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Use of inverse modelling and Bayesian optimization for investigating the effect of biochar on soil hydrological properties

Hamze Dokoohaki*, Fernando E. Miguez, Sotirios Archontoulis, David Laird

Agronomy Department, Iowa State University, Ames, IA, United States

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ABSTRACT

Physical properties of biochar such as small particle size and high porosity can modify soil properties and help to improve soil water dynamics. However, there has been no consistent long-term measurements of change in soil physical properties due to biochar application under real field conditions. In this study, we use a unique dataset of soil water content measurements in a corn-soybean cropping system (with biochar and no-biochar) for two years. Soil water content was measured every 30 min at 4 different depths and with 3 replications in corn plots. The effect of biochar was expected to be the difference between the physical soil properties of the two treatments. The APSIM model, a process-oriented crop model, was employed in order to find the physical properties of biochar and no-biochar treatments by using inverse modeling. First, a global sensitivity analysis was carried out to find the most sensitive inputs for the APSIM model for soil water simulation. Then the Metropolis-Hasting algorithm was used to inversely estimate the APSIM soil input properties using the soil moisture measurements. Results of the sensitivity analysis showed that the drainage upper limit (DUL) was the most sensitive soil property followed by saturated hydraulic conductivity (KS), saturated water content (SAT), maximum rate of plant water uptake (KL), maximum depth of surface storage (MAXPOND), lower limit volumetric water content (LL15) and lower limit for plant water uptake (LL). The difference between the posterior distributions (with and without biochar) showed an increase in DUL by approximately 10%. No considerable change was noted in LL15, MAXPOND and KS whereas SAT and LL showed a slight increase and decrease in biochar treatment respectively compared to no-biochar.

1. Introduction

Biochar has recently gained considerable attention due to its agronomic benefits and carbon sequestration potential. Among its many properties, biochar high surface area (Laird et al., 2010), small particle size (Hardie et al., 2014; Basso et al., 2013), low bulk density (Downie et al., 2009; Devereux et al., 2012) and high organic carbon content (Herath et al., 2013; Jones et al., 2010) which can effectively decrease soil bulk density, increase porosity and help coarse texture soils by increasing their capacity for holding water (Basso et al., 2013). However, despite the increased attention there is not yet a consensus on the effects of biochar on soil hydraulic properties (Hardie et al., 2014).

Short-term changes in physical and hydrological properties of amended soils with biochar have been observed in numerous lab and incubation studies (Streubel et al., 2011; Liu et al., 2012). However, laboratory-scale measurements of soil physical properties are mainly based on static steady flow assumption (Vrugt and Dane, 2006) and may produce large errors (Abbaspour et al., 1999). In addition, Mallants et al., (1997) and Reynolds et al., (2000) found that different lab techniques may result in different estimates for soil physical properties. Sensitivity to the geometry of the flow, sample size and sample collection procedure are among the reasons why dissimilar measurement of soil physical properties are observed (Reynolds et al., 2000). Although these studies allow for convenient implementation and measurements, they lack the dynamic interactions of soil properties with crop and management practices. For example, increase in porosity and water holding capacity of amended soils with biochar can potentially promote root penetration, aeration and lead to higher water and nutrient acquisition. However, increase in crop water and nutrient uptake cannot be fully investigated in lab studies and requires a dynamic method that is capable of directly and indirectly capturing the interaction among soil, biochar and crop.

One approach for indirectly estimating field-relevant soil physical properties of amended soils with biochar is use of inverse modeling. Inverse modeling searches the input parameters space of a model for the most plausible combination of inputs that yield the best fit between

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* Corresponding author.
E-mail address: hamzed@iastate.edu (H. Dokoohaki).

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Table 1
List of hydrologicalparameters with their lower and upper bound used for sensitivity analysis.

#	Parameter	Definition	Unit	Lower bound	Upper bound
1	CN2Bare	Curve number for bare soil	–	60	89
2	CNCov	The extent of the effect of surface residue on CN	–	1	100
3	DiffusConst	Diffusivity coefficients for unsaturated flow	–	1	300
4	DiffusSlope	Diffusivity coefficients for unsaturated flow	–	1	100
5	DUL (1)	Drained upper limit volumetric water contents-Layer1	cm^3 cm^{-3}	0.12	0.39
6	LL15 (1)	Lower limit volumetric water contents for-Layer1	cm^3 cm^{-3}	0.05	0.11
7	SAT (1)	Saturated volumetric water contents-Layer1	cm^3 cm^{-3}	0.4	0.55
8	DUL (2)	Drained upper limit volumetric water contents-Layer2	cm^3 cm^{-3}	0.12	0.39
9	LL15 (2)	Lower limit volumetric water contents for-Layer2	cm^3 cm^{-3}	0.05	0.11
10	SAT (2)	Saturated volumetric water contents-Layer2	cm^3 cm^{-3}	0.4	0.55
11	Salb	Soil albedo	–	0.1	0.7
12	Sini	Initial soil moisture (based on total soil fraction)	–	0.1	1
13	SummerCona	Second stage evaporation coefficient	–	1	50
14	SummerU	Potential amount of cumulative evaporation (before soil supply becomes limiting)	–	1	50
15	SWCON (1)	Drainage coefficient-Layer1	–	0.01	0.99
16	SWCON (2)	Drainage coefficient-Layer2	–	0.01	0.99
17	XF	Exploration Factor	–	0.01	0.99
18	KL	Maximum rate a plant can extract water from	day^{-1}	0	0.5
19	LL	crop LL	cm^3 cm^{-3}	LL15	DUL
20	BD (1)	Bulk density-Layer1	g cm^{-3}	1.0	1.8
21	BD (2)	Bulk density-Layer2	g cm^{-3}	1.0	1.8
22	KS (1)	Saturated hydraulic conductivity-Layer1	mday^{-1}	0.01	10
23	KS (2)	Saturated hydraulic conductivity-Layer2	mday^{-1}	0.01	10
24	MWCON (1)	Controls the water flow in soil saturation condition-Layer1	–	0.1	0.9
25	MWCON (2)	Controls the water flow in soil saturation condition-Layer2	–	0.1	0.9
26	MaxPond	Maximum depth of surface storage	–	1	10

model predictions and observations. Numerous studies have been conducted that use inverse methods with the aim of estimating soil physical properties, model verification or uncertainty analysis (e.g. Mertens et al., 2006; Abbaspour et al., 1999). For example, Wöhling et al., (2008), suggested that inverse modeling of process-oriented crop models like APSIM (Agricultural Production Systems Simulator) is a promising technique for obtaining “effective” hydraulic properties of soils. Application of this technique for estimation of hydrological parameters accounts for more dynamic interactions of soil properties compared to lab measurements.

This study used the APSIM model (Holzworth et al., 2014) along with a unique dataset of continuous soil water content measurements in two cropping systems (biochar vs. no-biochar treatment) for two years. We propose an optimization framework to inversely estimate hydraulic parameters for the APSIM model. This optimization framework uses measurements of soil moisture for two years as input data. We hypothesize that the analysis of this dataset with a process-oriented crop model will allow us to derive reasonable estimates of the effect of biochar on soil hydrological properties. Therefore, the main objective of this study is to derive posterior distributions for soil physical parameters using the APSIM model for biochar and no-biochar treatments. We expect that the difference between estimated posterior distributions (i.e. with and without biochar) will indicate the effect of biochar on soil physical properties in the field.

2. Materials and methods

2.1. Field experiment and measurements

The research site is located at the Armstrong Memorial Research and Demonstration Farm near Lewis, IA (41° 18′ N, 95° 10′ W). In 2011 biochar was applied at a rate of 10 Mg ha^{-1} in 3 out of 6 plots and paired plots were left as controls. Maize was planted on May 17 in 2013 and on May 8 in 2014; it was harvested on Oct 28 in both years. Soil water content, soil temperature, and EC were measured at 30 min intervals at 4 depths (10 cm, 25 cm, 42 cm and 60 cm) for both years in all plots. We used Decagon 5TE soil moisture sensors which have an estimated accuracy of about ± 0.03 m^3 m^{-3} after calibration. Sensors were installed May 2012 and they were in place until the end of the experiment. Calibration was performed using Topp’s equation (Topp et al., 1980) according to the sensor’s manual, which converts the bulk dielectric constants to bulk volumetric soil water content. Soil moisture measured in the time interval from Nov 20th in 2013 until the end of May in 2014 was not included in this study because the soil was frozen and the sensors were not working properly.

During early 2014 there were more extreme cold days compared to 2013, and the total precipitation was 882 mm for the first year and 1123 mm for the second year. The experimental site received an average of 15.8 MJ m^{-2} solar radiation per day and 5778 MJ m^{-2} in total over the course of 2013 and 15.6 MJ m^{-2} per day and 5694 MJ m^{-2} in total in 2014. The highest temperature recorded in 2013 was 36 °C whereas −26 °C was the lowest temperature. Likewise, maximum temperature in 2014 was 34 °C and the minimum was −25 °C.

2.2. APSIM model

The APSIM model has been designed in a modular fashion, allowing users to perform their own simulations using numerous soil, crop, climate and management components (McCown et al., 1996). The APSIM model can simulate soil water content, soil temperature and nutrient cycling as well as their interaction with different crop and management practices (e.g. irrigation, fertilization) on a daily time step (Keating et al., 2003). Specifically, for the U.S Midwest, APSIM has been used as a way to examine the indirect effect of new management practices on different soil and crop properties (e.g. Basche et al., 2016; Archontoulis et al., 2014). The SOILWAT module in APSIM (Probert et al., 1998) estimates daily changes in soil water content for different soil layers due to infiltration of irrigation and rainfall, vertical drainage, unsaturated and saturated flow, soil evaporation, and root water uptake processes. The model uses a "tipping bucket" approach for computing soil water drainage (Ritchie, 1972). In this method, the excess water above the field capacity of a layer is passed directly to the layer below. Upward unsaturated flow is also computed using a conservative estimate of the soil water diffusivity and differences in volumetric soil water content of adjacent layers.