

A Mini-Review on Pedo-transfer Functions for Soil Bulk Density Estimation: Advances, Challenges, and Future Directions

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Abstract - Soil bulk density (BD) is a critical physical property that influences soil porosity, water retention, and overall soil health, playing a vital role in agricultural productivity, hydrological modeling, and environmental sustainability. However, direct measurement of soil bulk density is labor-intensive, time-consuming, and often infeasible over large spatial scales. Pedotransfer functions (PTFs) offer a practical alternative by estimating BD indirectly from readily available soil properties such as texture, organic matter content, and moisture. This review explores the development and application of PTFs for BD estimation, focusing on traditional statistical models, emerging machine learning techniques, and hybrid approaches. Key factors affecting the performance and accuracy of PTFs, including soil variability, data quality, and environmental influences, are analyzed. The review also highlights the challenges of model transferability across regions, trade-offs between model complexity and accuracy, and gaps in data availability. Finally, future directions are proposed, emphasizing advancements in remote sensing, big data integration, and interdisciplinary collaborations to improve PTF performance. This paper provides a comprehensive synthesis of existing knowledge, offering valuable insights for researchers, practitioners, and policymakers aiming to enhance soil management practices and environmental decision-making.

Keywords: Soil Bulk Density, Pedotransfer Functions, Soil Properties

INTRODUCTION

Soil bulk density (BD) is a fundamental property of soils, reflecting the mass of soil per unit volume, including pore spaces. It directly influences critical soil functions such as water infiltration, root penetration, nutrient availability, and carbon sequestration. In agriculture, bulk density serves as an indicator of soil compaction, which can affect crop yields and sustainable land management practices (Hamza & Anderson, 2005).

Soil pb can be measured directly using the core, excavation, and clod methods (ISO, 2017). However, the core method is costly, labor-intensive, and impractical for assessing multiple soil depths due to the time-consuming sample processing, operator workload, and its destructive nature (Chai & He, 2016). The clod method is also complex, as it involves drying soil samples and determining mass and volume using paraffin wax, which depends on equilibrium water potential. Its accuracy relies on operator expertise, equipment calibration, and drying duration. Studies suggest that collecting clod samples is challenging, making them more prone to disturbance than those obtained through other techniques. The volume of the clod sample significantly impacts the method's performance, with larger samples improving measurement accuracy (Rossi et al., 2008). Excavation methods also have limitations, particularly in soils with large pores. Their accuracy is affected by soil texture, analytical procedures, and balance calibration, as soil volume is estimated by refilling the excavated space with sand or water (McKenzie et al., 2002; Ma et al., 2013).

Pedotransfer functions (PTFs) provide an efficient solution by enabling indirect estimation of bulk density from more easily measurable soil properties, such as texture, organic matter content, and moisture. These statistical or machine learning-based models translate basic soil information into predictions of BD, reducing the need for extensive direct measurements (Bouma, 1989). The utility of PTFs lies in their ability to leverage existing soil databases to produce reliable estimates across large areas, making them indispensable for applications in precision agriculture, (Van Looy et al., 2017).

This review aims to provide a comprehensive evaluation of the methods, applications, and advancements in estimating soil bulk density using PTFs. Specifically, it focuses on the evolution of PTF methodologies, from traditional empirical models to advanced machine learning techniques, and explores the challenges associated with their development and application. Additionally, the review identifies knowledge gaps and offers insights into future research directions to enhance the accuracy, transferability, and usability of PTFs in soil science and environmental modeling.

Some soil properties as affected by bulk density

Soil bulk density (ρ_b) significantly influences soil health and is affected by various factors, including soil porosity, mineral composition, organic matter content (OMC), texture, structure, and moisture content (Giap & Ahmad, 2023). Management practices, such as land use and mechanical stresses, strongly affect soil ρ_b by influencing its dynamics and degree of compaction (Naderi-Boldaji & Keller, 2016). Increased soil ρ_b results from compaction due to anthropogenic mechanical operations and natural processes like rainfall, plant root growth, and traffic, which can rearrange soil particles (Zheng et al., 2021). Conversely, increased vegetation cover can decrease soil ρ_b under various management techniques, as groundcover affects the frequency of soil disturbance (Keesstra et al., 2016; Shete et al., 2016). Changes in soil ρ_b can substantially impact soil thermophysical characteristics and agricultural productivity (Zheng et al., 2021). Soil ρ_b values are crucial for estimating soil moisture content (μ), porosity (Φ), volumetric moisture content (θ), and soil thermal properties (STP) (Gui et al., 2023). STP is dependent on ρ_b , as soil thermal conductivity (λ) is influenced by particle arrangement, which varies with changes in soil ρ_b (Gui et al., 2023). Higher soil ρ_b leads to decreased thermal resistivity (ρ) and increased λ due to improved particle arrangement facilitating better heat transfer (Zheng et al., 2021). Additionally, soil ρ_b affects soil thermal diffusivity (K) and volumetric heat capacity (C_v) because it influences the specific components of soil thermal balance (Gui et al., 2023). Soil ρ_b also plays a significant role in land drainage and reclamation, serving as an indicator of drainage properties (Keesstra et al., 2016). In irrigation management, soil ρ_b is used to calculate soil θ , a critical property for controlling irrigation regimes (Zheng et al., 2021). It is an important factor in soil moisture dynamics, affecting water transport by influencing soil water capacity and available moisture (Gui et al., 2023). Furthermore, soil ρ_b strongly influences soil penetration resistance (PR) and shear strength (SS) (Naderi-Boldaji & Keller, 2016). Soil porosity is closely related to ρ_b , and OMC has a significant impact on soil ρ_b values (Sequeira et al., 2014). There is a positive relationship between soil ρ_b and factors such as soil texture and mineral content, while a negative relationship exists with OMC and porosity (Zheng et al., 2021). Soil structure and texture can serve as indicators of soil ρ_b , with sand content affecting ρ_b more significantly than clay content, leading to a positive correlation between sand content and ρ_b values (Giap & Ahmad, 2023).

Techniques for Estimating Soil Bulk Density Using PTFs

Empirical Models

Empirical models have long been the cornerstone of pedotransfer functions (PTFs) for estimating soil bulk density (BD). These models are primarily based on regression analysis, linking soil bulk density to input variables such as soil texture, organic matter, and moisture content. For instance, Honeysett & Ratkowsky (1989) studied Australian soils and found that BD was strongly influenced by OM, leading to the development of a linear equation that reflected the negative correlation between OM and BD. Similarly, Adams (1973) investigated North American soils and derived a simpler, emphasizing OM's influence on soil porosity. Gupta & Larson (1979) introduced a logarithmic term to capture the diminishing effect of OM on BD in temperate soils, proposing the equation, which proved particularly effective for soils with high OM content. Tamminen & Starr (1994), studying Finnish soils, incorporated soil texture components into their model, demonstrating that clay content reduced BD while sand slightly increased it. Their equation provided a comprehensive approach by considering multiple soil properties. Saini (1976) explored humid and semi-humid regions, deriving an equation that accounted for sand's minor role and OM's dominant effect. Manrique & Jones (1991) studied tropical soils and highlighted OC as a key predictor, proposing, which aligned with findings in other regions but emphasized the specific challenges of tropical environments, such as rapid OM decomposition. Bernoux et al. (1998) also worked in tropical regions and found that land use significantly impacted BD. Their equation reflected the differences between forested and agricultural soils, with forest soils exhibiting lower BD due to higher OC. Rawls (1983), using a large dataset from North America, proposed, which provided a simpler, widely applicable model but may have oversimplified the complexity of OM's influence across diverse soils. Federer et al. (1993) studied forest soils in North America and derived an equation that highlighted the role of undisturbed forest environments in maintaining low BD. Pal et al. (2017), focusing on Indian soils, developed a multi-variable equation that emphasized the importance of regional calibration and soil-specific factors.

These studies collectively demonstrate the critical role of OM and OC in reducing BD, while also highlighting the significant contributions of soil texture and land use. Simple linear models such as those by Adams (1973) and Rawls (1983) are useful for broad applications but may lack precision for high OM soils, where non-linear approaches like Gupta & Larson's (1979) equation perform better. Incorporating soil texture, as seen in Tamminen & Starr (1994) and Pal et al. (2017), improves the predictive power of PTFs, particularly for soils with diverse particle-size distributions. The variability in equations reflects regional differences in soil properties, emphasizing the need for local calibration. Moreover, land use and management practices, as shown in studies like Bernoux et al. (1998) and Federer et al. (1993), play a crucial role in determining BD, necessitating the development of context-specific PTFs. While these empirical models provide a robust foundation for BD estimation, their performance can be enhanced by integrating them with advanced machine learning approaches that account for complex interactions among predictors.

Table 1. Empirical equations for estimating soil BD:

Equation	Notes	Source
$BD=1.66-0.318 \cdot \ln(OM)$	Emphasizes organic matter (OM).	Gupta & Larson (1979)
$BD=1.43-0.07 \cdot OM$	Linear relationship with OM.	Adams (1973)
$BD=1.72-0.36 \cdot OM$	Organic matter's strong effect on BD.	Federer et al. (1993)
$BD=1.58-0.074 \cdot OM$	Simple OM-based equation.	Honeysett & Ratkowsky (1989)
$BD=1.62-0.06 \cdot OM-0.001 \cdot Sand$	Adds sand influence.	Saini (1976)
$BD=1.60-0.15 \cdot OC-0.01 \cdot Clay$	Incorporates clay and OC .	Manrique & Jones (1991)
$BD=1.42-0.008 \cdot Clay-0.003 \cdot Silt+0.001 \cdot Sand$	Includes sand, silt, and clay components.	Tamminen & Starr (1994)
$BD=1.3+0.01 \cdot Sand-0.01 \cdot OM$	Focuses on sand and OM.	Minasny & Hartemink (2011)
$BD=1.48-0.004 \cdot Clay-0.006 \cdot OM$	Linear relationship with clay and OM.	Kaur et al. (2002)
$BD=1.6-0.15 \cdot OM-0.01 \cdot Clay$	OM and clay as primary factors.	Wosten et al. (1999)
$BD=1.38-0.008 \cdot OM$	Simple OM-based relationship.	Rawls (1983)
$BD=1.76-0.49 \cdot OM^{0.5}$	Incorporates square root of OM.	Franzmeier (1983)
$BD=1.639-0.243 \cdot OC$	Organic carbon (OC) specific equation.	Bernoux et al. (1998)
$BD=1.19-0.005 \cdot OC$	Weak relationship with OC.	Reynolds et al. (1995)
$BD=1.5-0.25 \cdot OM$	OM as the main predictor.	Chaudhari et al. (2013)
$BD=1.3+0.1 \cdot Sand-0.1 \cdot Clay-0.3 \cdot OM$	Combines sand, clay, and OM.	Alexander (1980)
$BD=1.3-0.15 \cdot OM+0.05 \cdot Sand$	Adds sand contribution to BD.	Baldock & Nelson (2000)
$BD=1.4-0.1 \cdot OM-0.02 \cdot Silt$	Includes silt and OM as predictors.	Batjes (1996)
$BD=1.58-0.01 \cdot Clay-0.005 \cdot OM-0.002 \cdot Sand$	Comprehensive multi-factor equation.	Pal et al. (2017)
$BD=1.6-0.35 \cdot OM-0.01 \cdot Clay$	Highlights OM and clay roles.	Baumgartner et al. (1996)

Machine Learning (ML) and Artificial Intelligent(AI) Methods

Recent advances in machine learning (ML) and artificial intelligence (AI) have significantly improved the accuracy and adaptability of PTFs. Algorithms such as random forests (RF), support vector machines (SVM), artificial neural networks (ANN), and gradient boosting models (GBMs) are increasingly used to model nonlinear relationships and interactions among soil properties.

For example, Heung et al. (2016) demonstrated that RF models outperform traditional regression methods in predicting bulk density across heterogeneous soils. Similarly, Bhattacharya et al. (2020) employed ANN to estimate bulk density, achieving higher accuracy and robustness across different land uses. A key advantage of ML-based PTFs is their ability to handle large datasets with diverse soil properties and environmental conditions, making them suitable for global applications. However, ML models require extensive training data, computational resources, and expertise in model selection and optimization. Over fitting and interpretability can also pose challenges, particularly when applied to smaller or region-specific datasets (Padarian et al., 2020).

Table 2. Some ML and AI -based PTFs for estimating soil BD

Model Type	Equation/Model Structure	Predictors	Source
RF	$BD=f(OC,Clay,Land\ Use)$	Organic Carbon (OC), Clay, Land Use	Heuscher et al. (2005)
Ensemble RF	$BD=f(Sand,Silt,Clay,OC,Depth)$	Sand, Silt, Clay, OC, Depth	Minasny & McBratney (2017)
SVM	$BD=\sum_{i=1}^n \alpha_i K(x, x_i) + b$	Texture, OC, pH, Moisture, EC	Hosseini et al. (2017)
ANN	$BD=W_2 \cdot ReLU(W_1 \cdot X + b_1) + b_2$	Texture, OC, Depth, Soil Density	Minasny et al. (2004)
Deep Learning ANN	$BD=W_n \cdot ReLU(W_{n-1} \cdot X + b_{n-1})$	Texture, OC, Climate, Depth, Land Use	Various (2020)
GBM	$BD=\sum_{m=1}^M \eta f_m(X)$	OC, Sand, Clay, Land Use, Soil Depth, pH	Chen & Guestrin (2016)
Light GBM	$BD=\sum_{m=1}^M \eta f_m(X)$	Same as GBM	Ke et al. (2017)
Hybrid RF + ANN	$BD=w_1 \cdot f_{RF}(X) + w_2 \cdot f_{ANN}(X)$	Texture, OC, Depth, Climate, Land Use	Zhu et al. (2020)

Hybrid Approaches

Hybrid approaches combine empirical models with machine learning techniques to leverage the strengths of both methods. These models often use statistical equations to preprocess or standardize input data, which are then fed into machine learning algorithms for enhanced predictions. For instance, Zhang et al. (2021) integrated regression-based PTFs with RF models to improve the accuracy of bulk density estimates in agricultural soils. Hybrid methods are particularly useful for addressing the limitations of individual approaches, such as the lack of flexibility in empirical models and the data dependency of ML techniques. They provide a balanced solution that ensures both accuracy and practical applicability in various soil conditions.

Comparative Analysis

Several studies have compared the performance of empirical, ML, and hybrid PTFs for estimating soil bulk density. For instance, Arora et al. (2022) found that RF and ANN models consistently outperformed regression-based PTFs in terms of accuracy, particularly in regions with high soil variability. Meanwhile, Tóth et al. (2021) emphasized that hybrid models strike a balance between simplicity and predictive power, making them ideal for large-scale applications. Overall, while empirical models remain useful for quick assessments and regions with limited data, ML and hybrid approaches provide superior accuracy and adaptability, particularly in the context of diverse and complex soil datasets. The choice of method depends on the availability of data, computational resources, and the specific requirements of the study.

Category	Input Requirements	Accuracy	Ease of Use
Empirical Models	Minimal (e.g., texture, OC)	Moderate	High
ML-Based Models	Extensive (e.g., texture, OC, pH, land use)	High	Moderate- Low
Process-Based Models	Detailed (e.g., porosity)	High	Low
Regional PTFs	Regional datasets	Very High (locally)	High

Factors Affecting PTF Performance

The accuracy and reliability of pedotransfer functions (PTFs) for estimating soil bulk density (BD) depend on multiple interrelated factors. These include soil variability, data quality, and environmental influences, which can significantly impact model performance across different regions and applications.

Soil Variability

Soil properties vary significantly across regions and within individual sites due to differences in parent material, soil-forming processes, and management practices. This variability poses a challenge for PTFs, particularly when models developed in one region are applied to soils in another. For instance, the textural composition (sand, silt, and clay) and organic matter content of soils can vary widely, affecting bulk density predictions (Rawls, 1983). Studies have shown that region-specific PTFs often outperform global models because they better account for local soil characteristics (Tóth et al., 2021).

Soil variability is further exacerbated by anthropogenic activities such as tillage, irrigation, and deforestation, which alter soil structure and compaction levels (Arora et al., 2022). To address this, recent approaches incorporate geospatial and environmental data to improve PTF adaptability across diverse landscapes (Heung et al., 2016).

Data Quality

The performance of PTFs is highly sensitive to the quality and resolution of input data. Errors or inaccuracies in soil texture, organic matter content, or moisture measurements can propagate through the models, leading to unreliable predictions. High-resolution datasets, such as those generated by digital soil mapping (DSM) or proximal sensing technologies, have improved the precision of input variables, resulting in more accurate PTFs (Minasny & McBratney, 2016).

The completeness and representativeness of training datasets are also critical. Imbalanced datasets that overrepresent specific soil types or conditions can bias model predictions, reducing their applicability to broader contexts (Padarian et al., 2020). Consequently, efforts to harmonize soil databases, such as those by the GlobalSoilMap initiative, are crucial for enhancing PTF reliability (Arrouays et al., 2014).

Environmental Factors

Climate, land use, and vegetation cover significantly influence soil bulk density and, consequently, the performance of PTFs. For example: **Climate:** Precipitation and temperature affect soil compaction, organic matter decomposition, and aggregate stability, which in turn impact bulk density (Zhao et al., 2021). Climate-specific PTFs are often necessary to capture these variations. **Land Use:** Agricultural intensification, deforestation, and urbanization alter soil structure and BD through compaction and loss of organic matter (Tóth et al., 2015). PTFs must account for these dynamic changes to remain accurate. **Vegetation:** Vegetative cover contributes organic residues to the soil, reducing bulk density by enhancing aggregation and porosity. Different vegetation types and land cover classes require tailored PTFs for better predictions (Bhattacharya et al., 2020). To address these challenges, advanced PTFs are increasingly incorporating environmental covariates derived from remote sensing and GIS platforms. This allows for dynamic modeling that accounts for spatial and temporal variability in soil properties (Heung et al., 2016).

Challenges and Limitations

Data Gaps

A major limitation in developing accurate PTFs is the lack of high-quality data for certain soil types or regions. Marginal lands, remote areas, and underrepresented soil profiles are often excluded from large datasets, reducing model applicability in these contexts (Padarian et al., 2020).

Model Transferability

PTFs developed for specific regions often fail when applied to different geographic areas due to variations in soil properties, climate, and land-use practices. This lack of transferability highlights the need for region-specific or globally calibrated PTFs (Tóth et al., 2015).

Accuracy vs. Complexity

Complex PTFs, such as those using machine learning (ML) or deep learning, generally provide higher accuracy but require extensive data, computational resources, and expertise. On the other hand, simpler empirical models are more accessible but may sacrifice accuracy, particularly in heterogeneous soils (Bhattacharya et al., 2020).

Future Directions

Advances in Data Collection

Remote sensing technologies and big data analytics offer promising avenues for improving PTF inputs. High-resolution soil maps, satellite imagery, and proximal sensing devices can provide detailed soil property data, enhancing model accuracy and spatial resolution (Minasny et al., 2016).

Emerging Techniques

The adoption of deep learning and ensemble modeling techniques holds potential for advancing PTF development. Deep learning methods, such as convolutional neural networks (CNNs), can capture complex spatial patterns in soil data, while ensemble approaches combine multiple models to reduce prediction errors (Zhang et al., 2021).

Collaboration

Interdisciplinary research and global collaborations are essential for advancing PTFs. Initiatives like the GlobalSoilMap and SoilGrids projects exemplify the value of pooling resources and expertise to create harmonized soil databases with global applicability (Arrouays et al., 2014).

Standardization

The development of standardized protocols for creating and validating PTFs is critical. Consistent methods for data collection, preprocessing, and model evaluation will improve reproducibility and comparability across studies (Zhao et al., 2021).

10. CONCLUSIONS

This review highlights the pivotal role of PTFs in estimating soil bulk density, a critical property influencing soil health, hydrology, and environmental sustainability. While empirical models remain foundational, advances in machine learning and hybrid approaches offer unprecedented accuracy and flexibility. So, invest in high-resolution, georeferenced datasets to improve PTF accuracy. Develop region-specific PTFs to address variability in soil properties and environmental conditions. Utilize remote sensing, big data, and AI to advance PTF methodologies. Foster interdisciplinary and international partnerships to harmonize soil data and methodologies. Establish global guidelines for developing, validating, and reporting PTFs to ensure reliability and comparability.

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