P3.4

ACCOUNTING FOR TEMPORAL VARIATION OF HYDRAULIC CONDUCTIVITY IN THE CALIBRATION OF A DISTRIBUTED HYDROLOGIC MODEL

Heather M. Moser[12*], Jonathan J. Gourley[2], and Yang Hong[3]

[1]Cooperative Institute for Mesoscale Meteorological Studies, University of Oklahoma, Norman, OK
[2]National Severe Storms Laboratory, NOAA, Norman, OK
[3]Department of Civil Engineering and Environmental Science, University of Oklahoma, Norman, OK

1. INTRODUCTION

The Blue River basin in south-central Oklahoma (Fig. 1) has been the focus of considerable hydrologic research in recent years, including the National Weather Service's Distributed Model Intercomparison Project (DMIP; Reed et al. 2004) and the Oklahoma Water Resources Board's Arbuckle-Simpson Hydrology Study. More than 15 hydrologic models have simulated streamflow in the basin as part of various studies, including for DMIP. Several studies that used distributed hydrologic models to simulate streamflow in the basin reported overestimation during periods of low flow (typically late summer and fall) and underestimation of streamflow during high flow periods (Ajami et al. 2004; Carpenter et al. 2004; Gourley et al. 2006; Moser 2008).

The basin is dominantly composed of loam and clay soils (Fig. 2) that have a tendency to shrink or swell as a function of soil water content (Gourley et al. 2006). After prolonged dry periods, the soil shrinks and forms cracks that act as conduits for increased saturated hydraulic conductivity (Ksat), thus reducing runoff and eventually streamflow resulting from that runoff. During wet periods, the soil swells, restricting available pore space for infiltration and increasing the volume of runoff. Thus, Ksat can potentially vary over orders of magnitude for rainfall events occurring during the different soil moisture regimes, leading to significant changes in runoff volume. A similar relationship between Ksat and soil moisture content was observed in similar soil types in Pennsylvania (Fig. 3; Jabro 1996). Many input parameters for distributed hydrologic models are usually assumed to be constant, including Ksat. Thus, in a basin with vertic soils (soils that shrink and swell), the constant Ksat may be an underestimate when soils are very dry and an overestimate when soils are wet.

The goal of this study is to find a statistical relationship between real-time atmospheric and hydrologic data and in situ measurements of Ksat in

** Corresponding author address:* Heather M. Moser, Cooperative Institute for Mesoscale Meteorological Studies, Univ. of Oklahoma, Norman, OK 73072; email: hmoser@ou.edu

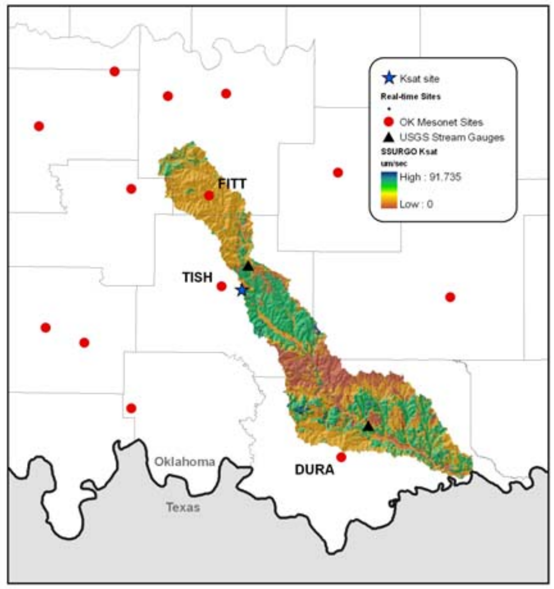

Figure 1. SSURGO Ksat estimates for the Blue River watershed and locations of nearby observing sites. Red circles represent Oklahoma Mesonet sites, black triangle represent USGS stream gauges, and the blue star represents the location of in situ Ksat measurements.

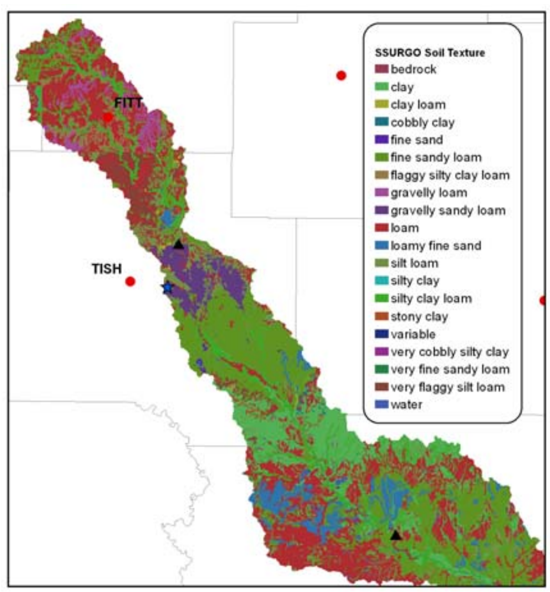

Figure 2. SSURGO soil texture classifications for the Blue River watershed.

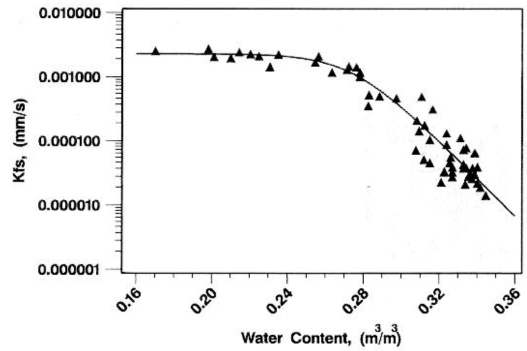

Figure 3. Reduction of field saturated hydraulic conductivity with increasing soil water content. (Jabro 1996).

the Blue River basin. The relationship can then be used for parameter estimation for a distributed hydrologic model to determine if variable Ksat input leads to better streamflow simulations in a basin with vertic soils.

2. METHODOLOGY

Saturated hydraulic conductivity is not a parameter commonly measured in real-time. However, with a large enough dataset of Ksat measurements in the basin that reflect annual variability of soil conditions, a first order multiple regression equation can be found that relates Ksat to observations that *are* available in the basin in real-time. The equation takes the form:

$$y=\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots \beta_n x_n$$

where the β terms are coefficients for the linear model that minimize the variance of the data through a least squares approach (Ott and Longnecker 2001). The x terms represent the independent variables used to predict y. In this study, the x terms are automated observations from the Oklahoma Mesonet, and y is the measured Ksat. Once the coefficients are determined, the regression equation can then potentially be used in place of real-time Ksat measurements (or a constant Ksat) for parameter estimation in a distributed hydrologic model.

a. Data

Saturated hydraulic conductivity measurements have been periodically recorded in the Blue River basin since June 2008 using a manual double ring infiltrometer. The measurements were taken at the Blue River Hunting and Fishing Wildlife Refuge near Connerville, OK, downstream of the Connerville USGS stream gauge (Fig. 1). Twelve Ksat measurements have been recorded as of December 1, 2008. Measurements continue to be recorded in order to encompass a full year of soil conditions at that location, but data collected so far support the theory that Ksat varies significantly with time in the basin, with a range of one order of magnitude from June to late July.

The Oklahoma Mesonet has been collecting real-time meteorological data since 1994 (McPherson et al. 2007). Real-time soil moisture sensors have been installed at most Mesonet sites that measure soil moisture at up to four standard depths. Other Mesonet data relevant to this study include: air temperature, relative humidity, and soil temperature at up to three depths. Archived real-time data for all of these variables (including soil moisture) were acquired for three Mesonet sites in and near the Blue River watershed: Fittstown (FITT), Tishomingo (TISH), and Durant (DURA). FITT was the only site located within the basin. However, TISH is a shorter distance from the Ksat measurement location (Fig. 1). Soil moisture measurements are available at three depths at FITT and DURA (5 cm, 25 cm, and 60 cm). Only the shallowest two depths are available for TISH.

b. Analysis

Daily means were computed (00Z to 00Z UTC) from the real-time measurements for the days when Ksat measurements were taken in order to represent general climatic trends rather than short-term variability associated with diurnal effects, particularly for the air and soil temperature data. Those daily values were then used as the predictors in the multiple regression with the

Correlation Coefficients for Saturated Hydraulic Conductivity and Fittstown Mesonet Data

	Ksat	Tair	RH	5cm SM	25cm SM	60cm SM	5cm ST	10cm ST	30cm ST
Ksat	1.00	-0.28	-0.79	-0.24	0.00	0.47	-0.50	-0.51	-0.54
Tair		1.00	0.41	0.13	0.07	-0.05	**0.93**	**0.92**	0.88
RH			1.00	-0.18	-0.26	-0.38	0.64	0.65	0.69
5cm SM				1.00	0.16	-0.22	0.10	0.09	0.04
25cm SM					1.00	0.61	-0.03	-0.05	-0.09
60cm SM						1.00	-0.07	-0.07	-0.06
5cm ST							1.00	**1.00**	**0.99**
10cm ST								1.00	**0.99**
30cm ST									1.00

Table 1. Correlation coefficients of measured saturated hydraulic conductivity and daily means of parameters from the Fittstown Mesonet site. Correlation coefficients greater than 0.9 are highlighted in red.

Fittstown Multiple Regression Statistics (R^2 = 0.9550)

	β Coefficient	Standard Error	t Value	Pr(>|t|)
Intercept	-1.250e-03	3.885e-04	-3.216	0.014733
Tair	5.453e-05	7.614e-06	7.162	0.000183
25cm SM	-5.046e-04	7.050e-05	-7.158	0.000184
60cm SM	9.684e-04	1.121e-04	8.639	5.56e-05
30cm ST	-1.635e-04	1.745e-05	-9.366	3.29e-05

Tishomingo Multiple Regression Statistics (R^2 = 0.5062)

	β Coefficient	Standard Error	t Value	Pr(>|t|)
Intercept	3.598e-03	1.099e-03	3.273	0.00964
RH	-3.448e-05	1.136e-05	-3.036	0.01412
5cm SM	-2.673e-04	1.683e-04	-1.588	0.14670

Durant Multiple Regression Statistics (R^2 = 0.8788)

	β Coefficient	Standard Error	t Value	Pr(>|t|)
Intercept	3.529e-04	6.926e-04	0.510	0.62600
Tair	3.973e-05	1.248e-05	3.182	0.01544
5cm SM	-5.911e-04	1.157e-04	-5.110	0.00138
25cm SM	5.474e-04	1.206e-04	4.541	0.00266
30cm ST	-1.137e-04	2.810e-05	-4.046	0.00490

Table 2. Statistics for the Fittstown, Tishomingo, and Durant multiple regression analyses using only predictors with t value > 1.5.

measured Ksat data as the criterion. Multiple regressions were computed (using the R statistical software) separately for each site and for an average of all three sites to determine which best correlated to the Ksat data trend.

Because the Ksat dataset is small (12 measurements), it was necessary to compute the multiple regression with as few predictor variables as possible. Variables with t value < 1.5 in the initial multiple regression analysis were not considered to be significant predictors and were discarded. Additionally, for variables that were highly correlated with other predictors (R^2 > 0.9), only the one with the highest t value was retained. The multiple regression was then recomputed using the remaining predictors to generate a final regression equation for each site and for the basin average.

3. RESULTS AND CONCLUSIONS

Table 1 shows the correlation coefficients for all the initial predictors for FITT. The soil temperature data for the 5 cm and 10 cm depths were highly correlated with each other and with air temperature (high correlation is highlighted as bold red in Table 1), which was also the result at TISH and DURA. Thus, the 5 cm and 10 cm soil temperature parameters were not used as predictors.

Table 2 lists the analysis statistics for the individual site multiple regressions including coefficients, standard error, t value, and p value. The multiple regression calculated for TISH had a much lower correlation to the Ksat measurements than the other two sites with an R^2 of 0.5062. The lower correlation might be the result of the lack of a 60 cm soil moisture dataset at that location. Another interesting result for TISH was that relative humidity and 5 cm soil moisture were the most significant predictors whereas air temperature and deeper soil moisture were more significant at the other two sites. The estimates of Ksat derived from the FITT and DURA regression equations were more highly correlated to the measured Ksat, with R^2 values of 0.9550 and 0.8788, respectively (Fig. 4). A higher correlation between FITT and the Ksat measurements than for DURA was expected due to the closer proximity of FITT to the Ksat site and because the FITT observations represented the upstream soil conditions that would have an impact on streamflow at the Connerville stream gauge site.

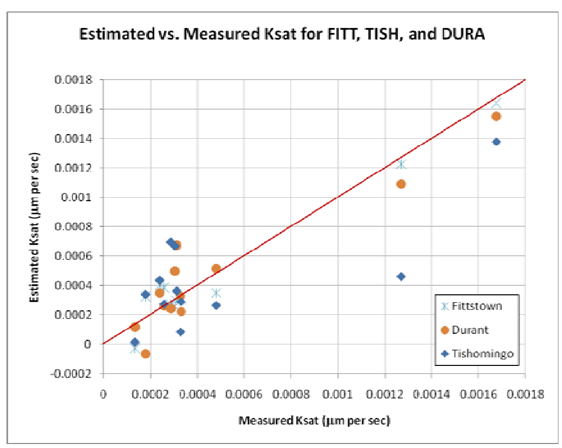

Figure 4. A scatterplot of measured Ksat and Ksat estimated from the multiple regression equation. The R^2 values for Fittstown, Tishomingo, and Durant are 0.9550, 0.5062, and 0.8788, respectively. The red line represents perfect correlation.

The multiple regressions for the average of all three sites and the average of only FITT and

DURA both produced lower correlations to the Ksat data than the individual regressions for FITT and DURA, so basin average observations were not better predictors of Ksat than the individual site observations.

The independent parameters selected as significant predictors of Ksat variation (air temperature, soil moisture, and deep soil temperature) do seem to indicate that deep soil vertic processes may be at least partly responsible for the change in infiltration rates and thus changes in runoff and streamflow. However, when taken independently as predictors of Ksat (such as the correlations in the Table 1), they do not appear to strongly correlate with the Ksat measurements. The multiple regression results imply that a combination of several parameters yielded the best fit. In other words, the occurrence of both high temperatures and dry soils coincided with changes in infiltration rates, but little correlation was found when looking at high temperatures or dry soils alone.

Caution must be taken when interpreting the statistics because of the small sample size of Ksat measurements. As more measurements are taken, particularly through the spring months, the multiple regression analysis will be recalculated to determine whether the high correlation is a physical reality or the result of too few measurements.

4. FUTURE WORK

Future research will focus on completing a multiple regression analysis for at least a full year of Ksat measurements to encompass the full range of soil moisture conditions in the basin. When the updated regression analysis is complete, the Ksat regression equation will be applied toward parameter estimation in a physics-based distributed hydrologic model that uses Ksat as input to determine if streamflow simulations are improved.

5. ACKNOWLEDGEMENTS

We would like to thank Jeremy Grams for his review of the methods and conclusions of this paper and for his thoughtful suggestions.

6. REFERENCES

Ajami, N. K., H. Gupta, T. Wagener, S. Sorooshian, 2004: Calibration of a semi-distributed hydrologic model for streamflow estimation along a river system. *J. Hydrol.*, **298**, 112-135.

Carpenter, T.M., and K. P. Georgakakos, 2004: Continuous streamflow simulation with the HRCDHM distributed hydrologic model. *J. Hydrol.*, **298**, 61-79.

Gourley, J. J., and B. E. Vieux, 2006: A method for identifying sources of model uncertainty in rainfall-runoff simulations. *J. Hydrol.*, **327**, 68-80.

Jabro, J. D., 1996: Variability of field-saturated hydraulic conductivity in a Hagerstown soil as affected by initial water content. *Soil Science*, **161**, 735-739.

McPherson, R. A., C. A. Fiebrich, K. C. Crawford, R. L. Elliott, J. R. Kirby, D. L. Grimsley, J. E. Martinez, J. B. Basara, B. G. Illston, D. A. Morris, K. A. Kloesel, S. J. Stadler, A. D. Melvin, A. J. Sutherland, H. Shrivastava, J. D. Carson, J. M. Wolfinbarger, J. P. Bostic, and D. B. Demko, 2007: Statewide monitoring of the mesoscale environment: A technical update on the Oklahoma Mesonet. *J. Atmos. Oceanic Tech.*, **24**, 301-321.

Moser, H. M., 2008: Toward an integrated support system for quantifying water resources: atmosphere to aquifer. M.S. thesis, School of Meteorology, University of Oklahoma, 71 pp.

Ott, R. L., and M. Longnecker, 2001: An Introduction to Statistical Methods and Data Analysis. Duxbury, Pacific Grove, CA.

Reed, S., V. Koren, M. Smith, Z. Zhang, F. Moreda, D.–J. Seo, and DMIP Participants, 2004: Overall distributed model intercomparison project results. *J. Hydrol.*, **298**, 27-60.