Soil & Tillage Research 157 (2016) 32–42

Contents lists available at ScienceDirect

Soil & Tillage Research

journal homepage: www.elsevier.com/locate/still

Estimation of soil mechanical resistance parameter by using particle swarm optimization, genetic algorithm and multiple regression methods

Mehdi Hosseini*, Seyed Alireza Movahedi Naeini, Amir Ahmad Dehghani, Yones Khaledian

Department of Soil and Water Engineering, Gorgan University of Agricultural Sciences and Natural Resources, Gorgan, Iran

ARTICLE INFO

Article history:
Received 27 April 2015
Received in revised form 13 November 2015
Accepted 14 November 2015
Available online 28 November 2015

Keywords:
Soil mechanical resistance
Multiple regression (MR)
Genetic algorithm (GA)
Particle swarm optimization (PSO)

ABSTRACT

Soil mechanical resistance directly affect seedling emergence and root growth. Tillage and irrigation managements decrease soil mechanical resistance in soil depth and increase root density in rhizosphere, wheat nutrient uptake and the yield. Soil mechanical resistance is high in the site of experiment due to high soil specific surface and cohesion between primary particles. Bulk density, pore size distribution and volumetric soil water content are important soil physical properties in relation to crop production through their effect on mechanical resistance. Determination of mechanical resistance in soils is difficult using penetrometer in fine textured soils particularly in hot and dry season. This study explores potentials of particle swarm optimization (PSO), genetic algorithm (GA) and multiple regression (MR) in the estimation of mechanical resistance value of soils. This research was carried out in a 3000 m^2 piece of land at Gorgan University of Agricultural Science and Natural Resource Research Farm, Grogan, Iran. The land was ploughed with five tillage methods, namely conventional tillage with moldboard ploughing (MT), rototiller (RT), double disc (DD), chisel plow (CP) and no-tillage (NT). Then bulk density, volumetric soil water content and soil mechanical resistance were measured at six stages during growing season of wheat. Two physical properties of soils that include the soil bulk density (BD) and volumetric soil water content (θ_v) were presented to the models as independent parameters to estimate soil mechanical resistance (Es). The performance of models was comprehensively evaluated some statistical criteria. The results showed that among the various tillage methods, Moldboard tillage (MT) reduced soil mechanical resistance which increased plant's root growth, water and nutrient uptake, head number per square meter, and wheat yield. Also, the results revealed that PSO and GA models are promising approach for the estimation of soil mechanical resistance in compare with MR model. The results also show that PSO model can estimate soil mechanical resistance more accurate than GA and MR with $R^2 = 0.932$ and RMSE = 0.301.

1. Introduction

Soil strength is strongly related to water content and may vary considerably throughout the year with wetting and drying cycles (Spain et al., 1990). The relationship between strength and water content for a particular soil is strongly influenced by the degree of compaction (Mirreh and Ketcheson, 1972), and this may affect management practices such as the timing of tillage and site preparation practices. While it is clear that mechanical resistance is related to water content and bulk density (Khaledian et al., 2012; Vazquez et al., 1991), it correlates well with root growth, and varies inversely proportional to it. When soil water content decreases, an increase in mechanical resistance occurs, because cohesion within the solid fraction of soil diminishes (Gerard et al., 1972; Becher, 1998; Benghough et al., 2001). Water, oxygen, temperature, mechanical resistance directly affect seedling emergence and root growth. Bulk density, aggregation, aggregate stability, and pore size distribution are important soil physical properties in relation to crop production through their effect on water, aeration, temperature, and mechanical resistance (Letey, 1985). A commonly accepted technique is to measure mechanical impedance with a penetrometer. Root growth can be affected by high soil mechanical resistance restricting water and mineral supply (Larney and Kladivko, 1989; Oussible et al., 1992) and also reduction in crop

* Corresponding author. Fax: +98 1714426436.
E-mail address: mehdi.h.2009@gmail.com (M. Hosseini).

http://dx.doi.org/10.1016/j.still.2015.11.004

yield due to the compaction has been related to increasing resistance to root growth and decreasing water and nutrient use efficiencies (Lal, 1996). Reductions in rooting depth for various tree species grown in compacted soils have been attributed to increases in mechanical resistance (Zisa et al., 1980; Tuttle et al., 1988).

According to Amini et al. (2012), irrigation timing needs to be based on mechanical resistance measurements rather than soil water content measurements in soils with increased mechanical resistance (due to high specific surface). The reason is that the mechanical resistance becomes restrictive to root growth and nutrient uptake (especially potassium) long before tissue water limits growth in these soils. A model predicting soil mechanical resistance accurately from the preset soil water contents in irrigation timing may assist recognizing tissue water stress-mechanical resistance relative restrictions in different soils for delineating irrigation timing map units. Bulk density is increased with increased relative coarse particles in a soil volume, thereby increasing soil mechanical resistance.

A number of laboratory and field studies also correlated mechanical resistance (Es) with soil parameters, such as bulk density (f_b), porosity, water content (θ), matrix potential (Ψ), soil texture, or plasticity via regression equations (Jakobsen and Dexter, 1987; Ayers and Bowen, 1987; Busscher, 1990; Ayers and Perumpral, 1982; Mielke et al., 1994; Smith et al., 1997; Hernanz et al., 2000; To and Kay, 2005; Whalley et al., 2007; Dexter et al., 2007; Vaz et al., 2011). They showed a strong negative correlation between Es and water content or matrix potential (Busscher et al., 1997).

Recently, genetic algorithms (GA) and particle swarm optimization (PSO) technique have attracted considerable attention among various modern heuristic optimization techniques.

Genetic algorithms (GA) are likely to be useful approaches for optimizing multivariable problems (Wilson, 2000). Genetic algorithms are a type of evolutionary computer program that mimics the process of natural selection (Mitchell and Taylor, 1999). Using GAs, it is feasible to test a large number of possible solutions in parallel, to select the best solutions based on fitness criteria, and to introduce novelty through stochastic mutation and combination of traits that are analogous to sexual reproduction. Applications of the GA techniques include model parameter estimation (Cropper and Anderson, 2004), drug and electronic circuit design, image processing, and optimization (Cropp and Gabric, 2002; Koza et al., 2003).

The genetic algorithm have been used in soil researches such as optimizing simulated fertilizer additions using a genetic algorithm with a nutrient uptake model (Cropper and Comerford, 2005), modeling of the angle of shearing resistance of soils using soft computing systems (Kayadelen, 2009), modeling the mechanical behavior of unsaturated soils using a genetic algorithm-based neural network (Johari et al., 2010), Prediction of soil–water characteristic curve using genetic programming (Johari et al., 2006).

Particle swarm optimization (PSO) is another relatively recent heuristic search method whose mechanics are inspired by the swarming or collaborative behavior of biological populations.

Feng et al. (2006) used an inverse technique for the determination of the parameters of viscoelastic constitutive models for rocks based on genetic programming and a particle swarm optimization (PSO) algorithm. Meier et al. (2008) presented a concept for the application of PSO in geotechnical engineering. Zhao and Yin (2009) presented a method for identification of geomechanical parameters using a combination of a support vector machine, PSO, and numerical analysis techniques. Sadoghi Yazdi et al. (2012) used a neuro-fuzzy model in conjunction with particle swarm optimization (PSO) for calibration of soil parameters used within a linear elastic-hardening plastic constitutive model with the Drucker–Prager yield criterion. It is shown that the model parameters can be determined with relatively high accuracy in spite of the limited insight gained by a single set of data.

In this study, the effect of different tillage systems on soil mechanical resistance and nutrient uptake by grain were considered. Furthermore, this paper focuses on two very similar evolutionary algorithms: genetic algorithm (GA) and particle swarm optimization (PSO) for estimation of soil mechanical resistance parameter. The results also were compared with multiple regression (MR) as a common approach.

2. Material and methods

This research was carried out in a 3000 m^2 piece of land in the Gorgan University of Agricultural Sciences and Natural Resources Research Farm located at 37°45′N, 54°30′E, and 13 masl, Grogan, Iran. Fertilizer applications were based on recommended regional guidelines and applied at the same rate in all tillage treatments. A 350 Kg ha^{-1} di-ammonium phosphate and 200 Kg ha^{-1} potassium sulfate and one split of urea (60 kg ha^{-1}) added to soil before plantation, and then mixed with soil. A second split of urea (60 kg ha^{-1}) was added to top dress in tillering stage. The soil texture was silty clay loam (19.4% sand, 57.5% silt, 23.1% clay) with pH 7.9 and organic carbon content of 0.67%. The climate was temperate sub-humid. Land was ploughed with five tillage methods namely conventional tillage with moldboard ploughing (MT), rototiller (RT), double disc (DD), chisel plow (CP) and no-tillage (NT). Conventional tillage consisted of moldboard ploughing followed by one discing; a method commonly used by farmers in this region to help break clods and make a proper seedbed. The double disc consisted of two discings followed by one levelling. Primary tillage depths for MT and RT were 20–25 and 8–10 cm, respectively. All disc operations were performed to a depth of 8–10 cm. In this study, 200 soil samples were taken from 0 to 8 and 8 to 16 cm depths for measuring mechanical resistance, bulk density and volumetric soil water content in 6 stages of wheat growth (before tillering, tillering, booting, earing, milk development, maturity). Soil mechanical resistance was determined by a cone penetrometer. Bulk density was determined by cylinder. Bulk density and volumetric soil water content were determined as independent variables and mechanical resistance was determined as a dependent variable. Plant water was determined in six occasions throughout growing season. Root weights were measured before heading stage. At maturity, 2.25 m^2 from the center of each plot was harvested manually for determining fresh yield. After that the samples air dried. Grain yield, straw yield and nutrient elements such as phosphate, potassium, calcium and magnesium were measured after grain's separation at maturity. Head number, grain number per head and 1000 grains weight were also recorded at maturity. The data were divided into a calibration data subset (161 samples) and validation data subset (39 samples). Data subsets were used for determining the performance of three methods; particle swarm optimization (PSO), genetic algorithm (GA) and multiple regression (MR). Estimating soil mechanical resistance using multiple regression was initially carried out using statistical analysis system software (SAS).

2.1. Genetic algorithm

Genetic algorithms (GAs) are mathematical models of natural genetics where the power of nature to develop, destroy, improve and annihilate life is abstracted and used to solve complex optimization problems. Holland (1975) developed this powerful technique and it has been applied in various fields of science. GA is termed a global optimum seeking algorithm (Zheng, 1997). The algorithm works by mimicking the mechanisms of natural