Soil Systems for Upscaling Saturated Hydraulic Conductivity for Hydrological Modeling in the Critical Zone

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Successful hydrological model predictions depend on appropriate framing of scale and the spatial-temporal accuracy of input parameters describing soil hydraulic properties. Saturated soil hydraulic conductivity ($K_{\text{sat}}$) is one of the most important properties influencing water movement through soil under saturated conditions. It is also one of the most expensive to measure and is highly variable. The objectives of this research were (i) to assess the ability of Amoozemeters, wells, piezometers, and flumes to accurately represent $K_{\text{sat}}$ at a small catchment scale and (ii) to extrapolate $K_{\text{sat}}$ to a larger watershed based on available soil data and soil landscape models for simulating streamflow using the Distributed Hydrological Soil Vegetation Model. The mean $K_{\text{sat}}$ between Amoozemeters, wells, and flumes varied from 2.4 to $4.9 \times 10^{-7}$ m s$^{-1}$, and differences were not significant. Mixed trends in mean $K_{\text{sat}}$ for slope positions and soil series were observed. The strongest significant and consistent trend in mean $K_{\text{sat}}$ was observed for soil depth. The mean $K_{\text{sat}}$ decreased exponentially with depth, from $6.51 \times 10^6$ m s$^{-1}$ for upper horizons to $2.37 \times 10^{-7}$ m s$^{-1}$ for bottom horizons. Recognizing the significantly decreasing trend of $K_{\text{sat}}$ with soil depth and the lack of consistent trends between soils and slope positions for small catchments, $K_{\text{sat}}$ values were extrapolated from the small catchments occurring in Dillon Creek to another large watershed (Hall Creek) based on soil similarity and distribution. The Nash–Sutcliffe model overall efficiency of 0.52 indicated a good performance in simulating streamflows without model calibration. Combining $K_{\text{sat}}$ measurement methods in small catchments with an understanding of soil landscapes and soil distribution relationships allowed successful upscaling of localized soil hydraulic properties for streamflow predictions to larger watersheds.

Abbreviations: DHVSM, Distributed Hydrological Soil Vegetation Model; NS, Nash–Sutcliffe model efficiency; SSURGO, Soil Survey Geographic.

The success of predictions when modeling hydrologic processes depends on the accurate representation of spatial and temporal variability of major external drivers such as weather, land use, land management, geomorphic surface, and soils (Pachepsky et al., 2008; Seyfried and Sivapalan, 2005; Wilcox, 1995). The spatial and temporal variability of soils has been long recognized by soil science (Boul et al., 2003; Jenny, 1941; Lin et al., 2006; McBratney et al., 2003; Odeh et al., 1992, 1994; Runge, 1973; Simonson, 1959; Soil Survey Division Staff, 1993; Soil Survey Staff, 2003; Tugel et al., 2005; Wilding, 2000; Zhu et al., 1997). The evolution of soil models capturing the spatial and temporal variability has recently focused the attention of soil scientists on current soil information, especially soil properties as they relate to hydrologic modeling (MacMillan, 2008; McBratney et al., 2003; Pachepsky et al., 2008). Deriving soil hydraulic properties from current soil map unit polygons for hydrologic modeling has increased the focus on the spatial representation of these properties (Ersahin, 2003; Kozak and Ahuja, 2005). Most soil property data have been measured or estimated at the point or pedon scale and subsequently extrapolated to the polypedon (soil component) of soil map units (Soil Survey Division Staff, 1993). The spatial distribution of these properties is commonly presented...
as representative values (Soil Survey Staff, 2003) or as mean values with broad ranges. In neither of these forms is there any indication about spatial variability within soil map unit polygons (Lin et al., 2005). The question about how much any apparent or presumed variability of soil properties is real has a direct impact on hydrologic response. Nonetheless, Basu et al. (2010) found in their study in a mesoscale watershed (~700 km²) in northern Indiana that structurally heterogeneous soils with respect to taxonomic mapping units had fairly homogeneous hydrologic response when evaluated using a simple water balance model.

Bouma (2006) challenged soil scientists to better represent soil expertise in modeling. He recognized the fact that pedologists in general are not comfortable with representation of soils in terms of the homogeneity and isotropy assumed by hydrologists for modeling purposes. Evidence shows that in some cases soil properties (e.g., texture) and some of the measured hydraulic soil properties (e.g., available water holding capacity, soil moisture retention characteristics, etc.) display similar characteristics (Botros et al., 2009; Evans and Franzmeier, 1986; Harlan and Franzmeier, 1974; Haws et al., 2004; King and Franzmeier, 1981; Lin et al., 2006; Zeleke and Cheng Si, 2005). Soil scientists have based their understanding of soils on the deterministic CLORPT model (Jenny, 1941). However, it is understood that at certain scales soils can be described as largely homogenous with some stochastic variability. Laurensen (1974), Seyfried and Wilcox (1995), and Vogel (1999) acknowledged that spatial variability is “rarely entirely deterministic or stochastic” and demonstrated that it is a function of spatial scale. For the purposes of this discussion, the term deterministic usually implies a variability that is always explained with a degree of certainty by a set of predictors, contrary to stochastic, which implies a degree of uncertainty or “randomness,” given the scale at which factors can be deterministic and/or stochastic is clearly defined. In this context, Seyfried and Wilcox (1995) described a “deterministic length scale” below which the spatial variability of any parameter can be considered functionally as homogenous or stochastic rather than deterministic. Both stochastic and deterministic variability are found in every soil-related hydrologic parameter, and the dominance of one or the other has been found to be scale dependent (Haws et al., 2004; Zeleke and Cheng Si, 2005). However, as pointed out by Pachepsky et al. (2008), the difference in scale representation of spatial variability can be addressed and soil structure and hydrologic functioning at different scales can be related within the same spatial units. McBratney et al. (2003) emphasized that in the future continuum soil maps and soil property maps most likely will be in raster format. Raster format is compatible with distributed hydrologic modeling at various spatial scales, where unit cell or pixel varies in size based on the spatial scale of model inputs.

The challenge is to accurately represent the spatial variability of soil properties and to relate this variability to appropriate scales. For hydrologic modeling purposes, this means that soil morphological differences need to be viewed from the perspective of identifying hydrologic processes that lead to functional hydrologic property maps, with a focus on commonality of function rather than just morphological differences. The approach parallels that of the major catchment hydrology challenge described by McDonnell et al. (2007) and Sivapalan (2005). This is a shift from describing patterns of catchment heterogeneity to searching for (i) geomorphic or landform processes (e.g., hillslope processes) that generated these patterns, (ii) processes that underlie this heterogeneity and complexity (e.g., interaction of geomorphic processes), and (iii) the ecological, pedological, and geomorphological functions of these processes (e.g., sediment or solute removal, transport, or accumulation).

Saturated soil hydraulic conductivity ($K_{sat}$) represents one of the major challenges in identifying the “representative” measurement scale and is one of the most important parameters in any hydrological modeling. It describes water movement through soils, with direct and substantive impact on the timing and volume of streamflow (Bouma et al., 1982; Guber et al., 2006; Mohanty et al., 1994). It is also one of the most difficult properties to accurately represent due to its high variability across short-range distances (Oosterbaan and Nijland, 1994) and because soil structural elements such as macropores and voids may result in $K_{sat}$ being completely unrelated with unsaturated soil hydraulic conductivity $K(h)$. For example, Perret et al. (1999, 2003), Watson and Luxmoore (1986), and White (1985) have identified the presence of structural and/or root macropores as one of the major contributors to $K_{sat}$ variability. The terms preferential flow and bypass flow have been applied by many researchers to acknowledge the mechanisms of soil water movement through macropores (White, 1985).

Although by definition $K_{sat}$ is evaluated (or is assumed to be) under fully saturated soil moisture conditions, the presence of macropores combined with the soil moisture conditions between wet and dry soil matrices contributes to highly variable $K_{sat}$ Measurements (Bouma et al., 1989; Mohanty et al., 1994). Many field (in situ) and laboratory methods have been developed to overcome such limitations (Bouma et al., 1982; Klute, 1986; Reynolds and Elrick, 1985). Some of the field measurement methods include lysimeters (Barkle et al., 2010) and variations of constant- and falling-head permeameters (Amoozegar, 1989; Amoozegar and Warrick, 1986; Nimmo et al., 2009). Whether measured under in situ or laboratory conditions, these methods have limitations related specifically to the determination of an appropriate representative soil volume needed to reduce the variability due to the presence of preferential flow and wet–dry boundary conditions (Bouma et al., 1989; Mohanty et al., 1994). Techniques such as X-ray computed tomography that allow $K_{sat}$ measurement in a larger volume of soil (on the order of 1 m³) and in a nondestructive manner have been developed and implemented to address the effects of macropores on $K_{sat}$ (Anderson et al., 1990; Peyton et al., 1992, 1994). However, most of the $K_{sat}$ field methods and techniques are expensive and time consuming, and many $K_{sat}$ measurements
across large areas and extended periods of time would be required to fully capture spatial and temporal variability. Bouma et al. (1989) discussed some of the techniques for estimating the appropriate area and volume of soil for representative measurements of $K_{sat}$ in the field. He also recognized the challenges for upscaling such soil hydrological parameters for modeling (Bouma, 2006). Different approaches to upscaling have been developed by many researchers and mostly include pedotransfer functions (Guber et al., 2006; Rawls et al., 1998; Wösten et al., 1999, 2001). The objectives of this research were (i) to assess the use of Amoozometers, wells, piezometers, and flumes to characterize the $K_{sat}$ at a small catchment scale and (ii) to assess upscale $K_{sat}$ from the small catchment to a large watershed for distributed hydrological modeling based on available soil data and soil landscape model. Assessing multiple methods and techniques could potentially provide cost-effective alternatives for $K_{sat}$ determination in the field. In this study, the Distributed Hydrology Soil Vegetation Model (DH-SVM) was selected to evaluate the simulated hydrological impact of $K_{sat}$ on stream flow (Wigmosta et al., 1994). We selected this model for two main reasons: (i) its ability to distribute the soil hydraulic properties and water budget on a pixel-by-pixel basis across the watershed and (ii) its sensitivity to soil hydraulic conductivity (Beckers and Alila, 2004). However, other similar distributed hydrological models could have been selected for this study.

Materials and Methods

Study Sites

This study was conducted in the large Hall Creek watershed and in two small forested and pasture catchments located in the large Dillon Creek watershed (30 km$^2$). All sites are part of the Southern Hills and Lowland physiographic region in the Crawford Upland physiographic subregion that has high-relief bedrock hills with slopes varying from 2 to $\geq 60\%$ in most areas (Franzmeier et al., 2004) (Fig. 1). The mean annual temperature is 12°C and varies from 5 to 18°C; minimum temperatures can be as low as −8°C (January), and maximum temperatures can be as high as 31°C (July) (Unterreiner, 2006). The mean annual precipitation is 121 cm and varies from 64 to 161 cm (Unterreiner, 2006). The majority of the soils in the area are formed in loess over materials weathered from the underlying sandstone, siltstone, and shale (Wingard et al., 1980) of Mississippian age. Loess varying in thickness from a few centimeters to several meters covered the entire area after glacial retreats. Most of the loess on the steep slopes was eroded and deposited in the valleys. This exposed the interbedded sandstone, siltstone, and shale residuum and has resulted in discontinuous loess over weathered sandstone and shale (Wingard et al., 1980). The majority of the study sites occur on the Unglaciated Southern Hills and Lowlands unconsolidated aquifer systems and Blue River and Sanders Groups bedrock aquifer system of Mississippian age (Grove, 2003; Unterreiner, 2006).

Soil Characteristics

Forest and Pasture Catchments

The small forested and pasture catchments are located in the Dillon Creek watershed (Fig. 2). According to soil descriptions (Schoeneberger et al., 2012), there are six dominant soils in both catchments. Apalona and Zanesville soils (both fine-silty, mixed, active, mesic Oxyaquic Fragiaudalfs) are located in summit and shoulder positions and formed on loess-capped uplands over residuum. Deuchars soils (fine-silty, mixed, active, mesic Oxyaquic Fragiaudalfs) are located on shoulder positions. Gilpin (fine-loamy, mixed, active, mesic Typic Hapludults) and Wellston (fine-silty, mixed, active, mesic Ultic Hapludults) soils are located on steep backslopes and formed from loess on materials weathered from sandstone, siltstone, and shale. Ebal soils (fine, mixed, active, mesic Oxyaquic Hapludults) are located on toeslope positions and formed in colluvium from loess and materials weathered from sandstone, siltstone, and shale.

The Dillon Creek and Hall Creek Watersheds

The Dillon Creek watershed, which is approximately 30 km$^2$, is the location of the small forested and pasture catchments (Fig. 2). The Hall Creek watershed, which is approximately 56 km$^2$, has a USGS stream gauge (03375800) near St. Anthony. Both watersheds are located in southern Indiana (Fig. 1). The watersheds are part of the Southern Hills and Lowland Physiographic Region in the Crawford Upland physiographic subregion that has high-relief bedrock hills (Franzmeier et al., 2004). There are 13 soil series mapped in both watersheds; however, two-thirds of the watersheds are covered by the Gilpin, Bartle (fine-silty, mixed, active, mesic Aeric Fragiudalfs), Tilsit (fine-silty, mixed, semiactive, mesic Typic Hapludalfs), Zanesville, and Wellston soil series. Tilsit soils are very similar to Zanesville soils, are located on broad summits and in shoulder positions, and formed on loess-capped uplands over residuum. The remaining area is dominated by Stendal (Fine-silty, mixed, active, acid, mesic Fluventic Endoaquepts), Steff (fine-silty, mixed, active, mesic Fluvaquentic Dystrudepts), and Cuba (fine-silty, mixed, active, mesic Fluventic Dystrudepts) soils, which occur on floodplains and are derived from alluvial loess deposits originating from hills.

The vegetation in both watersheds is predominantly pasture on broad summits and shoulders (33%), followed by broadleaf forest on steep backslopes (30%) and cropland (mainly corn [Zea mays L.]) on toeslopes (30%) (USGS, 2002). The remaining area (6.7%) is low-intensity urban areas represented by individual households and local roads that are mostly unpaved. A very small portion of the watersheds (0.3%) consists of small ponds scattered throughout.

Saturated Hydraulic Conductivity Measurements

The vertical and lateral $K_{sat}$ values were determined based on different measurement methods pertaining to different scales. The vertical $K_{sat}$ values were determined from in situ measurements
using a constant-head permeameter (Amoozemeter) and wells. The lateral $K_{sat}$ values were determined from piezometer data, and the catchment-scale $K_{sat}$, defined as “effective” $K_{sat}$, was determined based on flume streamflow data and was used for comparative analysis with the $K_{sat}$ derived from the other measurement methods.

Amoozemeter Measurements
Amoozemeter $K_{sat}$ in situ measurements (Amoozegar, 1989; Amoozegar and Warrick, 1986) were conducted for three key slope positions and their associated soils for two small forested and pasture catchments. The three key slope positions were summit, backslope, and toeslope (Fig. 2). At each slope position, the in
Fig. 2. Location of soil pits and water monitoring instruments in small forested and pasture catchments in Dillon Creek watershed.
situ $K_{sat}$ was determined for three depths, each in five replicates, which represented three major soil horizons: surface horizons (Ap, E, AB, and BE), argillic horizons (Bt1 and Bt3), and lower restrictive horizons (Btx, 3Bt, and Cr). The replicates were spaced approximately 1 m apart and lined up along contours (Fig. 3). This method measures a steady-state rate of water flow ($Q$) into a soil from a cylindrical hole with radius $r$ that is filled up with water to a constant height $H$. The $K_{sat}$ is calculated based on the Glover solution (Zangar, 1953) using

$$K_{sat} = \frac{\sinh^{-1}(H/r) - \left(\frac{r^2}{H^2} + 1\right)^{1/2} + r/H}{2\pi H^2}$$

Well Measurements

Wells were installed on three key landscape positions (summit, backslope, and toeslope at 134, 64, and 49 cm, respectively) directly above the bottommost restrictive layer (Fig. 4). Similar to the Amoozemeter measurements, the depths were chosen based on the field survey to represent the three major soil horizons. The $K_{sat}$ determination via wells is similar to the falling-head permeameter described by Klute (1986) and Reynolds and Elrick, (1985), with modifications of the formulae. The $K_{sat}$ from the wells was calculated based on Darcy’s law (Darcy, 1856):

$$Q = KA\left(\frac{h_0 - h_1}{L}\right)$$

Fig. 3. Amoozemeter diagram showing the main parts and equation parameters for calculating saturated hydraulic conductivity and the layout of instruments for taking repetitive measurements. The inset shows the wetting front boundary.

Fig. 4. Conceptual layout of nested wells and piezometers for key slope positions and soil horizons. The inset images show the actual field layout of wells, piezometers, and flumes.
To estimate $K_{\text{sat}}$ using Darcy’s law, measured discharge values are needed based on (Rawls et al., 1992)

$$Q = KA \left( \frac{b_0 - b_1}{t_0 - t_1} \right)$$

where $t_0 - t_1$ is the time difference during which $b_0 - b_1$ occurred [T].

Setting the two equations equal to each other and solving for $K$ produces

$$K = \left[ \frac{aL}{A(t_0 - t_1)} \right] \ln \left( \frac{b_0}{b_1} \right)$$

This equation can be simplified further by dropping $a/A$ by assuming that they both represent the cross-sectional area, which would be valid only for small cross-sectional areas:

$$K = \left[ \frac{L}{t_0 - t_1} \right] \ln \left( \frac{b_0}{b_1} \right)$$

where $L$ represents the length of the well during each event lasting between times $t_0$ and $t_1$, and it varies with each event. Twelve events, between February and May 2009, from the well measurement data for the summit, backslope, and toeslope positions from the small forested and pasture catchments were selected and used to derive $K_{\text{sat}}$, using the above equation (Fig. 5a and 5b). Events between February and May were selected to assure full saturation of the soil throughout and minimum evapotranspiration.

### Flume Measurements

Approximately 12 events from the flume hydrograph were selected between February and May 2009 (Fig. 7). The $K_{\text{sat}}$ from the flume data was determined using Darcy’s law:

$$Q = -k_i A$$

where $i$ is the hydraulic gradient and $A$ is the catchment area [L²].

The discharge on a volume basis, when divided by area, is the specific discharge or Darcy’s velocity [L T⁻¹]. Darcy’s law can then be written as

$$\frac{Q}{A} = -k_i$$

If the hydraulic gradient ($i$) is held at unity, then $Q/A = -K$. To satisfy this condition, only instantaneous peak discharge values ($Q_{pk}$) were selected from the flume data. In this case, the assumption was made that the soil column throughout the watershed was fully saturated and the water moved only through the soil column. The hydraulic gradient was represented by the difference in elevation between the flume and the highest elevation of the catchment and was assumed to be constant. The watershed size was used to represent the area $A$.

The discharge values ($Q$) were derived using (Water Resources Research Laboratory, 2001):

$$Q = Ch^n$$
where $h$ is the measured head [L], and $C$ and $n$ are coefficients related to the throat width of the flume.

Parshall H flumes were installed at the outlets of the pasture and forested catchments. The flume dimensions, especially the width of the throat, were determined based on the estimated stream peak discharge ($Q_{pk}$) using a formula suitable for small catchments (<100 ha) (Dunne and Leopold, 1978):

$$Q_{pk} = CIA$$
Fig. 6. Water level fluctuation for piezometers in summit, backslope, and toeslope positions for precipitation events during the period 27 Feb. to 29 Apr. 2009 at (a) forested and (b) pasture small catchments.
where \( C \) is the runoff coefficient, assumed to be 0.5, an estimate based on the fact that both pasture and forested catchments had ground cover and little compaction (American Society of Civil Engineers, 1969; Rantz, 1971), and \( I \) is the rainfall intensity [\( \text{L T}^{-1} \)]. The rainfall intensity was calculated based on 5-yr rainfall intensity–frequency–duration curves (US Weather Bureau, 1955).

**Water Level Measurements**

The change in water elevation in the wells, piezometers, and flumes was measured with HOBO pressure transducers U-Series with UX120-006M external-channel dataloggers at hourly intervals. The pressure transducers were set at hourly intervals and calibrated for water depths of 25, 50, 75, and 100 cm. Due to the sensitivity of the sensors to air pressure, the 0-cm water depth was not used for calibration purposes. The sensor readings were compared with actual readings and calibrated to within 0.1-cm accuracy.

The pressure transducers were connected to a datalogger to record their output values, and data were downloaded every 6 mo. To maintain sensor sensitivity and functionality, the batteries were replaced every 6 to 9 mo, depending on the weather conditions.

**Distributed Hydrological Soil Vegetation Model**

The DHSVM was used to evaluate the simulated hydrological impact of \( K_{\text{sat}} \). The DHSVM is a physically based, distributed hydrology–vegetation model for complex terrain designed for a wide range of spatial and temporal scales, from plot to large watershed, at subdaily to daily timescales (Wigmosta et al., 1994). The model integrates hydrology–vegetation dynamics (evapotranspiration model, energy balance for snow accumulation and melt, two-layer rooting zone model, and a saturated subsurface flow model) at the scale of the digital elevation model (Fig. 8). A distinguishing feature of the model is its ability to redistribute the downslope soil moisture on a pixel-by-pixel basis, which in turn requires the assignment of surface cover and soil properties to each pixel (Wigmosta et al., 1994). Under the model, each pixel exchanges water with its eight neighboring pixels, allowing quasi-three-dimensional subsurface flow. Several assumptions are made to represent the subsurface flow. First, the unsaturated subsurface moisture movement is calculated using Darcy’s law. However, Darcy’s law was derived for saturated subsurface flows only (Darcy, 1856); thus, the subsurface moisture movement in the model aggregates both saturated and unsaturated soil conditions throughout the entire soil profile. Because this assumption is critical for characterizing soil water movement through soil in a three-dimensional fashion, we selected events from late fall, winter, and early spring when the soil profile was probably saturated compared with late spring and summer. The model also assumes that for a saturated soil, when inflow exceeds \( K_{\text{sat}} \), the excess water re-infiltrates into neighboring pixels unless captured by the stream or road, if present, in the cell. The saturated hydraulic conductivity is assumed to decrease exponentially with depth, which was supported by our data measurements and confirmed by others (Lin, 2006). Although this could be true for most cases, there are exceptions for soils that develop cracks (smectitic) or soils with buried horizons.
and underlying coarser textured layers. The model used here considers only the matrix flow as the major mechanism of water movement through the soil. Beckers and Alila (2004) modified the model to incorporate preferential flow contributions to runoff generation, but this was not used in this study. As a spatially distributed model, DHSVM has important applications for the interpretation and prediction of the effects of changes in land use on hydrological indicators (Bowling and Lettenmaier, 2001; Bowling et al., 2000; Storck et al., 1998).

The DHSVM requires a series of input parameters for each pixel representing the watershed. The input parameters assigned to 30- by 30-m pixel resolution include meteorological observations (e.g., incoming short-wave and longwave radiation), air temperature, wind, humidity, and precipitation. The model uses spatially distributed information on elevation, slope, stream and road networks, and vegetation and soils, including vertical and lateral $K_{sat}$ values. The DHSVM inputs for the large watershed were continuous and generated based on digital soil mapping approaches (McBratney et al., 2003) in combination with existing soil information from the Soil Survey Geographic (SSURGO) database (Libohova et al., 2010). The DHSVM is particularly sensitive to soil hydraulic conductivity as one of the major controls of water flow through the watershed and subsequent streamflow discharge (Beckers and Alila, 2004). Other soil hydraulic parameters, such as porosity and pore size distribution, were assigned based on findings by Rawls et al. (1983). The values for the bulk density, field capacity, and wilting point of soil layers were assigned based on measurements from soil pits in the study area. The data were available at the National Soil Survey Laboratory in Lincoln, NE. The bulk density and field capacity values were similar among soil pits regardless of the landscape position, which reflects the relatively uniform loess parent material. Because the main objective of this study was to evaluate the possibility of extrapolating $K_{sat}$ from point and small catchment to a large watershed, special attention was paid to the $K_{sat}$ values and how they were measured and upscaled. Other hydrological parameters, such as bulk density, soil thickness, soil structure, soil texture, etc., are as important as $K_{sat}$ for describing water movement and streamflow predictions, but we did not conduct a sensitivity analysis to determine their relative importance regarding $K_{sat}$. These parameters were derived from measured data and were upscaled in a similar manner as the $K_{sat}$ using existing soil data from the SSURGO database (Libohova et al., 2010) and digital soil mapping approaches.

**Statistical Analysis**

The mean $K_{sat}$ values among the measurement methods (Amoozemeters, wells, piezometers, and flumes) and among slope position, soil series, and soil depth for each measurement method were compared. Initially, the Kolmogorov–Smirnov normality and skewness were tested to determine whether the data needed transformation for subsequent statistical analyses.

The ANOVA on log-transformed $K_{sat}$ conducted in JMP (SAS Institute, 2003) was used to assess the effects of slope position, soil series, and soil depth on $K_{sat}$-response variables. The ANOVA mean comparisons were performed independently within each measurement method (i.e., Amoozemeters, wells, and piezometers) using the pairwise comparisons LSMeans Tukey HSD test for comparing differences in $K_{sat}$ due to slope position, soil series, and soil depth. A pairwise $t$-test was used to compare $K_{sat}$ between the forested and pasture catchments. The null hypotheses were rejected at a significance level of 0.05. The curvilinear exponential regression models were used to assess the relationships between $K_{sat}$ and soil depth.

**Comparison of Simulated vs. Observed Streamflow (Validation)**

The Nash–Sutcliffe model efficiency (NS) was used to compare the observed and simulated daily streamflow data from the DHSVM (Nash and Sutcliffe, 1970):

$$NS = 1 - \frac{\sum_{i=2}^{N} (O_i - S_i)^2}{\sum_{i=1}^{N} (O_i - \bar{O})^2}$$

where $O_i$ is observed daily streamflow, $S_i$ is simulated daily streamflow, and $N$ is the number of days in the assessment period.

This test indicates how well calculated and observed daily streamflows compare in volume and shape. Values vary from $-\infty$ to 1. An efficiency of 1 indicates a perfect match between observed and simulated streamflow, an efficiency of 0 indicates that the simulated streamflow is as accurate as the observed one, and an efficiency of <0 indicates that the simulated streamflow does not match the observed streamflow. In this study, the model performance was...
The mean measured $K_{sat}$ from Amoozemeters was $1.3 \times 10^{-6} \text{ m s}^{-1}$, which was significantly greater than for the other measurement methods (Fig. 9b; Table 1). However, the measured $K_{sat}$ values were not normally distributed and were positively skewed, especially for the Amoozemeter method (Fig. 9a). The skewness for the Amoozemeter $K_{sat}$ was 6.6; this value was greater than for the other methods. The logarithmic transformation of the data reduced the skewness overall to 0.3, and subsequent statistical analyses were conducted on log-transformed data. However, the reported mean $K_{sat}$ values in Tables 1 through 4 are in their "native" format for easy interpretation, whereas statistical comparisons are based on log-transformed data.

The overall mean $K_{sat}$ for untransformed data from the piezometer method was $2.0 \times 10^{-7} \text{ m s}^{-1}$, which was significantly smaller than for the other methods. The mean $K_{sat}$ among Amoozemeters, wells, and flumes varied from $2.4 \times 10^{-7}$ to $4.9 \times 10^{-7} \text{ m s}^{-1}$, and differences were not significant (Fig. 9a). The positively skewed distribution of measured soil $K_{sat}$ values is not surprising, and other researchers have found similar trends (Dieleman and Trafford, 1976; Mohanty et al., 1994). In addition, the measured soil $K_{sat}$ values at point scale have been found to be highly variable (Perret et al., 1999, 2003; Watson and Luxmoore, 1986; White, 1985). The degree of $K_{sat}$ variability varied also among measurement methods. The Amoozemeter-measured $K_{sat}$ values showed the highest variability compared with values from the other methods. The CV for measured $K_{sat}$ from the Amoozemeter was 344, compared with the mean CV of 78 for the other measurement methods. Point measurements, such as those from Amoozemeters, wells, and piezometers, are expected to be more prone to local variability due to differences in soil volume surrounding the instruments and soil structure, more specifically pore size and distribution (Bouma et al., 1989). The $K_{sat}$ values from flumes integrate the variability in pore size and distribution across the entire catchment and may be less sensitive to local variability. None of the calculated $K_{sat}$ values from the flume was used as input for the DHSVM model. They

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**Results and Discussion**

**Comparisons between Different Measurement Methods at Small Catchment Scale**

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**Table 1. Mean comparisons of saturated hydraulic conductivity values for slope positions among different measurement methods for forested and pasture small catchments.**

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<thead>
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<th>Measurement method</th>
<th>Slope position</th>
<th>Forest</th>
<th>Pasture</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amoozemeter mean</td>
<td>summit</td>
<td>$5.0 \times 10^7 (7.1 \times 10^7)$ a at $8.8 \times 10^7 (1.7 \times 10^8)$ a</td>
<td>$5.6 \times 10^7 (5.1 \times 10^8)$ a</td>
</tr>
<tr>
<td></td>
<td>shoulder</td>
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<td>$3.7 \times 10^7 (2.6 \times 10^8)$ a</td>
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<tr>
<td></td>
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<td>$5.4 \times 10^6 (1.3 \times 10^8)$ a</td>
</tr>
<tr>
<td></td>
<td>toeslope</td>
<td>$3.3 \times 10^7 (8.2 \times 10^7)$ a</td>
<td>$1.3 \times 10^8 (3.2 \times 10^9)$ a</td>
</tr>
<tr>
<td></td>
<td>overall mean</td>
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<td>$3.1 \times 10^8 (7.4 \times 10^9)$ a</td>
</tr>
<tr>
<td>Well mean</td>
<td>summit</td>
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<td>$5.6 \times 10^7 (5.1 \times 10^8)$ b</td>
</tr>
<tr>
<td></td>
<td>backslope</td>
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<td>$7.8 \times 10^7 (4.9 \times 10^8)$ a</td>
</tr>
<tr>
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<td>toeslope</td>
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<td>$3.3 \times 10^8 (4.9 \times 10^9)$ c</td>
</tr>
<tr>
<td></td>
<td>overall mean</td>
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<td>$5.5 \times 10^8 (3.3 \times 10^9)$ b</td>
</tr>
<tr>
<td>Piezometer mean</td>
<td>summit</td>
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<td>$1.2 \times 10^7 (2.4 \times 10^8)$ b</td>
</tr>
<tr>
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<td>$2.7 \times 10^7 (3.4 \times 10^9)$ a</td>
</tr>
<tr>
<td></td>
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<td>$3.3 \times 10^7 (4.3 \times 10^8)$ a</td>
<td>$1.3 \times 10^8 (2.4 \times 10^9)$ b</td>
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<td>overall mean</td>
<td>$2.5 \times 10^7 (2.3 \times 10^8)$ a</td>
<td>$1.5 \times 10^7 (2.2 \times 10^8)$ b</td>
</tr>
<tr>
<td>Flume mean</td>
<td>summit</td>
<td>$8.2 \times 10^7 (3.6 \times 10^8)$ a</td>
<td>$6.6 \times 10^7 (3.6 \times 10^8)$ a</td>
</tr>
</tbody>
</table>

† Means with standard errors in parentheses. Means followed by the same letter are not significantly different at the 0.05 probability level within measurement methods. Overall means of each measurement method followed by the same letter are not significantly different at the 0.05 probability level between forested and pasture catchments.
were, however, used as a check for the $K_{sat}$ values determined by Amoozemeters, wells, and piezometers. We found that wells and piezometers have variability, as indicated by CVs, that are more similar to flume $K_{sat}$ measurements than to Amoozemeter measurements. The fact that wells and piezometers were less sensitive to local variability in pore size and distribution could be related to the water saturation conditions across the entire watershed during the measurement period. The $K_{sat}$ values from wells, piezometers, and flumes were measured during the February to early May period, when soils are presumed saturated. Because the DHSVM assumes no surface runoff, by default the entire precipitation is stored in the soil column, especially during the winter months prior to the February to early May period. Although limited by lack of the surface runoff component, the water balance during the period under consideration is dominated by precipitation that leads to soil column saturation conditions and quick peak flows from short-duration storms. We speculate that the relative contribution of macropores to the overall $K_{sat}$ under fully saturated conditions is less than the measurements conducted under unsaturated soil conditions. The $K_{sat}$ values from Amoozemeters were measured during summer and under saturated soil moisture conditions but only within a short distance from the hole (Fig. 3, inset). The presence of macropores could result in greater measured $K_{sat}$ values overall (Perret et al., 1999, 2003; White, 1985). However, their relative contribution seems to be related to the spatial extent of saturated soil moisture conditions. In the case of Amoozemeters, the saturated moisture conditions extend only a short distance from the hole (Fig. 3, inset). As a result, the measured $K_{sat}$ values reflect not only the presence of macropores but also the presence of unsaturated soil conditions at the boundaries of the wetting front, which may result in larger soil $K_{sat}$ values and greater variability.

**Comparisons between Forested and Pasture Catchments**

There were no significant differences for Amoozemeter-measured soil $K_{sat}$ values between the forested and pasture catchments (Table 1). The lack of significant differences between the two types of catchments could be the result of great variability in the measured values, as indicated by the standard error values that were an order of magnitude greater ($7.4\times10^7\text{ m s}^{-1}$) than for the wells and piezometers ($2.2\times3.3\times10^8\text{ m s}^{-1}$). The mean measured $K_{sat}$ value for wells for the pasture catchment was $5.5\times10^7\text{ m s}^{-1}$, which was significantly greater than that for the forested catchment ($2.4\times10^7\text{ m s}^{-1}$). However, the mean measured $K_{sat}$ value for piezometers from the pasture catchment ($1.5\times10^7\text{ m s}^{-1}$) was significantly less than that from the forested catchment ($2.5\times10^7\text{ m s}^{-1}$).

The mean pasture catchment $K_{sat}$ value for the flume was $6.6\times10^8\text{ m s}^{-1}$, which is significantly greater than the mean $K_{sat}$ value for the forested catchment ($3.2\times10^8\text{ m s}^{-1}$). The relatively larger size of the pasture catchment may have resulted in greater stream flows (Fig. 7) and could partially explain the differences compared with the forested catchment. The total area of the pasture catchment was 4.3 ha, which is almost three times the size of the forested catchment (1.5 ha). However, the surface soil compaction by grazing animals in the pasture catchment may have also contributed more than the catchment size to greater $K_{sat}$ values compared with the forested catchment. During the field data collection, platy soil structures for the surface horizons were observed. Soil compaction causes great reduction in infiltration rates (Hamzaa and Anderson, 2005; Mulholland and Fullen, 1991; Zimmermann et al., 2005) and subsurface soil physical properties that directly affect $K_{sat}$ (Drewry et al., 2004). Indeed, the hydrograph from the pasture catchment compared with the forested catchment shows relatively greater peaks, due to greater streamflow volumes, and steeper falling limbs, perhaps due to greater surface runoff rates resulting from compaction (Fig. 7). Similar findings have been reported by Zimmermann et al. (2010) in a comparative study of a forest–pasture–forest transient system conducted in humid tropic soils in Brazil.

**Comparisons between Slope Positions and Soil Series at Small Catchment Scale**

As expected, there were no significant differences for Amoozemeter $K_{sat}$ between slope positions for the forested and pasture catchments, probably due to greater variability between replicated measurements (Table 1). For the well method, the summit $K_{sat}$ for the forested catchment was $3.3\times10^7\text{ m s}^{-1}$, which is significantly greater compared with the other slope positions. This could be the result of the presence of a fragipan in the summit position. Fragipans overall restrict water movement down through the soil profile; however, there are vertical streaks between impenetrable prisms that may conduct water at greater rates (Franzmeier et al., 1989). For the pasture catchment, $K_{sat}$ for the backslope was $7.8\times10^7\text{ m s}^{-1}$, which is significantly greater than that for the summit at $5.6\times10^7\text{ m s}^{-1}$. The well depth for this slope position was relatively shallow at 58 cm, and the slope gradient was close to 50%, which was greater than the other slope positions. Both conditions contribute to greater $K_{sat}$ values. The $K_{sat}$ for the toeslope was $3.3\times10^7\text{ m s}^{-1}$, which is significantly smaller than for the summit and backslope positions. For the piezometer method, there were no significant differences in measured $K_{sat}$ between slope positions for the forested catchment. For the pasture catchment, only the $K_{sat}$ for the backslope was significantly greater ($7.8\times10^7\text{ m s}^{-1}$) compared with the summit and toeslope positions, and this was because of the shallower depth installation of the backslope piezometer and gradient, similar to the wells.

Similar trends in measured $K_{sat}$ values were observed for the soil series (Table 2). No significant differences were observed among soil series for the Amoozemeter method between slope positions for the forested and pasture catchments. The differences between slope positions for wells and piezometer methods were the same as for the slope positions. This is to be expected because each soil series is associated with characteristic slope positions. For example, the Apalona and Zanesville series are associated with summit and
shoulder positions; the Deuchars series are associated with shoulder and backslope positions; and the Ebals, Gilpin, and Wellston series are associated with toeslope positions.

Mixed trends in differences between slope positions for the measured $K_{sat}$ have been observed by other researchers (Elsenbeer et al., 1992; Eneje et al., 2005; Mohanty and Mousli, 2000; Papanicolaou et al., 2008). The differences in many instances have been attributed to local variability due to soil texture, soil horizons, and management. For example, Papanicolaou et al. (2008) found greater $K_{sat}$ values along drainage ways in the Clear Creek watershed in an Iowa glaciated managed watershed and related them to clay content. On the other hand, Mohanty and Mousli (2000) found a clear trend overall with slope position on two major soils in loess-covered Iowa glaciated landscapes. Eneje et al. (2005) found significant differences in $K_{sat}$ along a toposequence in which lower slope positions had the highest $K_{sat}$ followed by mid-slope and summits. However, these differences were more pronounced for the 0- to 15-cm surface layer than the 15- to 30-cm soil layer.

**Comparisons with Soil Depth at Small Catchment Scale**

The decrease of $K_{sat}$ with soil depth in our study followed an exponential decay function (Fig. 10), which explained >85% of the total variability ($R^2 = 0.86$). There was a clear decreasing trend with soil depth for the Amoozemeter-measured $K_{sat}$ values (Table 3). The measured $K_{sat}$ values were significantly greater for the surface layer compared with the other soil layers for both catchments. The mean $K_{sat}$ for the forest layer for the forested catchment was $3.9 \times 10^6$ m$^{-1}$ s$^{-1}$, which was significantly greater than the $4.3 \times 10^7$ m$^{-1}$ s$^{-1}$ found for the second layer. The difference between the second layer and the bottom two layers was also significant; however, there were no significant differences between the two bottom layers. Similar trends were observed for the Amoozemeter-measured $K_{sat}$ values for the pasture catchment.

Overall, the $K_{sat}$ values for wells and piezometers showed similar decreasing trends with soil depth for both catchments, with the exception of wells in the forested catchment. The $K_{sat}$ for the bottom depth (134 cm) was $3.3 \times 10^7$ m$^{-1}$ s$^{-1}$, which was significantly greater than the $2.0 \times 10^7$ m$^{-1}$ s$^{-1}$ for the topsoil depths (64 and 79 cm). This exception from the overall trend could be the result of the presence of fractured bedrock, shale, or a fragipan. The presence of these layers at such depths is not uncommon (Franzmeier et al., 1989, 2004), and if the well is near or intersects them, it could lead to preferential flow that would result in relatively greater $K_{sat}$ values (Bouma et al., 1989). However, despite the significantly different values related to depth, probably caused by low standard errors, the mean values are much closer to one another (unlike those from the other methods, which were different by an order of magnitude). The decrease of $K_{sat}$ with soil depth by orders of magnitude, especially between the surface layer and the rest of the layers, has been observed by others (Lin, 2006).

**Upscaling of Saturated Soil Hydraulic Conductivity Values for Model Inputs at Watershed Scale**

So far we have discussed the $K_{sat}$ results from point, hillslope, and catchment measurement scales. We first assessed the differences among measurement methods at point, hillslope, and catchment scales followed by comparisons between two major forest and pasture land uses. The last comparisons were conducted for different measurement methods across two major forest and pasture small catchments. The most important features of $K_{sat}$ comparisons were (i) the lack of differences overall among measurement methods, with the exception of piezometers; (ii) the lack of significant differences and consistent trends in measured $K_{sat}$ between different soils and hillslope positions; (iii) the presence of a strong exponential decay of $K_{sat}$ with soil depth; and (iv) a lack of significant trends between forest and pasture land uses.

The $K_{sat}$ values from piezometers were significantly lower than those from other methods. This could be related to construction characteristics, especially the length of the perforated or slotted pipe. Thus, the length (or height) of the perforated or slotted...
section of the piezometers was located at the bottom and was only 10 to 15 cm, which would restrict water flow, whereas the wells were perforated or slotted from the bottom to the soil surface.

Table 3. Mean comparisons of saturated hydraulic conductivity values by soil depth among different measurement methods for forested and pasture small catchments.

<table>
<thead>
<tr>
<th>Measurement method</th>
<th>Forest</th>
<th>Mean</th>
<th>Pasture</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
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<td>17</td>
<td>8.2 $\times$ 10^6 (1.5 $\times$ 10^6) a</td>
<td></td>
</tr>
<tr>
<td></td>
<td>4.3 $\times$ 10^7 (5.6 $\times$ 10^7) b</td>
<td>40</td>
<td>9.5 $\times$ 10^7 (1.5 $\times$ 10^6) b</td>
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</tr>
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<td></td>
<td>8.7 $\times$ 10^8 (5.6 $\times$ 10^7) c</td>
<td>86</td>
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</tr>
<tr>
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<td>7.4 $\times$ 10^8 (8.9 $\times$ 10^7) c</td>
<td>125</td>
<td>2.6 $\times$ 10^8 (4.3 $\times$ 10^6) c</td>
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<td>58</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>2.1 $\times$ 10^7 (2.6 $\times$ 10^8) b</td>
<td>75</td>
<td>3.3 $\times$ 10^7 (4.9 $\times$ 10^8) c</td>
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<td>3.3 $\times$ 10^7 (2.7 $\times$ 10^8) a</td>
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<tr>
<td>Piezometer mean 41</td>
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<td>43</td>
<td>2.0 $\times$ 10^7 (1.9 $\times$ 10^8) ab</td>
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<tr>
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<td>2.7 $\times$ 10^7 (3.5 $\times$ 10^8) a</td>
<td>74</td>
<td>1.1 $\times$ 10^7 (3.3 $\times$ 10^8) bc</td>
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<tr>
<td></td>
<td>5.2 $\times$ 10^8 (8.5 $\times$ 10^8) b</td>
<td>152</td>
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<td>overall mean 62</td>
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<td>71</td>
<td>1.5 $\times$ 10^7 (2.2 $\times$ 10^8) b</td>
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<tr>
<td>Flume 65</td>
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<td>49</td>
<td>6.6 $\times$ 10^7 (3.6 $\times$ 10^8) a</td>
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</table>

† Means with standard errors in parentheses. Means followed by the same letter are not significantly different at the 0.05 probability level within measurement methods. Overall means of each measurement method followed by the same letter are not significantly different at the 0.05 probability level between forested and pasture catchments.

The lack of clear trends between soils is expected because these soils are taxonomically and morphologically very similar. These soils are only differentiated based on the underlying parent material (i.e., sandstone or shale; for example, Apalona soils vs. Zanesville soils), which in this case is the bottommost restrictive layer. On the other hand, Gilpin, Ebal, Deuchars, and Wellston soils are similar and are differentiated based on the suggested SSURGO slope categories.

The depth $K_{sat}$ measurements for the Amoozemeters, wells, and piezometers were conducted based on genetic soil horizons. Most of the measurements were conducted for the upper horizons that originated mostly from loess. The upper horizons probably conduct most of the water through the soil and across the slope, as found by other researchers (Endale et al., 2006; Needelman et al., 2004). The fact that soil depth seemed to be a major and consistent driver of measured $K_{sat}$ differences (compared with measurement methods and slope position) within small catchments, and when combined with similarities in mean measured $K_{sat}$ between land uses and soils and with the representativeness of forest or pasture land uses and soils to larger watersheds, allowed the $K_{sat}$ upscaling from the small catchment to the larger watershed. This was accomplished by assigning mean soil $K_{sat}$ aggregated values based on soil horizon similarity across measurement methods, slope positions, soils, and land uses from forested and pasture catchments to soils in the large watershed. In addition, the impact of $K_{sat}$ upscaling to streamflow predictions using DHSVM was tested for the Hall Creek watershed rather than the Dillon Creek watershed, where the forested and pasture catchments were located. This was possible because of the similarities between the Dillon Creek and Hall Creek watersheds with respect to parent material, physiographic characteristics, and soils.

The mean $K_{sat}$ of $6.51 \times 10^6$ m s$^{-1}$ was assigned for upper horizons (Ap, E, AB, and BE), $7.27 \times 10^7$ m s$^{-1}$ was assigned for Bt and Bw horizons, $2.37 \times 10^7$ m s$^{-1}$ was assigned for Btx horizons, $5.81 \times 10^7$ m s$^{-1}$ was assigned for Bt2 horizons, and $3.44 \times 10^7$ s$^{-1}$ was assigned for C horizons (Table 4). The lateral $K_{sat}$ values for depths >40 cm were assigned based on the piezometer data. The shallowest piezometers were at the 40-cm depth; thus, values from shallow piezometers were assigned to Bt and Bw horizons, and values from the deep piezometers were assigned to Btx, Bt2, and C horizons. However, for the horizons above 40 cm (Ap, AB, and BE), the measured vertical $K_{sat}$ values were also assigned to the lateral $K_{sat}$.

The depths for each soil layer for the soil series were assigned based on the soil profile descriptions of field-surveyed soil pits in the study area (Table 4). The soil pits were located on different slopes and thus represented the spatial variability of the soil depth in the small catchments and in the large watershed. As a result, spatially distributed raster maps of soils and their hydraulic properties for the large Hall Creek watershed were generated.
based on the distribution and similarities between the soils in the small forested and pasture catchments (Fig. 11). The continuous $K_{\text{sat}}$ maps were based on a digital soil mapping approach using the fuzzy logic membership method (Zhu et al., 1997) combined with existing soil information (Libohova et al., 2010). Soil series and their associated properties were assigned to each pixel of the large Hall Creek watershed (Table 4). The underlying assumption was that the relationships between soil series distribution and their properties within the forested and pasture catchments would hold true to the larger watershed. Scale dependency of $K_{\text{sat}}$ variability with soil physical properties has been recognized and studied by many researchers (McBratney, 1998; Sobieraj et al., 2004; Zeleke and Cheng Si, 2005). For example, Zeleke and Cheng Si (2005) found that $K_{\text{sat}}$ spatial variability for sandy loam soils developed from glacio-fluvial materials in Canada was significantly correlated with sand and silt within a distance of 170 m. Most soils in our study area were developed from loess materials dominated by the silt fraction. The occurrence of common soils and similar landscapes between small catchments and a large watershed supported the upscaling or extrapolation of $K_{\text{sat}}$ to the large watershed. This provided the opportunity for testing the impact of soil hydraulic properties, especially $K_{\text{sat}}$, on streamflow predictions for the larger watershed. Thus, soil properties, especially measured $K_{\text{sat}}$ values, from soils in the forested and pasture catchments were assigned to similar soils in the Hall Creek watershed, where the USGS stream gauge was located. Differences in the soil type proportions within the main slope positions between the small catchments and Hall Creek watershed combined with the fuzzy logic membership approach resulted in continuous maps of $K_{\text{sat}}$ spatial distribution.
Comparison between Observed and Simulated Streamflows at Watershed Scale

Daily hydrographs of observed and simulated discharge showed that the model captured hydrograph rises, peaks, and falling limbs for the majority of precipitation events (Fig. 12). Overall, the NS was 0.52, indicating a good performance of the model. However, the NS for the streamflow during the wet season (early winter–late spring) was 0.72, greater than the 0.32 value for the dry season (late spring–late fall). Thus, the simulated discharge for the summer events between May and August were underpredicted. This is perhaps due to the roles that the soil moisture deficit and evapotranspiration play in capturing precipitation. During the summer, soils in the study area are generally water deficient (Wingard et al., 1980). In the DHSVM, precipitation goes toward satisfying the moisture deficit and evapotranspiration demands before contributing to the stream. However, a few isolated precipitation events with intensity greater than the soil infiltration rate may contribute more to the streamflow, perhaps due to overland flow and preferential flow through macropores and voids. This may have been the case for the precipitation event on 7 July 1998 that resulted in a peak discharge much greater than the simulated one (Fig. 12). In addition, the uneven distribution of summer precipitation events may have had a significant effect on the energy and water budget. These conditions, combined with the fact that the leaf area index in the model is provided on only a monthly basis, when it changes significantly (especially in spring), could have contributed to the underprediction of the simulated discharge during the early summer due to overestimation of the evapotranspiration.

Observed and simulated cumulative discharges were in good agreement. On average, the model underpredicted discharge by 5.8%; however, the underprediction was greater for the largest precipitation events. The difference between mean simulated and mean observed cumulative streamflow was only 68 mm yr⁻¹, or 7% of the annual precipitation, during the 5-yr simulation period.

The model slightly over-simulated discharges, with exceedance probabilities between 0.01 and 0.2 (discharges between 1 and 15 m³ s⁻¹), and under-simulated discharges, with exceedance probabilities <0.01 (discharges >15 m³ s⁻¹). One of the reasons could be that the stream network in our study area was underrepresented because the threshold contributing area for channel initiation was set at 0.56 km² (1% of the watershed area). In addition, the intersection of the road network with the stream network and the subsequent contribution to the streamflow were not captured by the model; this could explain in part the underestimation of simulated peak discharge. The road network is known to contribute to peak streamflows when intersecting the stream network (Duncan et. al., 1987; La Marche and Lettenmaier, 2001; Lane and Sheridan, 2002; MacDonald et. al., 2001; Wemple et al., 1996). Also, the three major underlying model assumptions—(i) representing unsaturated soil moisture movement using Darcy’s law, which is derived for saturated subsurface flows; (ii) no surface runoff; and (iii) no preferential flow
due to differences in soil texture and underlying bedrock (sandstone vs. shale and limestone)—may not have been met during certain periods of the model simulation. This partial failure to meet these assumptions may have contributed to the underestimation of simulated peak discharge. Despite these limitations, the overall good agreement between observed and simulated streamflows was achieved without model calibration. This supports the idea that intensive multiple $K_{sat}$ measurement by different methods at the small catchment scale combined with soil data and soil landscape knowledge is a valuable approach for upscaling soil hydraulic properties for streamflow predictions at the larger watershed scale, especially when soils in smaller catchments and/or areas represent most soils in the larger watersheds.

Conclusions

Saturated hydraulic conductivity of soil is one of the most important parameters for characterizing and modeling water movement. However, $K_{sat}$ is highly variable, and field measurements are expensive and time consuming. We attempted to assess the utility of determining field $K_{sat}$ using different measurement methods in small catchments and upscaling to a larger watershed for streamflow predictions based on existing soil data and soil landscape models using a distributed hydrological model. The measured $K_{sat}$ values from Amoozemeters were highly variable compared with those from wells, piezometers, and flumes. However, overall the differences among measurement methods were not significant, except for piezometers. The $K_{sat}$ values from piezometers were significantly lower, perhaps due to the shorter length and deeper location of the water intake. There were no clear trends in measured $K_{sat}$ related to slope positions and soils. The most significant trend was the $K_{sat}$ exponential decrease by orders of magnitude with soil depth increments that were grouped based on genetic horizons.

The lack of consistent, significant differences among soils and the significant trend with soil genetic horizons, combined with an understanding of soil landscape models and distribution, allowed the extrapolation of $K_{sat}$ from small catchments to a large watershed. This approach resulted in streamflow simulations by a distributed hydrological model that were in good agreement with observed streamflows, even without any model calibration.

This study demonstrates the value of understanding soil landscape models and soil distribution for hydrological modeling. The soils in the study area—forested and pasture catchments and the Hall Creek watershed—were mostly of loess origin and morphologically similar. The study area was also dominated by forest and pasture. This relatively simple soil system facilitated the upscaling of $K_{sat}$ measurements with good results in streamflow predictions. However, the approach needs to be evaluated for other more complex and diverse soil systems with respect to soils and vegetation.

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American Society of Civil Engineers. 1969. Design and construction of sanitary and storm sewers. Manuals and Reports on Engineering Practices no. 37. ASCE, Reston, VA.


