The effect of soil hydraulic properties vs. soil texture in land surface models

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[1] Proper selection of parameters for a land surface model is critical, but is difficult due to the lack of data and difficulties in scaling existing data. In particular, the spatial distribution of Soil Hydraulic Properties (SHPs) is not well known. This study focuses on the effect of SHP selection on modeled surface fluxes following a rain storm in a semi-arid environment. SHPs are often defined based on a Soil Texture Class (STC). To examine the effectiveness of this approach, we run the Noah land surface model with each of 1306 soils in a large SHP database. Within most STCs, the outputs have a range of 350 Wm^{-2} for latent and sensible heat fluxes, and 8K for surface temperature. The average difference between STC median values is only 100 Wm^{-2} for latent and sensible heat. STC explains 5–15% of the variance in model outputs and should not be used to determine SHPs. **Citation:** Gutmann, E. D., and E. E. Small (2005), The effect of soil hydraulic properties vs. soil texture in land surface models, *Geophys. Res. Lett.*, *32*, L02402, doi:10.1029/2004GL021843.

1. Introduction

[2] Soil hydraulic properties (SHPs) play a critical role in land surface models (LSMs). SHPs define the relationship between soil moisture (θ), hydraulic head (ψ), and hydraulic conductivity (K), thus controlling how water moves through the soil. This movement controls the water balance partitioning between evapotranspiration and runoff. In addition, the availability of soil moisture at different depths in the soil column controls the partitioning of the two key energy fluxes of concern in climate models, latent and sensible heat. Moisture availability also controls the partitioning between evaporation and transpiration which has implications for carbon cycling. LSMs have evolved substantially in the last 30 years, both in physics and techniques. Here, we focus on the hydrology component of LSMs, which has evolved from a single-layer "bucket" model [*Manabe*, 1969] to a multi-layer solution to the Richards equation [*Dickinson et al.*, 1993; *Mahrt and Ek*, 1984; *Sellers et al.*, 1986]. More recently, the focus has shifted towards "greening" LSMs by including complex vegetation components [e.g., *Sellers et al.*, 1986]. These models have been criticized for the discrepancy between the complexity of above-ground processes, and the simplicity of below-ground processes [*Pitman*, 2003]. The evolution of LSMs has not balanced the importance of SHPs with that of other model components. As the parameterization of hydrologic processes becomes more complex, the importance of accurately identifying SHPs will increase. *Pitman* [2003] targets the improvement of hydrologic processes in LSMs as one of the key challenges for future work, and comments on the need for global data sets of SHPs. Some of the most promising work on the more general problem of parameter estimation is by *Vrugt et al.* [2003].

[3] SHPs are difficult to measure, thus researchers have often relied on relationships between SHPs and soil texture. Numerous methods have been developed for the measurement of SHPs, but most are time-consuming and expensive [*Stolte et al.*, 1994]. For this reason, pedotransfer functions (PTFs) have been developed to translate more readily available soil texture data or soil texture class into SHPs [*Wosten et al.*, 2001]. *Soet and Stricker* [2003] note substantial variability between SHPs derived using different PTFs. In addition, none of the PTFs tested captured the variability measured in the field. This suggests that the relationship between SHPs and soil texture may not be very strong.

[4] In many LSM applications, simple PTFs are used to estimate SHPs according to soil texture class. This approach is based on the assumption that there is a one to one mapping between soil texture class and SHPs. However, there is little evidence that this is the case. Indeed, there appears to be more variability of the van Genuchten "n" [*van Genuchten*, 1980] SHP within a soil texture class then there is between classes (Figure 1).

[5] The uncertainty in determining SHPs from texture requires the land surface modeling community to question the use of soil texture class as a proxy for SHPs. To determine the error associated with using soil texture class as a proxy for SHPs, we need to know the effect this has on model output. To that end we examine output from the Noah LSM when run with a variety of SHPs from a large database of SHPs, as compared to output when run with the average SHPs for a given soil texture class.

2. Methods

2.1. Soils Database

[6] We used the SHP database of *Schaap and Leij* [1998] to perform this study. This database is a collection of 3 other databases (RAWLS, AHUJA, and UNSODA), and as such it is one of the largest SHP databases available. This database contains 1306 soils with retention and saturated conductivity measurements. This database is biased towards coarser textured soils, it contains 253 sands and but only 60 clays. Only three soil texture classes in the database are represented by fewer than 50 soils. This database is based on lab and field measurements of relatively small soil samples that would cover an area around 100 cm^2. These

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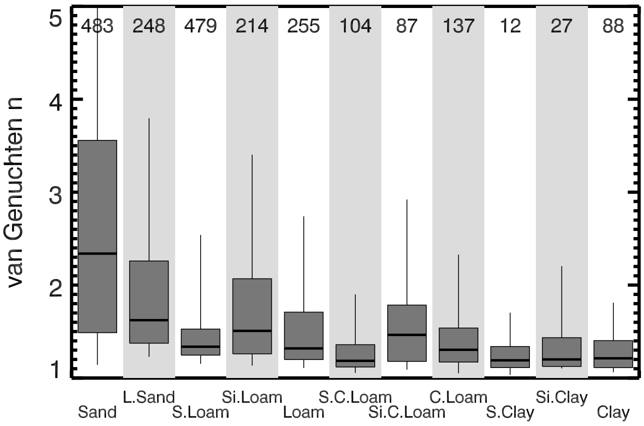

Figure 1. Variability of van Genuchten "n" parameter within each soil texture class. Boxes represent the middle 50% of sample, bars represent the full range, and middle lines are the median value. Numbers on top are the number of samples used in each class.

are likely to show more variable SHPs than would be seen in SHPs derived at the larger scales used in LSMs (0.1–1000 km^2). However, features such as macropores and calcite horizons will introduce additional variability at the field scale not captured in small scale measurements. Currently, no large database of SHPs measured at the LSM scale exists, and properly scaling SHPs from small scale measurement to LSM scales requires multiple SHP measurements from the same location [*Zhu and Mohanty*, 2002].

2.2. Soil Hydraulic Property Model

[7] We used the soil hydraulic property model of *van Genuchten* [1980]. Several SHP models exist to estimate the relationship between soil moisture, hydraulic conductivity, and hydraulic head. The SHP database of Schaap and Leij uses the van Genuchten model, and translating between SHP models is difficult [e.g., *Morel-Seytoux et al.*, 1996]. In addition, the van Genuchten model has been shown to fit measured data better and does not suffer from numerical problems when fitting SHP parameters to data [*Milly*, 1987].

2.3. Modeling

2.3.1. Land Surface Model

[8] We used the Noah land surface model [*Chen and Dudhia*, 2001] to examine the effects of SHPs on LSM fluxes. Noah is based on the OSU land surface model [*Mahrt and Ek*, 1984]. The hydrologic component of the model solves the diffusion form of the Richards equation in one dimension and we used the *van Genuchten* [1980] model for the relation between hydraulic head, moisture content, and hydraulic conductivity. The standard Noah model uses the Cambell SHP model [*Campbell*, 1974], but for the reasons outlined above we used the van Genuchten formulation. The fluxes at the land surface are determined to conserve both mass and energy based on a Penman type combination equation.

2.3.2. Site Parameters, Boundary and Initial Conditions

[9] Weather forcing data for the Noah model were collected from the Sevilleta National Wildlife Refuge and LTER grassland site of *Kurc and Small* [2004]. This is a semi-arid site with 50% vegetation cover, but only 25% is active [*Matsui et al.*, 2003]. The following data were collected: air temperature, pressure and humidity, wind speed, and both short and longwave downward radiation. Data were collected at a reference height of 2 m. Surface roughness (0.03 m) was determined as one tenth the height of vegetation cover. Albedo (0.14) was determined from measurements of incoming and outgoing radiation. The soil at the site is classified as a sandy loam, and measurements of SHPs at the site are close to the average SHPs for sandy loams in the SHP database. Table 1 summarizes the non-SHP parameters used in the model.

[10] We ran the Noah LSM once for each soil in the SHP database of *Schaap and Leij* [1998]. We initialized the model soil moisture as dry, consistent with observations at this site [*Small and Kurc*, 2003], and the model was allowed to spin up for 18 months. To determine the model sensitivity to SHPs, we analyzed model output following a large rain storm (30 mm) on September 10th 2002 (day 261). We analyzed mid-day average flux values (11AM–2PM) on the following day (day 262). We ran the model both with and without vegetation. Although active vegetation covers 25% of the ground at the site, bare soil runs allow us to simplify the system to see the impact of SHPs more directly, and our results focus on these simulations.

3. Results/Discussion

[11] For all soils, latent heat flux (LE) is low (0–150 Wm^{-2}) before the storm. It rained 30 mm over 12 hours on day 261. In all cases, LE increases sharply following the storm (Figure 2). However, the peak values of LE vary greatly between soils. To quantify the differences in dry-down curves we look at mid-day LE on the day after the storm (day 262; Figure 3).

[12] LE values varied more within a soil texture class then they do between soil texture classes. On average, mid-day LE varies by 350 Wm^{-2} within a soil texture class. However, the median value of each class varies by only 210 Wm^{-2} (Table 2). This indicates that soil texture class has less impact on LE than the variability of SHPs within a class have. It is evident from Figures 2 and 4 that this result would be the same if we looked at any of the days following the storm. There is only one exception to this, the sand texture class.

[13] The sand texture class is significantly different from all other soil texture classes (Figure 4). Within the sand class, LE varies by only 110 Wm^{-2}, and 75% of LE modeled output for sands fall between 0 and 16 Wm^{-2} on day 262. In contrast, most non-sands fall between 150 and 350 Wm^{-2}. Though loamy sands also stand out on some

Table 1. Table of Non-SHP Model Parameter Inputs

Variable	Value	Definition
NLayers	8	Number of model soil layers
ZSoil(1)	5 cm	Top soil layer thickness
RS_{min}	40 sm^{-1}	Minimum stomatal Resistance
RootDepth	35 cm	Depth to which roots extend
T_{bot}	287.5 K	Bottom soil temperature
Fg	0 or 0.25	Active vegetation cover
Z_o	0.08 m	Roughness length

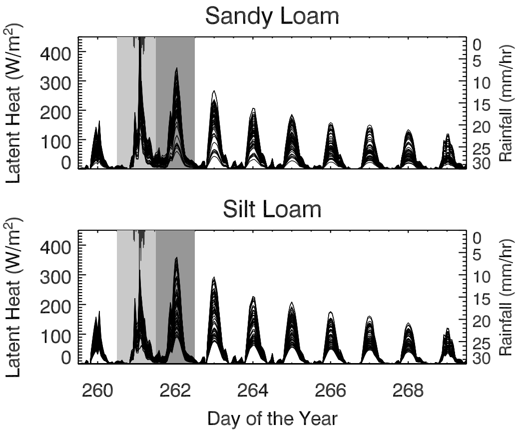

Figure 2. Time series of latent heat flux before during and after a rainstorm. Inverted dark bars show the distribution of 30 mm of rainfall on day 261 (lt.grey). Statistics for Table 2 come from day 262 (dk.grey). (top) 50 random samples from the sandy loam soil texture class. (bottom) 50 random sample from the silt loam soil texture class. A random subset is presented because if all soils are shown, it becomes impossible to distinguish individual lines.

days, they show substantial overlap with other classes. It is critical that LSMs can distinguish between more than just sand and non-sand because, according to a larger soils survey of 15737 soils across the United States, sands make up only 5% of soils [*Carsel and Parrish*, 1988].

[14] To quantify the degree to which soil texture vs SHPs control model output, we calculate coefficients of determination (r^2) for different predictor variables (texture class, particle size distributions, van Genuchten "n", Ks) and different fluxes. The van Genuchten "n" parameter explains the vast majority of variance in modeled LE output (79%; Table 2). In contrast, soil texture class explains only 16% of the variance in modeled LE, and much less of the variance in other fluxes. When sands are included, this number increases to 41%. This large change is due to the fact that sands are very distinct from all other soils, but they are uncommon in nature and we treat them as an outlier. It is possible to improve on soil texture class by using the particle size distributions (% sand, silt, and clay). However, even with the additional information, it is only possible to explain 44% of the variance in LE. Though we have focused on the latent heat flux in this paper, a similar pattern is seen for all fluxes (Table 2). The results are similar when vegetation is included in the model, only 5% of LE variance is explained by soil texture class, while 72% is explained by n (Table 2). The model runs that contain vegetation are similar to those without because vegetation is very sparse in this area, and the primary difference in Noah's simulation of transpiration vs evaporation is the depth it can draw water from, and the shape of the moisture limitation curve. At this site soil moisture is primarily in the upper soil layers, so water is equally available for evaporation and transpiration. The limited utility of soil texture is expected given the imperfections of pedotransfer functions, as demonstrated by the variability in SHPs generated with different pedotransfer functions by *Soet and Stricker* [2003]. This may be a slight over estimate of the range of output values as the SHPs used are based on small soils samples which may show more variability than site scale SHPs. However, it is unlikely that using SHPs derived at an

Table 2. Summary of r^2 Values for Different SHP and Texture Predictor Variables, and Average Range of Output Values Within and Between Soil Texture Classes (Txt.Cls)[a]

Predictor	LE	LE(veg)	H	Ts
$\log(K_s)$	0.31	0.26	0.35	0.34
$1/n$	0.79	0.72	0.80	0.80
Txt.Cls.	0.16	0.05	0.13	0.13
Txt.Cls.(w/Sand)	0.41	0.24	0.42	0.39
log(S.Si.C.)	0.18	0.21	0.12	0.12
log(S.Si.C.)(w/Sand)	0.44	0.41	0.43	0.41
Average Range within Txt.Cls.	$347\frac{W}{m^2}$	$322\frac{W}{m^2}$	$290\frac{W}{m^2}$	7.7 K
Range of Txt.Cls. medians	$207\frac{W}{m^2}$	$156\frac{W}{m^2}$	$125\frac{W}{m^2}$	3.3 K

[a]LE:Latent Heat Flux (bare soil and with vegetation), H:Sensible Heat Flux, Ts:Skin Temperature. To remove the bias towards sandy soils in the SHP database, we randomly selected 40 soils from each soil texture class when computing r^2. If a class contained fewer than 40 soils, all soils in that class were used. This process was repeated with 1000 different random samples.

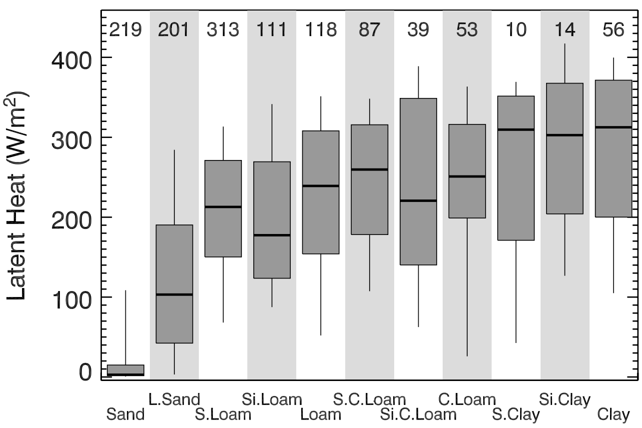

Figure 3. Variability of mid-day latent heat flux resulting from the variability of SHPs within each soil texture class on the day after a rain storm (day 262). Bars and boxes as in Figure 1.

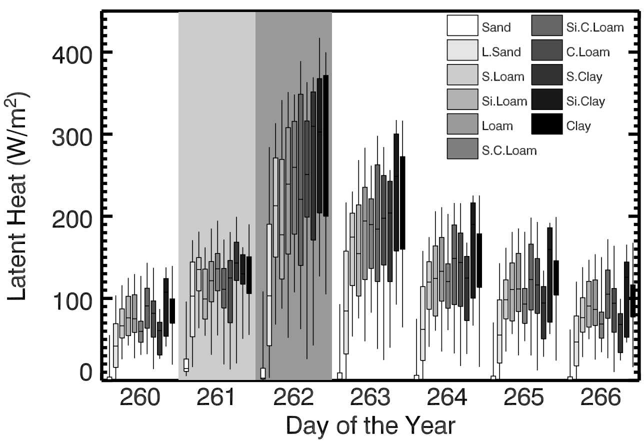

Figure 4. Variability of mid-day latent heat flux over a drydown period. 30 mm of rain occurred on day 261 (lt.grey). Statistics in Table 2 and box-whisker plot in Figure 3 use day 262 (dk.grey). Bars and boxes as in Figure 1.

appropriate scale would substantially improve the correlation with texture class.

4. Conclusions

[15] The use of soil texture class alone is an inadequate method of determining SHPs for LSMs. The main functions of LSMs in climate and weather modeling is the calculation of energy and moisture fluxes to the atmosphere. Of the total variance in these fluxes, soil texture class accounts for only 4–14%, while the van Genuchten "n" SHP alone accounts for 80%. If particle size fractions are used, it is possible to explain up to 30% of the variance, but, this is still far short of ideal. These results are consistent for all surface fluxes in the model, with and without vegetation cover, and indicate the importance of understanding SHPs, at least for the semi-arid environment modeled here.

[16] Our results indicate that a global data set of SHPs is necessary for accurate land surface modeling. Currently, soil texture class is used as a proxy for SHPs, but this is clearly inadequate. Particle size fractions yield more information, but a global map of SHPs would be a vast improvement. Due to the inherent difficulties of measuring SHPs directly, we suggest that this dataset must be constructed via inverse modeling based upon remotely sensed data sources such as skin temperature derived from IR measurements or soil moisture derived from active or passive microwave systems [e.g., *Burke et al.*, 1998]. These methods have the further advantage of deriving SHPs at a scale commensurate with LSMs, as compared to conventional methods which measure SHPs over a small ($\approx$100 cm^2) area.

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