Soil Bulk Density Estimation Methods: A Review

Article *in* Pedosphere · August 2018

DOI: 10.1016/S1002-0160(18)60034-7

Pedosphere **28**(4): 581–596, 2018
doi:10.1016/S1002-0160(18)60034-7
ISSN 1002-0160/CN 32-1315/P

Published by Elsevier B.V. and Science Press

PEDOSPHERE

www.elsevier.com/locate/pedosphere

Soil Bulk Density Estimation Methods: A Review

Ahmed Abed Gatea AL-SHAMMARY[1,3,*], Abbas Z. KOUZANI[1], Akif KAYNAK[1], Sui Yang KHOO[1], Michael NORTON[1] and Will GATES[2,*]

[1] *School of Engineering, Deakin University, Geelong VIC 3216 (Australia)*
[2] *Institute for Frontier Materials, Deakin University, Burwood VIC 3125 (Australia)*
[3] *Soil Science and Water Resources Departments, College of Agriculture, University of Wasit, Kut 964 (Iraq)*

(Received March 21, 2018; revised July 11, 2018)

ABSTRACT

Measurement of soil bulk density is important for understanding the physical, chemical, and biological properties of soil. Accurate and rapid soil bulk density measurement techniques play a significant role in agricultural experimental research. This review is a comprehensive summary of existing measurement methods and evaluates their advantages, disadvantages, potential sources of error, and directions for future development. These techniques can be broadly categorised as direct and indirect methods. Direct methods include core, clod, and excavation sampling, whereas indirect methods include the radiation and regression approaches. The core method is most widely used, but it is time consuming and difficult to use for sampling multiple soil depths. The size of the coring cylinder used, operator experience, sampling depth, and *in-situ* soil moisture content significantly affect its accuracy. The clod method is suitable for use with heavy clay soils, and its accuracy is dependent on equipment calibration, drying time, and operator experience, but the process is complicated and time consuming. Excavation techniques are most commonly used to evaluate the bulk density of forest soils, but have major limitations as they cannot be used in soils with large pores and their measurement accuracy is strongly influenced by soil texture and the type of analysis selected. The indirect methods appear to have greater accuracy than direct approaches, but have higher costs, are more complex, and require greater operator experience. One such approach uses gamma radiation, and its accuracy is strongly influenced by soil depth. Regression methods are economical as they can make indirect measurements, but these depend on good, quality data of soil texture and organic matter content and geographical and climatic properties. Also, like most of the other approaches, its accuracy decreases with sampling depth.

Key Words: measurement accuracy, direct measurement methods, gamma radiation, indirect measurement methods, regression methods, sampling depth, soil properties

Citation: Al-Shammary A A G, Kouzani A Z, Kaynak A, Khoo S Y, Norton M, Gates W. 2018. Soil bulk density estimation methods: A review. *Pedosphere*. **28**(4): 581–596.

INTRODUCTION

Soil compaction is a major agricultural problem because of its significant effect on productivity (Keesstra *et al*., 2016; Yang *et al*., 2016). The bulk density (ρ_b) of soil is regarded as a key factor that is correlated with soil compaction and many physical, chemical, and biological properties of soil. It is calculated as the ratio of the dried mass of soil to its total volume (Han *et al.* 2016; Walter *et al.* 2016).

Soil ρ_b can be determined from measurements of soil organic carbon using regressions methods, such as pedotransfer functions (PTFs) (Holmes *et al*., 2012; Rudiyanto *et al*., 2016; Xu *et al*., 2016; Yi *et al*., 2016). Accurate soil ρ_b data is also an indicator of soil porosity and moisture content as it is dependent on soil texture and structure (Casanova *et al*., 2016; Moret-Fernández *et al*., 2016; Han *et al*., 2017; Lu *et al*., 2017). Such data also provide valuable information on soil compaction stress (Lestariningsih and Hairiah, 2013) and can be used to calculate soil penetration resistance (Gao *et al*., 2016; Hosseini *et al*., 2016; da Silva *et al*., 2016). Furthermore, some studies (Masseroni *et al*., 2014; Al-Shammary and Al-Sadoon, 2014; Russell *et al*., 2015; Lu *et al*., 2017) claim that the ρ_b value of a soil is an essential characteristic of its thermal properties. The soil property parameters (soil volumetric heat capacity, thermal conductivity, and physical and biological processes) affected by ρ_b are listed in Table I. Soil depth influences ρ_b value; soil ρ_b values can be used to estimate soil productivity, quality, and carbon storage.

Measurement of soil ρ_b is important for calculating the physical qualities of soil because many of these are affected by soil ρ_b, while climatic factors and agricultural use have significant effects on soil organic car-

*Corresponding author. E-mail: ahmedabd192000@yahoo.com, agatea@deakin.edu.au.

TABLE I

Soil properties affected by soil bulk density

Soil property	Definition	Formula or model[a)]	Reference(s)
Porosity (Φ, %)	Percentage of the bulk volume not occupied by solids	$\Phi = \left(1 - \frac{\rho_b}{D_p}\right) \times 100$	Casanova *et al.* (2016)
Volumetric moisture content (θ, cm^3 cm^{-3})	Ratio between the mass of water and the mass of dry soil	$\theta = \frac{p_w \rho_b}{d_w}$	Smith (2000)
Thermal conductivity (λ, W m^{-1} K^{-1})	A property that plays a significant role in calculating heat transfer at the soil surface under ambient air conditions and depends on dry density and moisture content	$\lambda = 0.144\,2(0.9\log w - 0.2)10^{0.01\rho_b}$	Blázquez *et al.* (2017), Al-Shammary *et al.* (2017)
Volumetric heat capacity (C_v, J m^{-3} K^{-1})	Amount of heat needed to increase the temperature of a unit volume of soil by 1 K	$C_v = \frac{2.01 \times 10^6 \rho_b}{2.65 + 4.19 \times 10^6 \theta}$	Evett *et al.* (2012)
Penetration resistance (PR, Pa)	A property that plays a key role in estimating soil mechanical properties, which are commonly used to estimate soil strength, and depends on soil bulk density, soil moisture content, and soil type	$\mathrm{PR} = \exp(a + b\rho_b^* + cS_p)$	Vaz *et al.* (2013)

[a)] ρ_b is the soil bulk density (Mg m^{-3}), D_p is the soil particle density (Mg m^{-3}), ρ_w is the soil moisture by weight (%), d_w is the water density (Mg m^{-3}), w is the soil weight, a, b, and c are the fitting parameters, and ρ_b* and S_p are the normalized bulk density and water content, respectively.

bon (Lobsey and Viscarra Rossel, 2016). In addition, knowing soil ρ_b values is important for soil management (Ferreira *et al.*, 2015). Therefore, observing the dynamics of soil ρ_b can elucidate the dynamics of soil productivity and ecosystem functioning, allowing local variability in soil quality to be measured.

Soil ρ_b can also be influenced by the efficiency of agricultural production. To date, various methods have been developed to measure soil ρ_b, including direct and indirect methods. Shiri *et al.* (2017) noted that the choice of method used for measuring soil ρ_b strongly affects estimates of soil organic carbon content. ISO (2017) and ASTM (2015) state that soil ρ_b can be directly measured by the core method (in a volumetric cylinder), *via* the excavation and clod methods. However, the core method is expensive, difficult, and time consuming to perform at multiple soil depths. This is because the processing of the soil samples removed requires much time and puts pressure on the operator; also, this method is destructive (Chai and He, 2016). Measuring soil ρ_b using the clod method is a complicated process. Drying of soil samples and calculating their mass and volume using paraffin wax are dependent on equilibrium water potential. The performance of this method is dependent on the experience of the operator and calibration of the equipment, as well as drying time. Studies have indicated that collecting clods is difficult, and, as a result, clod samples are more prone to disturbance than those obtained by other methods. This is worthy of note because the volume of a clod sample has a significant effect on the performance of the clod method. Increasing the volume of the clod can lead to greater accuracy when measuring soil ρ_b in the field (Rossi *et al.*, 2008). The main limitation of such excavation methods is that they cannot be used in soil that contains large pores. Furthermore, their accuracy is influenced by soil texture and analysis processes, as well as the calibration of the balance used to measure mass, because the volume of the soil sample is estimated by filling the excavated region with sand or water (McKenzie *et al.*, 2002; Ma *et al.*, 2013). Lobsey and Viscarra Rossel (2016) and Vanguelova *et al.* (2016) argued that soil ρ_b can be indirectly measured using a regression method, such as PTF, or the radiation method (Fig. 1). However, a number of studies have found that these soil ρ_b measurement techniques have several limitations, such as being difficult to use, time consuming, and prone to large errors when sampling different locations (Xu *et al.*, 2016).

The major objective of this review is to evaluate potential sources of error and uncertainty related to measurement of soil ρ_b using the different methods that exist. This review emphasises why it is imperative to measure soil ρ_b and which factors affect it. Furthermore, this review aims to provide academic researchers in the agricultural field with a summary of the key strengths and weaknesses of soil ρ_b measurement techniques in terms of their cost effectiveness, measurement accuracy, spatial scale, and analysis time.

IMPORTANCE OF ρ_b TO SOIL CHARACTERISTICS AND FACTORS AFFECTING SOIL ρ_b

Soil ρ_b significantly affects soil health and is influ-

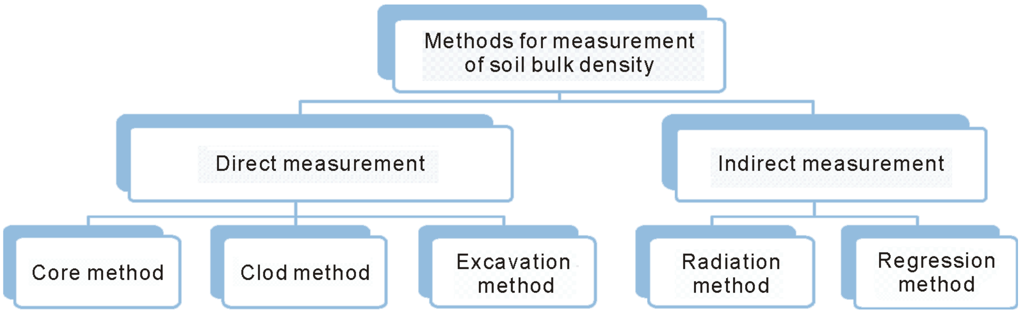

Fig. 1 Methods used for measurement of soil bulk density.

enced by several factors, including soil porosity, mineral type, organic matter content (OMC), texture, structure, and moisture content (Chaudhari *et al.*, 2013). Therefore, changes in soil ρ_b can have a significant influence on soil thermophysical characteristics and agricultural production. Soil ρ_b values are key to estimation of soil moisture content (μ), porosity (Φ), volumetric moisture content (θ), and soil thermal properties (STP) (Usowicz *et al.*, 2013; Al-Shammary and Al-Sadoon, 2014; Ahad *et al.*, 2015). The STP is dependent on ρ_b (Al-Shammary and Al-Sadoon, 2014; Russell *et al.*, 2015; Lu *et al.*, 2017). Specifically, Mahdavi *et al.* (2016), Alrtimi *et al.* (2016), and Hu *et al.* (2017) observed that soil ρ_b strongly influences soil thermal conductivity (λ), because soil λ is dependent on particle arrangement, which is influenced by variation in soil ρ_b. Zhang *et al.* (2017) demonstrated that soil ρ_b has a significant effect on the thermal resistivity (ρ) and λ of soil. Soil ρ decreases with increasing soil ρ_b because the improved particle arrangement in soils with higher ρ_b results in better heat transfer. In contrast, Arkhangel'skaya *et al.* (2016) argued that soil ρ_b significantly influences STP and found that soil ρ_b was correlated with soil thermal diffusivity (K) and volumetric heat capacity (C_v) because soil ρ_b affects the particular components of soil thermal balance (λ, ρ, K, and C_v). Furthermore, Shiri *et al.* (2017) stated that soil ρ_b significantly affects land drainage and reclamation and is an indicator of drainage properties. Furthermore, in irrigation management, Mohawesh *et al.* (2014) and Liu *et al.* (2016) argued that soil ρ_b can be used to calculate the soil θ, which is a significant property used to control irrigation regimes. Jia *et al.* (2017) stated that soil ρ_b is an important factor in soil moisture dynamics. Also, Yang *et al.* (2016) observed that soil ρ_b is an indicator of the physical characteristics of soil that affect water transport and found a significant correlation between soil ρ_b and soil moisture content. This is because soil ρ_b affects the soil water capacity and available moisture. Wilson *et al.* (2013) reported that soil ρ_b strongly influences soil penetration resistance (PR) and shear strength (SS). Meanwhile, Bayat *et al.* (2017) found that soil ρ_b is the most dynamic factor for predicting soil PR as soil PR and ρ_b tend to be correlated.

Soil porosity is strongly influenced by soil ρ_b (Naghdi *et al.*, 2016). Jalabert *et al.* (2010), Ghehi *et al.* (2012), Xu *et al.* (2016), and Yi *et al.* (2016) showed that OMC has a significant influence on soil ρ_b values. Ahad *et al.* (2015) indicated that soil ρ_b has a positive relationship with soil texture, as well as mineral and organic matter, but a negative relationship with OMC and porosity. Martín *et al.* (2017) argued that soil structure and texture could be indicators of soil ρ_b and found that the sand content of soil affects soil ρ_b more strongly than clay content and there is a positive correlation between soil sand content and soil ρ_b values. Similarly, Al-Qinna and Jaber (2013) reported that soil sand content has a more significant and positive correlation with soil ρ_b than soil silt and clay contents, which is because in arid soil silt and clay have lower ρ_b values. Other important influences on soil ρ_b come from management factors, such as a history of compaction. Naderi-Boldaji and Keller (2016) stated that land use and mechanical stresses strongly affect soil ρ_b because they influence its dynamics and degree of compaction. Increased soil ρ_b results from soil compaction due to anthropogenic mechanical operations, as well as natural processes such as rain, plant roots, and traffic, which can rearrange the solid particles of soil (Al-Kaisi *et al.*, 2017; Busse *et al.*, 2017; Cambi *et al.*, 2017). In contrast, Keesstra *et al.* (2016) found that increased vegetation cover can result in decreased soil ρ_b under various soil management techniques. Shete *et al.* (2016) also showed that plantations influence soil ρ_b because groundcover affects the frequency of soil disturbance. Sequeira *et al.* (2014) showed that soil ρ_b has a significant effect on soil moisture. Furthermore, according to Chaudhari *et al.* (2013), soil ρ_b increases with depth because subsurface layers are more compacted and have a lower OMC than surface layers. Their results also indicated that soil ρ_b is negatively related to OMC.

METHODS FOR MEASUREMENT OF SOIL BULK DENSITY

Measuring soil ρ_b under different conditions provides useful information on the physical properties of soil (Ali, 2010). In recent studies, ρ_b has been measured using one of two groups of methods: 1) well-established direct methods, or 2) indirect methods (Campbell, 1994). These two groups differ according to the technology used, duration of measurement, accuracy, cost, operator experience, and suitability to different soil types and conditions..

Direct methods

Direct methods for measuring soil ρ_b are often more practical and, thus, are generally used by agricultural soil scientists and civil engineers (Ma *et al.*, 2013). They include measurements of the mass and volume of oven-dried soil samples. The volume of a soil sample can be obtained by measuring the size of the sampling cylinder or the quantity of sand or water (Campbell, 1994). Direct measurements can be obtained from core, excavation, and clod methods (Martín *et al.*, 2017). A number of studies have found that these methods depend on measurements of the volume and mass of the soil sample because the mass of a dry soil sample is obtained by weighting, whereas the total volume of the soil, including air and moisture, is observed by indirect measurement (Ferreira *et al.*, 2015). The dry soil ρ_b can be calculated using the formula:

$$\rho_b = M_s/V_s \quad (1)$$

where ρ_b is in Mg m^{-3}, M_s is the weight of the dry soil sample in Mg, and V_s is the volume of the dry soil sample in m^3 (Han *et al.*, 2016).

Core method (volumetric cylinder method). The core sampling method is the most common method used to determine $\rho_b$in agricultural soils (Casanova *et al.*, 2016). This method is based on the procedure outlined in ISO (2017). This method requires a solid ring or volumetric cylinder to be hammered or pressed into the soil (Walter *et al.*, 2016) to take a core sample. The total volume of the soil is estimated as the internal volume of the cylinder. Samples are dried at 105 °C for 2–3 d depending on core size and moisture content, and then the mass of the dry soil sample is measured and soil ρ_b estimated as shown in Fig. 2 (Ali, 2010; Yang *et al.*, 2016; Zolfaghari *et al.*, 2016). A calculation sheet for determining soil ρ_b *via* the core sampling method is given in Table II (Ali, 2010). Often, the moisture conditions in the field at the time of sampling are also recorded by weighing the wet soil sample prior to oven drying.

This method is simple and inexpensive and, thus, has been applied in many practical and investigative studies. After reviewing the recent literature, Vanguelova *et al.* (2016) found little evidence that the core diameters used had any significant influence on the accuracy of soil ρ_b measurement at different depths. However, they indicated that a 100-cm^3 volume steel core was the most reliable for use at different depths. Casanova *et al.* (2016) observed an interesting negative correlation between the size of the core used and the value of soil ρ_b obtained, which was due to extreme soil shattering and compaction if the core was too small. Walter *et al.* (2016) stated that accurate and efficient methods of measuring soil ρ_b are important when recording soil organic carbon. They compared soil ρ_b measurements using three soil core methods and three soil probe types at four locations and discovered that soil depth, soil type, and systematic error can all affect soil ρ_b recordings, with inaccuracies due to issues with small sample size relative to aggregate size. Lestariningsih and Hairiah (2013) indicated that the accuracy of soil ρ_b measurements using the core method is dependent on sampling time and depth. Additionally, in China, Chai and He (2016) used 11 845 samples to assess soil ρ_b measurement by the core method and demonstrated that reproducibility of measurements in the field was limited. They also found that a major limitation of the core method is that it is challenging to control the quality of ρ_b data collected. Quraishi and Mouazen (2013) argued that errors in field measurements may be potentially large because their accuracy is dependent on the experience of the operator, soil type, and the field conditions at the time of sampling. In addition, they found that this method is time consuming. Lin *et al.* (2014) studied a model-based relationship between the core method and soil ρ_b using dual-sensor penetrometer data. They found that soil ρ_b values were influenced by the physical conditions of the soil. They reported that while the core method was practical for measuring soil ρ_b, it was difficult and time consuming when multiple soil depths were sampled. This is because accuracy decreases with soil depth and is also affected by the sample collection and drying processes. Furthermore, field conditions can also have an effect on the values obtained. The performance of the core method is dependent on soil type and has the most practical application in soft cohesive soils (loams, silt loams, clay loams, and clays). It has

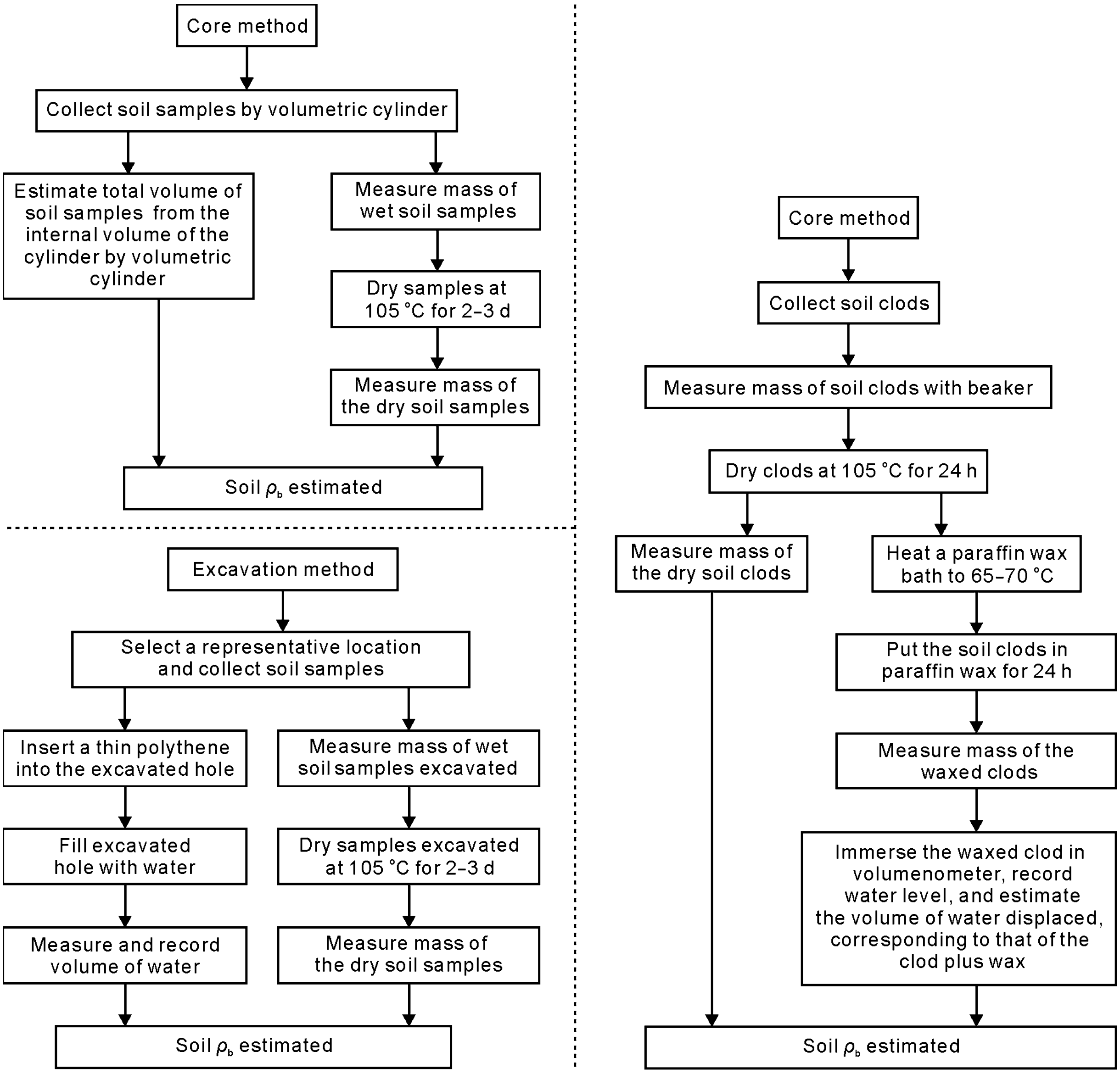

Fig. 2 Schematic diagram of the core, clod, and excavation methods for measuring soil bulk density.

TABLE II

Calculation sheet for determining bulk density (ρ_b) for soil using the core method (Ali, 2010)

Sample number	Weight of oven-dried soil core (C1)	Weight of core (C2)	Core size			Actual soil sample volume (C4)	Weight of oven-dried soil (C5) (C5 = C1 − C2)	Soil ρ_b value (C6) (C6 = C5/C4)
			Height (h)	Diameter (d)	Volume ($\pi d^2 h/4$) (C3)			
	g	g	cm	cm	cm^3	cm^3	g	g cm^{-3}
1	160	25	6	5	117.8	117.8	135	1.15

limited application in measuring the ρ_b of sandy or gravelly soils (Brahim *et al.*, 2012).

Clod method (paraffin-sealed clod). The clod method is the second most widely used technique for measuring soil ρ_b (Casanova *et al.*, 2016) and is laboratory based (Ali, 2010). This method is also based on the procedures outlined by ISO (2017). In this method, soil ρ_b is measured by calculating soil mass and volume using paraffin wax, saran rubber, or wax mixtures using the following steps. First, a clod is weighed, and then its volume is estimated by coating it in paraffin wax, which is done by heating a wax bath to 65–70 °C and submerging the clod in a cylinder (volumenometer) in the wax bath for approximately 24 h. Alternatively, the waxed clod is weighed in the air. After this, it is weighed while submerged in a known mass (volume) of water, as shown in Fig. 2, where the water temperature is noted and the mass is recorded again. Table III shows a calculation sheet for determining soil ρ_b using the clod method (Ali, 2010). Moret-Fernández *et al.* (2016) reported that one major problem with this method is that it is time consuming because the experimental process is complex and slow. The clods also need to be sufficiently stable for this method to work; for most soils, this limits the clod size to 4–10 cm in diameter. Furthermore, the process of immersing and weighing a coated clod is challenging and tedious, and measurement error can increase during the immersion process. Casanova *et al.* (2016) observed that the clod method can overestimate soil ρ_b compared to the core sampling and excavation techniques because it does not account for inter-aggregate pores. They also found that the structure of the soil and the sample collection methods result in considerable differences in measurements. Rossi *et al.* (2008) presented the specifications and cost-effectiveness of the clod method by comparing it with the non-destructive scanning method. Their results showed that the clod method is more labour intensive than the scanning method because it requires more complicated calculations and is dependent on operator experience. In addition, inconsistencies in paraffin coating may cause errors. Ali (2010) found that the accuracy of the clod method depends on user experience, calibration, and soil properties. Furthermore, a number of soil samples must be taken at each depth to decrease measurement error.

Excavation method (volume replacement). The excavation method can be used to measure soil ρ_b in conditions where the core sampling and clod methods cannot be applied, such as when there is a high stone content, a high gravel content, or a sloping topography (Bauer *et al.*, 2014). However, this method is not suitable for measuring ρ_b of soils with large pores (Frisbie *et al.*, 2014). Instead, the excavation method is appropriate for soils that have a high proportion of coarse fragments, such as those in forests. The soil sample collected should be dried at 105 °C for approximately 24 h, depending on moisture content. Then, the soil volume can be determined by filling the excavated hole with a measured quantity of sand or water, as shown in Fig. 2. The excavated hole is usually about 10 cm in diameter. This is a time-consuming procedure, with approximately 30 min needed to estimate the volume of a single soil sample (Smith, 2000; McKenzie *et al.*, 2002; Abzalov, 2016). In the case of sand excavation, the soil ρ_b can be calculated using the following formula (Abzalov, 2016):

$$\rho_b = M_s/[(M_s - M_{sw})/d_w] \quad (2)$$

where ρ_b is in g cm^{-3}, M_s is the weight of the soil sample after being air dried at 105 °C for about 24 h in g, M_{sw} is the weight of the sample in water in g, and d_w is the water density (1 g cm^{-3}).

Ali (2010) found that the main advantages of the excavation method were the ease of use and relative high accuracy. Recently, Vanguelova *et al.* (2016) showed that the excavation method took a greater amount of time to complete because it needed to fulfil certain requirements, such as filling an excavated area with water and polyurethane. They also found that error in the evaluation of soil volume was high when measuring soil ρ_b on sloped surfaces. McKenzie *et al.* (2002) argued that the correction applied for the volume of polyurethane used has a significant effect on the accuracy of the soil ρ_b value obtained. Furthermore, accuracy also increases with increasing size of excavation.

A recent study by Casanova *et al.* (2016) indicated that the precision of the excavation method is lowered by soil texture properties, the analysis process, and non-uniformity in the original samples. Similarly, Ma *et al.* (2013) demonstrated a method for measuring soil ρ_b that was dependent on volume replacement and compared this method to the conventional oven-drying

TABLE III

Calculation sheet for determining soil bulk density (ρ_b) using the clod method (Ali, 2010)

Sample number	Fresh weight of clod (C1)	Weight of beaker (C2)	Weight of beaker and dry clod (C3)	Weight of dry clod (C4) (C4 = C3 − C2)	Weight of coated clod (C5)	Weight of coated clod in water (C6)	Temperature of water (C7)	Weight loss in water (*i.e.*, weight of displaced water) (C8) (C8 = (C5 − C6)	Volume of clod (*i.e.*, volume of displaced water) (C9) (C9 = C8/d_w)[a]	Soil ρ_b value (C10) (C10 = C4/ C9)
	Mg						°C	Mg	m^3	Mg m^{-3}
1	40	20	45	25	29	13	26	16	16.3	1.53

[a] d_w = water density at the measured temperature.

method. The procedure for this measurement is dependent on calculating the volume of soil particles, water, and sand, and a major problem with the excavation method is that it is more time consuming and less convenient under field conditions compared with the volume replacement method. Furthermore, they concluded that the experimental procedure for the volume replacement method is more accurate, easy, and time efficient. Bauer *et al.* (2014) noted that excavation method has been widely applied to measure ρ_b of forest soils. However, they indicated that these methods suffer from some limitations, such as rehabilitation of soil surface after taking samples, deficient soil sample sizes, and problems with the measurement of stone-rich soils. Abzalov (2016) observed that there are several sources of error when using replacement methods to obtain soil ρ_b measurements. The main errors are the altered volume of polyurethane used and the calibration of the balance used because they strongly influence the accuracy of soil ρ_b values.

Indirect methods

Radiation method. Soil ρ_b can be determined indirectly by using radiation techniques (Smith, 2000). The main principle of the radiation method is that gamma-ray attenuation is used to measure soil ρ_b (Sowerby and Rogers, 2005) and moisture content (Ferronsky, 2015). The gamma-ray attenuation through soil is defined by Beer-Lambert's law (Smith, 2000; Lobsey and Viscarra Rossel, 2016) as follows:

$$\frac{l}{l_o} = \exp[-x(\mu_s \rho_b)] \tag{3}$$

where l is the detected photon count rate, l_0 is the radiation count rate of the source, x is the thickness of the soil sample in cm, μ_s is the coefficient of mass attenuation in cm^2 g^{-1}, and ρ_b is in g cm^{-3}. The theory behind this method assumes that radiation scattering and absorption are related with the soil chemical composition (Ün *et al.*, 2011). The gamma-ray transmission method can be utilized accurately for the study of soil physical properties. Using the radiation method, it is possible to identify soil ρ_b with high accuracy because the transmission of gamma radiation does not have profound consequences on the physical structure of the soil. Being a non-destructive method, this reduces time and labour in the characterisation of soil composition. However, the accuracy of the composition measurement decreases with soil depth (Alam *et al.*, 2001) because the attenuation coefficient is related to soil ρ_b (Smith, 2000).

Lobsey and Viscarra Rossel (2016) used μ_s and visible-near infrared spectroscopy for measuring soil ρ_b. They demonstrated that μ_s is a function of soil ρ_b, and its value is influenced by soil minerals and texture. Furthermore, soil ρ_b measurement by μ_s is fast and accurate: the process takes approximately 15 min and is verifiable under field conditions.

Moret-Fernández *et al.* (2016) used photogrammetry to measure soil ρ_b values at two locations with different tillage systems. Their results demonstrated that this technique had good performance in measuring soils containing rough stones. However, the procedures involved are difficult and require calibration. Segnini *et al.* (2014) investigated different measurement methods and compared estimates of ρ_b for soils of different textures using X-ray computerised tomography. They then compared these data to those obtained using the direct methods, core and clod sampling. Their results indicated that the accuracy of soil ρ_b values is influenced by beam hardening and polychromatics in X-ray microtomography.

The radiation method is the most readily available for measuring soil ρ_b and uses gamma backscatter density gauges and transmission gauges, as shown in Fig. 3a, b. Tominaga *et al.* (2002) stated that the backscatter gauge (BG) is one of the most widely used instruments, and it is used by civil engineers for measuring soil ρ_b below foundations and in road construction work. The BG method is dependent on photons being scattered within the soil. Figure 3c shows the mechanisms of a nuclear density gauge (gamma-ray gauge), including the gamma-ray source, detector, and shielding. This can prevent the diversion of transmitted photons, making BG a rapid, economical, easy, and accurate method for measuring soil ρ_b. Timm *et al.* (2005) measured and compared soil ρ_b values obtained by different methods in thin soil. They used the BG method to measure the ρ_b of a clay soil. They discovered that the BG method is non-destructive because the soil ρ_b measurement can be obtained without having to collect any soil samples. Consequently, there is no damage to the soil physical structure. It was also found that the time required to use BG was minimal although it is still dependent on operator experience, soil depth, and the test site. Soil ρ_b measurements can be taken using this method within a soil layer approximately 0–15 cm thick.

Khater and Ebaid (2008), Pires *et al.* (2009), and Beamish (2015) showed that the transmission density gauge (TDG) is an important tool for estimating soil ρ_b, which is dependent on gamma photons and chemical properties. Costa *et al.* (2014) found that ρ_b evaluation of sand and clay soils could be influenced

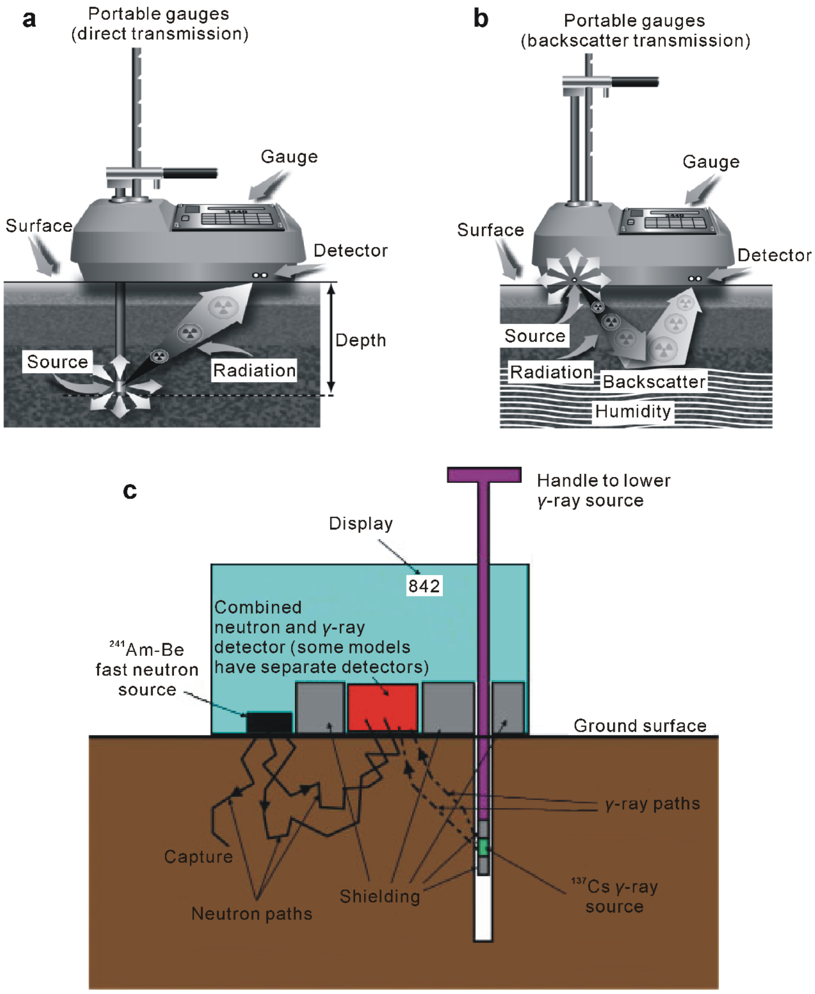

Fig. 3 Direct transmission (a) and backscatter (b) modes of nuclear gauges and a schematic diagram of the basic components of a nuclear gauge (c) (Cooper, 2016).

by the geometry of the TDG and the collimator size. Moreover, soil ρ_b measurements are also influenced by the absorbent thickness of the TDG, which is measured by ^{137}Cs and ^{241}Am gamma rays. Through this study, they demonstrated that the thicknesses of both soil types had a strong effect on the soil ρ_b measurements obtained from each source. The radiation method was shown to have many benefits in comparison to other methods. For example, it is non-destructive, which reduces time and labour requirements.

Ferronsky (2015) argued that the gamma rays used to measure soil ρ_b can also ascertain further information on soil properties, such as its mineralogical and chemical compositions, aggregate state, structure, and texture. Moreover, this study indicated that one of the advantages of using this method is that soil ρ_b measurements can be taken indirectly in the field with low labour costs. Additionally, gamma rays can estimate the ρ_b values of soil and rock materials of any consistency and soil type (*e.g.*, quicksand, water-saturated sand, and clay). Another study by Tominaga *et al.* (2002) determined soil ρ_b values and the moisture content of surface layers using a neutron gamma gauge. This study found that the radiation method is useful for obtaining information on the hydrological properties of field sites.

Beamish (2015) and Islam *et al.* (2015) reported that the nuclear gauge is a widely available tool for ρ_b measurement in wet soils, which is also easy and convenient to use. The aim of that study was to investigate the experimental and theoretical computation of wet soil density using a nuclear gauge. A positive correlation was established between experimental and theoretical estimates of soil ρ_b, and it was found that wet soil ρ_b values increased with soil depth when a nuclear gauge was used. In contrast, the radiation method had expansion limitations and was difficult to use under field conditions. Campbell (1994) found that high cost, complex methodology, and operator experience requirements seriously limited the utility of the radiation method. Furthermore, they reported that soil type and instrument calibration also had strong influences on the accuracy of measurements. This is because the requirements for measuring soil ρ_b can be broad and varied. To obtain better accuracy, this method should be replicated with a large number of soil samples and use a set sampling time period. In addition, Chen *et al.* (2016) found that the accuracy of nuclear gauge testing is strongly influenced by the calibration equation used, which depends on the engineering conditions, various requirements of the technique, and the soil physical properties. Beamish (2015) studied the relationship between the gamma-ray attenuation method and soil properties in England and found a nonlinear correlation between the mechanism of attenuation and soil ρ_b. Ün *et al.* (2011) investigated measurement of soil ρ_b values using the gamma-ray transmission method. Their study, conducted in Turkey, showed that the μ_s values increased with water concentration and decreased with gamma-ray energy. They reported that the gamma-ray transmission method for measuring soil ρ_b is practical, inexpensive, and fast.

Regression methods (PTFs). Use of regression methods, or PTFs, is a fundamental technique in modelling flow and can be used indirectly to estimate soil ρ_b according to the available data including those of soil organic carbon content, texture, structure, depth, and water content and field and climatic conditions (Al-Qinna and Jaber, 2013; Keesstra *et al.*, 2016; Yi *et al.*, 2016; Ghanbarian *et al.*, 2017). Teixeira *et al.* (2014) reported that soil organic carbon content negatively affects soil ρ_b and soil clay content is positively influenced by soil ρ_b because of the moisture content. Their study provided an equation and techniques for improving indirect evaluations of soil composition. When obtaining soil ρ_b estimates in the field, regression methods are time consuming (Martin *et al.*, 2009; Taalab *et al.*, 2013). Furthermore, Vasiliniuc and Patriche (2015) and Walter *et al.* (2016) found that field and climatic conditions have a strong influence on PTFs, and this could possibly result in substantial systematic errors. Both physical and experimental types of PTFs have been employed for estimating soil ρ_b (Beutler *et al.*, 2017). The PTFs are dependent on the mass transfer rate that is responsible for changes in the organic and mineral fractions of the soil.

The PTFs for calculating soil ρ_b have been improved by various techniques, such as multiple linear regression (Beutler *et al.*, 2017), artificial neural networks (Yi *et al.*, 2016), genetic programming, decision tree analysis, grouping methods of data handling, support vector machines, contrast pattern-aided regression, and heuristic gene expression programming. Estimates from these techniques have been compared with experimental measurements (Sequeira *et al.*, 2014). In contrast, experimental PTFs are influenced by soil organic matter, soil texture, field conditions, and the soil databases used (which contain information on sand content, silt content, temperature, rainfall, and elevation). They have been improved by many researchers in several regions, and can be utilised to estimate soil ρ_b according to soil organic matter (Hollis *et al.*, 2012). Table IV shows studies using different regression methods for the estimation of soil ρ_b.

Nanko *et al.* (2014) estimated the ρ_b values of forest soils in Japan employing the PTF method and used these data to improve both physical and experimental aspects of the PTF method. Their results demonstrated that soil organic matter, soil texture, and field conditions of forest significantly influence soil ρ_b estimates. They derived an equation for the climate conditions of forest soils in Japan as follows:

$$\rho_b = 100/[\mathrm{OM}/0.140 + (100 - \mathrm{OM})/1.152] \tag{4}$$

where ρ_b is in Mg m^{-3} and OM is the mass fraction of organic matter in Mg kg^{-3}.

Akpa *et al.* (2016) used multiple linear regression and the random forest model to estimate soil ρ_b at three depths using PTFs. They employed different information sets: soil information (PTF-1), environmental information (PTF-2), as well as the interaction between soil and environmental information (PTF-3) for improving PTF estimation. The results of their study indicate that PTF-3 significantly outperforms PTF-1 and PTF-2 in estimating soil ρ_b. Another important finding is that soil databases containing information such as sand, silt, temperature, rainfall, elevation, normalised difference vegetation index, and enhanced vegetation index are strong predictors of soil ρ_b. Akpa *et al.* (2016) applied equations for predicting soil ρ_b of PTF-1, PTF-2, and PTF-3 as follows:

$$\rho_b = 1.177 + 0.002\,63\mathrm{Sand} - 0.043\,9\mathrm{logSilt} + 0.002\,08\mathrm{Silt} \tag{5}$$

for PTF-1,

$$\rho_b = 0.903 + 0.002\,83 - 0.095\,8\mathrm{logEL} - 0.001\,84\mathrm{SPI} - 1.355\mathrm{NDVI} + 1.451\mathrm{EVI} - 0.025\,1\mathrm{logFLACC} + 0.008\,53\mathrm{TWI} - 0.000\,14\mathrm{Asp} \tag{6}$$

for PTF-2, and

TABLE IV

Studies using regression methods for estimation of soil bulk density

Study	Method(s)[a)]	Soil type(s)	Country or region	Other soil properties used[b)]
Jalabert *et al.* (2010)	GBM	Forest soils	France	OC and ST
Ghehi *et al.* (2012)	*k*-NN, BRT	Various soils	Rwanda	SPS (sand, silt, and clay), OC, pH, CEC, and SD
Al-Qinna and Jaber (2013)	SLR, NLR, SWR, PLS, ANNs	Various soils	Jordan	ST and OC
Yi *et al.* (2016)	MLR, ANNs	Alpine steppe soils and alpine desert soils	China	OC, ST, and SD
Nanko *et al.* (2014)	MLR	Forest soils	Japan	ST, SS, MC, Φ, SD, and OC
Botula *et al.* (2015)	MLR, *k*-NN	Various soils	Central Africa	SPS (sand, silt, and clay), OC, pH, CEC, DCB-Fe, and DCB-Al
Rodríguez-Lado *et al.* (2015)	MLR, RF, NNs	Acid soils	Spain	OC and ST
Akpa *et al.* (2016)	MLR, RFM	Various soils	Nigeria	SOC, pH, and SPS (sand, silt, and clay)
Xu *et al.* (2016)	MLR	Various soils	China	SOC, ST, and SD
Shiri *et al.* (2017)	GEP, NN, RF, SVM, BT	Various soils	Southwestern Iran	ST, OC, CEC, and pH
de Souza *et al.* (2016)	MLR, RF	Various soils	Southeastern Brazil	CEC, OC, pH, and ST
Martín *et al.* (2017)	MLR	Various soils	USA	ST, OC, and SD
Beutler *et al.* (2017)	MLR	Various soils	Brazil	ST and OC

[a)] GBM: generalised boosted regression modelling; *k*-NN: *k*-nearest neighbour; BRT: boosted regression tree; SLR: simple linear regression; NLR: multiple non-linear regression; SWR: stepwise multiple linear regression; PLS: partial least-squares; ANNs: artificial neural networks; MLR: multiple linear regression; RF: random forest; NNs: neural networks; RFM: random forest model; GEP: gene expression programming; SVM: support vector machine; BT: boosted regression trees.
[b)] OC: organic carbon content; ST: soil texture; SPS: soil particle size; CEC: cation exchange capacity; SD: sampling depth; SS: soil structure; MC: soil moisture content; Φ: soil porosity; DCB-Fe: dithionite-citrate bicarbonate-extractable Fe; DCB-Al: dithionite-citrate-bicarbonate-extractable Al.

$$\begin{aligned}\rho_b = {} & 1.440 + 0.000\,499\mathrm{Temp} + 0.002\,56\mathrm{Sand} - \\ & 0.071\,4\log\mathrm{SL} - 0.112\log\mathrm{EL} - 0.017\,4\log\mathrm{FLACC} - \\ & 0.000\,11\mathrm{Asp} - 1.331\mathrm{NDVI} + 1.429\mathrm{EVI} + \\ & 3.330\mathrm{ProfC} - 0.003\,31\mathrm{SPI} \end{aligned} \tag{7}$$

for PTF-3, where ρ_b is in Mg m^{-3}, Sand and Silt are the sand and silt contents in %, EL is the elevation, SPI is the stream power index, NDVI is the normalised difference vegetation index, EVI is the enhanced vegetation index, FLACC is the flow accumulation, TWI is the topographic wetness index, Asp is the aspect (°), Temp is the temperature (°C), SL is the slope gradient, and ProfC is the profile curvature.

Shiri *et al.* (2017) studied the possibility of extrapolating PTFs for soil ρ_b estimation from soil data using various techniques, such as heuristic gene expression programming (GEP), neural networks, support vector machines, boosted regression trees, and random forest techniques. Their study demonstrated that the heuristic GEP technique strongly outperforms the other techniques. Furthermore, GEP is more accurate than the other functional PTFs. Shiri *et al.* (2017) suggested that there is a relationship between soil ρ_b and various soil parameters such as soil components and carbon content. They derived a GEP-based model for predicting ρ_b of soils of southwestern Iran as follows:

$$\begin{aligned}\rho_b = {} & -0.247\mathrm{OCarctg}[\mathrm{Clay}/(\mathrm{CCE} + 7.002\,16)] + \\ & \mathrm{OCarctgpH}/(\mathrm{CCE} + 10.505) + 1.534\,33 \end{aligned} \tag{8}$$

where ρ_b is in g cm^{-3}, OC is the mass fraction of the soil organic carbon in %, Clay is the clay content in %, and CCE is the calcium carbonate equivalent in %.

Yi *et al.* (2016), among others, applied multiple linear regression (MLR) and artificial neural networks (ANNs) in using the PTF method (MLR-PTF and ANNs-PTF, respectively) to forecast ρ_b from data of soil texture, depth, and organic carbon content in the three-river headwater region of China. Their study presented a comprehensive outlook of the grouping strategies, and suggested that the type of statistical analysis used had strong effects on predictive performance of PTFs. Additionally, they suggested that the MLR-PTF and ANNs-PTF methods could be used to estimate soil ρ_b and the performance of ANNs-PTF was better than that of MLR-PTF, but was influenced by soil texture and depth. They showed that the accuracy of the PTFs in estimating soil ρ_b was dependent on soil depth, soil properties, and other environmental variables. Xu *et al.* (2016) used the PTF method to estimate soil ρ_b and examined the relationship between soil ρ_b and soil properties. Their results showed that the performance of PTF evaluation decreased with increasing soil depth. de Souza *et al.* (2016) reported an improvement in region-specific PTFs for estimating soil ρ_b from soil properties and environmental variables using MLR and random forest (RF) techniques. The performance of the PTFs was evaluated with data grouped according to soil conditions. Their findings showed that data concerning soil properties was more relevant than data concerning environmental variables for estimating soil ρ_b and the behaviour of PTFs was affected by soil variables and the type of techniques implemented. The PTF method with RF technique (RF-PTF), however, demonstrated perfect performance with environmental variables because it allowed direct prediction of location representation of soil ρ_b measurements. de Souza *et al.* (2016) derived an MLR-based model for predicting soil ρ_b in southeastern Brazil as follows:

$$\rho_b = 0.903\,932\,2 - 0.004\,401\,7\text{Clay} - 0.069\,520\,1\text{OC} + 0.124\,922\,8\text{pH} \tag{9}$$

where ρ_b is in Mg m^{-3} and Clay and OC are in g kg^{-1}.

Jalabert *et al.* (2010) used generalised boosted regression modelling to estimate forest soil ρ_b and found that variables for the scales of forest soil ρ_b were strongly influenced by soil organic carbon content and texture, tree species, and soil sampling depth. Ghehi *et al.* (2012) established k-nearest neighbour and boosted regression tree techniques for estimating the ρ_b of equatorial mountain soils in Rwanda. They found that soil organic content had a significant influence on soil ρ_b and the k-nearest neighbour and boosted regression tree methods depended on local information and did not measure soil ρ_b in equatorial forests as accurately as MLR models. Al-Qinna and Jaber (2013) improved and compared PTFs for predicting soil ρ_b in North Jordan using ANNs, linear regression, multiple nonlinear regression, and partial least-squares techniques. Their results indicated that ANNs were much more accurate than the other methods and showed that there were positive correlations between soil ρ_b and sand and organic carbon contents. These were found to have a significant influence on estimates of soil ρ_b using PTF techniques.

Botula *et al.* (2015) studied and developed the MLR-PTF technique in addition to a pattern-recognition approach (technique) k-nearest neighbour for ρ_b estimation of 196 soil samples from Central Africa. They utilised data of various soil properties to improve their techniques and found significant differences between the observed and predicted ρ_b values. This finding suggests that soil ρ_b is a difficult characteristic for PTF techniques to predict accurately because it is dependent on the agro-pedo-climatic conditions prevailing at the study site.

Rodríguez-Lado *et al.* (2015) compared MLR, RF, and ANNs for estimating soil ρ_b. They discovered that the accuracy of the RF technique was higher than that of the other techniques. Their results also showed that soil ρ_b at the study site was strongly affected by the organic content of the soil.

Martín *et al.* (2017) used MLR to predict soil ρ_b values using data such as soil texture, organic carbon content, and depth in Florida. They found that the soil texture and sampling depth had significant influences on soil ρ_b predictions. Abdelbaki (2016) reported that accurate and efficient PTF methods for estimating soil ρ_b were important when recording soil properties. They applied new PTF techniques for estimating soil ρ_b based on soil organic carbon content.

Beutler *et al.* (2017) evaluated two PTFs (PTF 1 and PTF 2) for estimating soil ρ_b from Brazilian soil data and compared their accuracy to nine other ρ_b PTFs. They found that PTF 1 and PTF 2 performed the best and observed that total organic carbon and clay content of a soil strongly influenced predicted ρ_b of the soil. They derived multiple linear stepwise regression models for predicting soil ρ_b:

$$\rho_b = [1.617\,9 - 0.018\,0(\text{Clay} + 1)^{0.46} - 0.039\,8\text{TOC}^{0.55}]^{1.33} \tag{10}$$

for PTF 1 and

$$\rho_b = (4.089\,9 - 2.397\,8\text{TOC}^{0.06})^{3.85} \tag{11}$$

for PTF 2, where ρ_b is in Mg m^{-3}, Clay is in g kg^{-1}, and TOC is the mass fraction of total organic carbon in g kg^{-3}.

Comparison of the methods for measuring soil bulk density based on criteria identified in this review

Numerous research articles have described a variety of methods for measuring soil ρ_b, which is a key physical property of soil. It is related to many of the soil chemical and biological properties and can be used as an indicator of soil thermal properties (Table I). Therefore, soil ρ_b significantly affects soil health and is influenced by several factors including soil porosity, mineral type, organic matter content, texture, structure, and moisture content. Furthermore, tillage management, soil compaction and crop growth are strongly influenced by soil ρ_b. This review focuses on methods utilised to estimate soil ρ_b, their potential sources of error, and factors that can influence soil ρ_b estimates.

The advantages and disadvantages of each method are discussed, and their key strengths and weaknesses examined. Selection of the most appropriate method is dependent on the measurement objectives and logistical constraints of a study, such as the time available, the required regulations, whether sample replicates are required, measurement expenses, operator experience, and equipment availability.

Depending on the measurements taken, time factors, accuracy requirements, soil type, cost, operator experience, and the apparatus required, the methods for measuring soil ρ_b classified into direct and indirect methods are compared as shown in Table V. Among direct methods, the core method is most commonly and widely used for soil ρ_b evaluation. Nevertheless, the core method is expensive, difficult, and time consuming to use at different soil depths because the spatial variability of soil requires that a large number of samples be taken to adequately represent a large area, sample collection is further complicated by extremely dry field conditions, and it is destructive as well (Chai and He, 2016). The diameter of the volumetric cylinder, the experience of the operator, and the soil depths sampled using the core method influence the accuracy of soil ρ_b measurements. The accuracy of soil ρ_b values is also dependent on soil moisture content, and therefore, the soil moisture should be measured at the time of sampling. The clod method is more appropriate for measurement of the ρ_b of heavy clay soils as it can estimate soil ρ_b at any depth. Nevertheless, it has been argued that sample collection strongly influences error in soil ρ_b estimates. Furthermore, the clod method is complicated. The excavation method is one of the most widely used approaches for estimating the ρ_b of forest soils. It can be used to measure ρ_b in high-stone content soils, for which the core and clod methods are unsuitable. However, the main limitations to this approach are that it cannot be used in soils containing large pores and its accuracy is influenced by soil texture, the analysis process, and calibration of the balance used to measure mass. This is because the volume of the soil sample is estimated by filling in the excavation with sand or water. In addition, studies (Ma *et al.*, 2013; Abzalov, 2016; Vanguelova *et al.*, 2016) have noted that there should be corrections made for the volume of polyurethane used because it strongly influences the accuracy of ρ_b values. It was also noted that the correlation between the water level and the diameter of the hole has a significant effect on the accuracy of soil ρ_b estimates. The time required to take these measurements is high because there are certain requirements, such as filling in the excavated areas with water and polyurethane, that take much time to complete (Vanguelova*et al.*, 2016).

Indirect methods include the radiation and regression methods. The radiation method is a field-based method that measures gamma radiation, which can be transmitted or scattered. The radiation method is rapid and provides results in approximately 15 min. Nevertheless, it suffers from some serious drawbacks, such as high cost and complexity, and it needs high operator experience as the requirements for measuring soil ρ_b can be broad and variable under field conditions. In addition, soil ρ_b measurement accuracy with this method decreases with soil depth (Campbell, 1994). Regression methods are economical, as they can make indirect measurements based on available property data, such as texture and pH; however, these depend heavily on good-quality data of soil texture and organic matter content and geographical and climatic properties. Like most of the other approaches, their accuracy also decreases with soil sampling depth (Casanova *et al.*, 2016).

CONCLUSIONS

Soil ρ_b is a fundamental property of soil that can be measured by two types of methods: direct and indirect methods. In agricultural experiments, direct methods have been more widely used over a longer period of time than indirect methods. The core method is one of the more practical ways of measuring soil ρ_b. However, it is difficult and time consuming to sample multiple soil depths. Measurement accuracy is dependent on the size of the volumetric cylinder used, the experience of the operator, and sampling depth. The core method may be prone to larger errors than other methods. The clod method has limited usefulness because it is expensive and difficult to conduct and its performance is dependent on the experience of the operator. The excavation method is also widely used to estimate the ρ_b of forest soils. However, its accuracy is strongly affected by soil texture. The radiation method has far greater accuracy and is, therefore, better suited to measuring soil ρ_b. However, it is costly, and its accuracy is dependent on operator experience and soil depth. A strong relationship between soil depth and the performance of the radiation method has been demonstrated. In addition, the regression method can

TABLE V

Comparison of direct and indirect methods used for measuring soil bulk density based on criteria identified in this review

Method	Criteria							Reference(s)
	Cost effectiveness	Accuracy	Spatial scale	Time	Experiment	Depth of measurement	Remarks	
Direct								
Core	About \$387, expensive because of increases in soil depth	Low because of sampling bias, errors in the volume of the sample, loss or gain of moisture content, or soil texture	Wide (typically used in agricultural soil)	$>$ 24 h, increasing with soil depth and drying time	Field	Any depth (measurement accuracy decreases with soil depth)	Practical with little or no stone content, compaction during sampling, destructive soil sampling at different depths	Bauer *et al.* (2014), Quraishi and Mouazen (2013), Walter *et al.* (2016), Wood *et al.* (2004)
Excavation	$<$ \$200, expensive because it requires additional effort	Low because of errors in soil volume and analysis processes	Limited (soil engineering)	$>$ 24 h, depending on soil depth and drying time	Field	Any depth (measurement becomes more time consuming and error prone with increasing soil depth)	Appropriate for flat surfaces, difficult on slopes or at depth, large-area destructive sampling	Bauer *et al.* (2014), McKenzie *et al.* (2002), Ma *et al.* (2013)
Clod	Not reported, considered expensive because it requires additional effort and much labour and soil samples should be replicated when sampling multiple soil depths	Low because the measurement accuracy is dependent on operator experience and calibration of equipment	Limited (suitable in clay soils with no compaction)	$>$ 48 h, depending on calculation processes and operator experience	Laboratory	Any depth (collecting clods is more difficult with increasing soil depth and may be more prone to disturbance)	Experience of operator, non-representative samples, high variability and experimental error, destructive sampling	Rossi *et al.* (2008)
Indirect								
Radiation	About \$1 122, expensive because the procedure is difficult and requires calibration, plus high cost of purchase	Moderate (this method does not have profound consequences on the physical structure of the soil and is non-destructive)	Wide (non-destructive and time and labour saving)	$<$ 15 min, depending on operator experience, soil depth, and test site	Field and laboratory	$<$ 30 cm (measurement accuracy decreases with increasing soil depth)	Operator experience, influenced by chemical properties and gravel, requiring moisture content measurement, more detail for soil, replication and maintenance	Chen *et al.* (2016), Lobsey and Viscarra Rossel (2016), Campbell (1994), Bretreger (2015), Islam *et al.* (2015), Chen *et al.* (2016), Walter *et al.* (2016)
Regression	Not reported, considered economical because it uses databases and statistical models	Low, depending on agro-pedo-climatic conditions prevailing at the study sites	Limited (statistical analysis applied and type of soil)	Short, depending on databases available	Laboratory	Any depth, depending on the quality of soil databases, which decrease with increasing soil depth	Local information, requiring more soil data from databases, such as organic matter, pH, texture, depth, and exchangeable cations	Casanova *et al.* (2016), Vasiliniuc and Patriche (2015)

be used to indirectly estimate soil ρ_b. It is economical, but its performance depends on the statistical analysis applied and the type of soil sampled. This method has limited spatial applicability. This systematic review of soil ρ_b measurement methods provides useful information to academic researchers in soil research. It highlights the key strengths and weaknesses of soil ρ_b measurement methods, such as their cost effectiveness, measurement accuracy, spatial scale, and time required for analysis.

ACKNOWLEDGEMENT

We would like to express sincere thanks to the Government and Ministry of Higher Education and Scientific Research, Iraq, for providing funding for this study as a scholarship for Ph.D. student for the first author Ahmed Abed Gatea Al-Shammary.

REFERENCES

Abdelbaki A M. 2016. Evaluation of pedotransfer functions for predicting soil bulk density for U.S. soils. *Ain Shams Eng J.* doi: 10.1016/j.asej.2016.12.002.

Abzalov M. 2016. Applied Mining Geology. Springer International Publishing, Cham.

Ahad T, Kanth T A, Nabi S. 2015. Soil bulk density as related to texture, organic matter content and porosity in Kandi soils of District Kupwara (Kashmir valley), India. *IJSR - Int J Sci Res.* **4**: 198–200.

Akpa S I C, Ugbaje S U, Bishop T F A, Odeh I O A. 2016. Enhancing pedotransfer functions with environmental data for estimating bulk density and effective cation exchange capacity in a data-sparse situation. *Soil Use Manage.* **32**: 644–658.

Al-Kaisi M M, Lal R, Olson K R, Lowery B. 2017. Soil Health and Intensification of Agroecosytems. Academic Press, Amsterdam.

Al-Qinna M I, Jaber S M. 2013. Predicting soil bulk density using advanced pedotransfer functions in an arid environment. *Trans ASABE.* **56**: 963–976.

Al-Shammary A A G, Al-Sadoon J N A. 2014. Influence of tillage depth, soil mulching systems and fertilizers on some thermal properties of silty clay soil. *Glob J Agric Res.* **2**: 18–32.

Al-Shammary A A G, Kouzani A, Kaynak A, Khoo S Y, Norton M. 2017. Experimental investigation of thermo-physical properties of soil using solarisation technology. *Am J Appl Sci.* **14**: 649–661.

Alam M N, Miah M M H, Chowdhury M I, Kamal M, Ghose S, Rahman R. 2001. Attenuation coefficients of soils and some building materials of Bangladesh in the energy range 276–1332 kev. *Appl Radiat Isotopes.* **54**: 973–976.

Ali H. 2010. Fundamentals of Irrigation and On-Farm Water Management. Springer Science & Business Media, New York.

Alrtimi A, Rouainia M, Haigh S. 2016. Thermal conductivity of a sandy soil. *Appl Therm Eng.* **106**: 551–560.

American Society for Testing and Materials (ASTM). 2015. D4531-15. Standard Test Methods for Bulk and Dry Density of Peat and Peat Products. ASTM International, West Conshohocken.

Anthony Bretreger E L I M. 2015. Field Density Testing by Using a Nuclear Density Gauge. Principal Engineer, Pavements and Geotechnical Engineering Services Branch, George Vorobieff. Transport Roads & Maritime Services, Sydney.

Arkhangel'skaya T A, Velichenko M V, Tikhonravova P I. 2016. Thermal properties of typical chernozems in Kursk Oblast. *Euras Soil Sci.* **49**: 1109–1116.

Bauer T, Strauss P, Murer E. 2014. A photogrammetric method for calculating soil bulk density. *J Plant Nutr Soil Sci.* **177**: 496–499.

Bayat H, Sheklabadi M, Moradhaseli M, Ebrahimi E. 2017. Effects of slope aspect, grazing, and sampling position on the soil penetration resistance curve. *Geoderma.* **303**: 150–164.

Beamish D. 2015. Relationships between gamma-ray attenuation and soils in SW England. *Geoderma.* **259–260**: 174–186.

Beutler S J, Pereira M G, Tassinari W D S, Menezes M D D, Valladares G S, dos Anjos L H C. 2017. Bulk density prediction for Histosols and soil horizons with high organic matter content. *Rev Bras Ciênc Solo.* **41**: e0160158.

Blázquez C S, Martín A F, Nieto I M, García P C, Pérez L S S, Aguilera D G. 2017. Thermal conductivity map of the Avila region (Spain) based on thermal conductivity measurements of different rock and soil samples. *Geothermics.* **65**: 60-71.

Botula Y-D, Nemes A, Van Ranst E, Mafuka P, De Pue J, Cornelis W M. 2015. Hierarchical pedotransfer functions to predict bulk density of highly weathered soils in Central Africa. *Soil Sci Soc Am J.* **79**: 476–486.

Brahim N, Bernoux M, Gallali T. 2012. Pedotransfer functions to estimate soil bulk density for Northern Africa: Tunisia case. *J Arid Environ.* **81**: 77–83.

Busse M D, Fiddler G O, Shestak C J. 2017. Conifer root proliferation after 20 years of soil compaction. *For Sci.* **63**: 147–150.

Cambi M, Hoshika Y, Mariotti B, Paoletti E, Picchio R, Venanzi R, Marchi E. 2017. Compaction by a forest machine affects soil quality and *Quercus robur* L. seedling performance in an experimental field. *Forest Ecol Manage.* **384**: 406–414.

Campbell D J. 1994. Determination and use of soil bulk density in relation to soil compaction. *Dev Agric Eng.* **11**: 113–139.

Casanova M, Tapia E, Seguel O, Salazar O. 2016. Direct measurement and prediction of bulk density on alluvial soils of central Chile. *Chilean J Agric Res.* **76**: 105–113.

Chai H, He N P. 2016. Evaluation of soil bulk density in Chinese terrestrial ecosystems for determination of soil carbon storage on a regional scale. *Acta Ecol Sin* (in Chinese). **36**: 3903–3910.

Chaudhari P R, Ahire D V, Ahire V D, Chkravarty M, Maity S. 2013. Soil bulk density as related to soil texture, organic matter content and available total nutrients of coimbatore soil. *Int J Sci Res Public.* **3**: 1–8.

Chen F L, He X, Wang L, Yin H M. 2016. Characterization and modeling of photon absorption for improved accuracy and consistency of density measurement using nuclear gauge with hydrogen effects. *Transport Infrastr Geotechnol.* **3**: 37–59.

Costa J C, Borges J A, Pires L F. 2014. Effect of collimator size and absorber thickness on soil bulk density evaluation by gamma-ray attenuation. *Radiat Phys Chem.* **95**: 333–335.

da Silva W M, Bianchini A, da Cunha C A. 2016. Modeling and correction of soil penetration resistance for variations in soil moisture and soil bulk density. *Engenh Agríc.* **36**: 449–459.

de Souza E, Fernandes Filho E I, Schaefer C E G R, Batjes N H, dos Santos G R, Pontes L M. 2016. Pedotransfer functions to estimate bulk density from soil properties and environmental covariates: Rio Doce basin. *Sci Agric.* **73**: 525–534.

Evett S R, Agam N, Kustas W P, Colaizzi P D, Schwartz R C. 2012. Soil profile method for soil thermal diffusivity, conductivity and heat flux: Comparison to soil heat flux plates. *Adv*

Water Resour. **50**: 41–54.

Ferreira T R, Borges J A R, Pires L F. 2015. Representative elementary area for soil bulk density measurements of samples collected in volumetric rings by CT image analyses. *Soil Till Res.* **152**: 74–84.

Ferronsky V I. 2015. Nuclear Geophysics: Applications in Hydrology, Hydrogeology, Engineering Geology, Agriculture and Environmental Science. Springer, Moscow.

Frisbie J A, Graham R C, Lee B D. 2014. A plaster cast method for determining soil bulk density. *Soil Sci.* **179**: 103–106.

Gao W D, Whalley W R, Tian Z C, Liu J, Ren T S. 2016. A simple model to predict soil penetrometer resistance as a function of density, drying and depth in the field. *Soil Till Res.* **155**: 190–198.

Ghanbarian B, Taslimitehrani V, Pachepsky Y A. 2017. Accuracy of sample dimension-dependent pedotransfer functions in estimation of soil saturated hydraulic conductivity. *Catena.* **149**: 374–380.

Ghehi N G, Nemes A, Verdoodt A, Van Ranst E, Cornelis W, Boeckx P. 2012. Nonparametric techniques for predicting soil bulk density of tropical rainforest topsoils in Rwanda. *Soil Sci Soc Am J.* **76**: 1172–1183.

Han D, Vahedifard F, Aanstoos J V. 2017. Investigating the correlation between radar backscatter and in situ soil property measurements. *Int J Appl Earth Observ Geoinform.* **57**: 136–144.

Han Y Z, Zhang J W, Mattson K G, Zhang W D, Weber T A. 2016. Sample sizes to control error estimates in determining soil bulk density in California forest soils. *Soil Sci Soc Am J.* **80**: 756–764.

Hollis J M, Hannam J, Bellamy P H. 2012. Empirically-derived pedotransfer functions for predicting bulk density in European soils. *Eur J Soil Sci.* **63**: 96–109.

Holmes K W, Wherrett A, Keating A, Murphy D V. 2011. Meeting bulk density sampling requirements efficiently to estimate soil carbon stocks. *Soil Res.* **49**: 680–695.

Hosseini M, Movahedi Naeini S A, Dehghani A A, Khaledian Y. 2016. Estimation of soil mechanical resistance parameter by using particle swarm optimization, genetic algorithm and multiple regression methods. *Soil Till Res.* **157**: 32–42.

Hu G J, Zhao L, Wu X D, Li R, Wu T H, Xie C W, Pang Q Q, Zou D F. 2017. Comparison of the thermal conductivity parameterizations for a freeze-thaw algorithm with a multi-layered soil in permafrost regions. *Catena.* **156**: 244–251.

International Organization for Standardization (ISO). 2017. ISO 11272-2017. Soil Quality—Determination of Dry Bulk Density. International Organization for Standardization, Geneva.

Islam M S, Sultana N, Ahmed A. 2015. Experimental and numerical investigations of the moisture content and wet density of soils. *J Civil Eng Res.* **5**: 1–9.

Jalabert S S M, Martin M P, Renaud J P, Boulonne L, Jolivet C, Montanarella L, Arrouays D. 2010. Estimating forest soil bulk density using boosted regression modelling. *Soil Use Manage.* **26**: 516–528.

Jia X X, Shao M A, Zhu Y J, Luo Y. 2017. Soil moisture decline due to afforestation across the Loess Plateau, China. *J Hydrol.* **546**: 113–122.

Keesstra S, Pereira P, Novara A, Brevik E C, Azorin-Molina C, Parras-Alcántara L, Jordán A, Cerdà A. 2016. Effects of soil management techniques on soil water erosion in apricot orchards. *Sci Total Environ.* **551-552**: 357–366.

Khater A E M, Ebaid Y Y. 2008. A simplified gamma-ray self-attenuation correction in bulk samples. *Appl Radiat Isotopes.* **66**: 407–413.

Lestariningsih I D, Hairiah K. 2013. Assessing soil compaction with two different methods of soil bulk density measurement in oil palm plantation soil. *Procedia Environ Sci.* **17**: 172–178.

Lin J, Sun Y, Lammers P S. 2014. Evaluating model-based relationship of cone index, soil water content and bulk density using dual-sensor penetrometer data. *Soil Till Res.* **138**: 9–16.

Liu X W, Feike T, Shao L W, Sun H Y, Chen S Y, Zhang X Y. 2016. Effects of different irrigation regimes on soil compaction in a winter wheat-summer maize cropping system in the North China Plain. *Catena.* **137**: 70–76.

Lobsey C R, Viscarra Rossel R A. 2016. Sensing of soil bulk density for more accurate carbon accounting. *Eur J Soil Sci.* **67**: 504–513.

Lu Y L, Liu X N, Zhang M, Heitman J, Horton R, Ren T S. 2017. Thermo-time domain reflectometry method: Advances in monitoring in situ soil bulk density. *Soil Sci Soc Am J.* doi: 10.2136/msa2015.0031.

Ma Y Y, Lei T W, Zhang X P, Chen Y X. 2013. Volume replacement method for direct measurement of soil moisture and bulk density. *Trans Chin Soc Agric Eng* (in Chinese). **29**: 86–93.

Mahdavi S M, Neyshabouri M R, Fujimaki H. 2016. Assessment of some soil thermal conductivity models via variations in temperature and bulk density at low moisture range. *Euras Soil Sci.* **49**: 915–925.

Martin M, Lo Seen D, Boulonne L, Jolivet C, Nair K M, Bourgeon G, Arrouays D. 2009. Optimizing pedotransfer functions for estimating soil bulk density using boosted regression trees. *Soil Sci Soc Am J.* **73**: 485–493.

Martín M Á, Reyes M, Taguas F J. 2017. Estimating soil bulk density with information metrics of soil texture. *Geoderma.* **287**: 66–70.

Masseroni D, Corbari C, Mancini M. 2014. Limitations and improvements of the energy balance closure with reference to experimental data measured over a maize field. *Atmósfera.* **27**: 335–352.

McKenzie N, Coughlan K, Cresswell H. 2002. Soil Physical Measurement and Interpretation for Land Evaluation. CSIRO Publishing, Collingwood.

Mohawesh O, Mahmoud M, Janssen M, Lennartz B. 2014. Effect of irrigation with olive mill wastewater on soil hydraulic and solute transport properties. *Int J Environ Sci Technol.* **11**: 927–934.

Moret-Fernández D, Latorre B, Peña C, González-Cebollada C, López M. 2016. Applicability of the photogrammetry technique to determine the volume and the bulk density of small soil aggregates. *Soil Res.* **54**: 354–359.

Naderi-Boldaji M, Keller T. 2016. Degree of soil compactness is highly correlated with the soil physical quality index *S. Soil Till Res.* **159**: 41–46.

Naghdi R, Solgi A, Labelle E R, Zenner E K. 2016. Influence of ground-based skidding on physical and chemical properties of forest soils and their effects on maple seedling growth. *Eur J For Res.* **135**: 949–962.

Nanko K, Ugawa S, Hashimoto S, Imaya A, Kobayashi M, Sakai H, Ishizuka S, Miura S, Tanaka N, Takahashi M, Kaneko S. 2014. A pedotransfer function for estimating bulk density of forest soil in Japan affected by volcanic ash. *Geoderma.* **213**: 36–45.

Pires L F, Rosa J A, Pereira A B, Arthur R C J, Bacchi O O S. 2009. Gamma-ray attenuation method as an efficient tool to investigate soil bulk density spatial variability. *Ann Nucl Energ.* **36**: 1734–1739.

Quraishi M Z, Mouazen A M. 2013. Development of a methodology for in situ assessment of topsoil dry bulk density. *Soil Till Res.* **126**: 229–237.

Rodríguez-Lado L, Rial M, Taboada T, Cortizas A M. 2015. A pedotransfer function to map soil bulk density from limited data. *Procedia Environ Sci.* **27**: 45–48.

Rossi A M, Hirmas D R, Graham R C, Sternberg P D. 2008. Bulk density determination by automated three-dimensional laser scanning. *Soil Sci Soc Am J.* **72**: 1591–1593.

Rudiyanto, Minasny B, Setiawan B I. 2016. Further results on comparison of methods for quantifying soil carbon in tropical peats. *Geoderma.* **269**: 108–111.

Russell E S, Liu H P, Gao Z M, Finn D, Lamb B. 2015. Impacts of soil heat flux calculation methods on the surface energy balance closure. *Agric For Meteor.* **214-215**: 189–200.

Segnini A, Vaz C M P, Posadas A, Guastal M D, Lasso P R O, Bernardi A C C, Milori D M B P. 2014. Comparative assessment of soil bulk density by computerized tomography methods for carbon stock quantification. *In* Oelbermann M (ed.) Sustainable Agroecosystems in Climate Change Mitigation. Wageningen Academic Publishers, Wageningen. pp. 237–248.

Sequeira C H, Wills S A, Seybold C A, West L T. 2014. Predicting soil bulk density for incomplete databases. *Geoderma.* **213**: 64–73.

Shete M, Rutten M, Schoneveld G C, Zewude E. 2016. Land-use changes by large-scale plantations and their effects on soil organic carbon, micronutrients and bulk density: Empirical evidence from Ethiopia. *Agric Hum Val.* **33**: 689–704.

Shiri J, Keshavarzi A, Kisi O, Karimi S, Iturraran-Viveros U. 2017. Modeling soil bulk density through a complete data scanning procedure: Heuristic alternatives. *J Hydrol.* **549**: 592–602.

Smith K A. 2000. Soil and Environmental Analysis: Physical Methods, Revised, and Expanded. CRC Press, New York.

Sowerby B D, Rogers C A. 2005. Gamma-ray density and thickness gauges using ultra-low activity radioisotope sourcesfillin. *Appl Radiat Isotopes.* **63**: 789–793.

Taalab K P, Corstanje R, Creamer R, Whelan M J. 2013. Modelling soil bulk density at the landscape scale and its contributions to C stock uncertainty. *Biogeosciences.* **10**: 4691–4704.

Teixeira W G, Ceddia M B, Ottoni M V, Donnagema G K. 2014. Application of Soil Physics in Environmental Analyses: Measuring, Modelling and Data Integration. Springer, London.

Timm L C, Pires L F, Reichardt K, Roveratti R, Oliveira J C M, Bacchi O O S. 2005. Soil bulk density evaluation by conventional and nuclear methods. *Soil Res.* **43**: 97–103.

Tominaga T T, Cássaro F A M, Bacchi O O S, Reichardt K, Oliveira J C M, Timm L C. 2002. Variability of soil water content and bulk density in a sugarcane field. *Soil Res.* **40**: 604–614.

Ün A, Demir D, Şahin Y. 2011. Determination of density and volumetric water content of soil at multiple photon energies. *Radiat Phys Chem.* **80**: 863–868.

Usowicz B, Lipiec J, Usowicz J B, Marczewski W. 2013. Effects of aggregate size on soil thermal conductivity: Comparison of measured and model-predicted data. *Int J Heat Mass Transfer.* **57**: 536–541.

Vanguelova E I, Bonifacio E, De Vos B, Hoosbeek M R, Berger T W, Vesterdal L, Armolaitis K, Celi L, Dinca L, Kjønaas O J, Pavlenda P, Pumpanen J, Püttsepp Ü, Reidy B, Simončič P, Tobin B, Zhiyanski M. 2016. Sources of errors and uncertainties in the assessment of forest soil carbon stocks at different scales—review and recommendations. *Environ Monit Assess.* **188**: 630.

Vasiliniuc I, Patriche C V. 2015. Validating soil bulk density pedotransfer functions using a Romanian dataset. *Carpath J Earth Environ Sci.* **10**: 225–236.

Vaz C M P, Manieri J M, de Maria I C, van Genuchten M T. 2013. Scaling the dependency of soil penetration resistance on water content and bulk density of different soils. *Soil Sci Soc Am J.* **77**: 1488–1495.

Walter K, Don A, Tiemeyer B, Freibauer A. 2016. Determining soil bulk density for carbon stock calculations: A systematic method comparison. *Soil Sci Soc Am J.* **80**: 579–591.

Wilson M G, Sasal M C, Caviglia O P. 2013. Critical bulk density for a Mollisol and a Vertisol using least limiting water range: Effect on early wheat growth. *Geoderma.* **192**: 354–361.

Wood M J, Douglas R A, Sands R. 2004. A comparison of three methods for measuring the density of a forest soil in New Zealand. *Int J Forest Eng.* **15**: 71–80.

Xu L, He N P, Yu G R. 2016. Methods of evaluating soil bulk density: Impact on estimating large scale soil organic carbon storage. *Catena.* **144**: 94–101.

Yang Q Y, Luo W Q, Jiang Z C, Li W J, Yuan D X. 2016. Improve the prediction of soil bulk density by cokriging with predicted soil water content as auxiliary variable. *J Soil Sediment.* **16**: 77–84.

Yi X S, Li G S, Yin Y Y. 2016. Pedotransfer functions for estimating soil bulk density: A case study in the three-river headwater region of Qinghai Province, China. *Pedosphere.* **26**: 362–373.

Zhang T, Cai G J, Liu S Y, Puppala A J. 2017. Investigation on thermal characteristics and prediction models of soils. *Int J Heat Mass Transfer.* **106**: 1074–1086.

Zolfaghari Z, Mosaddeghi M, Ayoubi S. 2016. Relationships of soil shrinkage parameters and indices with intrinsic soil properties and environmental variables in calcareous soils. *Geoderma.* **277**: 23–34.