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Methods to estimate plant available water for simulation models

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ABSTRACT

Agricultural simulation models are increasingly being used in decision support tools at regional and national scales for crop production and water management. These models require hydrologic inputs; in particular plant available water (PAW) is a critical parameter that helps determine if precipitation infiltrates and is stored as soil water, is lost directly to the atmosphere through soil evaporation, or is transported as groundwater flow. Accurate or realistic estimations of PAW for many geographic regions and soil types must be readily available as model input for simulating crop growth and many downstream processes, such as water quality, soil erosion, sediment loss, nutrient/pesticide fate and transport, and greenhouse gas emissions. In this study, we present a new algorithm for PAW estimation, termed the BNW algorithm, which was developed primarily based on principles of soil properties. The new BNW algorithm outperformed several commonly used algorithms for overall soil pedon fit and by USDA texture class. The BNW algorithm has the best fit and accuracy on sandy clay and sandy clay loam soils. Incorporation of the BNW algorithm into process based simulation models will improve the accuracy of crop production estimates and environmental impacts estimates at regional and national scales.

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1. Introduction

Process based simulation models, such as ALMANAC, APEX, CROPSYST, DAYCENT, DSSAT, EPIC, and SWAT, are widely used to simulate plant growth (or crop yield), water quality, water erosion, sediment loss, nutrient/pesticide fate and transport, greenhouse gas emission, etc. (Arnold et al., 1998; Jones et al., 1998; Kiniry et al., 1992; Parton et al., 1998; Stockle et al., 1994; Williams et al., 1998, 1989). These models require inputs that describe dynamics related to soil water retention. Precipitation that infiltrates is stored as soil water, which can be extracted by plants and returned to the atmosphere by plant transpiration, lost directly to the atmosphere through soil evaporation, or transported as groundwater flow. Accurately estimating the quantity of stored soil water available for plant extraction is critical to simulate plant growth and soil water balance, which impact many downstream processes, such as water percolation, water runoff, sediment loss, nitrogen and phosphorous leaching, and soil organic carbon dynamics. These simulation models are increasingly being used at regional and national scales as decision support tools to help determine the impacts of conservation practices, best management practices, impact and feasibility of biofuel production, effects of climate change and land-use change, and state of water quality (Arnold et al., 2014; Behrman et al., 2013; Gelfand et al., 2013; Powers et al., 2011; Tuppad et al., 2010).

Plant available water (PAW) is defined as the volumetric water content a plant can extract (m^3 of water per m^3 of soil) from the soil. It is typically estimated as the difference between volumetric water content at the drained upper limit (field capacity) and lower limit (wilting point) of the soil. Field measurements of soil water retention are costly and time consuming (Ratliff et al., 1983; Ritchie et al., 1987). As a consequence, predictive functions have been developed to estimate PAW from commonly measured soil properties, such as particle size distribution, bulk density, and organic matter (Jagtap et al., 2004; Timlin et al., 1996).

In order to utilize simulation models to assess the impact of conservation practices on water management and crop production at large regional and watershed scales, it is critical to develop reliable estimates of PAW for many geographic regions and soil types. However, there is a lack of consensus regarding the most accurate method to estimate PAW, and large discrepancies have been observed depending on the region and input variables (Gijsman et al., 2002; Nemes et al., 2009; Wosten et al., 2001). Most PAW algorithms are fit by linear or non-linear parametric regression or non-parametric machine learning or clustering algorithms (Nemes et al., 2006; Rawls and Brakensiek, 1989; Rawls et al., 1982; Saxton

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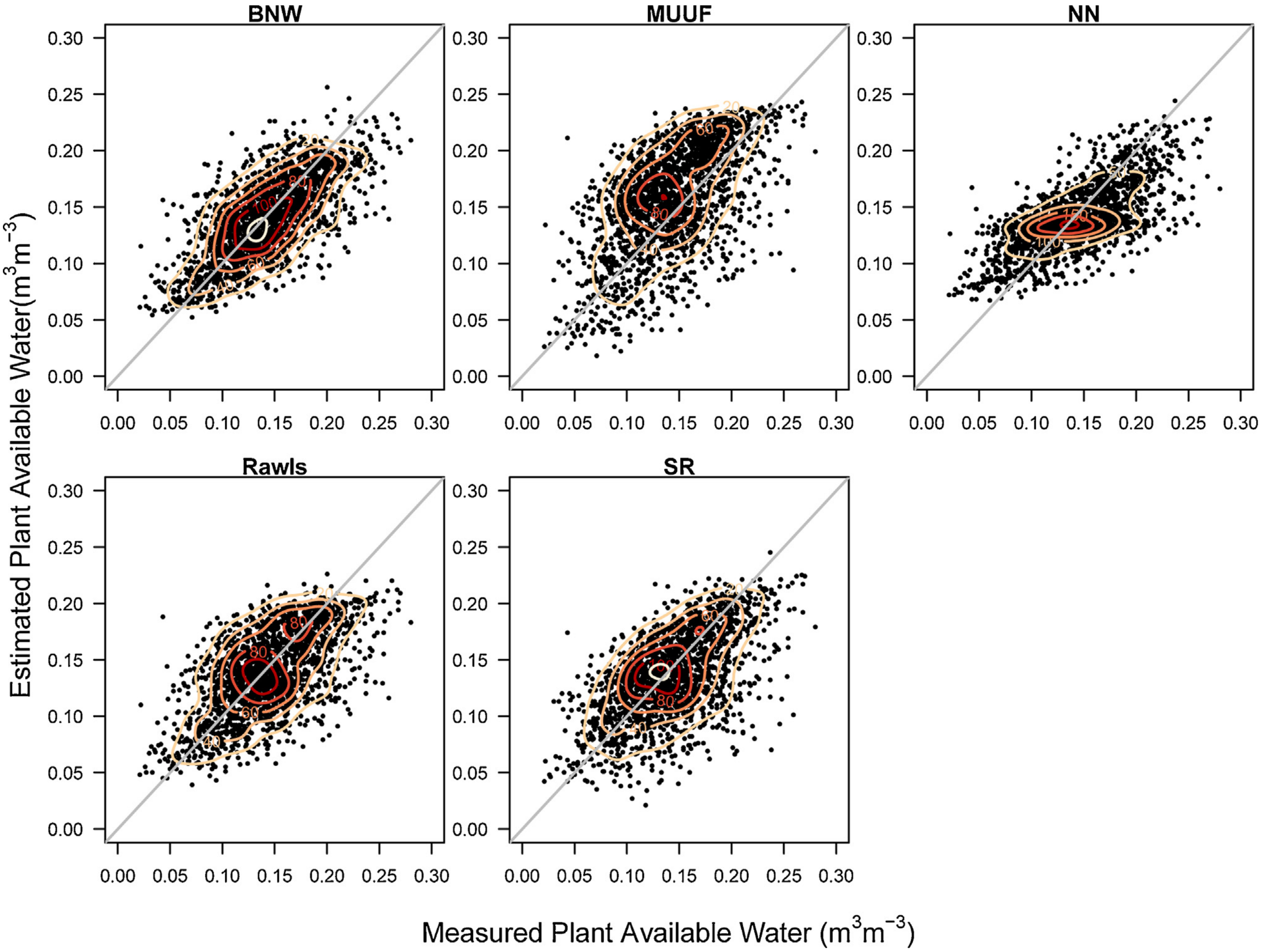

Fig. 1. Measured PAW versus estimated PAW for each pedon. Contours highlight how point density changes. The gray line is the one-to-one line.

and Rawls, 2006; Saxton et al., 1986; Schaap et al., 1998). Consensus on model fit is problematic because data used for model calibration is often not available and the algorithms are seldom refit as new data becomes available (Gijsman et al., 2002).

In this study, we present a new approach to estimate PAW based on the theoretical water holding capacity and bulk density of soil particle size classes. This method is unique amongst most the other PAW algorithms because it is not a statistical fit or data mining algorithm that is dependent on the dataset used. It is named after the authors and termed the "BNW" algorithm. Next, we compare model fit to several commonly used predictive functions, including two linear regression techniques (Baumer and Rice, 1988; Rawls et al., 1982), one non-linear parametric regression method (Saxton and Rawls, 2006), and one non-parametric method using a clustering algorithm based on nearest neighbors (Nemes et al., 2006). This comparison demonstrates how the newly developed algorithm compares to other commonly used techniques, but is not intended to provide a comprehensive review or comparison of all possible methods. Lastly, we evaluate the ability of the all algorithms to predict PAW for a wide range of measured soils and USDA texture classes.

2. Materials and methods

2.1. Soil dataset for comparison

Laboratory soil measurements from the United States Department of Agriculture (USDA) National Cooperative Soil Survey (NCSS) Soil Characterization Data were used to develop a test dataset to validate the new BNW algorithm and compare the BNW algorithm to several existing algorithms for a wide variety of agricultural soils (NCSS, 2005). The test dataset is composed of 1852 complete pedons with 10,890 layers. The following criteria were designed to remove extreme data values not common on agricultural soils and soil pedons with incomplete records or incorrectly entered data values.

This analysis is limited to pedons that have or had agricultural tillage or disturbance as noted in the taxonomic description by the Ap designation. We excluded volcanic soils with orders Gelisols and Andisols or great/sub-groups Gypsic and Vitric. We also restricted this analysis to layers with bulk density between 0.8 and 2.0 g m^{-3}, organic carbon less than 5.75%, and plant available water less than 0.3 m^3 m^{-3}. Values that are typical of agricultural soils.

Pedons were removed when the following data values were missing. First, pedons were removed if they did not have at least two soil layers and if all layers were not present to 1 m depth or to bedrock. Second, each soil layer must have a data value for all eight required variables: plant available water (PAW), wilting point (WP), percent sand (Sa), percent silt (Si), percent clay (Cl), percent organic carbon (OC), cation exchange capacity (CEC), and bulk density (Bd). As typical for mechanistic modeling, PAW (m^3 m^{-3}) is defined as the volume of water released when the soil is dried from 1/3 bar to 15 bar water tension (Richards and Weaver, 1943). Wilting point (WP) by volume (m^3 m^{-3}) is the measured gravimetric water content of 15 bar water tension on air-dry soil times Bd (g m^{-3}). Field capacity (FC) is equal to the sum of WP and PAW. Last, incorrectly