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Comparison of Measured and Simulated Urban Soil Hydrologic Properties

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Abstract

Urban communities use hydrologic models to plan for and assess the effectiveness of stormwater control measures. Although emphasis is placed on soils as permeable surfaces that regulate the rainfall-runoff process, representative soil hydrologic parameters for urban areas are rare. The extent to which measured and commonly simulated hydrologic data may differ is also largely uncharacterized. As part of the US EPA urban soil assessment, infiltration and drainage rates were measured in 12 cities, and the authors compared these measured data to estimates generated from the EPA National Stormwater Calculator (NSWC), United States Department of Agriculture (USDA) Soil Survey Geographic Database (SSURGO), and USDA Rosetta. The analysis highlights the overall lack of soil hydrologic data for many cities in the NSWC and SSURGO and show that common prediction algorithms for infiltration and drainage poorly represent urban soil hydraulics. Paired comparison of field-measured values and model-estimated values resulted in root-mean-square errors ranging from 23 to 173 mm=h. These findings are presented in the context of planning for effective stormwater and wastewater management practices, and the need for confirming simulation results with site-specific field data.

Keywords

Hydraulic conductivity; National stormwater calculator; USDA Rosetta; Soil Survey Geographic Database (SSURGO); Green infrastructure; Pedotransfer functions; Urban soil

Introduction

Simulation of the urban hydrologic cycle is complicated by interspersed impervious and pervious surfaces. While the hydrology of impervious surfaces is relatively straightforward, pervious surfaces move between unsaturated and saturated states and regulate runoff losses

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via the infiltration process (e.g., infiltration excess), and thus the trajectory of its runoff hydrograph (Woolhiser et al. 1996). Pervious surfaces are typically constituted from soils of various textures that may support vegetative cover. Therefore, in mixed impervious-pervious urban landscapes, it is soil hydraulic conductivity that regulates the runoff process, and thus the runoff dynamic.

Urbanized soils have been subjected to various forms of disturbance that take place over ecologically and geologically short time scales and at irregular time intervals: intermixing with demolition debris, cut and fill processes, and unregulated packing and compaction. Therefore, these soils markedly differ from their agricultural counterparts, which are disturbed by tillage and are subject to erosion, but in a highly regulated and periodic manner.

Another difference between urban and agricultural soils is that the latter have been surveyed and mapped, and in this process some effort was made to determine soil hydrologic properties by measurement or by prediction as pedotransfer functions based on texture. The Soil Survey Geographic Database (SSURGO) is comprehensive, with >95% of the US soils mapped. Yet this database lacks coverage in most cities. Where soil surveys have not been conducted, county soil survey maps describe unmapped city soils as urban land, urban land-complex, made land variations on local named soil series, or, more plainly, area not investigated. For these areas, there is no soil hydrologic information—qualitative or otherwise—that explains the hydrologic role a soil may play in the local water cycle. This reveals a gap in soil hydrologic estimators and limits its application to accurately predicting the hydrology of urbanized landscapes and their underlying soils (Schifman et al. 2018). Inferences may be made from naturally occurring soils that are adjacent to these urban communities, though urbanization impacts (e.g., soil compaction, excavation, filling, land conversion, or grading) on soil hydrologic functions are not accounted for (Schifman et al. 2018; Herrmann et al. 2017; Pouyat et al. 2002; Raciti et al. 2012; Shuster et al. 2014). Alternately, the determination of site-specific soil hydrology can be decoupled from a soil survey context and estimated from algorithms such as USDA Rosetta, which uses pedotransfer functions based on known soil characteristics (i.e., soil textural class and bulk density) (Nemes et al. 2009; Schaap et al. 2001; Schaap and Leij 1998). For example, Rosetta provides an increasingly detailed hierarchy of data inputs to improve the accuracy of hydraulic conductivity prediction (e.g., proportion of sand, silt, and clay; bulk density and soil water retention) (Schaap et al. 2001). However, the high degree of uncertainty in soil hydrologic characteristics is explicitly constrained by the range of variability captured by large sample sets of paired soil texture–hydraulic data taken from predominantly rural, agricultural soils (Rawls et al. 1982). Regional-scale modeling exercises that rely on highly interpolated field data, provided by different methods of estimation such as Rosetta or SSURGO soil hydrologic data, have been documented to show bias in prediction (Anderson et al. 2006; Di Luzio et al. 2004; Mednick 2010; Peschel et al. 2003). Similarly, the US EPA National Stormwater Calculator (NSWC), which is designed to be used as a rainfall-runoff estimator for smaller scale catchments up to 5 acres, shows significant variation in runoff depth outputs, depending on the source of data used (Schifman et al. 2018).

As it stands, the problem here is that the hydrology of urban soils adds complexity to runoff prediction and has not yet been assessed in a structured manner. Urban soils undergo

processes that vastly alter hydrology at the anthropogenic time scale, e.g., a demolition that alters soil conditions in under 1 week. Similarly, the variation in urban soil hydrology at the spatial scale can vary at the submeter scale (Shuster et al. 2014, 2015), making even the highly interpolated mapping efforts of SSURGO inadequate. This begs the question: are tools like USDA Rosetta or soil hydrologic data obtained from either the NSWC or SSURGO adequate for modeling hydrologic responses of urban systems?

The objectives were to take measured soil texture and infiltration, and drainage rates from urban soils in 12 conurbations across the United States and the Republic of the Marshall Islands that cover the major soil orders and compare these values with their estimated counterparts generated by simulation in the NSWC, SSURGO, and USDA Rosetta. For the NSWC and SSURGO simulations, the authors predicted that estimations of urban soil hydrology will be influenced by either a lack of representative data, the grounding of these models in the hydrology of agricultural soils, or both sources of variability. The paper also discusses the implications of these comparisons for representing soil hydrology in the design process for urban green infrastructure stormwater control measures.

Methods

Field Sampling

Soils were assessed for hydrologic and pedologic characteristics in urban core areas of Atlanta (ultisols); Camden, New Jersey (aquic spodosols); Cincinnati (unglaciated alfisols); Cleveland (aquic alfisols); Detroit (alfisols and mollisols); New Orleans (vertisols, histosols); Omaha, Nebraska (ustic alfisols and mollisols); Phoenix (aridisols); Portland, Maine (upland spodosols); Tacoma, Washington (andisols); San Juan, Puerto Rico (oxisols); and Majuro atoll, Republic of the Marshall Islands (entisols) (Table 1). Potential sites were identified along gradients of parent material and topography, though site selection was ultimately opportunistic due to local governance controls on accessibility and gaining right of entry to vacant lots and city parks. The authors used core sampling techniques with truck-mounted or tracked Geoprobe units (Geoprobe Systems, Keyr Inc., Salina, Kansas). Cores were 6 cm in diameter and taken up to 4 m depth in 1.3-m core sections, unless limited by paralithic contact or buried debris. Horizons were identified and evaluated for texture (Fig. S1) and color based on commonly accepted standards (Schoeneberger et al. 2012). Qualitative field textural analyses of soils (Thien 1979) were confirmed with the pipette method (Gee et al. 1986) for top soil and subsoil horizons where changes in texture were evident. For soils where fine sands were observed, the sand fraction was sieved into very coarse, coarse, medium, fine, and very fine sand fractions. Surface and subsurface hydrological processes were differentiated by defining infiltration as the rate at which water moves from the soil–atmospheric boundary into the typically unsaturated surface soil, whereas drainage is the rate of flow in a saturated subsoil horizon. Infiltration was measured adjacent to the soil core in at least four locations at each site as near-saturated hydraulic conductivity (K_{unsat}) using tension infiltrometers (Mini-Disk Infiltrometer, Decagon Devices, Pullman, Washington) at a suction head of -2 cm (Dohnal et al. 2010; Zhang 1997) (Table 1). This technique served to more closely match the hydraulics of the typically unsaturated condition at the soil surface; and for these disturbed, mixed urban soils, the

approach excluded high variation in K_{unsat} that may otherwise be caused by structural macroporosity (e.g., cracks and biopores) sinks for flow, and rather emphasize the measurement of matrix flow into surface soils. Borehole saturated conductivity, referred to herein as drainage rate, was measured with Amoozemeters (K_{sat} , Inc., Raleigh, North Carolina) at the bottom of the 6-cm-diameter borehole, which was advanced to a depth just inside of the hydraulically restrictive layer. This borehole was drilled adjacent to the original soil core.

Statistical Analysis and Parameter Estimation

Because fine sand fractions play an important role that is similar to silt in controlling soil hydrology, the authors carried out principal component analyses (PCAs) that evaluated the multivariate relationships among various soil characteristics on field-measured infiltration and drainage rates. Because fine sand fractions (i.e., very coarse sand, coarse sand, medium sand, fine sand, and very fine sand) were not encountered in all cities that were part of the assessment, the sample set for this analysis was limited to the six cities, which included Atlanta, Georgia; Camden, New Jersey; Detroit, Michigan; New Orleans, Louisiana; Portland, Maine; and Tacoma, Washington. The following information was included in the analyses: surface or subsoil texture (very coarse sand, coarse sand, medium sand, fine sand, very fine sand, silt, clay), bulk density, percent carbon, and percent nitrogen, with separate PCA runs for infiltration rate (K_{unsat}) or drainage rate (K_{sat}). After data transformation (Table S1), normality of the data was confirmed through a Shapiro-Wilks test. Missing values in the data were imputed using the missMDA package in R (Josse and Husson 2016). Following this, a PCA was carried out using the FactorMineR package (Lê et al. 2008), which directed the authors to truncate variables into two new categories (fines and coarse material), wherein fines consisted of clay, silt, and very fine and fine sands, while the coarse material consisted of very coarse, coarse, and medium sands. The same procedure was followed for the drainage rate (K_{sat}). Visualization and interpretation of PCA results was done through the factoextra package (Kassambara 2015). Variables with a factor contribution that was greater than $1/n$, with n being the number of variables, were considered significant or strong contributors to the factor.

Infiltration and drainage rates acquired through the field campaign were compared with modeled estimates generated for infiltration rates (NSWC and SSURGO, through the WebSoil Survey interface) and drainage rates (USDA Rosetta). While the NSWC is intended as a stormwater management screening tool for small sites with uniform soil conditions, it is customarily used for simulating runoff production in urban areas. On a larger scale, SSURGO data on soil hydrology are often used in simulation of landscape runoff models.

In SSURGO, hydraulic conductivity is estimated based on soil texture or measurements using Amoozemeters (Amoozegar 1989; Schoeneberger et al. 2012). Even though SSURGO data provide the underlying framework on soil hydrology to the NSWC, the data acquisition around a point of interest within the NSWC can introduce variation in hydrologic estimates compared with the same location in SSURGO (Schifman et al. 2018). These measurements reflect estimated or otherwise interpolated conductivity under moisture conditions that are typically assumed to be saturated but are more typically in unsaturated moisture conditions.

For this reason, the authors compared the values obtained by both SSURGO and NSWC with measurements of hydraulic conductivity at near-saturated conditions. The NSWC provides a great deal of flexibility in this matter and presents three options to parameterize hydrologic parameters: Option A assigns a default conductivity of 10 mm=h, Option B queries SSURGO for soil hydrologic parameters (used in this study), and Option C allows the user to specify hydraulic conductivity based on local knowledge of the soil (recommended for model simulations). In the NSWC and SSURGO, each site was geolocated and when soil data were available in the queried database, the corresponding infiltration rate was recorded.

The Rosetta pedotransfer functions developed by Schaap et al. (2001) parameterize the van Genuchten (1980) closed-form expression for unsaturated conductivity, which is based on the van Genuchten (1980) water retention function and Mualem (1976) pore size distribution model. The output provides the user with estimates of the van Genuchten (1980) water retention, as well as estimates of the saturated hydraulic conductivity, K_{sat} , and unsaturated conductivity, K_{unsat} . For estimates of K_{unsat} , the authors assessed five formulations: K_{unsat1} used texture class; K_{unsat2} used sand percent, silt percent, and clay percent (SSiC); K_{unsat3} used adjusted sand percent, silt percent, and clay percent, where silt included fine and very fine sand fractions (adjusted SSiC); K_{unsat4} used sand percent, silt percent, clay percent, and bulk density (SSiC + BD); and K_{unsat5} used adjusted sand percent, silt percent, clay percent, and bulk density (adjusted SSiC + BD). For K_{sat} , the authors carried out the same procedure; however, a lack of bulk density measurements in the subsoil allowed the authors only to parameterize the model with three formulations: K_{sat1} as in texture class, K_{sat2} as in SSiC, and K_{sat3} as in adjusted SSiC.

For all comparisons of measured and predicted values, the authors visually compared data distributions generated from logtransformed data and used the root-mean-square error (RMSE) as a metric of overall magnitude in differences between measured and estimated values

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (\phi'_i - \phi_i)^2} \quad (1)$$

Mean estimation errors were compared using the mean error (ME)

$$ME = \frac{1}{N} \sum_{i=1}^N (\phi'_i - \phi_i) \quad (2)$$

For both formulas, N = number of samples, and ϕ' and ϕ = estimated and measured infiltration (or drainage) rate values, respectively. For both errors, values closer to 0 indicate a better estimate; however, for the ME, a positive value indicates that modeled values are on average overestimated, and for negative values, modeled values are on average underestimated.

Results and Discussion

Field-Measured Infiltration and Drainage Rates

Infiltration Rates—Infiltration rates ranged from 0 to 494 mm=h, with a mean of 19 ± 2 mm=h [average $\pm$ standard error (SE), Table 1]. The highest measured rates occurred in New Orleans, where a sandy backfill was predominant in many of the post-Katrina vacant lots, and the lowest measures were obtained in Omaha, Nebraska, where top soils were in some cases hydrophobic, sealed, or exhibited both conditions (Table 1). PCA indicated that 80% of the variance in the infiltration (surface soil) data set is explained by the first three components, which show relationships among infiltration rate, soil textural class, sand separates, bulk density, and carbon and nitrogen content [Fig. 1(a); Table S2]. The strongest (first) component (34%) shows positive loadings in carbon, nitrogen, very coarse, and coarse sands (collectively contributing 62% to the factor) that are opposite of the negative loadings for infiltration rate (contributing 10%; Table S3; Fig. S2). The second component (29%) has positive loadings in medium, coarse, and very coarse sands that are correlated with infiltration rate significantly contributing to the factor (collectively 46%), opposed by negative loadings in very fine sand, silt, and clay, which collectively contribute 52% to the factor loadings (Table S3; Fig. S2). The third component (17%) has positive loadings in soil nitrogen, carbon concentration, and fine sand, (contributing 52%), along with a negative loading in bulk density that contributed 41%. The authors focused on the second component, where an increase in the proportion of finer particles in top soils (very fine sand, silt, and clay) was correlated with a decrease in infiltration rate. The authors adjusted the model to account for the impact of finer sands, thereby reducing the number of variables by combining the very coarse, coarse, and medium sand fractions; and clay, silt, very fine, and fine sand fractions into coarse and fine material categories, respectively. Focusing on the second component (26% of total variance), the variance structure more clearly illustrates the degrading impact of fines on infiltration rate [as K_{unsat} ; Table S3; Figs. 1(b) and S2]. Similar findings have been reported in other studies that focus on finer sand fractions in top soils because these may regulate infiltration more than coarser sand fractions (Handreck 1983; Puckett et al. 1985; Skaggs et al. 2001). Short of having full grain size distributions, other efforts have involved the development of pedotransfer functions that use fine and very fine sand fractions in addition to total sand (Puckett et al. 1985; Skaggs et al. 2001). In both cases, the importance of these finer sand fractions was recognized in regulating soil hydrology, as well as other types of soil media (Handreck 1983). Similarly, larger scale hydraulic conductivity testing in the form of aquifer tests relies on grain size diameter rather than texture class with the explanation that specific grain size is more telling than grain size class alone because sand fractions are usually defined as grains ranging from 0.05 to 2 mm (Alyamani and Sen 1993; Nemes and Rawls 2004; Vienken and Dietrich 2011). Other studies that focus on site-specific infiltration rates have developed models that use grain size distributions as input data for estimates on hydraulic conductivity (Barbu and Ballesterio 2014). As demonstrated here, this theory holds true on a smaller site scale as well where our taxonomic assessments indicated that the finer sand fractions also regulated hydraulic conductivity.

The infiltration rates in this study were determined under near-saturated conditions [i.e., $K(-2\text{ cm})$], such that larger macropores do not contribute to infiltration flux. These values can therefore be somewhat less than saturated hydraulic conductivity measurements, which account for combined macropore and matrix fluxes. This difference in infiltration measurement process will contribute to differences between measured and predicted or simulated values. However, the infiltration measurement process is parsimonious with the unsaturated soil surface condition predominantly observed under field conditions, and thereby best accounts for infiltration behavior in the drier to early-onset of rainfall stages of the infiltration process. In this way, the authors endeavored to control for and incorporate measurements made under parsimonious soil hydrologic conditions so as to determine combined process and simulation uncertainty. Overall, and in very general terms, soils with finer surface structure and low macroporosity may narrow the difference between K_{unsat} and K_{sat} .

Drainage Rates—As part of the field soil taxonomic description of soil layering and horizons, the authors identified the layer closest to the surface that was hydraulically restrictive based on the presence of a pan, a transition, or shift in soil texture, or an underlying subsoil of very low permeability (e.g., a silty lacustrine layer). Drainage measurements were made just above and within this hydraulically restrictive layer in the subsoil. The averaging across soil characteristics in three dimensions likely yielded a conservative measurement of drainage rate. Measured drainage rates across all sites ranged from 0 to 1,343 mm/h with an arithmetic mean of 64 ± 10 mm/h (mean $\pm$ SE) and median equal to 3 mm/h, indicating skew in the overall distribution (Table 1). On average, the highest drainage rates were measured in the highly weathered, carbonitic loamy sand soils underlying the Majuro atoll; and the slowest were in clayey ultisols arranged along vacant hillslope parcels in the Proctor Creek area of Atlanta (Table 1). For many of the cities, mean drainage rates exceeded and were more variable than the corresponding (and co-located) measured infiltration rate. The authors offer a twofold explanation of this. First, that the infiltration rate was made under near-saturated conditions, which will exclude the flux contribution from macropores, and so infiltration rates would be expected to be less than that expected under saturated conditions. This would especially be the case for unsaturated, compact, and usually slaked urban surface soils. However, the infiltration process accounts for surface soil hydrology. Secondly, the authors observed in these urban soil assessments a great deal of structural macroporosity as void space among large pieces of debris, and layering of different sources of fill soils, each with potentially very high or low hydraulic conductivity. Taken in turn, these fill and packing conditions led to higher mean drainage rates, with higher standard error of the mean. Since these infiltration and drainage measurement techniques were appropriate to the particular unsaturated and saturated conditions, respectively, and conducted in a consistent manner, they characterize the unique hydrologic setting of urban soils (see also Shuster et al. 2014).

The authors explored whether a correction for fine sands would be meaningful for subsoils and measured drainage rate. For the subsoil-drainage PCA model, the first three components explained 76% of total variance in the data [Fig. 2(a); Table S2]. The first component (40%) shows positive loadings that correlate drainage rate, very coarse, coarse, and medium sands,

which are opposed by negative loadings in very fine sand, silt, and clay that contribute 34% to the component (Table S3; Fig. S3). The second component did not have any bearing on soil texture and hydrologic relationships, though the third component explained a relatively small 17% of total variance and showed positive loadings in very fine and fine sands, drainage rate (65% of the component), and negative loadings with the permeable very coarse sand fraction. The second component and the seemingly contradictory outcome of the third may indicate that texture alone is not the soil predictor of drainage rate. Other unmeasured factors affecting drainage that are not directly tied to soil texture include the presence or absence of artifacts and debris from demolition or past land uses, the degree of packing of subsoils, and the root activity, carbon content, and their interactive potential for building soil structure and macroporosity. The overall contribution to total variance of these factors is low and suggests that the role of processes or characteristics that were not accounted for nor measured is relatively small. Consequently, the authors found the adjusted PCA model clarified the degrading impact of the finer sand fractions on drainage rates, showing a strong increase in total explanatory power from the base model (95%) from the first three components [Fig. 2(b); Table S3]. The first component (47%) grouped fine and very fine sands with silt and clay fractions; and likewise, medium and coarse sands, as well as drainage rate (Fig. S3), corroborating findings that grain size itself has greater influences than grain size classes (Alyamani and en 1993; Handreck 1983; Vienken and Dietrich 2011). The second component retained the theme of having no explanatory power on soil hydrology, and although the trend of the third component was the same, the regrouping of variables reduced its significance to be negligible.

Estimates for Modeling and Measured Values: Infiltration Rates

The authors used the US EPA NSWC's ability to derive estimates of infiltration rates from SSURGO soil mapping resources. Due to poor coverage of soil maps and infiltration rate estimates (as saturated hydraulic conductivity in SSURGO), of the 357 sites investigated in this study the NSWC could retrieve soils information for only 126 sites (Table 2). When the authors went directly to SSURGO, the number of sites that were represented with data decreased to 86. In some cities, soil hydrologic data were entirely absent (Table 1), whereas other cities, e.g., New Orleans and Portland, Maine, had high geodatabase coverage. The expectation would be to have similar coverage between the two tools because NSWC relies on SSURGO for data queries. However, NSWC has built-in algorithms that extend the query for soil data in a radial form from the point of interest for locations without data. In such a case, available data are integrated over the area of interest and a representative conductivity value is presented, resulting in the appearance of more complete coverage for soil hydrologic data (Rossman 2013; Schifman et al. 2018).

Due to differences in the availability of field-measured input parameters, the authors were able to predict the infiltration rate as unsaturated hydraulic conductivity (K_{unsat}) in Rosetta for a low of 107 sites (proportions of soil textural separates SSiC and bulk density, referred to as $K_{\text{unsat}3}$ SSiC + BD) to a maximum of 306 sites, which would have had soil textural class ($K_{\text{unsat}1}$ soil texture class) and normal SSiC ($K_{\text{unsat}2}$ SSiC) as the only predictors. For cities with sand separation, the soil texture was adjusted by adding fractions of fine and very fine sands to the silt fraction, and the coarse fraction composed of medium, coarse, and very

coarse sands ($K_{\text{unsat}4}$ adjusted SSiC) for which K_{unsat} was likewise predicted in Rosetta for 111 sites. There were 64 sites that had more detailed sand fraction and bulk density measurements, and this group is referred to as $K_{\text{unsat}5}$ adjusted SSiC + BD (Table 2).

As shown in Fig. 3(a), log-transformed measured data form an approximately normal distribution, which is similar to the queried estimates available through soil surveys. The measured distribution is flanked by the corresponding multimodal distributions of log-transformed estimates drawn from NSW and SSURGO, which tend to be lower and higher than measured, respectively. The MEs for these two distributions emphasize this observation with values of -14 mm/h for NSW and 49 mm/h for SSURGO. The overlapping ranges of predicted infiltration estimates obtained from the NSW were from 0.1 to 113 mm/h (average $\pm$ SE = 7 ± 1 mm/h, median = 1 mm/h), and from SSURGO they were 0 to 360 mm/h (average $\pm$ SE = 74 ± 19 mm/h, median = 14 mm/h) [Table 2; Fig. 3(a)]. Comparing the distributions on a pairwise level with the measured values, NSW estimates are generally better than SSURGO, where RMSEs are 62 mm/h, and 152 mm/h, respectively. In practical terms, the NSW predictions will yield estimates that are more conservative such that a given soil would be less infiltrative. On the other hand, SSURGO predicts faster infiltration compared with measured. However, the measured standard is an estimate of hydraulic conductivity at near-saturated equilibrium conditions (measured at 2 -cm tension head) (Dohnal et al. 2010), whereas both the NSW and SSURGO estimates represent saturated hydraulic conductivity. This makes more sense for the overestimates of SSURGO because saturated hydraulic conductivity (or estimated infiltration rate at saturation) does not discriminate between macropore and matrix contribution to flow. It bears mentioning that NSW Option A, which assigns a default conductivity of 10 mm/h, may serve cities like Detroit, Michigan; Portland, Maine; and San Juan, Puerto Rico, which have mean infiltration rates close to this preset value (Table 1).

A hallmark of methods to measure unsaturated hydraulic conductivity is to deliver water at different tension heads to specify and hydraulically activate the pore size range of interest. In the experimental context, the authors used tension infiltrometers to measure infiltration and lessen the potential contribution of larger, surface-connected macropores (e.g., cracks). Another impact on fair comparison between measured and predicted data is that the sample sizes (measured versus simulated or interpolated) are different. Even though SSURGO acts as the primary soils geodatabase for the NSW, the NSW generates soil hydrologic information from an area-averaging approach that extends up to $5,000$ m from the point of interest (Rossman 2013; Schifman et al. 2018). For this reason, the number of sites with soil hydrologic information appear to be greater in the NSW compared to SSURGO (Table 2). The multimodal distributions in predicted estimates in Fig. 3(a) may be an artifact of less than $1:1$ correspondence among soil conditions among soils in the same series (soils that are mapped as distinct, but have similar hydrology as K), a lack of consistency in methods used to determine field-saturated hydraulic conductivity in the data sets that form SSURGO over the course of the soil survey history, and that SSURGO is largely based on county soil surveys that focused on agricultural soils. This is all in contrast to the data set obtained through the EPA urban soils assessment, which documents hydraulic conductivity measurements in a consistent form.

It is a distinct possibility that the urban areas that are mapped in SSURGO were originally agricultural or forested soils that have since been developed and otherwise urbanized. The process of urbanization can alter soil hydrology and therefore its role in regulating local hydrology (Shuster et al. 2014). Soils are excavated and become fill elsewhere, and lowland surface horizons are buried by fill, which is laid in lifts with varying amounts of compaction. Construction operations ensue, and then years later buildings are demolished, leaving a vacant lot with compromised hydrologic conditions at the surface. The authors observed many vacant and park areas—without vegetative cover—and these subareas usually presented with surface seals, which limit infiltration. All of these processes can singly or in the aggregate affect hydraulic conductivity by changes in the pore size distribution, and restrictive pans as surface sealing, and thus outline comparisons between infiltration rates observed on agricultural rather than urban soils.

Using Rosetta, which is functionally closer to the measurement approach, the authors also generated estimates of infiltration rate as K_{unsat} and compared them with measured values. Rosetta models appear to have good predictive ability for soils that have infiltration rates of up to 5 mm/h, yet the model cannot properly capture factors that affect the hydrology of soils with higher infiltration rates. The K_{unsat3} SSiC + BD input ensemble to Rosetta produced a narrower multimodal distribution [Fig. 3(b)], leaving gaps in the tails of the measured distribution. The other, not yet adjusted input ensembles to Rosetta, K_{unsat1} texture class and K_{unsat2} SSiC + BD, produced multimodal outputs, which categorically underestimated infiltration rate compared with measured values, as reflected in the negative MEs (Table 2). Rosetta did not yield improved agreement with measured values after adjustment of texture, which lumped fine sand separates with the silt fraction in the K_{unsat4} adjusted SSiC input ensemble. However, sensitivity to a higher proportion of fines was observed. These effects on prediction accuracy are illustrated by the output distributions for K_{unsat4} adjusted SSiC and K_{unsat5} adjusted SSiC + BD, which yielded distributions that were shifted lower for the K_{unsat2} SSiC and K_{unsat3} SSiC + BD and predicted overall lower infiltration rates than that for measured values [Table 2; Fig. 3(b)]. Using conservative estimates in the design of infiltration stormwater management practices would be more in keeping with risk management priorities, especially to prevent undersizing the stormwater control measure. Yet oversizing presents its own issues. In terms of financial return on investment, unused capacity can be expensive from an operational standpoint unless additional sources of stormwater volume can be routed to the stormwater control measure.

Within-City Variation in Infiltration Rate Prediction

To elucidate some more specific trends in how each of these predictive models respond to conurbations, the data for Camden, New Jersey; New Orleans, Louisiana; Portland, Maine; and Tacoma, Washington were selected for further evaluation (Fig. 4). Despite relatively uniform soils, there were still within-city patterns in prediction error. This is easily understood for New Orleans whose geography puts it at the mouth of the Mississippi River, and is therefore built on soils with high clay contents. Here, New Orleans soils are described as clays and silty clays in soil surveys (NRCS 2009), whereas backfill and landscape restoration assessed in the field campaign described the fill soils as loamy fine sand, fine sand, or fine sandy loam (Fig. S1). This discrepancy can be attributed to backfilling housing

lots with sand, which was employed as the best-available fill material, and its relatively coarse texture enhanced infiltration rates for a subset of post-Katrina vacant lots. Since both SSURGO and the NSWC use soil textural data based on county-level soil surveys to determine infiltration behavior, underestimation is expected in areas like New Orleans that have not recently been resurveyed. For example, at one site in New Orleans a measured value (291 mm/h) was four orders of magnitude greater than the NSWC prediction (0.07 mm/h) and three orders of magnitude greater than the value queried from SSURGO (0.9 mm/h). However, this uncertainty in estimation is not isolated to SSURGO the NSWC, or soil surveys. Rosetta, which uses measured soil textural data to predict K_{unsat} , also generally underestimates infiltration rates for New Orleans. This finding highlights that pedotransfer functions developed for agricultural soils may not be appropriate for urban areas. Similarly, after a shift in landscape form and hydrologic characteristics (such as that experienced by New Orleans in August 2005), an updated soil taxonomic and hydrologic assessment is called for. Despite periodic updates of soil surveys, conurbations are actively changing, dynamic environments. Moreover, in some cities (Detroit, Cleveland), numerous demolitions are backfilled with largely unregulated, locally available (and thereby low-cost) fill material, creating soil layerings that differ vastly from their native or prior state (Herrmann et al. 2018). These soil materials may be highly variable in texture and composition and can contain construction debris or other materials that influence hydrological characteristics in an unpredictable way (Shuster et al. 2014). This textural deviation from the original soil due to backfilling, mixing, and compaction will likely outweigh the small differences in the degree of saturation and water content in the soil can have on K_{unsat} , highlighting the importance of measuring K_{unsat} values.

Estimates for Modeling and Measured Values: Drainage Rates

To estimate drainage rates, the authors were limited to using soil texture class data (K_{sat1} texture class) and normal SSiC (K_{sat2} SSiC) as the sole input to Rosetta, such that 328 predictions were obtained for each, and 114 for the adjusted SSiC (K_{sat3} adjusted SSiC) (Table 2). Fig. 5 shows the distributions for the log-transformed measured borehole saturated conductivity contrasted with Rosetta model estimated values. The range of measured drainage rates covered six orders of magnitude, whereas the kurtotic Rosetta estimated distributions fall roughly between 1 and 100 mm/h (Table 2). Specifically, the K_{sat1} texture class model output covered a range from 3 to 268 mm/h (mean $\pm$ SE = 33 ± 4 mm/h) with a multimodal distribution. Here, the peaks fall out along soil textural classes, representing high proportions of loam and sandy clay loam, sandy loam, loamy sand, and sand (Fig. 5) according to the Rosetta lookup table. Yet the distribution is skewed with most samples falling into the finer loam and sandy clay loam category. Compared with the K_{sat2} SSiC texture model output, the two distributions cover similar ranges of SSiC ranging from 2 to 368 mm/h. (mean $\pm$ SE = 28 ± 3 mm/h). Although the K_{sat2} SSiC distribution is not multimodal, it skews similar to the K_{sat1} texture class distribution. The distribution of samples that were predicted using the K_{sat3} adjusted SSiC show a more kurtotic, nearly normal distribution spanning the range of 4 to 114 mm/h, with the highest predicted drainage rates shifted to a lower range of drainage rates (mean $\pm$ SE = 17 ± 2 mm/h), indicating that Rosetta K_{sat} predictions are sensitive to adjustment in texture (Fig. 5). The wide range of drainage rates measured in the urban soils as part of this assessment and the

narrow ranges of drainage rates estimated by Rosetta led to poor agreement between pairwise measured values and predicted values, with RMSE greater than 150 mm/h for all samples (Table 2). Mean errors for the estimated distributions compared with the measured values revealed that all Rosetta models underpredicted subsurface K_{sat} (Table 2). Although underpredictions of hydraulic conductivity lead to more conservative design plans, there remains a wide range of soils that have lower conductivities than those being predicted by Rosetta. Alternately, soils that are closer to the middle of the soil textural triangle, namely, silty loams, sandy clays, silty clays, and loams, all have predictions that compare well with measured values.

Within-City Variation in Drainage Rate Prediction

When the authors extended the analysis to determine site-specific differences between drainage measurements and predictions in Camden, New Jersey; New Orleans, Louisiana; Portland, Maine; and Tacoma, Washington, there appeared to be a pattern of Rosetta overestimating drainage in clayey soils and underestimating soils with high sand content (Fig. 6). Depending on their mineralogy and shrink-swell characteristics, clay content can impact soil hydrologic properties. Although Rosetta pedotransfer functions were developed based on soil databases consisting of thousands of samples from soils around the globe (Schaap et al. 2001), predicting K_{sat} for soils on either end of the texture spectrum remains a challenge for Rosetta. The specific soil condition (e.g., anthropogenic disturbance, construction debris) and particle size contribution to proportion of fines are not well represented in this predictive model, offering direction for its further development.

These findings are corroborated in other studies, e.g., Cronican and Gribb (2004) found that Rosetta, along with other pedotransfer functions, was only able to accurately predict hydraulic conductivity values within one to two orders of magnitude for sandy soils. In another study, Rubio (2008) developed site-specific pedotransfer functions that included organic matter content and sand fractions to improve the ability to predict hydraulic conductivity values for grasslands and forests and found the site-specific pedotransfer functions were more accurate than Rosetta. Both Wagner et al. (2001) and Tietje and Hennings (1996) have evaluated pedotransfer functions for saturated and unsaturated soils in Germany and found that with an increase in clay content and macropores the accuracy of predicted conductivity values decreased.

Implications for Integration into Hydrologic Models and Soil Survey Context

The assessment of near-surface site hydrology can be represented as infiltration rate, drainage rate, and corresponding hydropedological data (e.g., texture and redox status). From a practical standpoint, the cost of obtaining field-measured values as model inputs is high compared to prediction with available geodatabases and models (David Cicalone, Sr. hydrogeologist, Roux Inc., personal communication, 2016). However, the authors have found that although prediction of hydraulic conductivity is accurate under certain conditions, there are significant gaps in prediction performance. Similar reports have been made by others in relation to the specific soil hydrology prediction tools presented here: Rosetta (Alvarez-Acosta et al. 2012; Rubio 2008), SSURGO (Anderson et al. 2006; Peschel et al. 2003; Tietje and Hennings 1996), and the NSWC (Schifman et al. 2018). While various

studies have assessed the impacts of missing infiltration data by overcoming this lack of information with advanced or simplified models (Grimaldi et al. 2013; Petroselli et al. 2013; Petroselli and Grimaldi 2015), the mosaic of variable source areas, disconnected pervious areas, and constant changes in antecedent surface conditions and ongoing development in urban systems are all sources of uncertainty.

In urban soils, hydrologic properties are modulated by processes and mechanisms that are incompletely represented in available geodatabases and predictive models. In estimating infiltration or drainage rates either through database queries or through pedotransfer functions, it is important to remember that soil hydrologic parameters can be profoundly altered by anthropogenic influence, and specifically through processes like compaction, vegetation, excavation, and land application of chemicals such as road salts that affect aggregation and the development of soil structure.

In the context of contemporary stormwater management, urban communities are increasingly integrating different types of green infrastructure (as intentional infiltration and storage) into their portfolio of stormwater control measures (Fletcher et al. 2014). In this context, green infrastructure serves as a break in impervious surface and can be used to increase sewershed detention capacity, keep stormwater volume from entering the centralized collection system, and temper the inlet storm hydrograph peak. Properly designed, green infrastructure technologies can play a key role in reducing the amount of inflow into wastewater collection systems, minimize return flow, and lower the risk of system malfunctions as combined or septic sewer overflow events (Shuster et al. 2017). However, an inaccurate assignment of soil hydrology can result in error propagation that is initiated early in the design process and may lead to over- or undersizing infrastructure. This can result in cost trade-offs involved with replacing existing soils with engineered soil mixes, which are uniform and possess favorable hydrologic properties. Further, soils that are dominantly sandy or clayey or ones that have been engineered for specific purposes, such as bioretention, may be difficult to predict through pedotransfer functions. Studies reviewing Rosetta and other data sets, such as that of Rawls et al. (1982), on which many pedotransfer functions are based, also report poor representation of clayey soils and therefore state that these models are not effective in prediction for such soils (Nemes et al. 2003, 2009; Schaap and Leij 1998). Similarly, since many of these pedotransfer functions, including Rosetta, are based largely on agricultural soils where there is more uniformity and fewer extremes in soil textures and rock fragment percentages (Nemes et al. 2009), applying these models to urban soils is not recommended. Finally, large-scale application of these models across various climate regions presents additional challenges. Many pedotransfer functions rely on data sets that have been derived for particular regions or soil types (Rubio 2008) or include overrepresented regions, skewing that data set (Nemes et al. 2003, 2009). Using pedotransfer functions that are based on national data sets that have extensive overrepresentation of particular regions and soil types can lead to inaccurate outputs for underrepresented regions (Nemes et al. 2003).

The data from the EPA urban soils assessment fits into SSURGO in a unique way that informs recent USDA Natural Resources Conservation Service (NRCS) soil surveys (Detroit, Michigan, Camden, New Jersey) by (1) assessment of deeper horizons, because

investigations often went to 4–5 m, and beyond the typical 2 m; and (2) standardizing the collection of hydrologic data as opposed to saturated hydraulic conductivity estimates in SSURGO, the sources of which are not well documented. Although there is variability in prediction arising from misalignment between unclassified urban land complex (that lack attribution to a specific soil series), the authors present data drawn from a novel, consistent assessment that couples urban soil taxonomy and hydrology.

Conclusions

The authors measured urban soil infiltration and drainage rates and used these values as a benchmark for comparison to corresponding predictions of the same parameters in the NSWC, a direct query into SSURGO, or through estimates using pedotransfer functions in USDA Rosetta. Because all estimates have inherent uncertainty, measured and predicted estimates are imperfect for different reasons. In the case of measurements, these were made in a consistent manner across a wide variety of urbanized soil orders and land-use conditions, and are representative of conditions found in accessible vacant and park landscapes. Prediction by tools (i.e., NSWC), spatial databases (i.e., SSURGO), and models (i.e., Rosetta) is restricted by the completeness of coverage and alignment of location with measurements, consistency of measurement in the basic data, and sample sets that are used to develop pedotransfer functions. This work indicates that hydrogeological data from a standardized urban soil hydrologic assessment protocol—such as that applied herein—would guide the proper selection (i.e., infiltration and storage) and design of green infrastructures. This is particularly important when considering designs for green infrastructure with a focus on stormwater management, aquifer recharge, or an ensemble of services where the ability of a soil to infiltrate and then drain water is essential to water resources management, particularly in the face of shifting precipitation patterns with climate-affecting socioenvironmental change. With this in mind, the authors recommend that field measurements and field testing of site or localized soil hydrologic parameters become routine practice. This is especially important when designing green infrastructure with the intent of managing stormwater as a part of a larger water resources network. Future work includes extending the field observations and results to the National Cooperative Soil Survey to expand on and otherwise confirm SSURGO data sets, and generally improve understandings of the role of urban soils in the local water cycle.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Fig. 1. Comparison of (a) base and (b) adjusted PCA models for top soil characteristics. The coordinates are colored by percentage contribution with strongly contributing variables in dark gray, compared with weakly contributing variables in light gray.

Fig. 2.

Comparison of (a) base and (b) adjusted PCA models for subsoil characteristics. The coordinates are colored by percentage contribution with strongly contributing variables in dark gray, compared with weakly contributing variables in light gray.

Fig. 3. (Color) Measured Kunsat values compared with the hydraulic conductivity values given by (a) the NSW and acquired through a SSURGO query as well as (b) predictions obtained by Rosetta. All values are log-transformed and plotted as density functions to compare distributions.

Fig. 4.
(Color) Selection of four cities to highlight the deviation between estimates and field measurements of infiltrating rates using NSWC, SSURGO, and Rosetta.

Fig. 5. (Color) Measured K_{sat} values compared with the hydraulic conductivity values predicted by Rosetta. All values are log-transformed and plotted as density functions to compare distributions.

Fig. 6.
(Color) Selection of four cities to highlight the deviation between estimates and field measurements of drainage rates using Rosetta.

Table 1.

Summary of the measured infiltration and drainage rates (mm/h) for each of the locations considered in this study along with the average number of measurements taken at each site per city

Measures	Summary characteristics	Atlanta	Camden, New Jersey	Cincinnati	Cleveland	Detroit	Majuro	New Orleans	Omaha, Nebraska	Phoenix	Portland, Maine	San Juan, Puerto Rico	Tacoma, Washington
Climate	Average annual precipitation (mm)	1,263	1,194	1,073	994	787	3,365	1,586	778	204	1,200	1,289	997
	Average annual temperature (°C)	16.3	14.6	12.6	10.8	9.3	27.3	20.9	10.6	23.9	8.0	27.8	11.9
Infiltration	Site <i>N</i>	12	21	40	109	55	7	20	26	10	20	20	17
	Mean measurements per site	7.7	9.0	4.5	3.2	4.4	6.4	6.6	7.8	8.6	9.2	5.5	6.3
	Mean $\pm$ standard error	17 $\pm$ 4	54 $\pm$ 20	6 $\pm$ 1	17 $\pm$ 2	10 $\pm$ 3	82 $\pm$ 13	95 $\pm$ 27	3 $\pm$ 1	8 $\pm$ 1	8 $\pm$ 2	7 $\pm$ 2	32 $\pm$ 9
	Minimum	1.0	2.0	0.0	0.0	0.0	17.0	1.0	0.3	4.0	1.0	0.0	2.0
	Medial	14.3	28.0	5.0	13.0	4.0	77.0	56.0	2.0	7.0	6.0	4.0	19.0
	Maximum	59.0	445.0	18.0	106.0	136.0	148.0	494.0	9.0	17.0	22.0	26.0	156.0
	NSWC (%)	7	11	100	2	16	0	100	0	100	100	57	12
Drainage	SSURGO (%)	7	7	14	0	0	0	95	47	100	100	26	0
	Site <i>N</i>	30	48	33	108	63	13	29	29	10	40	26	18
	Mean measurements per site	2.1	2.1	1.0	1.0	1.3	1.6	1.5	2.3	2.1	1.8	1.1	1.1
	Mean $\pm$ standard error	4 $\pm$ 1	65 $\pm$ 29	58 $\pm$ 22	53 $\pm$ 15	54 $\pm$ 39	224 $\pm$ 34	35 $\pm$ 16	11 $\pm$ 6	33 $\pm$ 13	98 $\pm$ 29	97 $\pm$ 61	30 $\pm$ 19
	Minimum	0.0	0.0	0.0	0.0	0.0	90.0	0.0	0.0	0.0	1.0	0.0	0.0
	Medial	2.0	12.0	1.0	2.0	1.0	165.0	2.0	4.0	17.0	8.0	1.0	3.0
	Maximum	18.0	1328.0	489	1265	541.0	562.0	403.0	158.0	131.0	806.0	1343.0	294.0

Note: For infiltration rates, the percentage NSWC and percentage SSURGO rows denote the percentage of sites assessed in the field study that had conductivity data available through a NSWC or SSURGO query.

^aMaximum measured drainage that did not drain to infinity.

Table 2.

Summary statistics for infiltration rates (mm/h) obtained through NSWC, SSURGO, and Rosetta (K_{unsat}) as well as for drainage rates estimated using Rosetta (K_{sat})

	Infiltration rate (mm/h)							Drainage Rate (mm/h)				
Summary Statistics	Field data	SSURGO	NSWC	Texture class K_{unsat1}	Normal SSiC K_{unsat2}	Normal SSiC+BD K_{unsat3}	Adjusted SSiC K_{unsat4}	Adjusted SSiC+BD K_{unsat5}	Field data	Texture class K_{sat1}	Normal SSiC K_{sat2}	Adjusted SSiC K_{sat3}
N^a	357	85	126	306	306	107	111	64	477	328	328	114
Measured minimum in range	0	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0	0	0	0
Measure maximum in range	494	494	494	494	494	116	494	116	1,343	1,343	1,343	1,328
Minimum estimate	N/A	N/A	N/A	1	1	1	1	1	N/A	3	2	4
Maximum estimate	N/A	360	114	10	15.6	83	11	7	N/A	268	368	114
Mean estimate	N/A	74	7	5	5	11	2	2	N/A	33	28	17
SE estimate	N/A	13	1	0	0	1	0	0	N/A	4	3	2
Median estimate	N/A	14	1	3	4	7	1	1	N/A	8	9	13
RMSE	N/A	151.8	61.8	41.1	41.7	22.7	69.3	32.4	N/A	159	163	173
ME	N/A	49.1	-13.7	-15.7	-13.2	10.9	-30.4	1.7	N/A	-21	-25	-49
Kernel bandwidth	0.16	0.30	0.28	0.11	0.11	0.13	0.10	0.10	0.28	0.11	0.14	0.11
Skewness	6.9	1.5	3.9	0.24	0.69	3.2	3.3	2.5	5.1	3.1	3.6	3.8
Kurtosis	63.2	3.5	25.7	1.7	2.3	16.5	16.1	10.1	32.2	8.3	19.4	20.3

^aFor infiltration rate there were a total of $N = 357$ measurements taken, whereas for drainage there were a total of $N = 477$ measurements taken.