Chapter 21

Soil Cation Exchange Capacity Predicted by Learning From Multiple Modelling: Forming Multiple Models Run by SVM to Learn From ANN and Its Hybrid With Firefly Algorithm

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ABSTRACT

Prediction models of cation exchange capacity (CEC) in soil management is investigated by using artificial intelligence for a balanced approach between advantageous CEC-rich and negative CEC-deficient soil conditions. The modelling strategy formed here comprises: (1) artificial neural networks based on feedforward multi-layer perceptron (MLP) and their backpropagation using Levenburg-Marquardt (LM) algorithm; (2) FireFly algorithm (FFA) to replace LM; (3) learn the dependency of CEC on soil characteristics (clay, silt, sand, gypsum, organic matter) by both models to produce outputs; and (4) feed these outputs as inputs to support vector machine using the least squares algorithms (SVM-LS) together with observed values as target values. This is referred to as multiple models (MM-SVM) strategy. The results of a study area with 380 soil samples collected from different horizons of 80 soil profiles show that the learning by MM-SVM is considerable and capable of reducing inherent uncertainty with benefits to CEC soil management by reducing uncertainty due to solution methods.

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INTRODUCTION

This chapter uses Artificial Intelligence (AI) to investigate the prediction of the quantity of negative charges in soil, which is known as Cation Exchange Capacity (CEC). It is among important soil properties required in soil databases and serves as an input to soil and environmental models, see Evans (1989), Manrique et al. (1991) and Keller et al. (2001). The importance of the CEC of the soil particles is due to (1) holding onto nutrients and prevent them from leaching beyond the roots; (2) the ease of exchange of cations with one another and as a result, they are readily available for plants. CEC is a measurable quantity but can also be estimated through easily measurable and readily available soil properties such as particle size distribution (clay, sand and silt content), gypsum and Organic Matter (OM), which are referred to as Pedo-Transfer Functions (PTFs) in soils science, a term coined by Bouma (1989). The chapter develops a strategy to reduce the dependency of CEC soil management on solution methods.

Previous modelling efforts reported in the literature underline the important of improved modelling accuracy in predicting CEC values. Asadu and Akamigbo (1990) found that clay and OM contents are most sensitive to CEC estimations. Tang et al. (2009) used radial basis function neural networks into the estimation of CEC from soil physicochemical properties such as soil horizon, pH, organic carbon content, and clay, silt, and sand contents as the input variables. They indicated that their model had high correlation coefficients between the predicted and measured CEC values and also, clay and organic carbon contents and soil horizon were most sensitive to CEC estimation. Manrique et al. (1991) also found that clay and OM accounted for up to 67% of the variation in CEC. Pachepsky et al. (1996), Tamari et al. (1996), Mermoud and Xu (2006) investigated the accuracy of ANN models for the estimation of CEC values. According to their reports, ANNs can predict the easily measurable soil parameters with more accuracy and less error. They investigated that clay and organic carbon contents are most sensitive to CEC estimations. Seybold et al., (2005) developed a PTF for the prediction of CEC for most soils of the United States. Data were stratified into more homogeneous groups based on the organic carbon contents, soil pH, taxonomic family mineralogy class and CEC-activity class, and taxonomic order. Their results show that OM and non-carbonate clay contents are the main predictor variables used. The above overview underlines the need for improvements on prediction of CEC values.

Artificial Intelligence (AI) techniques have emerged as working tools since the 1990s and these include the techniques such as Artificial Neural Network (ANN), Support Vector Machines (SVM), Fuzzy Logic, Genetic programming and many other methods. These models are used widely to model various complex environmental problems, see Khatibi et al. (2017) and Yilmaz and Kaynar (2011). These are often nature-inspired techniques and exploit a certain working complexity prevailing in nature, such as the working of the brain or genetic reproduction. These techniques are capable of a diversity of problem-solving activities and this includes their applications as prediction tools or optimisation tools. Two of these tools are used in the chapter, which are ANN and SVM. AI techniques generally comprise prediction and parameter identification techniques. Thus, the implementation of ANN in the chapter comprises the use of a Multilayer Perceptron (MLP) feed-forward neural network technique as a predictive tool and its parameter identification comprises the Levenburg-Marquardt (LM) method. SVM was proposed by Vapnik (1998) and has emerged as a powerful tool for regression and time series prediction (Wang, Sun, & Zhao, 2008).

In recent years, a new generation of nature-inspired AI techniques have emerged, which emulate the working of species against the background of the first generation emulating deep concepts of evolutionary processes. New algorithms include Whale Optimisation Algorithm, Grey Wolf Optimizer and
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