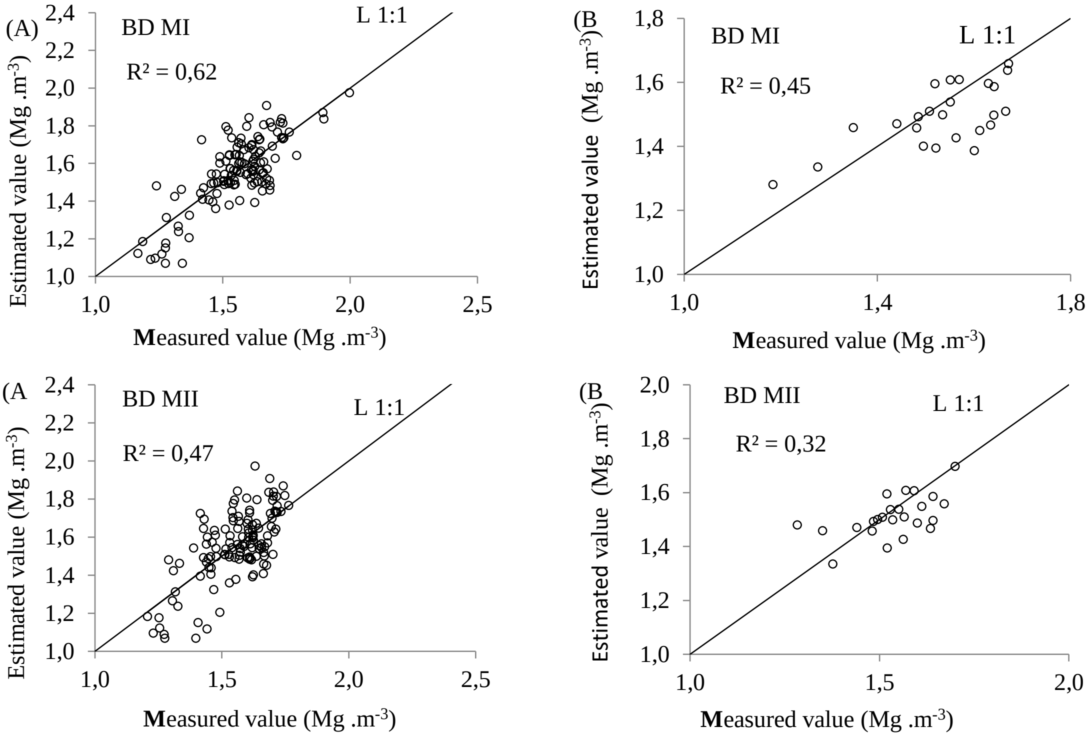


Figure 4. Scatter plots between measured values vs. estimates of BD by models I and II for the Ferralsols class, (A) dataset used in the construction of the model; (B) dataset used for model validation.

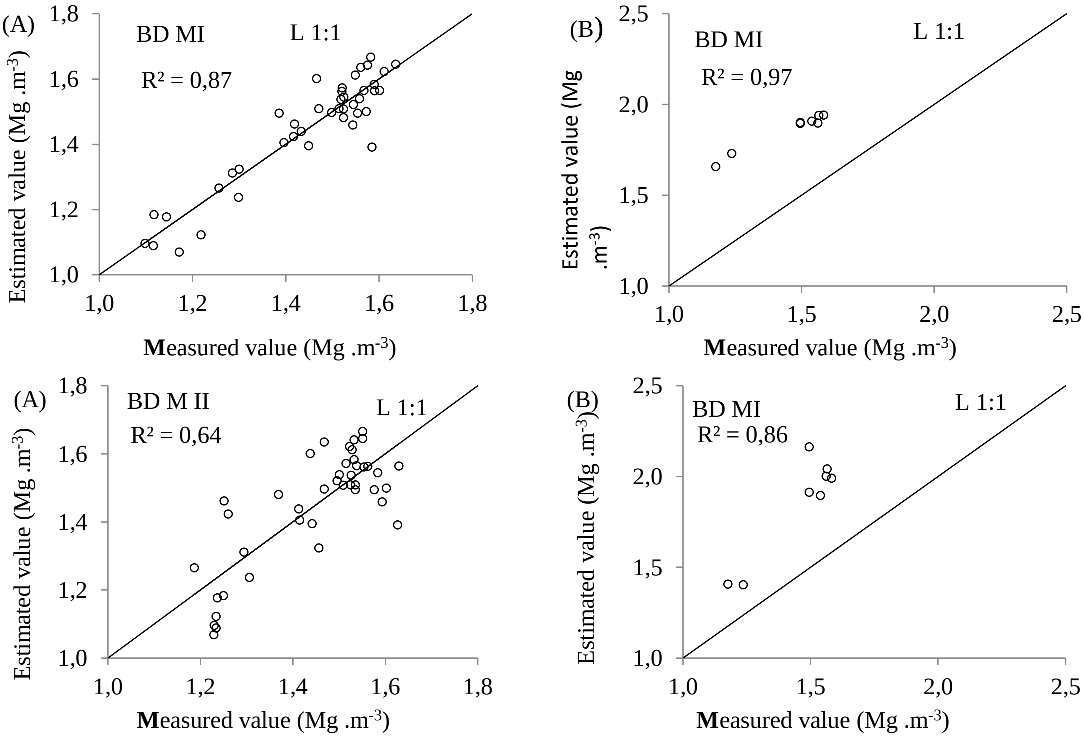


Figure 5. Scatterplots between measured values vs. estimates of BD by models I and II for the Acrisols class, (A) dataset used in the construction of the model; (B) dataset used for model validation.

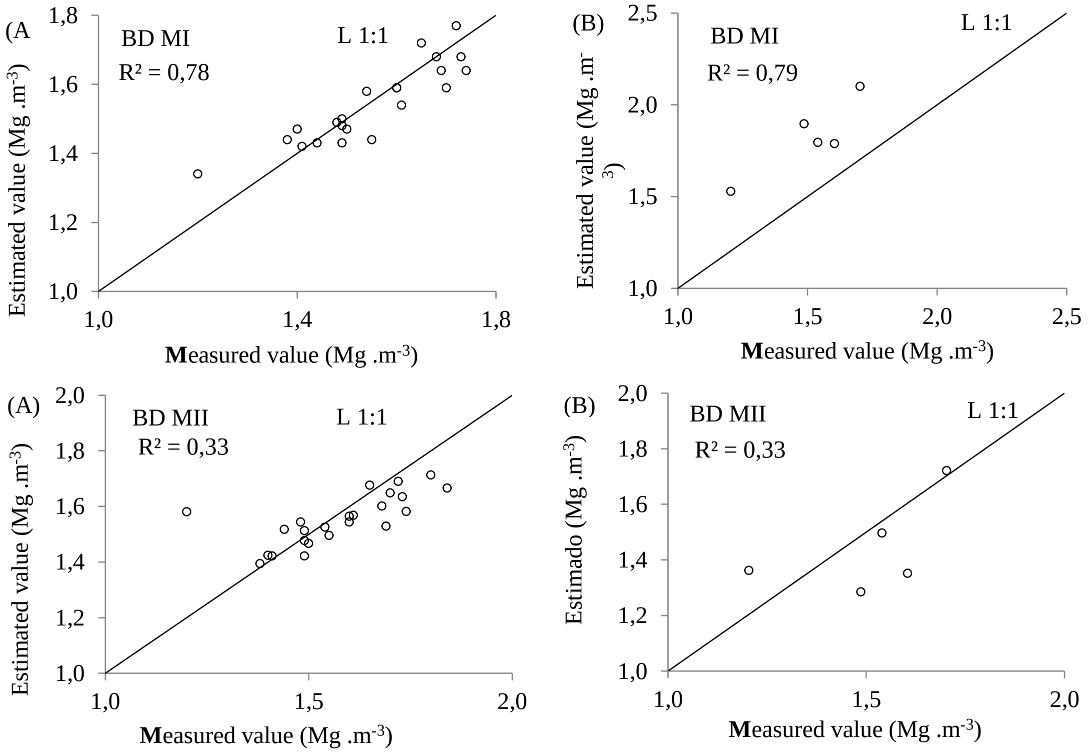


Figure 6. Scatterplots between measured values vs. estimates of BD by models I and II for the Arenosols class, (A) dataset used in making the model; (B) dataset used for model validation.

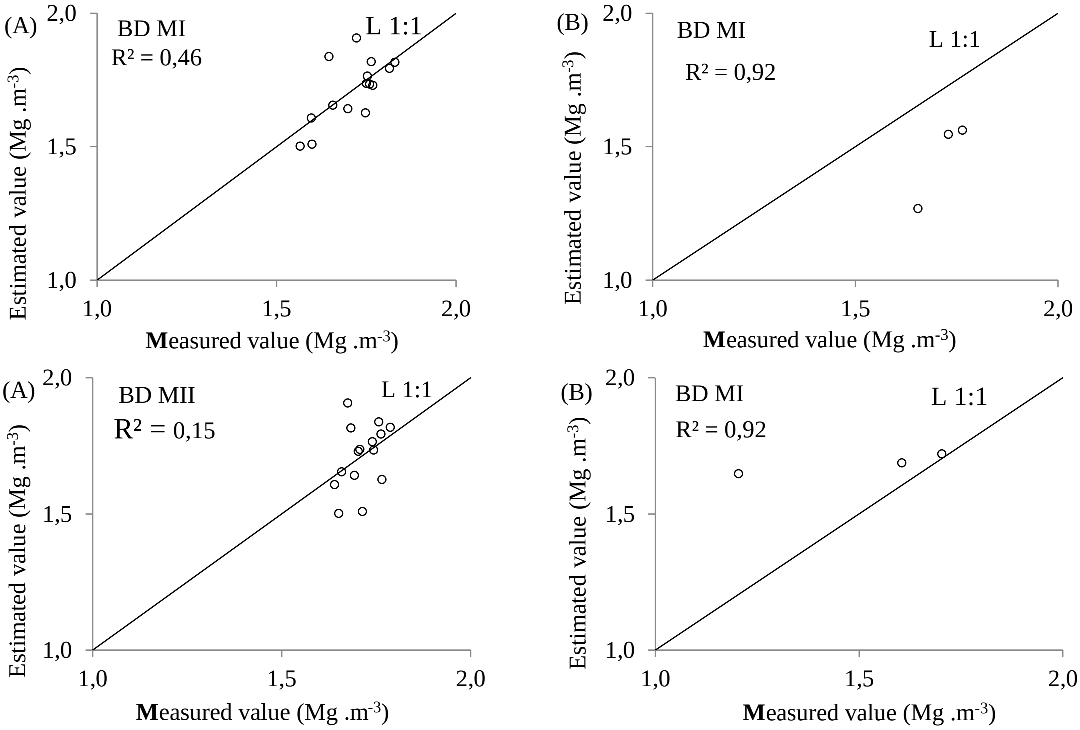
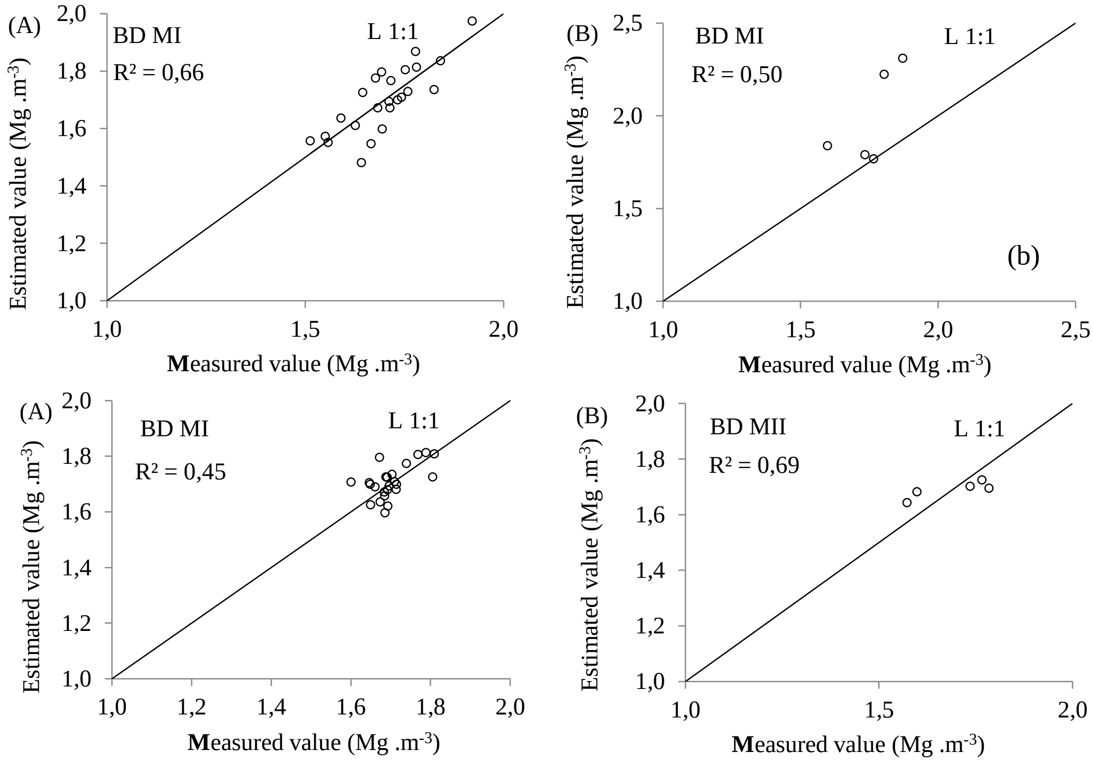


Figure 7. Scatterplots between measured values vs. estimates of BD by models I and II for the Plinthosols class, (A) dataset used in the construction of the model; (B) dataset used for model validation.



The highest correlations were obtained for model I of Ferralsols and Acrisols. It is also observed in the graphs that the distributions of the points were basically around the line, showing a good agreement of the estimates.

In the grouping using only the particle size and total organic carbon content, there is a greater dispersion of points, due to the presence of anomalous values (points far from the main line 1:1). These values contributed negatively to the efficiency of the models.

Similar results were obtained by Padua et al. (2015), when they observed a better distribution for Ferralsols. According to the same authors, stratification by taxonomic order provided significant improvements in the accuracy of the models.

4 CONCLUSIONS

Bulk density of soil can be estimated with reasonable accuracy from data on particle size, potential acidity, aluminum content, sodium content, magnesium content, phosphorus content, base saturation, and total organic carbon.

The pedotransfer function, with the "excellent" performance in predicting bulk density under the conditions of this study, was the model I for the "Latossolos" (Ferralsols) and "Argissolos" (Acrisols), which included a greater number of variables in the construction of the predictive model of bulk density.

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