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Estimation of the moisture content of tropical soils using colour images and artificial neural networks

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ABSTRACT

Information on soil moisture is important for various agricultural, environmental, and hydrological applications; thus, moisture must be determined with the greatest possible accuracy. In this study, based on the fact that soil changes colour as the moisture content changes, artificial neural networks (ANNs) were applied to estimate the moisture content of tropical soils from colour photographs taken with a digital camera. Three different soils were used to train and test the network, and data were collected from disturbed samples subjected to different water contents in the laboratory. MLP (multilayer perceptron) ANNs with one hidden neuron layer and three input variables (red, green, and blue) related to colour were used. To train the networks, various tests were performed by varying the number of hidden layer neurons and using input data of the three soils. The best performing ANN had a hidden layer with twelve neurons and used the tan-sigmoid transfer function. It was found that a single network could estimate the moisture content of all the soils studied from the photographs. The best ANN, which was trained with data of the three soils simultaneously, was also tested with individual soil data separately, and better results were obtained (RMSE ranging from 0.0321 to 0.0650 g/g and r^2 ranging from 0.6675 to 0.8231). Although the results are satisfactory, the simplicity of the experiment likely restricted a stronger characterisation of the pattern of soil colour variation due to the change in its moisture content, which thus reduced the performance of the method. However, the proposed method represents an advancement in the indirect estimation of soil moisture content because it has the advantages of being practical, rapid, and non-destructive; requiring relatively low cost; and automating the process in the field.

1. Introduction

Soil moisture represents a significant volume of water stored in the land phase of the water cycle (Seneviratne et al., 2010; Western et al., 2002). This parameter must be considered in environmental, agricultural, hydrological, and geotechnical studies and projects (Brocca et al., 2014; Heathman et al., 2012b; Hirschi et al., 2010; Legates et al., 2010; Ray et al., 2010; Suseela et al., 2012; Zehe et al., 2010).

Soil moisture influences several soil characteristics and physical properties, such as the shear strength, compressibility, hydraulic conductivity, and infiltration capacity, which directly influence soil and water management and conservation practices and water availability for crops (Baker and Frydman, 2009; Seneviratne et al., 2010).

From a hydrological point of view, soil moisture is an important variable that influences runoff, infiltration, evapotranspiration, storage, and drainage in watersheds (Brocca et al., 2014; Moore et al., 2011; Shaw et al., 2013; Zehe et al., 2010). In agriculture, knowledge of soil moisture allows proper irrigation management and forecasting of crop yields (Grabow et al., 2013; Heathman et al., 2012a).

There are several methods used to determine soil moisture content, such as the gravimetric method, which is considered the standard method. Several of these methods use physical soil properties, such as temperature, electrical resistance, capacitance, spectrometry, or the apparent dielectric constant, to indirectly estimate soil moisture (Altendorf et al., 1999; Anderson and Croft, 2009; Antonucci et al., 2011; Calamita et al., 2012; Francesca et al., 2010; Imhoff et al., 2007; Lihua et al., 2005; Noborio, 2001; Souza and Matsura, 2002). However, many of the methods that make use of such properties, although efficient, have relatively high costs that limit their widespread use.

Soils tend to be darker with increased moisture, which decreases their spectral reflectance (Bowers and Hanks, 1965), i.e., the water content in the soil influences its spectral behaviour (Dalmolin et al., 2005). Considering that a change in the colour shade of the soil represents a change in its moisture, quantifying the soil colour can be used to indirectly estimate the water content of the soil (Persson, 2005). This technique has shown promise and can be considered a breakthrough for indirect estimation of soil moisture because it has the advantages of

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being practical, fast, non-destructive, relatively low cost, and automates the process in the field.

Lihua et al. (2005) and Persson (2005) tested several empirical models to estimate soil moisture (θ) using the RGB (red, green, and blue) and HSV (hue, saturation, and value) colour spaces. Lihua et al. (2005) indicated a linear regression to estimate θ as a function of G, B, H, and S (Eq. (1)) or only as a function of RGB colour model (Eq. (2)), whereas Persson (2005) estimated θ based on only S and V (Eq. (3)). In these studies, the values of H, S, and V were obtained from a mathematical transformation of the RGB colour space.

$$\theta = \beta_1 + \beta_2\,G + \beta_3\,B + \beta_4\,H + \beta_5\,S \tag{1}$$

$$\theta = \beta_6 + \beta_7\,R + \beta_8\,G + \beta_9\,B \tag{2}$$

$$\theta = \beta_{10} + \beta_{11}\,S + \beta_{12}\,V \tag{3}$$

Based on the high correlation between the moisture and the near-infrared radiation emitted by soil reported in the literature, Lihua et al. (2005) also tested the inclusion of soil spectral data in Eq. (1), which corresponded to a wavelength of 835 nm obtained with a portable spectrometer. However, the authors found no improvement in their results, which indicates that the GBHS model (Eq. (1)) is the most viable model.

Artificial neural networks (ANNs) have been successfully used to model processes in various knowledge fields. In the area of water resources, there have been many studies that have evaluated the efficacy of ANNs; however, studies using ANNs to model soil moisture are seldom found in literature (Elshorbagy and Parasuraman, 2008). The majority of studies found address the calibration of time-domain reflectometry (TDR) (Arsoy et al., 2013; Namdar-Khojasteh et al., 2010; Persson et al., 2001, 2002). ANNs could potentially be used to estimate the water content of soil reasonably well and are certainly better than linear regression models (Altendorf et al., 1999).

The increased awareness of the need for rational use of natural resources, particularly water, coupled with the advancement of electronic equipment and computational resources has contributed to advances in technology and the intensification of studies on soil water monitoring and automation of data acquisition processes. Considering the importance of this issue and because there is not a similar study found in the literature using tropical soils, the goal of the present study is to assess the feasibility of using digital colour photographs, regression models and artificial neural networks to estimate soil moisture from different tropical soils in Brazil.

2. Materials and methods

The present study consisted of fitting multiple linear regression models and training ANNs to estimate the moisture of tropical soils from digital colour photographs. Data were collected from soil samples with different water contents, which were determined by the standard gravimetric method. Photographs of the soils were obtained with a Canon® PowerShot A710 IS digital camera, which has a resolution of 7.1 megapixels. The results were compared with the TDR equipment, and a calibration was performed by fitting third-order polynomial equation (Topp et al., 1980), called the Topp-like equation. Such a calibration was performed to mathematically correlate the soil water content with the apparent dielectric constant (K_a), which was obtained using the TDR 100 equipment (Campbell Scientific®) via three-rod probes (CS-610).

2.1. Soil sampling and TDR measurements

Three types of soil were used: two samples from red–yellow Latosol (Oxisol) with different particle sizes from the municipality of Alegre (state of Espírito Santo — ES), denoted as soil 1 and soil 3; and a sample from Cambisol (Inceptisol) from the municipality of Guaçuí (ES), denoted soil 2. The soils were listed in order of decreasing clay content. The soil samples were taken at a depth between 0 and 10 cm. Three samples were collected from each soil, representing three replicates. To characterise the soils, two types of samples were taken in the field: disturbed samples and undisturbed samples. The disturbed samples were used to determine the particle size distribution (texture) and the organic matter content in the laboratory, which followed the standard methods described by Brazilian Corporation of Agricultural Research (EMBRAPA, 1997). Undisturbed soil samples were used to determine the soil bulk density using the volumetric ring method. Table 1 presents the descriptive characteristics of the studied soils.

In the experiment, nine plastic containers of known weight with dimensions of approximately 30 cm, 15 cm, and 7 cm (length × width × depth, approximate volume of 3 l) were used. The lower surfaces of the containers had been previously perforated to allow drainage of excess water and were closed with a fine mesh screen to prevent soil loss.

A TDR probe of known weight was fixed horizontally in the vertical and longitudinal middle section of each container such that it would not move on the ground while being handled.

Soil samples were broken apart and packed in plastic containers. The mass of the soil used to fill each container was determined by obtaining a density that was similar to that observed in the field. The use of undisturbed soil samples did not interfere significantly in the calibration of the TDR (Santos et al., 2010) and also, was unlikely to interfere in estimating the moisture content using photographs.

The containers were partially immersed in water trays for a period of 48 h to saturate the soil samples from bottom to top. After saturation, the containers were maintained such that the surface of the soil was exposed to allow water loss by evaporation. The samples were allowed to stand for a few hours inside the laboratory to evaporate a portion of the water from the soil. A thick cotton tissue was used to cover the samples intending to avoid over drying soil surface and to keep a homogeneous distribution of soil moisture along its depth. The following data were collected after periodic intervals of rest: mass of the soil-probe-container set, K_a and photographs from the soil surface, which were obtained with a precision balance, TDR probes, and the digital camera, respectively. This procedure was performed every day until the soil reached approximate hygroscopic equilibrium with atmospheric air.

After the last measurement, a soil sample was removed from each container to obtain the residual moisture by means of the standard oven (gravimetric) method. After drying, the dry mass of the soil in the containers was determined. Thus, the water content of the soil at the time of each measurement was determined using the difference between the wet and dry mass measured.

To standardise the procedures, all of the pictures were taken in the dark, where the camera flash was the only source of light incident on the soil surface. The photographs used the following RGB colour model described by Gonzalez and Woods (2007): composed of three 8-bit monochrome images (R, G, B), each with a capacity to represent 2^8 or 256 colours through the variation in the pixel values, which range from 0 to 255. In other words, the photographs are full-colour, a term that denotes colour 24-bit RGB images with the capacity to represent $(2^8)^3$ or 16,777,216 distinct colours (Gonzalez and Woods, 2007). Fig. 1 shows examples of the photographs of soil 3 with different moisture contents. The darker shades refer to a higher soil water content.

ImageJ software (Rasband, 2014) was used to crop representative samples of the photographs to obtain quantitative data for each pixel (values between 0 and 255), which concern the elementary RGB

Table 1
Descriptive characteristics of the three soils used in the study.

Soil	Sand (%)	Silt (%)	Clay (%)	Bulk density (g cm^{-3})	Organic matter (%)
1	35.3	6.7	58.0	0.91	1.54
2	47.0	10.7	42.3	1.41	1.79
3	56.0	7.3	36.7	1.59	1.62