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Predicting soil properties in the tropics

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ABSTRACT

It is practically impossible to measure soil properties continuously at each location across the globe. Therefore, it is necessary to have robust systems that can predict soil properties at a given location. That is needed in many tropical countries where the dearth of soil property measurements is large. This paper reviews the use of pedotransfer functions (PTF) for predicting properties of soils in the tropics. First, the guiding principles of prediction and the type of predictors are discussed, including laboratory data, field description and soil morphology, electromagnetic spectrum, proximal and remote sensed data. In the subsequent section, PTFs are discussed for soil physical and chemical properties followed by infrared spectroscopy, proximal sensing and remote sensing. An analysis of ISRIC (mainly tropical) and USDA (mainly temperate) soil databases showed that soils in the tropics have higher clay content, lower cation exchange capacity, higher bulk density, lower water content at −10 kPa and −1500 kPa than soils in the temperate regions. Various methods developed in temperate regions can be applied for the soils in the tropical regions although calibration and careful selection of predictors remains necessary. It is concluded that PTFs are an important tool to overcome the dearth of soil data in many tropical countries.

Contents

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1. Introduction

Most soil properties are time-consuming and costly to measure, and also change over time. Fast and accurate prediction of soil properties is a necessary to overcome the lack of measured soil property information. In the past three decades, considerable progress has been made in such predictions following the development of geostatistics whereby predictions were made with calculated levels of accuracy and error. Following advances in a range of sensing techniques (aircraft, satellite, on-the-ground spectroscopy etc.), soil properties can now be accurately predicted with new tools and methodologies — like digital soil mapping (McBratney et al., 2003). This development is largely led and used by soil scientists in the developed world — fewer efforts are devoted to the soils in the tropics where there the need for accurate and up-to-date soil property information is even more urgent.

Soil forming factors in tropical areas are not different from areas in the temperate zone (Prescott and Pendleton, 1952), but the extent of particular soil forming factors is different. Many soils in the tropics have been formed from materials that have been reworked since the Precambrian by surface erosion and deposition (Sanchez and Buol, 1975). As a result, many of the soils are intensively weathered and although the areal extent of recent volcanic ash deposits is larger in tropical regions, there are a larger proportion of relatively younger soils in the temperate regions. We know far less about soils in the tropics than about soils in the temperate regions and this is mainly due to less research (Hartemink, 2002), and a shrinking soil research capacity (Bekunda, 2006). Yet it is in the tropical regions that the largest population growth occurs and that problems of food insecurity, soil degradation, climate change and water scarcity are greatest (Sanchez, 2000; Sanchez, 2002).

Until the 1980s there were active soil survey programmes in many tropical countries. (Eswaran et al., 1997; Nachtergaele and Van Ranst, 2003; Hartemink, 2008). Many of the soil chemical and physical analyses in these survey programmes were undertaken to characterise and classify the soils in the survey area. Data are available from composite samples and from soil pit descriptions. In addition, a considerable amount of soil information is available from soil fertility research of thousands of experimental plots. Both the soil survey and soil fertility data can be used to predict soil properties in areas where no data are available or can be used to predict for a given area, like for example bulk density from the soil organic carbon and clay content. Such predictions are highly relevant in light of the current efforts to digitally map the global soil resources (Sanchez et al., 2009). Some of these data are old and the soil properties may have changed (e.g. pH, organic carbon) but others are more stable and change little over time (e.g. clay content). It is, however, the best data that are available and obviously the uncertainty in the predictions will increase with older data, or when data are sparser.

Soil properties that are expensive to measure or unavailable can be predicted from other more easily measured properties using *pedotransfer functions*. The term pedotransfer functions (PTF) was first coined by Bouma (1989) and can be described as *translating data we have into what we need*. Pedotransfer functions allow basic soil information from surveys or geographic information system (GIS) data layers to be translated into other more laborious and expensively determined soil properties. They bridge the gap between available soil data and required data and information.

In digital soil mapping, the use of pedotransfer functions is to provide more useful information in terms of soil attributes, soil quality and soil function (Reuter, 1998). There are two approaches when using pedotransfer functions. In the first pedotransfer functions are used to estimate soil properties, e.g. available water capacity. The second approach take this prediction further, whereby the predicted soil properties are used as inputs into a simulation or decision-support model. Such models can be used to run scenarios on the effects of different agricultural management practises on the functioning of the soil.

Review on the development and the use of PTFs can be found in: Rawls et al. (1991), Wösten (1997), Wösten et al. (2001), and Pachepsky and Rawls (2004). Tomasella and Hodnett (2004) gave a review of pedotransfer functions in the tropics. Most of these reviews are limited to prediction of soil hydraulic properties. Monographs such as the *Soil Physical Measurement Handbook* in Australia (McKenzie et al., 2002) and *Methods of Soil Analysis* in the U.S. (Dane and Topp, 2002) include chapters on the use of pedotransfer functions to predict soil hydraulic properties.

In this paper, we review pedotransfer functions that have been used for soils of the tropics. The target audience of this review is primarily for users of soil information; however we also provide some guidelines for PTF developers. Here, we only discuss prediction of soil properties from other soil properties or sensors. We do not delve into prediction from terrain attributes or other environmental variables. The relationship between soil and environmental variables are more location dependent and less general. This is dealt with in the digital soil mapping (Hartemink et al., 2008).

We discuss the history of PTFs, the principles of prediction, the types of predictors, and some statistical approaches. Hereafter, we discuss the prediction of hydraulic properties, chemical properties and some other physical and soil mechanical properties.

2. A brief history of pedotransfer functions in the tropics

The concept of the pedotransfer function has long been applied to estimate soil properties that are difficult to determine and in the earliest stage, various ‘rules of thumb’ were used. De Leenheer and Van Ruymbeke (1960) at the 7th International Congress of Soil Science in Madison, Wisconsin asked the question: Is it possible to predict some physical soil characteristics, knowing the soil components? This proved usefulness in water management but most soil physical measurements are difficult, time-consuming and costly. The most comprehensive research in developing PTFs has been for the estimation of water retention, in particular correlating sand, and clay content with water content at field capacity and wilting point, and available water content.

One of the first studies was by Stirk (1957) working in tropical North Queensland, Australia. Permanent wilting point (PWP) was estimated for soils with clay contents up to 60%, as follows:

$$\mathrm{PWP} = 2/5\ \mathrm{clay}.$$

The USDA Soil survey staff (1975) provided a PTF to estimate gravimetric water content at wilting point or −1500 kPa (w_{-1500}) for Oxic horizons:

$$w_{-1500} = 0.4 * \mathrm{clay}$$

In 1990, it was revised as: $w_{-1500} = 1/3$ clay and in 1992 as: $w_{-1500} = 1/3$ clay + c, with c as a constant. FAO (1974) has developed a PTF for ferralitic horizons: $w_{-1500} = 0.23$ clay + 10.

Since the 1970s PTFs functions have been used to predict soils in the tropics although the number of studies is limited compared with areas in the temperate region (Table 1). Researchers in 1970s to 1980s working in Africa developed various PTFs predicting field capacity, wilting point, and available water capacity from particle size distribution and organic matter content (MacLean and Yager, 1972; Pidgeon, 1972; Aina and Periaswamy, 1985). Lal (1979) provided an overview on PTFs for predicting field capacity and wilting point from soils in various tropical countries. In his overview, all PTFs use clay, sand, silt, and organic matter content as predictors. These studies were mostly conducted with a relatively small number of samples and care must be taken when using such functions in other environments.

With the development of models for hydraulic properties (van Genuchten, 1980) and computer modelling of soil-water and solute transport, there was a need for hydraulic properties as an input to these models. Van den Berg et al. (1997) and Tomasella et al. (2000) developed PTFs to predict parameters of the van Genuchten water retention equation for soils in Brazil. Suprayogo et al. (2003) developed a Pedotransfer Resource Database (PtfRDB) which contains input parameters to estimate soil properties for water balance calculations. The database is a summary of 8915 data (from various horizons) from tropical soils. Water retention curve were derived for different USDA soil orders and land-use. Young et al. (1999) showed that PTFs developed in the USA and Europe do not reliably predict the hydraulic properties of the soils in Tanzania. Tomasella and Hodnett (2004) summarised various PTFs predicting water retention developed for tropical soils.

Highly weathered soils in the tropics may have high phosphorus sorption, especially soils containing high amount of Fe- and Al oxides, and various PTFs were developed to predict P sorption and fixation (Le Mare, 1981). The main predictors for P sorption are clay content, organic C, and oxalate-extractable iron.

3. The principles of prediction

3.1. For the user and the developer

Many pedotransfer functions have been developed over the past few decades and here we define the four principles for developing and using PTFs. The first three principles are for the developer of PTFs, the fourth principle is for the user.

3.1.1. Do not predict something that is easier to measure than the predictor

Since the objective of pedotransfer functions is to predict properties that are difficult or expensive to measure, the predictor should be measured more easily or cheaper. In other words, the cost and effort to obtain the information on the predictor should be much less than that to obtain information on the predicted. This implies that the quality of information out of a PTF should be higher (or the information should be more useful) than the predictor. This principle extends to the use of existing data to predict values that are missing.

Table 1
Predicted properties and their predictors used in soils of the tropics.

Predicted properties	Soil type	Countries	Predictors	References
Water retention curve (van Genuchten parameters)	Oxisols	Global	Clay, silt, sand, OC, CEC, Al_{dith}, and Fe_{dith}	Van den Berg et al. (1997) and
Water retention curve (θ at −6, −10, −33, −100, and −1500 kPa)	Various	Brazil	Coarse sand, fine sand, silt, clay, BD, and moisture equivalent	Tomasella et al. (2003)
Water retention curve (van Genuchten parameters)	Various	Global	Sand, silt, clay, CEC, OC, BD, and pH	Hodnett and Tomasella (2002)
Available water capacity (θ-33–q-1500 kPa)	Ultisols, Alfisols	Nigeria	Sand, silt, clay, and BD	Aina and Periaswamy (1985)
w at −10, −33 and −1500 kPa	Ferralitic soils	Uganda	Sand, silt, clay, and OC	Pidgeon (1972)
θ at −33 and −1500 kPa	Crushed samples, low activity clay(LAC) and non LAC soils	Southern part of Niger and in the north-east Brazil	OC, clay, and silt	Gaiser et al. (2000)
Infiltration rate	Fluvents, Vertisols	Papua New Guinea	BD	Hartemink (1998)
Infiltrability	Various	Namibia and western South Africa	Water-dispersible silt, water-dispersible clay, very fine sand, and medium sand	Mills et al. (2006)
Saturated hydraulic conductivity	Ultisols, Inceptisols, Alfisols, Oxisols	Volta basin of Ghana	Digital terrain attributes, clay, silt, CEC, OC, and BD	Agyare et al. (2007)
Saturated hydraulic conductivity	Various	Brazil	Effective porosity (porosity − θ at −10 kPa)	Tomasella and Hodnett (1997)
Unsaturated hydraulic conductivity	Various	Brazil	Water retention curve	Tomasella and Hodnett (1997)
Bulk density	Various	Rio de Janeiro, Brazil	Organic C, clay content, sum of cations	Benites et al. (2007)
Reference bulk density (proctor density, −800 kPa)	Various	Subtropical Brazil	Clay and silt	Reichert et al. (2008)
Soil penetration resistance	Oxisols	Brazil	Organic C, clay content, and bulk density	Da Silva et al. (2008)
Volumetric shrinkage, liquid limit, plastic limit	Ultisols, Vertisols, Inceptisols, Entisols, Alfisols	Nigeria	OC, clay, and CEC	Mbagwu and Abeh (1998)
Cation exchange capacity	Ustalf, Tropofluvent, Pellustert	Mexico	Clay, pH, and OC	Bell and van Keulen (1995)
P adsorption	Ultisol, Alfisol, Inceptisol, Entisol & Mollisol	Nigeria	Fe_{ox}, OC	Le Mare (1981)
P adsorption	Red Oxisols and red Ultisols	Thailand	pH in NaF	Trakoonyingcharoen et al. (2005)
P adsorption capacity	Alfisols, Entisols, Inceptisols, Oxisols, Spodosols, and Ultisols	Denmark, Ghana, and Tanzania	Al_{ox}, Fe_{ox}, and Fe_d	Borggaard et al. (2004)
Residual P	Oxisols, Ultisols	Brazil	pH in NaF	Alves and Lavorenti (2006)
Organic C	Oxisols	Brazilian Cerrado	depth, clay + silt	Zinn et al. (2005)
pH buffering capacity	Complex association	Semi-arid tropics of central and northern Queensland and the Northern Territory, Australia.	Silt and clay content, organic carbon content	Noble et al. (1997)

Although this principle seems obvious, there are various PTFs that are not efficient, e.g. estimating particle-size fractions of soil from its geochemical concentration (Rawlins et al., 2009).

3.1.2. When predicting a variable, there should be a physical basis for the predictors

Developing pedotransfer functions should is not a statistical exercise. The developer should understand soils, and use this knowledge to select logical predictors. For example, there are studies that suggest that soil physical properties based on soil structure and pore–space relationships such as bulk density, volumetric water retention (Janik et al., 2007) and saturated hydraulic conductivity (Cohen et al., 2007) can be predicted by mid-infrared spectroscopy (MIR). The samples used in the MIR analysis are ground-up samples and there is no physical base why pore–space relationships can be predicted from infrared spectroscopy. Such correlative studies should be avoided.

3.1.3. Developer should explicitly list the statistics of their training variables

The developers should provide information that describes where their PTFs come from, which training domain, the statistics, and the accuracy of the function. This information or PTF meta-data is essential for PTF users and can help them deciding whether the PTFs is suitable for their own data (McBratney et al., 2011).

3.1.4. Do not use PTFs unless you can evaluate the uncertainty, and for a given problem, if a set of alternative PTFs is available, use the function with the lowest variance

The fourth principle is for the user of PTFs, which means that the uncertainty of PTFs should be quantified by the PTF developer. Many PTFs have been developed to predict the same or similar soil properties. For example, in Brazil at least 20 functions are available for the prediction of field capacity and wilting point, while worldwide there are more than 200 functions for these properties. Therefore, it is advisable to choose the function that has the smallest error variance or fit within the soil type where for it was calibrated. This is particularly important for soils with distinct properties like strongly aggregated Ferralsols or soils with andic properties. Tranter et al. (2009) devised a protocol that allows users to determine the similarity between a PTFs calibration data and a subject of interest. The protocol uses Mahalanobis distances, to determine the distance from the mean of the calibration data and the subject. Distances exceeding a designated cut-off limit are deemed distinct from the calibration data and as such unsuitable for the application of the function. This is useful for determining if a published PTF is applicable for a particular data set.

4. Predictors

For the developer

There are several sources of information that can be used to predict soil properties. Potential predictors can come from a soil analytical laboratory, field description and soil morphology, or the soil electromagnetic spectrum.

4.1. Laboratory data

Laboratory analysis in soil survey is usually conducted for classifying soils and for characterising soil mapping units. The high costs of laboratory analysis stimulates the development of empirical relationship relating more easily or routinely measured properties to other properties that are more useful. The development in pedotransfer functions is boosted by the availability of large soil databases, which allows the use of data mining tools. Except for coarse scale soil and terrain databases like SOTER, there are few databases on soil properties in tropical regions. For example, the WISE database contains only 4500 geo-referenced soil profiles for the whole of Sub-Sahara Africa (Batjes, 1996; Batjes, 2008).

4.2. Field description and soil morphology

Soil colour is an indicator of organic matter, drainage conditions, mineralogy and iron content and often described in the field using the Munsell colour notation (Soil Survey Staff, 1951). Gobin et al. (2000) working in south-eastern Nigeria demonstrated that colour indices correlated well with organic carbon content and dithionite-extracted Fe_2O_3 and Al_2O_3. Ketterings and Bigham (2000) observed the changes in soil colour in Sumatra after field burning. Munsell values and chromas decreased and hues became yellower with increasing heat severity, suggesting that post-burn soil colour patterns can be used to indicate fire severity. The colour of soils can also be used as indicators of the duration of soil waterlogging as was found by Blavet et al. (2000) in central Togo.

Soil morphological descriptions can be used as predictors and there are various examples from the temperate regions (O'Neal, 1949, 1952; McKeague et al., 1982; McKenzie and MacLeod, 1989; McKenzie and Jacquier, 1997). The amount of visible macropores, shape and size of the soil structure affects the infiltration capacity or water permeability. These morphological descriptions are important because as some soil survey reports in tropical countries contain limited detailed soil physical or chemical data. Calhoun et al. (2001) stated that soil morphology and field description have been under utilised in the development of pedotransfer functions. They presented the representation of Jenny's state factors for predicting bulk density, and demonstrated that morphology and field descriptors account for more variability in predicting bulk density than laboratory measurement of particle size and soil organic C. The usefulness of physiographic description and soil morphological characterisation was illustrated by Rawls and Pachepsky (2002). They successfully used slope gradient, position of the slope and horizon classes collected from soil survey data to predict soil water retention.

McKenzie and Jacquier (1997) reasoned that good predictive relationships should only be expected when the field criteria used have a logical physical connection with hydraulic properties. They demonstrated the value of measuring the visible channel morphology along with data on texture and structure to derive useful predictions of the saturated hydraulic conductivity. From these studies, it can be concluded that additional morphological descriptors to those routinely surveyed are needed to improve the predictive capacity of several soil properties.

4.3. Infrared spectroscopy

In traditional soil surveys, soil scientists used the visible light spectrum through the Munsell soil colour chart to determine soil colour and the presence of pedological features like mottles. Observational techniques have become available like infrared diffuse reflectance spectroscopy that is based on the fact that molecules have specific frequencies at which they rotate or vibrate corresponding to discrete energy levels. Absorption spectra of compounds are a unique reflection of their molecular structure. Infrared spectroscopy in both the visible-near (Vis-NIR, 400–700–2500 nm) and mid infrared (MIR, 2500–25,000 nm) ranges allows rapid acquisition of soil data. Spectral signatures of soil materials are characterised by their reflectance to a particular wavelength in the electromagnetic spectrum. Several soil properties related to the surface area of the soil can be predicted from NIR and MIR spectroscopy.

As soil is a three-phase mixture of inorganic and organic materials it is difficult to assign specific features of the spectra to specific chemical components. Multivariate calibration techniques are often employed to predict soil properties. Soil spectra usually contain hundreds or thousands of reflectance values as a function of wavelength. Since there are typically more predictor variables than the observation and predicted variables, methods that reduce the dimension of the predictors are required. Principal component regression and partial least squares (PLS) method are commonly utilised (Martens and Naes, 1989; Chang et al., 2001). Partial Least Squares extracts successive linear combinations of the predictors, which optimally address the combined goals of explaining response variation and explaining predictor variation. As a result, PLS balances the two objectives of explaining response variation and explaining predictor variation.

Shepherd and Walsh (2002) used near infrared diffuse reflectance spectroscopy (NIRS) on over 1000 archived topsoils from Eastern and Southern Africa. Soil properties were correlated to soil reflectance showing good predictions for effective cation-exchange capacity (ECEC), organic carbon content, and clay content. Awiti et al. (2008) used NIRS as a tool to assess soil fertility status along a topo-sequence in Kenya. Dematte et al. (2006) demonstrated the use of NIR spectroscopy for identifying major soil mineralogy in tropical Brazil. Viscarra Rossel et al. (2006) showed that NIR can predict with good results total C, total N, and clay content.

NIR spectrometers are being developed for use in the field on soil samples, soil profile wall and soil cores. With proper calibration using PTFs, field estimates of many soil properties will be improved and estimates of other soil properties (e.g. CEC, organic C) can be made in the field.

Mid-infrared (MIR) spectroscopy usually produces better predictions than NIR and vis-NIR. MIR is shown to accurately predict soil organic C, total C, total N, CEC, carbonate, pH, clay and sand content. Chemical properties that are related to the mineral and organic components can be predicted because of the interaction between the soil properties and the active soil components: organic matter, clay minerals, and oxides. Soil physical properties based on the soil solid composition and surface area, clay content and shrink–swell potential can be well predicted. As mentioned, soil properties that are based on pore–space relationships such as bulk density, water retention and hydraulic conductivity cannot be predicted using infrared spectroscopy. Moreira et al. (2009) suggested that NIR spectroscopy can be used to predict soil bulk density based on a study in a reforestation area in the Brazilian Amazon basin. However, their result showed that the PLS model using NIR spectra was able to weakly predict bulk density ($R^2 = 0.14$); this result is slightly better than published PTFs which used organic carbon, sand and clay as predictor. There is no physical basis of NIR spectroscopy that can predict the density of soils other than indirect correlation with organic carbon content and particle-size distribution.

4.4. Proximal sensing

The development of spectroscopy is related to the deployment of on-the-go (real-time) proximal soil sensing systems and scanners. These sensing systems overcome some of the high cost, labour, time, and imprecision of traditional soil sampling. It results in more efficient and accurate representation of the spatial variability of a specific soil property.

Electromagnetic induction and soil resistivity instruments attached to a vehicle provides rapid and spatially referenced soil electrical conductivity. The conductivity reflects a combination of soil mineralogy, salts, moisture and texture, and is a compound measure of soil properties. Such proximal sensing offers the possibility of producing high resolution maps of soil properties. In the absence of high salt concentration, electrical conductivity measurements often reflect the soil clay and moisture content. Regression equations have been developed to predict moisture content, topsoil thickness and clay content but the values of electrical conductivity reading is a combination of these properties and little research has been done to unravel their interactions. Slavich et al. (2006) used an EM-38 (electromagnetic induction) instrument for identifying the risk of soil salinity in tsunami-affected areas in Aceh, Indonesia. This allowed in-situ assessment of soil salinity risk and gives an indication of the extent of salt leaching.

Overall, there is limited use of on-the-go electrical conductivity measurement or other proximal sensors for mapping soil properties in tropical regions.

4.5. Remote sensing

The value of remote sensing over proximal sensing is that large spatial extents can be covered and many soil properties can be estimated. The inferred value of remotely sensed data – either airborne or satellite – are efficient for assessing soil conditions at a reasonably broad scale (larger than a field scale). The remotely sensed data can include spectral, radar, thermal and radiometric signals. These data reflects the environmental condition and are linked with soil properties. Ben-Dor (2002) gave a review on the application of remote sensing in quantitative assessment of soil properties. Dematte et al. (2007) showed the use of Landsat data for characterization of soil physical and chemical properties in Brazil. They found a good relationship between the spectral data from LandSat with sand, clay, organic matter and CEC.

5. Pedotransfer functions in the tropics

5.1. Predicting soil physical properties

There are differences in physical properties of soils in the tropics as compared with soils from temperate regions. Hodnett and Tomasella (2002) showed that soils in tropical regions can have a kaolinite clay content between 60 and 90%. When compared to soils in temperate regions, they have on average lower bulk density, higher hydraulic conductivity, higher water content at field capacity and wilting point, and consequently: lower available water capacity. This is summarised in Fig. 1, where the distribution of soil properties from the tropics (from ISRIC databases) is compared with soils from the USDA databases that are mostly from soils in the temperate regions.

Van den Berg et al. (1997) and mentioned that Ferralsols have well developed and stable sand-sized and silt-sized micro-aggregates, and as result their water retention at low suction resembles sandy soils, i.e. much water is released below 30 kPa. However, at higher suction (>100 kPa) the rate of moisture release decreases rapidly, even though appreciable amounts of moisture may still be present in the pores within the micro aggregates, and therefore not available to crops.

Gaiser et al. (2000) using data from semi-arid tropical region in NE Brazil and SE Niger compared water content at −33 kPa and −1500 kPa using disturbed samples from soils containing predominantly low activity clay (LAC: CEC<24 cmol/kg clay) and non-LAC soils. It was found that in soils with sand, loamy sand, sandy loam, and sandy clay loam textures, the soil water contents at −33 kPa were significantly smaller in LAC soils than in non-LAC soils. There was no significant difference in water content at −1500 kPa for LAC and non-LAC soils. The study used disturbed samples which contradicts the findings of Hodnett and Tomasella (2002).

A common problem encountered using soil databases from tropical countries is that water content at −10 or −33 kPa was measured on disturbed samples (Bell and van Keulen, 1996). This is because the samples collected during the soil survey were mainly for mapping and classification purposes, and usually bulk density and soil clods were not collected. Bell and van Keulen (1996) mentioned that field capacity data derived from disturbed samples should be used with caution. Field capacity data from disturbed soil samples overestimates in-situ field capacity for all soils except for coarser textured soil. Pidgeon (1972) derived a formula to predict in-situ water content at field capacity from disturbed Ferralitic soil samples from Uganda.

De Condappa et al. (2008) found that many subsoils in tropical and subtropical regions have a bi-modal particle-size distribution, that is: a textural triangle with a low silt fraction compared to the fractions of sand and clay. Such soils have a particle-size distribution function showing two maxima in weight percentage for the particle-size ranges of sand and clay. As a result hydraulic properties are different from mono-modal soils commonly found in temperate countries. It could imply that bi-modally textured soils may have hydraulic properties that are also bi-modally distributed.

To our knowledge this possible difference is not observed and reported for tropical soils in the literature, perhaps due to the scale and the accuracy of soil physical measurements. Using the tropical soil data from the ISRIC databases (excluding organic soils and Andosols) it can be observed that the PTF predicting PWP between tropical and temperate soils is similar (Fig. 2). The black dotted curve is the PTF based on soils in the UK (Hall et al., 1977) whereas the line curve is fitted through the data. Although the clay content is much higher for tropical soils, the relationship is similar.

Manyame et al. (2007) found that Campbell's PTFs for water retention and hydraulic conductivity function can be applied for sandy soils in Niger. However, Medina et al. (2002) showed that water retention PTFs developed in the USA and for soils in Europe cannot be used for Ferralsols in Cuba. It was found that PTFs developed in Brazil by Tomasella et al. (2000) showed better predictions.

Sobieraj et al. (2001) working in La Cuenca catchment in Peru found that PTFs estimating saturated hydraulic conductivity do not give good prediction and cannot be used for modelling storm flow

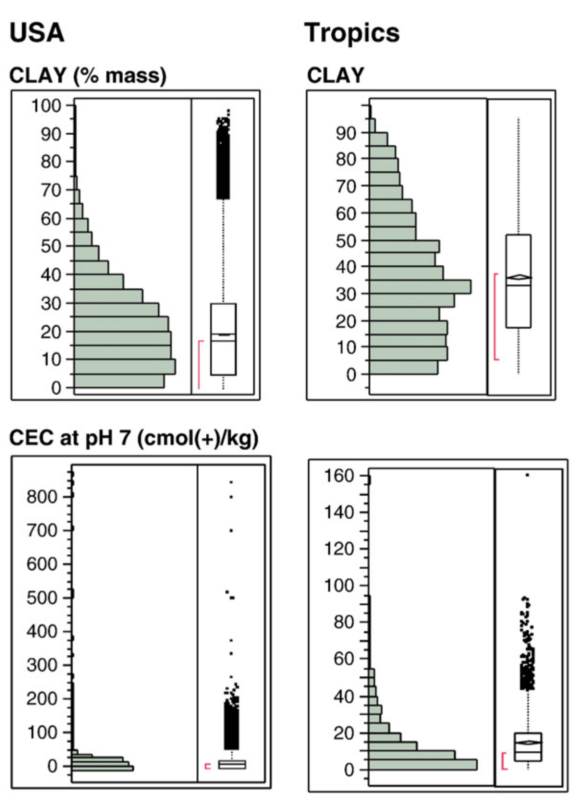

Fig. 1. The distribution of clay content, bulk density, cation exchange capacity (CEC), volumetric water content (θ) at −10 and −1500 kPa for soils in the tropics and soils in the temperate region (USA).

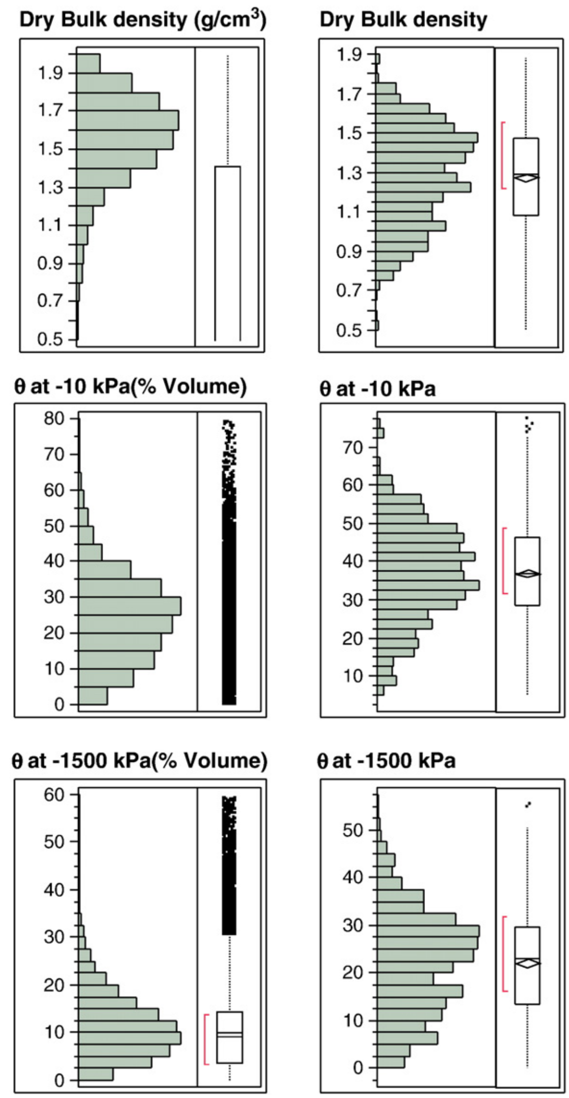

Fig. 1 (*continued*).

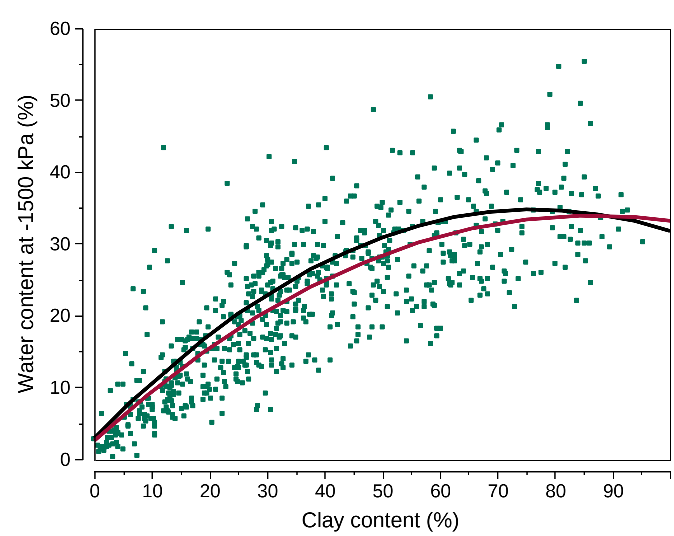

Fig. 2. Relationship between clay content and water content at −1500 kPa for soils in the Tropics. The red line represent fitted curve, while the Black curve represents PTF derived from soils in the UK (Hall et al., 1977).

generation. They suggested that improvement on PTFs can be achieved when considering macroporosity.

Although most PTFs are developed using empirical relationships that are based on detailed soil knowledge, it is possible to attempt to generalise and formulate a rationale for prediction. PTFs are not a statistical exercise to find the best fit and correlation coefficients using various data mining algorithms. Although soils in the tropics may be from soils in the temperate regions, most of the predictors used in the PTFs can be the same. Except for organic soils and soils containing high amount of amorphous minerals, the relationships are similar. We caution that most PTFs are developed under “normal” soil conditions, meaning no extraneous behaviour, such as extremely high organic matter content, salt concentration, or compaction.

The following are observations based on mineral soils, and without andic properties:

(1) The general properties which are related to surface area of the soils can be predicted from clay content, sand content, CEC, and organic C:
- Water retention at −1500 kPa
- Plastic limit and liquid limits
- Specific surface area
- Shrinkage properties, such as linear shrinkage or COLE.

(2) Properties that are related to soil aggregates, require particle-size, organic matter content, and depth information:
- Bulk density: which is closely related to organic matter content and depth
- water stable aggregates, where organic matter as a binding agent in macro-aggregates

(3) Properties that are related to structural or pore-size distribution require basic properties and bulk density or some other measure of aggregates:
- water retention curve
- penetration resistance

(4) Properties that are related to pore connectivity require bulk density, and water retention as predictors:
- saturated hydraulic conductivity
- unsaturated hydraulic conductivity
- infiltration capacity
- sorptivity

The following are PTFs generated from the ISRIC databases on mineral soils in the tropics. For bulk density, firstly the mineral bulk density is predicted:

$$BD_{min} = 0.935 + 0.049\,\mathrm{Log}(depth) + 0.0055\,Sand + 0.000065(Sand-38.96)^2 \quad \left(R^2 = 0.34, \mathrm{RMSE} = 0.20\ \mathrm{g\ cm^{-3}}, n = 670\right) \tag{1}$$

where BD_{min} is mineral bulk density (g cm^{-3}), Sand is percentage mass of sand content, Log(depth) is natural log of depth (in cm), R^2 is coefficient of determination, RMSE is root mean square error, and n is the number of observations used in the model.

The effect of organic matter is then added using the model by Adams (1973):

$$BD = \frac{100}{\frac{OM\%}{BD_{OM}} + \frac{(100-OM\%)}{BD_{min}}} \tag{2}$$

where OM% = organic matter percentage, and BD_{OM} = organic matter bulk density = 0.224 g cm^{-3}. Using this relationship, the prediction of bulk density now improved with R^2 = 0.46 and RMSE = 0.19 g cm^{-3} (n = 670). Although Eq. (2) was developed for soils in the UK, it is a general relationship to account for the amount of organic matter contribution in bulk density and that can be applied for soils in the tropics.

The following simple relationship can be used to predict volumetric water content at −10 kPa (θ_{-10}), −33 kPa (θ_{-33}) and −1500 kPa (θ_{-1500}):

$$\theta_{-10}(\%) = 59.9 - 8.78BD - 0.31\,Sand \qquad R^2 = 0.60, \mathrm{RMSE} = 8.07\%, n = 632 \tag{3}$$

$$\theta_{-33}(\%) = 56.5 - 7.49BD - 0.34\,Sand \qquad R^2 = 0.62, \mathrm{RMSE} = 8.15\%, n = 652 \tag{4}$$

$$\theta_{-1500}(\%) = 7.95 + 0.86{*}OC + 0.4{*}Clay - 0.004(Clay-37.7)^2 \qquad R^2 = 0.65, \mathrm{RMSE} = 6.48\%, n = 648 \tag{5}$$

where Clay is clay content in percent mass, Sand is sand (particles 50–2000 μm) content in percent mass, OC is organic carbon content in percent mass, R^2 is coefficient of determination, RMSE is Root mean Squared Error.

5.2. Predicting soil chemical properties

Clay content is the most common predictor for soil chemical properties. Uehara (2003) stated that in addition to clay content the best predictors are soil mineralogy and specific surface area. Soil mineralogy provides information on the physicochemical nature of the surfaces, whereas specific surface area provides information on the surface charge. With quantitative mineralogy, specific surface and total chemical analysis, various properties can be predicted including surface charge characteristics, ion exchange capacity, adsorption–desorption reactions, aggregation, aggregate stability, pore size distribution and water and gas transport coefficients (Uehara, 2003). However, detailed mineralogical measurements and specific surface area are expensive and rarely made in soil surveys. Through infrared spectroscopy some of this information could be obtained.

The following are some relationships that were found in the literature.

- Soil carbon content related to soil colour. Fernandez et al. (1988) showed good linear relationships between the Munsell value, and organic matter content, and diuron adsorption.
- Haematite content related to soil colour. Torrent et al. (1983) developed a relationship between soil redness rating, which is calculated from [(10−hue)×chroma]/value, with haematite content.
- For CEC, the most useful predictors are clay content, organic C, and pH since both are predictors related to the negative charge of the soil as well as its surface area.
- For P adsorption capacity, extractable Fe and Al are commonly the best predictors. Le Mare (1981) has conducted an analysis on the various factors for predicting soil P adsorption parameters, and found that Fe oxide can be used for Oxisols. Singh and Gilkes (1991) also suggested pH in NaF as a rapid technique; this is adopted by Trakoonyingcharoen et al. (2005) and Wisawapipata et al. (2009) for Oxisols and Ultisols from Thailand.
- Sorption capacity of heavy metals. Freundlich adsorption parameters of heavy metals can be related to clay content, CEC, Fe and Al oxides, and pH, for example Elzinga et al. (1997).

These studies suggest that chemical parameters that are related to the surface area of the soil (such as adsorption capacity) can be predicted from other, more easily, measured soil properties. Nutrient concentration that requires particular chemical extraction, such as available P, cannot be easily predicted well as is depends on the extraction procedure. This concentration depends on soil solution chemistry and is also more transient in nature. Stoorvogel and Smaling (1990) showed good example on the use of pedotransfer functions for evaluating nutrient balances, they compiled a suite of

Table 2
Various statistical and data mining techniques used for prediction and its usage in characterising tropical soils. Compiled from: Everitt (2002) The Cambridge Dictionary of Statistics, Statistics Glossary http://www.statsoftinc.com/textbook/glosfra.html, and Hastie et al. (2009).

Type	Description	Example
Multiple linear regression	The general purpose of multiple linear regression is to analyse the relationship between several independent or predictor variables and a dependent or predicted variable. Multiple regression analysis fits a straight line (or plane in an n-dimensional space, where n is the number of independent variables) to the data.	Mbagwu and Abeh (1998)
Generalised linear models (GLM)	A class of models that arise for a natural generalisation of ordinary linear models. The transformed dependent variable values are predicted from (is linked to) a linear combination of predictor variables; the transformation is referred to as the link function; also, different distributions can be assumed for the dependent variable values.	Mills et al. (2006)
Generalised additive models (GAM)	Models that use smoothing techniques, such as splines to identify and represent possible nonlinear relationship between the predictor and predicted variables. GAM is a generalisation of GLM where the linear function of the predictor is replaced by an unspecified (non-parametric) function, obtained by applying a scatterplot smoother to the scatterplot of partial residuals (for the transformed dependent variable values).	Mills et al. (2006)
Partial least squares (PLS)	Alternative to multiple linear regression to deal with data having more independent variables than observation points. PLS constructs a new set of components as regressor variables which are linear combination of the original variables. The components in partial least squares are determined by both the response variable(s) and the predictor variables.	Awiti et al. (2008)
Artificial neural networks	A mathematical structure modelled after the functioning of the nervous system. The essential feature is a network of simple processing elements joined together by weights.	Agyare et al. (2007)
Regression tree	Alternative to multiple regression, rather than fitting a model to the data, a tree structure is generated by dividing the sample recursively into a number of groups, each division being chosen so as to maximise some measure difference in the predicted variable in the resulting two groups. The resulting structure provides easy interpretation as variables most important for prediction can be identified quickly.	Tittonell et al. (2008)
Random Forests	is a classifier or regression model which consists of many decision or regression trees where each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the data. The output of the model is an average of all the regression or decision trees.	Grimm et al. (2008)
Support vector machines	Or SVM is a set of supervised learning methods used for classification and regression. It performs classification by constructing a nonlinear n-dimensional hyperplane that optimally separates the data into two categories. This is done by constructing a linear boundary in a large, transformed space of the feature space. Support vector regression is a form of SVM which is applied to regression problems.	Sá et al. (2009)

pedotransfer functions to predict leaching and gaseous losses of N in a supranational study in Sub Sahara Africa.

6. Statistical approaches

6.1. For the PTF developer

Most soil survey agencies have their own 'rule of thumb' for predicting soil properties. This is often translated into a look-up table, for example, relating field texture to properties such as clay content, or available water capacity. These rules or tables are usually derived from experience, expert knowledge, or from means of properties for particular class in a soil database. Several of these have been summarised in Booker Tropical Soil Manual (Landon, 1991).

For continuous predicted variables, a range of models can be used to derive PTFs, and various methods have been developed for data mining purposes. The methods ranges from linear regression, generalised linear models (GLIM), generalised additive models (GAM), regression trees, neural networks, support vector machines, and random forests. Many statistical packages allow the use of these tools in a user-friendly environment or in an open-source programming language based software such as R (www.r-project.org). There are also specific software developed for data-mining purposes, they are usually more powerful and can handle large data sets.

The predictive power and interpretability varies between models depending on their complexity. Table 2 provides a guideline for PTFs developers on various mathematical models. The more complex the model, the more parameters it will have, and potential users need to be aware on the principle of parsimony: a general principle that any models, all of which provide an adequate fit for a set of data, the one with the fewest parameters is to be preferred. There is a limit for predictive models; users should choose the simplest model that can adequately account for the variation in prediction. Models with high complexity will appear to fit the data well but it may also cause over-fitting, or too many parameters in the model, thus the model will fit the noise of the data. It is recommended to split the data into a calibration and validation set, using the calibration data for fitting and then testing or validating the model with a validation set — see Hastie et al. (2009) for more detail (Table 3).

The study of Wösten et al. (2001) illustrated the importance of better data rather than more complicated models. The study compared the performance of three models to predict water content at −33 kPa from basic soil properties using the same data set. They revealed that the accuracy of all three methods is similar, and suggested that the improvement of fit may not be expected from the use of different models, but from better and more soil data.

Table 3
Comparison of different mathematical predictive models, 3 = good, 2 = fair, 1 = poor (Adapted from Hastie et al. 2009).

	Linear models	GLIM	GAM	Regression tree	Neural networks	Random forests	Support vector machines
Ease of use	3	2	2	3	1	3	2
Parsimony	3	2	1	3	1	1	1
Interpretability	3	2	1	3	1	1	1
Nonlinearity	1	1	3	3	3	2	3
Handling of mixed data type (Qualitative & quantitative)	2	3	3	3	1	2	1
Computational efficiency (large data)	3	3	2	3	1	3	1
Robustness to outliers in input space	1	1	1	3	1	3	1
Ability to deal with irrelevant inputs	1	1	1	3	1	3	1
Predictive power	1	2	2	2	3	3	3

7. Discussion and conclusions

7.1. For the user and the developer

As it is not possible to measure soil properties continuously at each location, it is necessary to have robust systems that can predict soil properties at a given location. That is particularly needed for several tropical countries where the dearth of soil property measurements is large. There are two emerging sub-disciplines in soil science active in the development and applications of PTFs:

7.2. Hydropedology

Hydropedology is an intertwined branch of soil science and hydrology that encompasses the multiscale basis and applied research of interactive and hydrologic processes and their properties in the unsaturated zone. This group developed and utilised PTFs to derive relationships between soil structure and soil hydraulic functions at different scales. Hydropedology addressed soil hydrologic functioning at various scales by applying data fusion, PTFs, and concurrent use of models (Pachepsky et al., 2008).

7.3. Digital soil mapping

Digital soil mapping is the creation of a spatial soil information system using field and laboratory observation methods coupled with quantitative spatial prediction techniques. It follows the advancement in soil and environmental observations using proximal and remote sensing, and utilises mathematical and statistical techniques that allow better prediction of soil properties in areas with little or no information as well as indicating the uncertainty of such predictions. In digital soil mapping, PTFs are used to translate basic soil properties into more useful functional soil properties (McBratney et al. (2003)). Overall, there is great potential for using these PTFs in tropical areas where there is limited information and in projects like *GlobalSoilMap.net* and AfSIS (Sanchez et al., 2009).

Pedotransfer functions have been generated in different parts of the tropics for predicting water retention and phosphorus adsorption for Ferrasols. Although soils in the tropics are different from soils in the temperate regions in several aspects, the general principles are the same. This is shown in many of the predictors (Table 1) that are also applied for PTFs from the temperate regions. Various methods developed in the temperate regions are waiting to be applied for the soils in the tropical regions although calibration and selection of predictors remains necessary.

With the proliferation of PTFs in the tropics, there is a need for reporting the effectiveness of such functions. The reporting of the training domain of PTFs such as discussed in Tranter et al. (2009) allow user to select functions which are closer to their soil environment.

While there are many similar pedotransfer functions generated using new or existing datasets there seems to be much less effort in gathering and using the available PTFs. McBratney et al. (2002) had proposed the concept of *soil inference system* (SINFERS), where pedotransfer functions are the knowledge rules for soil inference engines. A soil inference system takes measurements we more-or-less know with a given level of (un)certainty, and infers data that we don't know with minimal inaccuracy, by means of properly and logically linked pedotransfer functions.

We envision that a complete soil inference system will be built and can be adapted in a GIS context. The system should have a database of mean soil properties, such as particle-size distribution and organic matter content, for different soil types. The inference engine has knowledge rules which will determine what functions to use in realising their uncertainties. The output will be the predicted physical and chemical properties along with their uncertainties. This can be incorporated into a spatial framework, where a point in space can be predicted from the neighbourhood basic soil properties or soil class. Bouma (1989) defined pedotransfer functions only in terms of data translation. We can further describe this translation function as information. This information, when properly and logically linked, constitutes knowledge. Knowledge should guide policy and decision.

References

Adams, W.A., 1973. The effect of organic matter on the bulk and true density of some uncultivated podzolic soils. Journal of Soil Science 24, 10–17.

Agyare, W.A., Park, S.J., Vlek, P.L.G., 2007. Artificial neural network estimation of saturated hydraulic conductivity. Vadose Zone Journal 6, 423–431.

Aina, P.O., Periaswamy, S.P., 1985. Estimating available water-holding capacity of western Nigerian soils from soil texture and bulk density, using core and sieved samples. Soil Science 140, 55–58.

Alves, M.E., Lavorenti, A., 2006. Remaining phosphorus estimate through multiple regression analysis. Pedosphere 16, 566–571.

Awiti, A.O., Walsh, M.G., Shepherd, K.D., Kinyamario, J., 2008. Soil condition classification using infrared spectroscopy: a proposition for assessment of soil condition along a tropical forest–cropland chronosequence. Geoderma 143, 73–84.

Batjes, N.H., 1996. Development of a world data set of soil water retention properties using pedotransfer rules. Geoderma 71, 31–52.

Batjes, N.H., 2008. Mapping soil carbon stocks of Central Africa using SOTER. Geoderma 146, 58–65.

Bekunda, M., 2006. Managing Africa's agricultural soils: the future of soil science. In: Hartemink, A.E. (Ed.), The Future of Soil Science. IUSS, Wageningen, pp. 13–15.

Bell, M.A., van Keulen, H., 1995. Soil pedotransfer functions for four Mexican soils. Soil Science Society of America Journal 59, 865–871.

Bell, M.A., van Keulen, H., 1996. Effect of soil disturbance on pedotransfer function development for field capacity. Soil Technology 8, 321–329.

Benites, V.M., Machado, P.L.O.A., Fidalgo, E.C.C., Coelho, M.R., Madari, B.E., 2007. Pedotransfer functions for estimating soil bulk density from existing soil survey reports in Brazil. Geoderma 139, 90–97.

Ben-Dor, E., 2002. Quantitative remote sensing of soil properties. Advances in Agronomy 75, 173–243.

Blavet, D., Mathe, E., Leprun, J.C., 2000. Relations between soil colour and waterlogging duration in a representative hillside of the West African granito-gneissic bedrock. Catena 39, 187–210.

Borggaard, O.K., Szilas, C., Gimsing, A.L., Rasmussen, L.H., 2004. Estimation of soil phosphate adsorption capacity by means of a pedotransfer function. Geoderma 118, 55–61.

Bouma, J., 1989. Using soil survey data for quantitative land evaluation. Advances in Soil Science 9, 177–213.

Calhoun, F.G., Smeck, N.E., Slater, B.L., Bigham, J.M., Hall, G.F., 2001. Predicting bulk density of Ohio soils from morphology, genetic principles, and laboratory characterization data. Soil Science Society of America Journal. 65, 811–819.

Chang, C.-W., Laird, D.W., Mausbach, M.J., Hurburgh, C.R., 2001. Near-infrared reflectance spectroscopy — principal components regression analyses of soil properties. Soil Sci. Soc. Am. J. 65, 480–490.

Cohen, M., Mylavarapu, R.S., Bogrekci, I., Lee, W.S., Clark, M.W., 2007. Reflectance spectroscopy for routine agronomic soil analyses. Soil Science 172, 469–485.

Da Silva, A.P., Tormena, C.A., Fidalski, J., Imhoff, S., 2008. Pedotransfer functions for the soil water retention and soil resistance to penetration curves (In Portugese). Revista Brasileira de Ciencia do Solo 32, 1–10.

Dane, J.H., Topp, G.C. (Eds.), 2002. Methods of Soil Analysis Part 4 – Physical Methods. SSSA Book Seties 5. Soil Science Society of America, Madison, Wisconsin.

De Condappa, D., Gallea, S., Dewandeld, B., Haverkamp, R., 2008. Bimodal zone of the soil textural triangle: common in tropical and subtropical regions. Soil Science Society of America Journal 72, 33–40.

De Leenheer, Van Ruymbeke, 1960. Is it possible to predict some physical soil characteristics, knowing the soil components? 7th International Congress of Soil Science, Madison, Wisc. 1.25, pp. 272–278.

Dematte, J.A.M., Sousa, A.A., Alves, M.C., Nanni, M.R., Fiorio, P.R., Campos, R.C., 2006. Determining soil water status and other soil characteristics by spectral proximal sensing. Geoderma 135, 179–195.

Dematte, J.A.M., Galdos, M.V., Guimaratildees, R.V., Genuacute, A.M., Nanni, M.R., Zullo, J., 2007. Quantification of tropical soil attributes from ETM+/LANDSAT-7 data. International Journal of Remote Sensing 28, 3813–3829.

Elzinga, E.J., Vissenberg, H.A., van den Berg, B., van Grinsven, J.J.M., Swartjes, E.A., 1997. Freundlich adsorptievergelijkingen voor cadmium, koper en zink op basis van literatuurgegevens. RIVM Rep. 711501001. Bilthoven, the Netherlands.

Eswaran, H., Almaraz, R., Vandenberg, E., Reich, P., 1997. An assessment of the soil resources of africa in relation to productivity. Geoderma 77, 1–18.

Everitt, B.S., 2002. The Cambridge Dictionary of Statistics. Cambridge University Press, Cambridge, UK.

FAO, 1974. Management properties of Ferralsols. FAO Soils Bulletin No. 23. FAO, Rome.

Fernandez, R.N., Schulze, D.G., Coffin, D.L., van Scoyoc, G.E., 1988. Color, organic matter, and pesticide adsorption relationships in a soil landscape. Soil Science Society of America Journal 52, 1023–1026.

Gaiser, T., Graef, F., Cordeiro, J.C., 2000. Water retention characteristics of soils with contrasting clay mineral composition in semi-arid tropical regions. Australian Journal of Soil Research 38, 523–536.

Gobin, A., Campling, P., Deckers, J., Feyen, J., 2000. Quantifying soil morphology in tropical environments: methods and application in soil classification. Soil Science Society of America Journal 64, 1423–1433.

Grimm, R., Behrens, T., Marker, M., Elsenbeer, H., 2008. Soil organic carbon concentrations and stocks on Barro Colorado Island — digital soil mapping using Random Forests analysis. Geoderma 146, 102–113.

Hall, D.G., Reeve, M.J., Thomasson, A.J., Wright, V.F., 1977. Water Retention, Porosity and Density of Field Soils. Technical Monograph No. 9. Soil Survey of England and Wales, Harpenden.

Hartemink, A.E., 1998. Soil chemical and physical properties as indicators of sustainable land management under sugar cane in Papua New Guinea. Geoderma 85, 283–306.

Hartemink, A.E., 2002. Soil science in tropical and temperate regions — some differences and similarities. Advances in Agronomy 77, 269–292.

Hartemink, A.E., 2008. Soil map density and nation's wealth and income. In: Hartemink, A.E., McBratney, A.B., Mendonca-Santos, M.L. (Eds.), Digital Soil Mapping with Limited Data. Springer, Dordrecht, pp. 53–66.

Hartemink, A.E., McBratney, A.B., Mendonça-Santos, M.L. (Eds.), 2008. Digital Soil Mapping with Limited Data. Springer. 445 pp.

Hastie, T., Tibshirani, R., Friedman, J., 2009. The Elements of Statistical Learning: Data Mining, Inference and Prediction, Springer Series in Statistics, 2nd Edition. Springer-Verlag, New York.

Hodnett, M.G., Tomasella, J., 2002. Marked differences between van Genuchten soil water-retention parameters for temperate and tropical soils: A new water-retention pedo-transfer functions developed for tropical soils. Geoderma 108, 155–180.

Janik, L., Merry, R.H., Forrester, S.T., Lanyon, D.M., Rawson, A., 2007. Rapid prediction of soil water retention using mid infrared spectroscopy. Soil Science Society of America Journal 71, 507–514.

Ketterings, Q.M., Bigham, J.M., 2000. Soil color as an indicator of slash-and-burn fire severity and soil fertility in Sumatra, Indonesia. Soil Science Society of America Journal 64, 1826–1833.

Lal, R., 1979. Physical characteristics of soils of the tropics: determination and management. In: Lal, R., Greenland, D.J. (Eds.), Soil Physical Properties and Crop Production in the Tropics. John Wiley & Sons, Chichester, pp. 7–44.

Landon, J.R. (Ed.), 1991. Booker Tropical Soil Manual. Longman, Harlow.

Le Mare, P.H., 1981. Phosphorus sorption and release. In: Greenland, D.J. (Ed.), Characterization of Soils. Clarendon Press, Oxford, pp. 97–134.

MacLean, A.H., Yager, T.U., 1972. Available water capacities of Zambian soils in relation to pressure plate measurements and particle size analysis. Soil Science 113, 23–29.

Manyame, C., Morgan, C.L., Heilman, J.L., Fatondji, D., Gerard, B., Payne, W.A., 2007. Modeling hydraulic properties of sandy soils of Niger using pedotransfer functions. Geoderma 141, 407–415.

Martens, G., Naes, T., 1989. Multivariate Calibration. John Wiley and Sons, New York.

Mbagwu, J.S.C., Abeh, O., 1998. Prediction of engineering properties of tropical soils using intrinsic pedological parameters. Soil Science 163, 93–102.

McBratney, A.B., Minasny, B., Cattle, S.R., Vervoort, R.W., 2002. From pedotransfer function to soil inference system. Geoderma 109, 41–73.

McBratney, A.B., Mendonca Santos, M.L., Minasny, B., 2003. On digital soil mapping. Geoderma 117, 3–52.

McBratney, A.B., Minasny, B., Tranter, G., 2011. Necessary meta-data for pedotransfer functions. Geoderma 160, 627–629.

McKeague, J.A., Wang, C., Topp, G.C., 1982. Estimating saturated hydraulic conductivity from soil morphology. Soil Science Society of America Journal 46, 1239–1244.

McKenzie, N.J., Jacquier, D.W., 1997. Improving the field estimation of saturated hydraulic conductivity in soil survey. Australian Journal of Soil Research 35, 803–825.

McKenzie, N.J., MacLeod, D.A., 1989. Relationships between soil morphology and soil properties relevant to irrigated and dryland agriculture. Australian Journal of Soil Research 27, 235–258.

McKenzie, N.J., Coughlan, K., Cresswell, H.P. (Eds.), 2002. Soil Physical Measurement and Interpretation for Land Evaluation. CSIRO Publisihing, Collingwood, Victoria.

Medina, H., Tarawally, M., Valle, A.D., Ruiz, M.E., 2002. Estimating soil water retention curve in Rhodic Ferralsols from basic soil data. Geoderma 108, 277–285.

Mills, A.J., Fey, M.V., Gröngröft, A., Petersen, A., Medinski, T.V., 2006. Unravelling the effects of soil properties on water infiltration: segmented quantile regression on a large data set from arid south-west Africa. Australian Journal of Soil Research 44, 783–797.

Moreira, C.S., Brunet, D., Verneyre, L., Sá, S.M.O., Galdos, M.V., Cerri, C.C., Bernoux, M., 2009. Near infrared spectroscopy for soil bulk density assessment. European Journal of Soil Science 60, 785–791.

Nachtergaele, F.O., Van Ranst, E., 2003. Qualitative and quantitative aspects of soil databases in tropical countries. In: Stoops, G. (Ed.), Evolution of Tropical Soil Science: Past and Future. Koninklijke Academie voor Overzeese Wetenschappen, Brussel, pp. 107–126.

Noble, A.D., Cannon, M., Muller, D., 1997. Evidence of accelerated soil acidification under Stylosanthes-dominated pastures. Australian Journal of Soil Research 35, 1309–1322.

O'Neal, A.M., 1949. Some characteristics significant in evaluating permeability. Soil Science 67, 403–409.

O'Neal, A.M., 1952. A key for evaluating soil permeability by means of certain field clues. Soil Science Society of America Proceedings 16, 312–315.

Pachepsky, Ya., Rawls, W.J., 2004. Development of pedotransfer functions in soil hydrology. Developments in Soil Science Vol. 30. Elsevier.

Pachepsky, Y.A., Gimenez, D., Lilly, A., Nemes, A., 2008. Promises of hydropedology. CAB Reviews: Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources 2008 3, No. 040.

Pidgeon, J.D., 1972. The measurement and prediction of available water capacity of ferralitic soils in Uganda. Journal of Soil Science 23, 431–441.

Prescott, J.A., Pendleton, R.L., 1952. Laterite and lateritic soils. Technical communication no. 47. Commonwealth Agricultural Bureaux, Harpenden.

Rawlins, B.G., Webster, R., Tye, A.M., Lawley, R., O'Hara, S.L., 2009. Estimating particle-size fractions of soil dominated by silicate minerals from geochemistry. European Journal of Soil Science 60, 116–126.

Rawls, W.J., Pachepsky, Y.A., 2002. Using field topographic descriptors to estimate soil water retention. Soil Science 167, 423–435.

Rawls, W.J., Gish, T.J., Brakensiek, D.L., 1991. Estimating soil water retention from soil physical properties and characteristics. Advances in Soil Science 16, 213–234.

Reichert, J.M., Suzuki, L.E.A.S., Reinert, D.J., Horn, R., Hakansson, I., 2008. Reference bulk density and critical degree-of-compactness for no-till crop production in subtropical highly weathered soils. Soil and Tillage Research 102, 242–254.

Reuter, D.J., 1998. Developing indicators for monitoring catchment health: the challenges. Aust. J. Experimental Agriculture 38, 637–648.

Sá, S.O., Althmann, D., Figueiredo, K.L., Bernoux, M., Poppi, R.J., Cerri, C.C., 2009. NIRS-LS-SVM to estimate carbon content of agricultural land in Brazilian Cerrado soils. IOP Conf. : Series: Earth and Environmental Science, 6, p. 242037.

Sanchez, P.A., 2000. Linking climate change research with food security and poverty reduction in the tropics. Agriculture Ecosystems & Environment 82 (1–3), 371–383.

Sanchez, P.A., 2002. Soil fertility and hunger in Africa. Science 295 (5562), 2019–2020.

Sanchez, P.A., Buol, S.W., 1975. Soils of the tropics and the world food crisis. Science 188, 598–603.

Sanchez, P.A., Ahamed, S., Carré, F., Hartemink, A.E., Hempel, J., Huising, J., Lagacherie, P., McBratney, A.B, McKenzie, N.J., Mendonça-Santos, M.L., Minasny, B., Montanarella, L., Okoth, P., Palm, C.A., Sachs, J.D., Shepherd, K.D., Vågen, T., Vanlauwe, B., Walsh, M.G., Winowiecki, L.A., Zhang, G., 2009. Digital soil map of the world. Science 325, 680–681.

Shepherd, K.D., Walsh, M.G., 2002. Development of reflectance spectral libraries for characterization of soil properties. Soil Science Society of America Journal 66, 988–998.

Singh, B., Gilkes, R.J., 1991. Phosphorus sorption in relation to soil properties for the major soil types of South-western Australia. Australian Journal of Soil Research 29, 603–618.

Slavich, P., McLeod, M., Moore, N., Iskandar, T., Rachman, A., 2006. Rapid assessment of soil salinity in tsunami-affected areas. Experiences from Nanggore Aceh Darussalam province, Indonesia. NSW Department of Primary Industries, Australian Centre for International Agricultural Research, BPTP NAD. Indonesian Soils Research Institute.

Sobieraj, J.A., Elsenbeer, H., Veressy, R.A., 2001. Pedotransfer functions for estimating saturated hydraulic conductivity. Journal of Hydrology 251, 202–220.

Staff, Soil Survey, 1951. Soil Survey Manual. USDA, Washington DC. 503 pp.

Stirk, G.B., 1957. Physical properties of soils of the lower Burdekin valley, North Queensland. CSIRO Division of Soils Divisional Report 1/57. CSIRO, Australia.

Stoorvogel, J.J., Smaling, E.M.A., 1990. Assessment of soil nutrient depletion in Sub-Saharan Africa. Winand Staring Centre, Report 28. Wageningen, The Netherlands, 4 volumes.

Suprayogo, D., Widianto, Cadisch, G., van Noordwijk, M., 2003. A pedotransfer resource database (PTFRDB) for tropical soils: test with the water balance of WaNuLCAS. In: Post, D.A. (Ed.), Proceedings of the 2003 MODSIM Conference. Townsville, Australia, pp. 584–589.

Tittonell, P., Shepherd, K.D., Vanlauwe, B., Giller, K.E., 2008. Unravelling the effects of soil and crop management on maize productivity in smallholder agricultural systems of western Kenya — an application of classification and regression tree analysis. Agriculture, Ecosystems and Environment 123, 137–150.

Tomasella, J., Hodnett, M.G., 1997. Estimating unsaturated hydraulic conductivity of Brazilian soils using soil-water retention data. Soil Science 162, 703–712.

Tomasella, J., Hodnett, M.G., 2004. Pedotransfer functions for tropical soils. In: Pachepsky, Ya., Rawls, W.J. (Eds.), Development of Pedotransfer Functions in Soil Hydrology. : Developments in Soil Science, 30. Elsevier, pp. 415–429.

Tomasella, J., Hodnett, M.G., Rossato, L., 2000. Pedotransfer functions for the estimation of soil water retention in Brazilians soils. Soil Science Society of America Journal 64, 327–338.

Tomasella, J., Pachepsky, Ya, Crestana, S., Rawls, W.J., 2003. Comparison of two techniques to develop pedotransfer functions for water retention. Soil Science Society of America Journal 67, 1085–1092.

Torrent, J., Schwertmann, U., Fechter, H., Alferez, F., 1983. Quantitative relationships between soil color and hematite content. Soil Science 136, 354–358.

Trakoonyingcharoen, P., Kheoruenromne, I., Suddhiprakarn, A., Gilkes, R.J., 2005. Phosphate sorption by Thai Red Oxisols and Red Ultisols. Soil Science 170, 716–725.

Tranter, G., McBratney, A.B., Minasny, B., 2009. Using distance metrics to determine the appropriate domain of pedotransfer function predictions. Geoderma 149, 421–425.

U.S. Dept. of Agriculture. Soil Conservation Service. Soil Survey Staff, 1975. Soil taxonomy: a basic system of soil classification for making and interpreting soil surveys. U.S. Dept. of Agric. Handb. 436. U.S. Govt. Print. Off, Washington, DC. 754 pp., illus.

Uehara, G., 2003. Developments in soil chemistry and soil classification. In: Rice, T., Eswaran, H., Stewart, B.A., Ahrens, R. (Eds.), Soil Classification: A Global Desk Reference. CRC Press, Boca Raton, pp. 67–73.

van den Berg, M., Klant, E., van Reeuwijk, L.P., Sombroek, G., 1997. Pedotransfer functions for the estimation of moisture retention characteristics of Ferralsols and related soils. Geoderma 79, 161–180.

van Genuchten, M.Th., 1980. A closed-form equation for predicting the hydraulic conductivity of unsaturated soils. Soil Science Society of America Journal 44, 892–898.

Viscarra Rossel, R.A., Walvoort, D.J.J., McBratney, A.B., Janik, L.J., Skjemstad, J.O., 2006. Visible, near infrared, mid infrared or combined diffuse reflectance spectroscopy for simultaneous assessment of various soil properties. Geoderma 131, 59–75.

Wisawapipata, W., Kheoruenromne, I., Suddhiprakarn, A., Gilkes, R.J., 2009. Phosphate sorption and desorption by Thai upland soils. Geoderma 153, 408–415.

Wösten, J.H.M., 1997. Pedotransfer functions to evaluate soil quality. In: Gregorich, E.G., Carter, M.R. (Eds.), Soil Quality for Crop Production and Ecosystem Health. : Developments in Soil Science, 25. Elsevier, Amsterdam, pp. 221–245.

Wösten, J.H.M., Pachepsky, Y.A., Rawls, W.J., 2001. Pedotransfer functions: bridging gap between available basic soil data and missing soil hydraulic characteristics. Journal of Hydrology 251, 123–150.

Young, M.D.B., Gowing, J.W., Hatibu, N., Mahoo, H.M.F., Payton, R.W., 1999. Assessment and development of pedotransfer functions for semi-arid sub-Saharan Africa. Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere 24, 845–849.

Zinn, Y.L., Lal, R.., Resck, D.V.S., 2005. Texture and organic carbon relations described by a profile pedotransfer function for Brazilian Cerrado soils. Geoderma 127, 168–173.