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Understanding saturated hydraulic conductivity under seasonal changes in climate and land use

Mohamed Elhakeem[a], A.N. Thanos Papanicolaou[b,*], Christopher G. Wilson[b], Yi-Jia Chang[c], Lee Burras[d], Benjamin Abban[b], Douglas A. Wysocki[e], Skye Wills[e]

[a] Abu Dhabi University, Civil Engineering Department, Abu Dhabi, P.O. Box 59911, United Arab Emirates
[b] University of Tennessee, Hydraulics & Sedimentation Laboratory, Department of Civil & Environmental Engineering, Knoxville, TN 37996, USA
[c] DGR Engineering, Rock Rapids, IA 51246, USA
[d] Iowa State University, Department of Agronomy, Ames, IA 50011, USA
[e] USDA-NRCS National Soil Survey Center, Lincoln, NE 68508, USA

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ABSTRACT

The goal of this study was to understand better the co-play of intrinsic soil properties and extrinsic factors of climate and management in the estimation of saturated hydraulic conductivity (K_{sat}) in intensively managed landscapes. For this purpose, a physically-based, modeling framework was developed using hydro-pedotransfer functions (PTFs) and watershed models integrated with Geographic Information System (GIS) modules. The integrated models were then used to develop K_{sat} maps for the Clear Creek, Iowa watershed and the state of Iowa. Four types of saturated hydraulic conductivity were considered, namely the baseline (K_b), the bare (K_{br}), the effective with no-rain ($K_{e\text{-}nr}$) and the effective (K_e) in order to evaluate how management and seasonality affect K_{sat} spatiotemporal variability. K_b is dictated by soil texture and bulk density, whereas K_{br}, $K_{e\text{-}nr}$, and K_e are driven by extrinsic factors, which vary on an event to seasonal time scale, such as vegetation cover, land use, management practices, and precipitation. Two seasons were selected to demonstrate K_{sat} dynamics in the Clear Creek watershed, IA and the state of Iowa; specifically, the months of October and April that corresponded to the before harvesting and before planting conditions, respectively.

Statistical analysis of the Clear Creek data showed that intrinsic soil properties incorporated in K_b do not reflect the degree of soil surface disturbance due to tillage and raindrop impact. Additionally, vegetation cover affected the infiltration rate. It was found that the use of K_b instead of K_e in water balance studies can lead to an overestimation of the amount of water infiltrated in agricultural watersheds by a factor of two. Therefore, we suggest herein that K_e is both the most dynamic and representative saturated hydraulic conductivity for intensively managed landscapes because it accounts for the contributions of land cover and management, local hydropedology and climate condition, which all affect the soil porosity and structure and hence, K_{sat}.

1. Introduction

Saturated hydraulic conductivity (K_{sat}), or when the infiltration rate reaches steady state (e.g., Smith, 2002; McCuen, 2003), is a key, dynamic property for assessing the impacts of climate and management on the behavior of soil and water (e.g., Papanicolaou et al., 2015; Elhakeem et al., 2017). K_{sat} is often used in soil interpretations, hydropedological catena assessments across landscapes, and physically based modeling exercises to determine water budgets, water-plant relationships, soil suitability for agriculture, and leaching potential (Nearing et al., 1996; Arnold et al., 1998; Lin, 2003; Schoeneberger and Wysocki, 2005; West et al., 2008).

However, K_{sat} exhibits a nonlinear behavior in response to external forcings resulting in high spatiotemporal variability at both large and small scales. This complex response is due to the co-play of different intrinsic soil properties, such as texture and bulk density, and extrinsic factors, including land use, vegetation cover, and precipitation (Gupta et al., 1996; Webster and Oliver, 2001; Papanicolaou et al., 2008; Elhakeem and Papanicolaou, 2009; Safadoust et al., 2012). The intrinsic soil properties mostly dictate the spatial variability of K_{sat}, while the added temporal variability of K_{sat} is due to the extrinsic factors (Alleto and Coquet, 2009; Elhakeem and Papanicolaou, 2012).

Capturing this spatiotemporal variability in K_{sat} is challenging as instruments, such as double ring infiltrometers, are labor-intensive and

* Corresponding author.
E-mail address: tpapanic@utk.edu (A.N.T. Papanicolaou).

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expensive. Several spatially distributed point measurements that are conducted for long periods are necessary to measure the spatial and temporal variability of K_{sat} (Papanicolaou et al., 2008). Semi-automation of these instruments has helped ease the load (e.g., Papanicolaou et al., 2015). Yet, performing enough detailed, continuous measurements with the semi-automated instruments remains a daunting task, even in small hillslope-scale studies (10^3–10^5 m^2).

Implicit methods for estimating K_{sat} to address the spatial and temporal limitations related to in-situ measurements include the use of infiltration and watershed models coupled with geospatial tools (Mohatny, 2013). Needless to say, some field measurements are still necessary at representative sites for methods validation.

Several, semi-empirical, infiltration models (i.e., pedotransfer functions, PTFs) exist that estimate saturated hydraulic conductivity based on the correspondence between K_{sat} and intrinsic soil properties, such as texture and bulk density (Schaap, 1999; Ferrer Julia et al., 2004; Rezaei Arshad et al., 2013; Patil and Singh, 2016). K_{sat} estimates that only consider intrinsic soil properties provide a *baseline* saturated hydraulic conductivity, K_b, across space. Most K_{sat} estimates reported in public databases (e.g., NCSS, UNSODA, WISE, HYPRES) are baseline values (e.g., Leenhardt et al., 1994; Leij et al., 1996; Schaap and Leij, 1998; Wosten et al., 1999; Lin et al., 2014).

Watershed models adjust K_b values by considering extrinsic factors such as vegetation cover, land use, management practices, and precipitation, which vary on an event to seasonal time scale (e.g., Nearing et al., 1996; Arnold et al., 1998; Ju et al., 2010). The K_{sat} estimates that consider both the intrinsic and extrinsic factors provide an *effective* hydraulic conductivity, K_e (Paleologos et al., 1996; Deb and Shukla, 2012). In essence, K_e is a "corrected form" of K_b which accounts for climate seasonality and land use change. The models convert "static" K_b values into "dynamic" K_e values, thus making them more pertinent for watershed management.

The objective of this study was to understand better the co-play of intrinsic soil properties and extrinsic factors of climate and management in K_{sat} dynamics through the development of a physically based, geospatial modeling framework to estimate K_{sat} at the watershed scale and larger. The framework presented here integrates regionally representative PTFs, physically based watershed models, and Geographic Information System (GIS) modules to quantify four different K_{sat} types that reflect the influences of both the intrinsic properties and extrinsic factors. The framework estimates the following four types of saturated hydraulic conductivity: (1) the baseline hydraulic conductivity, K_b, that accounts for the intrinsic soil properties; (2) the bare saturated hydraulic conductivity, K_{br}, that adjusts K_b for the effects of soil crusting; (3) the effective saturated hydraulic conductivity with no-rain, $K_{e\text{-}nr}$, that adjusts K_{br} for the effects of vegetation cover; and ultimately, (4) the effective saturated hydraulic conductivity, K_e, that adjusts $K_{e\text{-}nr}$ for the effects of individual rainfall events, which makes it the most dynamic type among the four.

The modeling framework was established first in a representative, intensively managed watershed of the U.S. Midwest, Clear Creek, Iowa where detailed K_{sat} measurements exists (Papanicolaou et al., 2015). Then, the framework was extended to quantify K_b, K_{br}, $K_{e\text{-}nr}$, and K_e for the entire state of Iowa. Maps of the four K_{sat} types were developed for Clear Creek and Iowa for two time periods, October and April corresponding to the pre-harvest and pre-planting conditions, respectively. These maps demonstrate both the spatial and temporal variability of K_{sat} due to changes in soil properties, climate, and management. In addition, a statistical analysis and histograms were provided for the four types and comparisons are made to discern the effect of the extrinsic factors on K_{sat} dynamics.

2. Modeling framework development

2.1. Model selection

The first step towards developing the modeling framework was to select the appropriate PTF and watershed model based on physical reasoning and model performance (Vieux, 2004). The chosen PTF and model should adequately represent site conditions and capture the dynamicity of K_{sat} induced by climate and land management.

The estimates provided by the PTFs and models were compared using seven statistical criteria to direct K_{sat} measurements in selected fields of the test watershed, Clear Creek (Papanicolaou et al., 2015). These criteria included the mode, minimum, maximum, root mean square error, Akaike Information Criterion, geometric mean error ratio, and geometric standard deviation of the error ratio.

The mode was used to examine the symmetry of the observed and estimated values around the mean. The minimum and maximum evaluated the agreement between the ranges of the observed and estimated values.

The root mean square error is a quadratic scoring criterion, which measures the average magnitude of the error in the model estimates. The Akaike Information Criterion is a goodness-of-fit measure of a regression model that tries to minimize the model complexity by imposing a penalty for increasing the number of coefficients (Akaike, 1974; Bozdogan, 1987). For both the root mean square error and the Akaike Information Criterion, lower values indicate better performance of the model. A perfect agreement between the measured and estimated values is satisfied when $RMSE = 0$ and $AIC = 2k$, where k is the number of coefficients used in the model.

The geometric mean error ratio and standard deviation of the error ratio account for the log-tailed distribution of K_{sat} (Tietje and Richter, 1992; Papanicolaou et al., 2015). Perfect agreement between the estimated and the measured values is obtained when these values equal 1.0.

To evaluate the overall performance of the PTFs and models (Table 1), relative scores on a linear scale between 0 and 1 were assigned for each of the aforementioned criterion based on the degree of agreement between the measured and estimated values, and then summed (Shahin et al., 1993). The Rosetta PTF that considers bulk density (i.e., Rosetta - BD), as well as the Water Erosion Prediction Project (WEPP) model provided the closest agreement to the measured K_{sat} in Clear Creek and were incorporated into the modeling framework for this study. Papanicolaou et al. (2015) found that the bulk density dominated the infiltration process in soils experiencing the effects of compaction due to agricultural activity as it alters the soil porous network. Additionally, the WEPP PTFs capture the effects of management through changes in roughness and cover. Brief descriptions of Rosetta and WEPP, in the context of the modeling framework are given in following section.

2.2. Description of models

Rosetta is a modeling platform that estimates water retention parameters, as well as unsaturated and saturated hydraulic conductivity (Schaap et al., 1998, 2001). These parameters are determined using PTFs with various orders of complexity that incorporate sand, silt, and clay percentages, as well as bulk density and water retention points as model inputs. Therefore, it provides values for K_b.

WEPP is a physically based, spatially distributed, watershed model that estimates surface runoff and erosion from agricultural fields under different land uses and management practices (Flanagan et al., 1995, 2007). More detailed descriptions of WEPP and its applications are provided elsewhere (Alberts et al., 1995; Ascough et al., 1994; Abaci and Papanicolaou, 2009; Dermisis et al., 2010; Papanicolaou et al., 2017a).

WEPP can simulate the four K_{sat} types for different hillslopes on an