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Soil moisture modeling based on stochastic behavior of forces on a no-till chisel opener

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ABSTRACT

Crop-yield variability is frequently associated with soil moisture and its real-time measurement can be an alternative for the automatic control of no-till seeding to improve soil–crop conditions. Soil moisture has a significant influence on soil behavior, markedly on its temporal and spatial variability; however, the measurement of soil moisture is generally time consuming and expensive. Many studies employ electric, electromagnetic, optical, or radiometric sensors for the direct measurement of soil moisture. It is also possible to develop an estimation method employing existing machinery components using mechanical sensors such as load cells. Auto-regressive error function (AREF) combined with computational models is applied in this study for estimating soil moisture using a data set of forces acting on a chisel and speed as inputs to assess the feasibility of achieving more accurate results than previously obtained by Sakai et al. (2005). AREF is a stochastic method that can be applied to the analysis of soil-force patterns acting on a tool. Three computational models are developed, including two artificial neural networks (a Multi-Layer Perceptron (MLP) and a Radial Basis Function (RBF)) and one Neuro-Fuzzy model (ANFIS). These are compared with two multiple linear regression (MLR) models with two and six independent variables. The models' performances are evaluated using root mean square error (RMSE), determination coefficient (R^2), and average percentage error (APE). The computational models demonstrated superior performance compared to MLR, confirming the hypothesis. The neural network models had similar performances with RMSE between 1.27% and 1.30%, R^2 around 0.80, and APE between 3.77% and 3.75% for testing data. These results indicate that using AREF parameters combined with computational models may be a suitable technique to estimate soil moisture and has potential to be used in control systems applied to no-till machinery.

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1. Introduction

Crop-yield variability is frequently associated with soil physical properties and related parameters such as density and moisture; however, their measurements are generally time consuming and expensive. The development of microelectronic technology and its use in agricultural production has facilitated embedded electronic systems at more affordable costs. Consequently, studies have been developed addressing the continuous measurement (on-the-go) of soil properties (Adamchuk et al., 2004; Andrade-Sanchez et al., 2008; Lee et al., 2010). Lee et al. (2010) and Adamchuk et al. (2004) described a number of sensor types such as electric, electromagnetic, optical, and radiometric to measure soil properties. Hummel et al. (2001), Mouazen et al. (2005), Jiang and Cotton (2004) and Yin et al. (2013) employed these sensors for soil moisture estimation.

However, it is also possible to develop a method for estimating soil moisture employing an existing component in the machinery using mechanical sensors such as load cells.

The draft forces acting on a soil tool are mainly influenced by soil moisture, density, and internal friction angle (Andrade-Sanchez et al., 2007; Godwin and O'Dogherty, 2007) and, as observed by Young et al. (1988), these forces are not constant, rather cyclic in nature owing to the development of failures caused by soil shearing.

Shear strength is the internal resistance of the soil to external forces and is a function of cohesion between soil particles and intergranular friction (Graf et al., 2009). Soil shear strength is

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usually defined by the Mohr–Coulomb equation, which is composed of a cohesive and a frictional component (McKyes, 1985). The cohesive (soil cohesion) represents the resistance of soil particles to displacement owing to intermolecular attraction and surface tension of the held water and depends on the size of the clayey particles, type of clay minerals, valence bond between particles, moisture content, and proportion of clay. The frictional (soil internal friction angle) depends on the soil density, texture, and moisture in addition to the particle size distribution and shape (Jain et al., 2010).

Another important dynamic soil property that influences soil failure is adhesion, which is the force resulting from the attraction between soil and tool (metal) and, accordingly, is characterized by two components, the soil adhesion on the tool and soil–tool friction angle (Plasse et al., 1985). The same authors claim that soil cohesion and adhesion are the major contributors to draft force and are dependent on the soil moisture status.

Jayasuriya and Salokhe (2001) identified four soil failure mechanisms for all major soil types with a change of soil moisture content. They concluded that soil consistency limits (Atterberg limits) demonstrate clear boundaries of the different failure mechanisms in frictional–cohesive and cohesive soils. When moisture content increases from a dry condition close to the plastic limit, the fracturing failure mechanism predominates with cyclic variation in the force–time curves for these soil types. The authors concluded that draft forces and soil failure mechanisms possess a relationship with soil moisture content in frictional–cohesive and cohesive soils. Therefore, it is reasonable to presume that this cyclic force must be considered for modeling.

Hence, control systems for continuous adjustment of soil–tool components in a no-till seeder can be applied based on the real-time mapping of the soil moisture to achieve improved soil–crop conditions.

Sakai et al. (2005) analyzed the spatial power spectrum and autoregressive error distribution function (AREF) to study the relationship between the AREF parameters, which quantify the complexity of the soil cutting force fluctuation patterns, and soil properties. AREF is defined by the ratio between $\log\tau$ and $\log\sigma(\tau)$ where $\sigma(\tau)$ is the standard deviation of the force differences to different time delays (τ).

The authors classify the forces relationship into three groups, coherent, periodic, and stochastic; the linear portion represents the stochastic range and indicates, according to the authors, the existence of self-similarity in the soil cutting force.

The intercept (α) and slope (β) of the AREF linear portion are important parameters that can be used for estimating soil properties.

Parameter α quantifies the draft force variability for the smallest time delay and dictates the location of the variability range observed for the AREF parameters. Parameter β describes the growth rate of this variability considering the increase in time delay.

It can be noted in Sakai et al. (2005) that the space-state of α versus β clearly categorizes each different experimental treatment. They considered the parameters as effective candidates for soil property estimation and concluded that the soil moisture and cone index are functions of the slope and intercept of AREF.

To appraise the potential of using the AREF function for automatic control in no-till seeding, Araújo et al. (2012) evaluated the methodology of Sakai et al. (2005) to estimate soil moisture, density, and penetration resistance from the information of horizontal and vertical forces and momentum acting on a chisel. They concluded that the parameters of soil moisture and penetration resistance presented significant correlation with the slope and intercept of the AREF function, confirming the referenced authors. They used polynomial functions obtained by multiple regression analysis to relate α and β with soil properties, as performed by Sakai et al. (2005); however, the performance of this relation must be improved.

Huang et al. (2010) claimed that fuzzy computing had the ability of modeling complex problems when conventional models could not produce complete solutions. Similarly, according to Akbulut et al. (2004), complex real-world problems could require intelligent systems with human-like expertise to be adaptable to changes in the environment, such as artificial neural network (ANN) and neuro-fuzzy (NF). Their use is not limited to fitting data to a previously established curve; they also allow both data classification and output parameter estimation.

Fuzzy logic and fuzzy set theory are used to describe human thinking and reasoning in a mathematical framework and fuzzy rule-based modeling is a quantitative modeling scheme where system behavior is described using a natural language (Nayak et al., 2004).

In artificial networks, the mathematical concept aims to reproduce the functional basic behavior of a biological neuron. Their synaptic weights are adjusted by a learning algorithm whose goal is to reproduce the observed behavior during training (Huang et al., 2010). Their advantage is the adaptive behavior that allows identifying existing patterns in the training data.

Among the different types of ANN, Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) are widely used for modeling and many studies compare the performance of these two types of networks with NF models. RBF differs from MLP in terms of multidimensional space division and training algorithms.

MLP divides the data space into hyperplanes and the neurons in each layer are of the perceptron type and differ only by their activation function (Haykin, 2001). The training algorithm is a back propagation type, as the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm, which uses the Quasi-Newton method (Bishop, 1995).

RBF divides the space into clusters and generally has three layers. The neurons in the hidden layer are composed of Gaussian functions that measure the Euclidean distances between each point of the input data set and the center neuron; the output layer is usually composed of neurons with linear activation functions. The training algorithm is divided into two stages: in the first, neurons with Gaussian functions are defined by a clustering process; in the second stage, linear neurons are trained and use methods such as descent gradient (Haykin, 2001).

The disadvantage of ANNs is that the structure does not allow understanding the phenomenon. The values of the synaptic weights do not present an understandable relation with the observed phenomenon. NF allows integrating fuzzy modeling with ANN's while preserving the useful features of both techniques, namely, transparency and learning ability.

Adaptive Neuro-Fuzzy System (ANFIS) is an inference system with a universal approximator to represent nonlinear functions (Akbulut et al., 2004). ANFIS presents a structure of nodes divided into layers with different functions and its training is divided into two stages: a clustering method and a back propagation algorithm (Akbulut et al., 2004).

The hypothesis of the present study is that joining AREF to computational models will improve the performance of soil moisture estimation compared to the results of Sakai et al. (2005).

The research goals are:

- To use stochastic information of horizontal and vertical forces acting on a chisel opener of a no-till seeder exploring the methodology of Sakai et al. (2005) and the AREF parameters as model inputs associated with other operational parameters.
- To configure and test three computational models for more accurate estimation of soil moisture (Multi-Layer Perceptron, Radial Basis Function, and Adaptive Neuro-Fuzzy Inference System).

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