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# Spatial Variability of Surface and Subsurface Saturated Hydraulic Conductivity in a Semi-Arid Region: Results from a Field Campaign

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of the requirements for the degree Master of Science

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by

Rike Becker

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ABSTRACT OF THE THESIS

Spatial Variability of Surface and Subsurface Saturated Hydraulic Conductivity in a Semi-Arid Region: Results from a Field Campaign

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Rike Becker

Master of Science in Civil Engineering

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Professor Mekonnen Gebremichael, Chair

The accurate estimation of saturated hydraulic conductivity (Ks) is of high relevance to correctly reproduce water movement in hydrological simulations. Yet, estimation of Ks is challenging particularly in semi-arid regions with particular soil surface characteristics like crusting and sealing. This study presents results of a field campaignin the semi-arid Walnut Gulch Experimental Watershed, Arizona (US), where surface and subsurface Ks measurements were undertaken across the watershed. Results reveal that the following commonly-used assumptions used in estimation of Ks are not plausible in such regions: (i) Ks decreases with increasing soil depth, (ii) soils with coarse-grained texture (sandy loam) have higher surface Ks values compared to relatively fine-grained texture (fine sandy loam), and (iii) pedo-transfer functions are not reliable methods of estimating Ks. Our results also reveal that remote sensing data can provide useful information for estimation of surface and subsurface Ks values.

The thesis of Rike Becker is approved.

Timu Gallien

Steven A. Margulis

Mekonnen Gebremichael, Committee Chair

University of California, Los Angeles

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# 1 Introduction

Saturated hydraulic conductivity (Ks) is a key parameter for controlling soil moisture storage and water movement in the soil layer[*Wang et al.*, 2013]. Ks is therefore one of the principal parameters used in hydrological and land-surface modeling for land surface hydrology, and land surface-atmosphere dynamics. However, due to the high spatial and temporal variability of Ks as well as the effort needed for a sound ground based data collection, it is often difficult to obtain accurate Ks information at the resolution required by most hydrological or land surface models.

Often, Ks at the topsoil (hereafter referred to as "surface Ks") is indirectly estimated from spatially available soil data like soil texture information through pedo-transfer functions (PTFs) [*Saxton and Rawls*, 2006; *Sobieraj et al*., 2001]. Yet it has been shown by several researchers [*Gutmann and Small*, 2007; *Soet and Stricker*, 2003] that this approach produces large errors in the resulting Ks estimates particularly when these empirical relationships are applied to areas they were not developed for. The Ks in the subsurface layer approximately 15-20 cm (hereafter referred to as "subsurface Ks") is typically estimated either from PTFs [*Cosby et al.,* 1984*; Saxton and Rawls,* 2006] or from surface Ks through an exponential decay function where, the decay parameter varies with soil texture [*Wang et al*., 2006].

Semi-arid regions have unique land surface characteristics where the soil surface layer is dominated by soil crusts, which could significantly reduce infiltration capacities and increase surface runoff [*Assouline et al.,* 2015*; McIntyre,* 1957, 1975*; Mualem and Assouline,* 1996*; Ries and Hirt*, 2008; *Valentin and Bresson*, 1992]. Strong raindrop impact on sparely vegetated soils leads to a disaggregation and "washing-in" of fine soil particles from the topsoil into the deeper near-surface layer, as well as to the compaction of the immediate soil surface, enabling the formation of so called “structural crusts”.As a consequence of this crusting effect infiltration capacities are significantly reduced and surface runoff increases. This in turn results in an increase in surface transportation of soil particles by overland flows, leading to the formation of “sedimentary crust” when particles are deposited (Fig. 1).

*Figure 1: Crusted surfaces in the Walnut Gulch Experimental Watershed*

Many studies have indicated the importance of incorporating soil crust information into hydrological and land surface models [*Casenave and Valentin*, 1992; *Mualem and Assouline*, 1996]. Simple empirical and complex numerical equations have also been developed to estimate the infiltration through soil crusts [*Edwards and Larson,* 1969; *Hillel and Gardener*, 1969; *Nciizahand Wakindiki*, 2015]. However, such equations are rarely used in models primarily because of the several parameters that need to be estimated from field data. As a result, currently hydrological and land surface studies in semi-arid regions still use the typical approach, where surface Ks is estimated from soil texture through PTFs and subsurface Ks is estimated from surface Ks through exponential decay function whose parameter depends on soil texture.

Past studies have shown the potential of remote sensing data for the derivation of soil hydraulic properties[*Ines and Mohanty*, 2008; *Mattikalli et al*., 1998; *Santanello et al.*, 2007; *Shin et al.*, 2013]. These approaches are promising as they offer spatially distributed soil information over large areal extents. Nevertheless it still has to be investigated how precisely soil data can be derived from satellite images and can be used for the parameterization of hydrological or land-surface models. One important factor which has to be considered when soil hydraulic properties are derived from satellite imagery is the vertical variation of Ks. Like previous studies [*Baumhardt et al.*, 1990; *Ramadas et al.*, 2016] have shown, Ks varies significantly with depth. Surface and subsurface properties might show significant differences which have to be included into land surface and subsurface hydrological simulations.

The purpose of this study is to investigate the spatial variability of surface and subsurface Ks and test the validity of commonly-used approaches of estimating surface and subsurface Ks in a semi-arid region setting. Furthermore the study gives an outlook on the potential of using hyperspectral and high resolution satellite images to derive spatially distributed information on specific soil surface characteristics, which could be incorporated into hydrological models in order to improve their performance. Study region is the Walnut Gulch Experimental Watershed (WGEW), a semi-arid region that was the site of NASA's SMAP (Soil Moisture Active Passive) Validation Experiment in 2015 (SMAPVEX-15).

# 2 Materials and Methods

## 2.1 Study Area

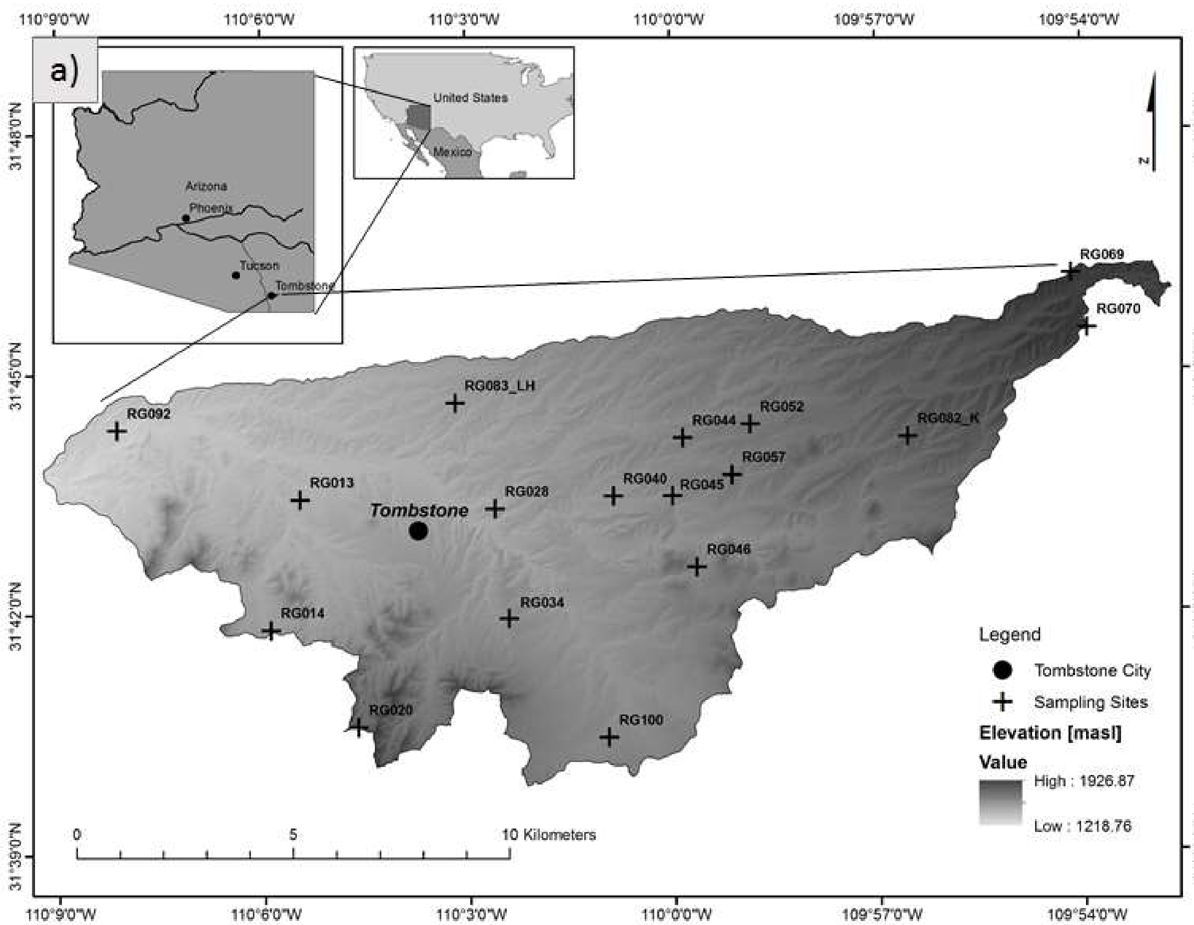


*Figure 2: Study Area - The Walnut Gulch Experimental Watershed (WGEW)*

The Walnut Gulch Experimental Watershed (WGEW), located in southeast Arizona, USA, with a catchment area of 149km$^2$, is one of the best instrumented research watersheds of the U.S. Department of Agriculture's Agricultural Research Service (Figure 2).It lies in the transition zone between the Chihuahuan and the Sonoran Deserts.Its climate is semi-arid, with long term average rainfall of 350 mm/year and potential evapotranspiration of 260 cm/year which is approx. 7.5 times the annual precipitation [*Renard et al*., 2008]. Two-thirds of the annual rainfall falls in just two months (July and August) during the North American Monsoon season. These summer rainfall events are caused by excessive surface heating and moisture influx from the Gulf of Mexico and the Gulf of California, which lead to the formation of intense convective storms (Fig. 3). The precipitations events are characterized by short duration, high-intensities and small areal extent, leading to a high spatial and temporal variability of moisture fluxes such as surface drying and wetting throughout the entire catchment. During the winter months, precipitation occurs mainly due to slower moving, frontal systems which cause longer lasting events of larger areal extent.The meteorological as well as soil hydrological characteristics of this catchment have been well documented in *Goodrich et al.* [2008] and *Keefer et al*. [2008].

*Figure 3: Convective summer storm during the field campaign in the Walnut Gulch Catchment. August 2015.*

Land use is dominated by grasscover in the upper catchment areas and shrub covered rangelandin the lower catchment part (Fig. 4). Vegetation density is highly variable and overall very low in this semi-arid region, exposing the bare soil to the intense weather characteristics described above. Soils in the WGEW have developed on top of a complex underlying geology of consolidated rocks and fan and alluvial deposits. Aridisols (soils of arid regions with clay and calcium carbonate accumulation in the subsurface) cover 75% of the catchment area. Entisols (young soils, generally without deep horizon genesis) developed on steeper slopes and cover 17%. Vertisols (clay-rich soils with swell/shrink dynamics) are found in river beds (5%), and Mollisols and Alfisols (soils with higher organic material) cover 3% of the catchment. Soil properties vary between sand and loam textures, with deeply, well drained as well as thin, young and poorly drained soil layers [*Osterkamp*, 2008]. During our sampling activities, a clear development of soil crusts (figure 1), particularly in the low-lying, flash flood prone areas, could be observed in vast parts of the watershed which led us to the focus of this study.

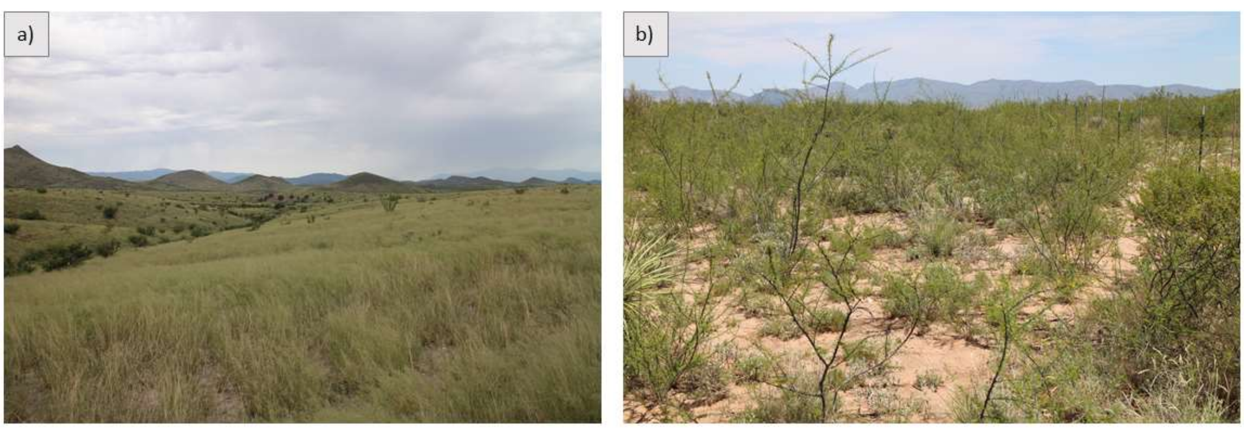


*Figure 4: Land use cover in the Walnut Gulch Catchment, dominated by grass rangeland (a) in the upper catchment areas and shrub covered rangeland (b) in the lower areas.*

## 2.2 Field Campaign

Field work was conducted for this study during NASA's SMAP-Validation-Experiment-2015 (SMAPVEX15) that took place at the WGEW in September 2015, with the aim to validate soil moisture data products obtained from the SMAP (Soil Moisture Active Passive) satellite. Along with the SMAPVEX15 activities we collected data on hydraulic conductivity in order to analyze the spatiotemporal variability of soil hydraulic properties at the surface and near subsurface.The sampling sites were chosen adjacent to the USDA-ARS meteorological measuring sites in the WGEW to take advantage of the long-term database of climate data at these sites. A well-documented long-term data base exists for this area, covering a time span from 1990 until today, with event based rainfall data and detailed meteorological parameters such as air temperature, relative humidity, wind speed, wind direction and solar radiation as well as soil hydrology data on soil moisture, soil temperature and soil heat flux [*Keefer et al*., 2008a]. Data on soil texture classes and spatial soil data sets can be obtained from SSURGO GIS soil survey (http://www.tucson.ars.ag.gov/dap/). We adapted the USDA nomenclature for the station enumeration. "RG" stands for "Rain Gauge" and the number indicates the selected USDA rain gauge station of the dense WGEW gauging network (Fig.2).

To obtain surface Ks measurements, tension infiltrometer tests were performed at each site using a Hood Infiltrometer (IL 2700, Umweltgeräte Technik GmbH, Müncheberg) at the undisturbed soil surface [*Schwärzel and Punzel*, 2007] (Fig. 5a). A closed hood is placed on the undisturbed soil surface and filled with water. Infiltration takes place over the area of the circular surface underneath the hood. The hydraulic pressure head under which infiltration occurs is controlled by a mariotte water supply system and a U-tube manometer. In our study the pressure head is set close to zero to simulate atmospheric pressure head conditions. The water and pressure level in the hood is kept constant throughout the measurement, and the final infiltration rate is taken once steady state flow conditions are reached. This final infiltration rate is used to calculate the surface Ks through the following equation [*Gardener*, 1958; *Wooding*, 1968]:

$$Ks = \frac{Qe^{-\alpha h}}{\left(1+\frac{4}{\pi\alpha r}\right)(\pi r^2)} \qquad [1]$$

Where, $Q$ is the steady state infiltration rate [$cm^3$/h], $r$ the radius of the infiltration chamber [$cm^2$], α the soil pore size depending Gardener constant, $h$ is the hydraulic pressure head under which the infiltration tests were taken [hPa], and $Ks$ is in [$cm^2$/h].

To obtain subsurface Ks measurements, a constant head permeameter (Amoozemeter, Ksat Ltd; [*Amoozegar*, 1989a]; Fig. 5b) was used. We measured at 15-30cm depth. Similar to the Hood-Infiltrometer method, we recorded the final infiltration rate once a steady flow is reached and used this steady flow value to calculate the saturated hydraulic conductivity through the Glover's equation [*Amoozegar*, 1989b; *Zangar et al*., 1953]:

Where, $H$ is the constant water level depth, and $r$ is the radius of the auger hole.

$$Ks = QA = Q\,\frac{\sinh^{-1}\left(\frac{H}{r}\right)-\left[\left(\frac{r}{H}\right)^2+1\right]^{\frac{1}{2}}+\frac{r}{H}}{2\pi H^2} \qquad [2]$$

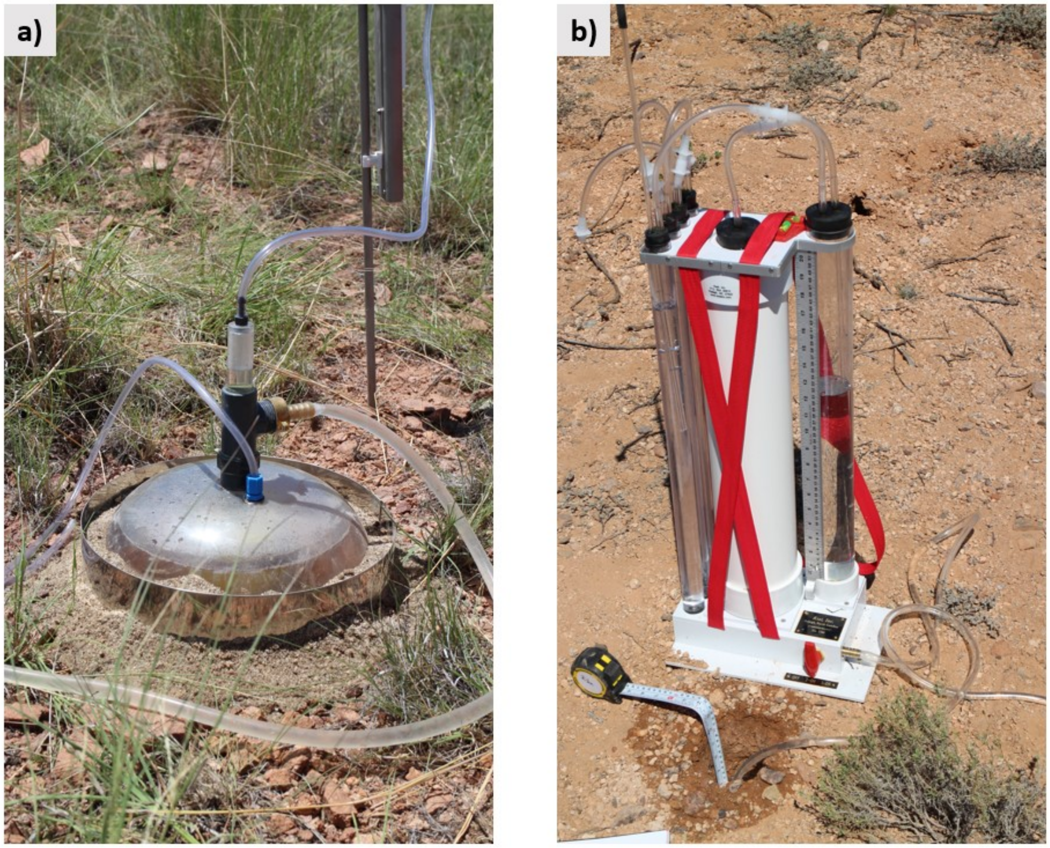


*Figure 5: a) Hood-Infiltrometer to measure saturated hydraulic conductivity at the soil surface and b) Compact Constant Head Permeameter to measure saturated hydraulic conductivity in the soil subsurface*

### 2.3 Data Quality

In order to test the collected data for potential measuring errors, which might have occurred due to the complex instrument setup, we compare our data with saturated hydraulic conductivities estimated by *Cosby et al.* [1984]. *Cosby et al.* analyzed 1448 US-soil types with respect to their hydraulic properties. The results of their study are commonly used for parameterization of soil processes in Land Surface Models (e.g. NOAH-LSM). The comparison could be accomplished for sandy loam and loam soil texture classes. Table 1 indicates that both data sets show a close match for the measured Ks. *Cosby at al.* [1984], estimated a mean Ks of 2.23 cm/h for a sandy loam soil texture class. Our field measurements revealed average conductivities of 2.14 cm/h for the surface and 2.75 cm/h for the subsurface. For the soil texture class "loam", we measured mean hydraulic conductivities of 0.9 cm/h and 1.85 cm/h for the surface and subsurface, while *Cosby et al.* [1984] found Ks to be 1.84 cm/h.

The comparison therefore shows that Ks values, obtained through our field measurements coincide well with the research results fromthe large soil sample analysis by *Cosby at al.* [1984]. We therefore rule out significant systematic errors in our data set and consider the variability in our data to be caused by particular environmental conditions and not by the instrument setup or measurement procedure.

*Table 1: Comparison of collected in-situ Ks data and Ks estimates from Cosby et al. (1984)*

| **Soil Texture Class** | **Saturated hydraulic conductivity [cm/h]** | | |
|---|---|---|---|
| ***Ks*** | ***Cosby et al.*** | ***WGEW surface*** | ***WGEW subsurface*** |
| **Sandy loam** | 2.23 | 2.14 | 2.75 |
| **Loam** | 1.84 | 0.9 | 1.85 |

# 3 Results and Discussions

### 3.1 Saturated Hydraulic Conductivity (Ks) at the soil surface and subsurface

Following the results of the in-situ measurements are presented and their variability is discussed with respect to Ks influencing parameters like soil texture classes, soil organic matter, rainfall-soil moisture responses, vegetation cover and topography. In conclusion methods for a spatially distributed estimation of Ks are analyzed and validated with respect to the collected field data.

The results of the field measurements of surface and subsurface saturated hydraulic conductivity (Ks) can be found in Table 2. On average, subsurface Ks values in the semi-arid study area are higher (mean of 2.66 cm/h) than corresponding surface Ks values (mean of 2.01 cm/h). This is consistent with findings of previous studies, which showed that under crusted conditions infiltration rates at the soil surface are significantly reduced [*Assouline et al., 2015; Valentin and Bresson*, 1992; *McIntyre*, 1957, 1975; *Ries and Hirt*, 2008].

Surface and subsurface Ks values for each measurement siteare illustrated in Figure 6. The extreme surface Ks values have opposite relationships with the extreme subsurface Ks values: the highest surface Ks values (4 – 5.56 cm/h) are associated with low subsurface Ks (< 3 cm/h), and the lowest surface Ks values (< 0.8 cm/h) match the highest subsurface Ks (4 – 6.63 cm/h). The moderate surface Ks values are about the same as the corresponding subsurface Ks values. Figure 6 presents a one-on-one comparison between surface and subsurface Ks values. Three classes could be broadly distinguished. The first class, where surface Ks > subsurface Ks, is characterized by high surface Ks (> 3 cm/h). The second class, where surface Ks < subsurface Ks, is characterized by high subsurface Ks (> 3 cm/h). The third class, where surface Ks ≈

subsurface Ks, is characterized by moderate values of both surface and subsurface Ks. In hydrological modeling, water movement through soils is typically modelled based on the assumption that saturated hydraulic conductivity decreases exponentially with increasing soil depth. Thefield measurements clearly indicate this assumption fails in semi-arid soils where the surface Ks is not very high due to crust formation.

*Table 2: Results from field measurements of saturated hydraulic conductivity (Ks [cm/h]) in the semi-arid Walnut Gulch Experimental Watershed, Arizona, US*

| Station ID | Texture Classes* | Surface Ks [cm/h] | Subsurface Ks [cm/h] |
|---|---|---|---|
| **RG013** | sandy-loam | 1.16 | 1.69 |
| **RG014** | loam | 0.9 | 2.4 |
| **RG020** | sandy-loam | 0.71 | 5.91 |
| **RG028** | sandy-loam | 1.63 | 2.8 |
| **RG034** | fine sandy loam | 4.29 | 2.1 |
| **RG040** | coarse sandy loam | 2.64 | 3.51 |
| **RG044** | sandy-loam | 1.93 | 0.54 |
| **RG045** | fine sandy loam | 5.56 | 2.15 |
| **RG046** | sandy-loam | 0.41 | 6.63 |
| **RG052** | sandy-loam | 2.75 | 1.59 |
| **RG057** | sandy-loam | 1.71 | 4.18 |
| **RG069** | loam | 0.94 | 1.33 |
| **RG070** | fine sandy loam | 0.55 | 4.43 |
| **RG082_K** | fine sandy loam | 2.31 | 1.52 |
| **RG083_LH** | sandy-loam | 0.99 | 1.34 |
| **RG092** | sandy-loam | 1.1 | 0.84 |
| **RG100** | fine sandy loam | 4.64 | 2.21 |
| | **Minimum** | 0.41 | 0.54 |
| | **Maximum** | 5.56 | 6.63 |
| | **Mean** | 2.01 | 2.66 |
| | **Standard deviation** | 1.48 | 1.68 |

*From SSURGO data base

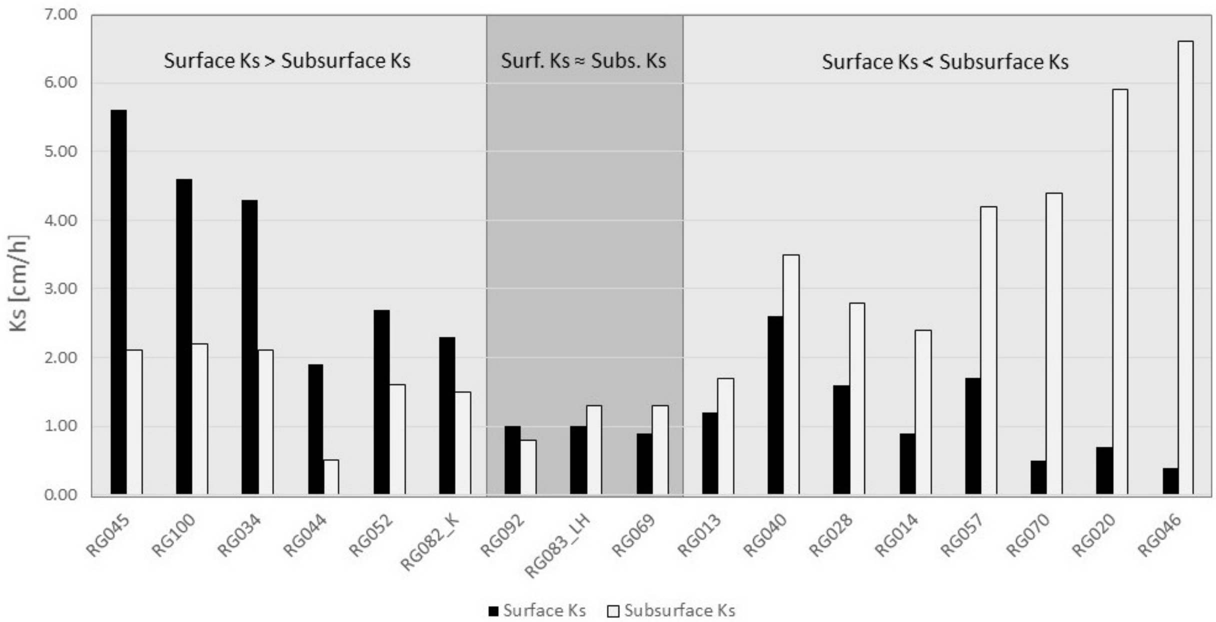


*Figure 6: Comparison of surface and subsurface Ks at each sampling site*

### 3.2 Effect of Soil Texture

Saturated hydraulic conductivities are closely related to soil texture classes since the grain size distribution controls the porosity and hence the permeability of soil material. [*Clapp and Hornberger*, 1978] found, that saturated hydraulic conductivities can vary over 3 orders of magnitude depending on the soil texture, with values of approx. >1 cm/min for sandy soils and <0.008 cm/min for clay soils. For this reason the percentage of clay, silt or sand content of a soil is taken as an important parameter to define its hydraulic conductivity. Pedo-transfer functions (PTFs), which derive soil hydraulic properties, such as Ks, from different soil characteristics, mainly soil texture, are therefore widely used in hydrological models [*Carsel and Parrish*, 1988; *Saxton and Rawls*, 2006]. Nevertheless, as stated in the introduction the accuracy of deriving Ks from soil texture classes has been discussed and questioned be several authors. We therefore analyze our measurements of Ks with respect to the soil texture class of each sample site in order to examine if our results align with the general assumption that Ks increases with decreasing soil grain size distribution.

Figure 7 presents the relationship between surface and subsurface Ks, as a function of soil texture. Most of the soil samples are taken in two soil texture classes: sandy loam, and fine sandy loam. Between the two classes, the sandy loam soils exhibit the highest subsurface Ks (6.63 cm/h), whereas the fine sandy loam soils exhibit the highest surface Ks (5.56 cm/h). For sandy loam soil, the relationship between surface and subsurface Ks is as follows: for the majority of soil samples surface Ks values are lower than subsurface Ks values, and those with very large subsurface Ks values are associated with the smallest surface Ks values. On the other hand, the fine sandy loam has mostly higher Ks value for the surface layer than for the subsurface layer.

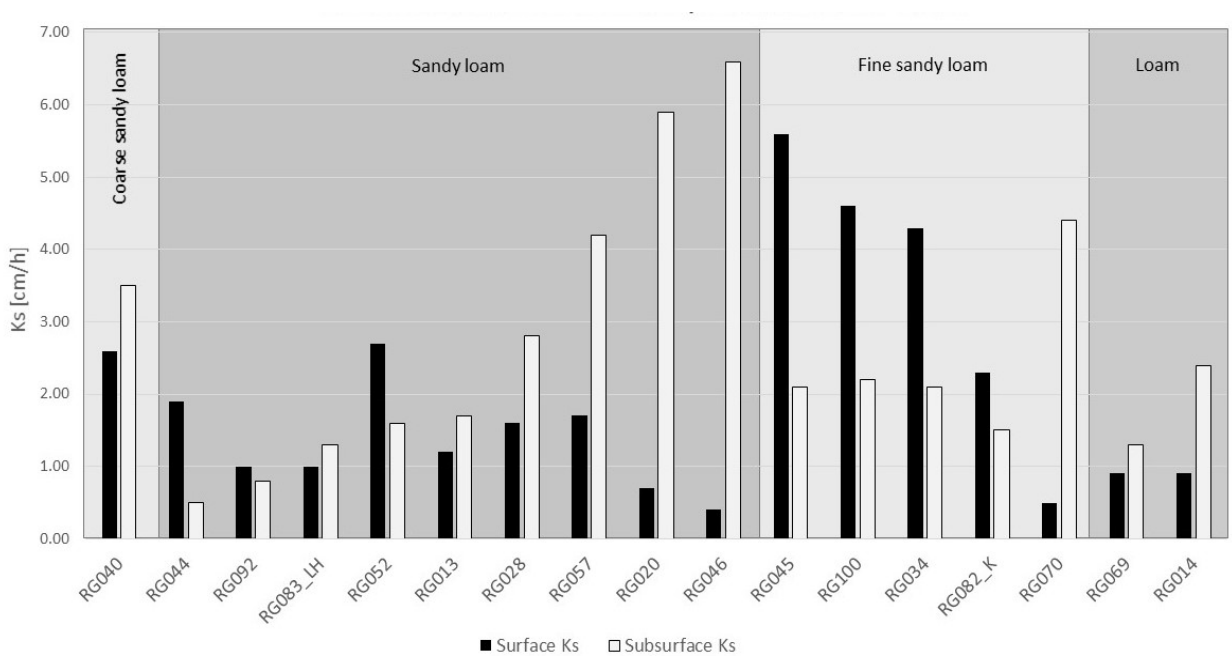


*Figure 7: Comparison of surface and subsurface Ks at each sampling site, grouped by soil texture class*

The distribution of surface and subsurface Ks for 4 soil texture classes is displayed in Figure 8. Soils with coarse-grained texture (sandy loam) have strikingly lower surface Ks values compared to relatively finer-grained texture (fine sandy loam). This unexpected result may be due to crust formation on the coarse-grained soils or simply the limitation of soil texture classification. The information on soil texture, which is taken from the SSURGO data base, gives an average grain size distribution for the entire upper soil column (approx. 5-25cm for the study region) and therefore may not correctly match the texture for the soil surface. This indicates the importance of other factors, such as crust presence/absence besides just soil texture in estimating surface Ks. The subsurface Ks values are higher for the coarse-grained soils than for the fine-grained soils,

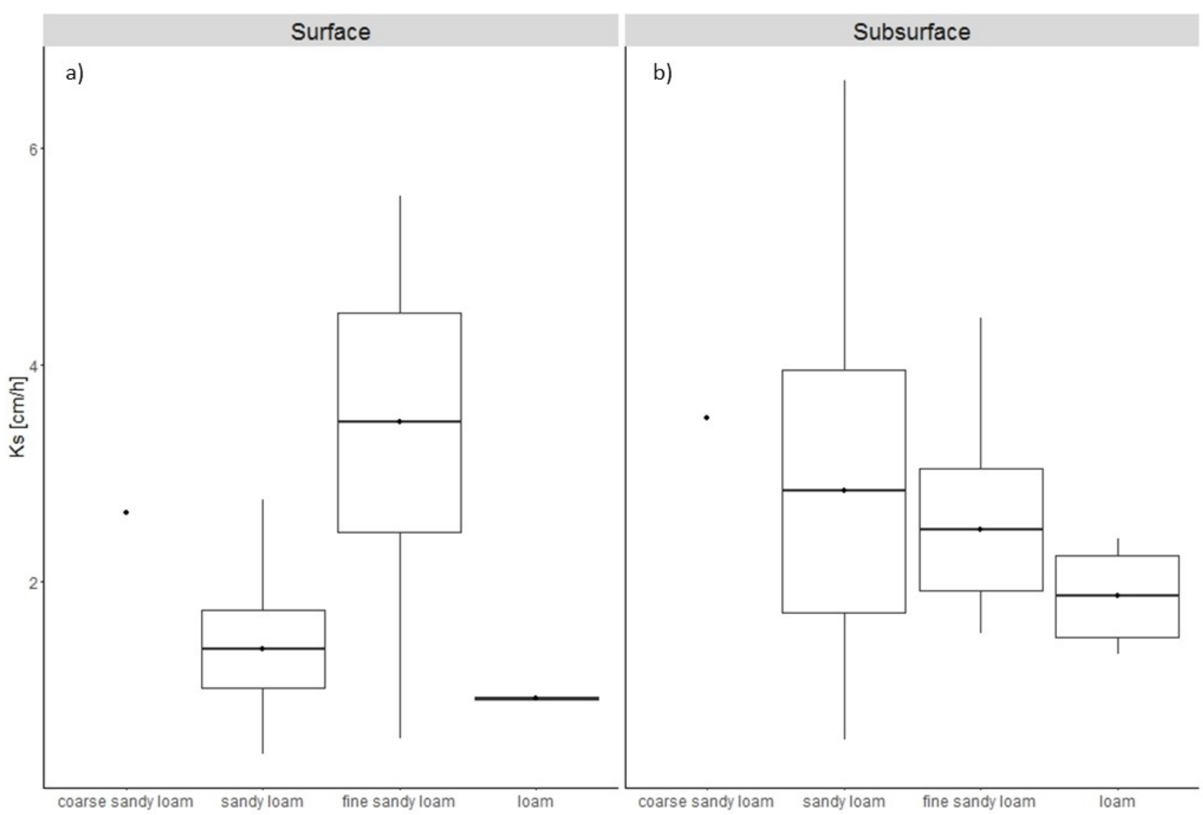


*Figure 8: Distribution of Ks for each soil texture class: (a) surface Ks, and(b) subsurface Ks. Horizontal bars are representing the mean Ks value for each class. Only one sample could be taken from a coarse sandy loam texture class.*

and therefore shows the expected general relationship between Ks and soil, while the surface layer does not.

### 3.3 Ks and Soil Organic Matter

Similar to the soil texture-Ks dependence, an empirical relationship between saturated hydraulic conductivities and soil organic matter (OM) has been elaborated by several studies. Many of these studies show an increase of Ks with increasing content of organic matter [*Lado et al.,* 2004*; Saxton and Rawls*, 2006], explaining this positive correlation by improved soil aggregation and higher porosity in soils with higher OM content, which enhances conductivities. Other researchers however show a negative correlation between OM and Ks[*Nemes et al.*, 2005], arguing that OM content not necessarily leads to larger porosity and therefore to increased Ks, but might also more effectively retain water in the upper soil layers and reduce conductivities.

In order to investigate if a clear relationship between OM and Ks can be found in our data and could furthermore be used to explain the spatial variability of the measured Ks values we correlated the soil organic matter (OM) content (taken from SSURGO data base) with our in-situ Ks values.

Results (Fig. 9) show that for our field data no significantcorrelation between surface Ks and soil organic matter can be found. Surface Ks values (Fig. 9a) seem to have a weak positive correlation with OM (correlation coefficient = 0.38), but this correlation can't be proven to be statistically significant (p-value = 0.14). For subsurface Ks and OM no correlation could be found (Fig. 9b). Again, the small sample size has to be considered as it limits the applicability of this statistical method. Furthermore, looking at the overall very low organic matter content (0.25-

2%) the missing correlation is not unexpected. Considering the fact that in semi-arid areas layers of soil organic matter are found to be very shallow due to low rates of organic decomposition,this result not surprising. A stronger dependency between OM and Ks would be

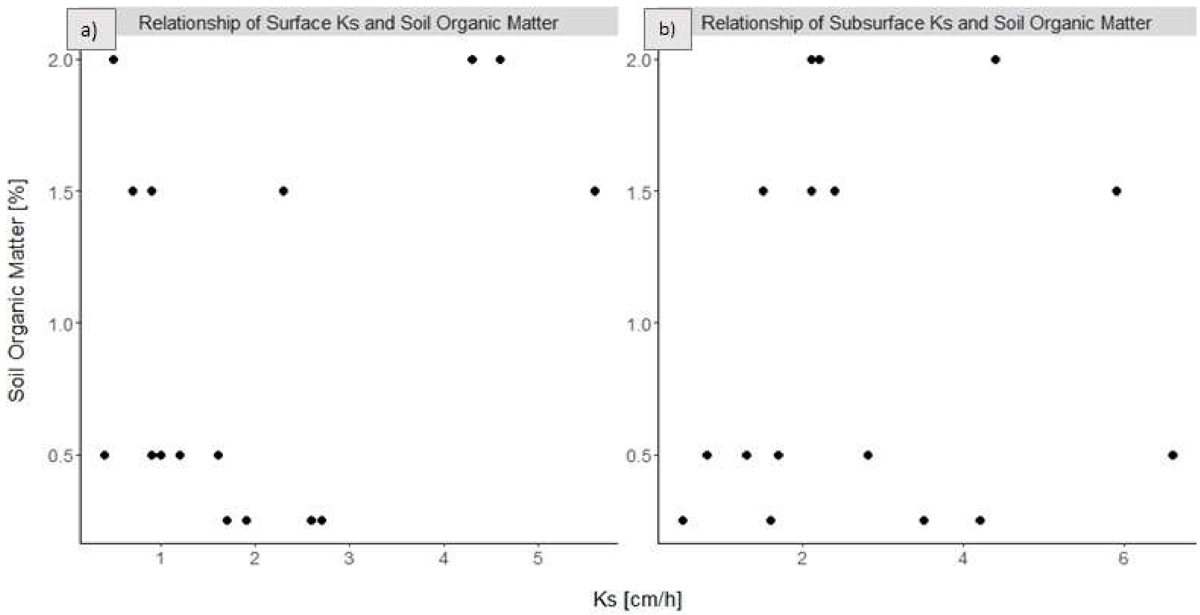


*Figure 9: Relationship between Ks and Soil Organic Matter. No significant relationship could be found.*

expected if significant OM content would be present and furthermore reveal significant spatially differences.

The same is true for the relationship between Ks and vegetation cover.

### 3.4 Ks and Vegetation Cover

Vegetation cover is an important parameter for soil hydraulic properties as it controls processes such as infiltration rates, soil macropore structure or formation of organic matter. To investigate if the type of vegetation explains the variation of the measured Ks values we compared the surface and subsurface saturated hydraulic conductivities according to land cover types at each site. Dominant land cover classes are shrub and grass land, showing a higher vegetation density under grass cover and more sparsely vegetated shrub covered areas. Expected results would show reduced surface Ks for less vegetated areas, as the bare soil is exposed to strong raindrop force impact, which facilitates the formation of the soil crusts as described above. On the other hand a higher vegetation cover would increase the Ks as it weakens the raindrop impact and facilitates infiltration into deeper soil layers due to its macropore structure.

However for the WGEW no correlation could be found between the Ks values and the land cover type, neither for the surface nor for the subsurface saturated hydraulic conductivities. This aligns with findings from other authors [*Ritchie et al.*, 2005], who found that in the Walnut Gulch catchment, soil modifying processes such as soil loss, soil redistribution or erosion processes are not significantly related to vegetation cover. We assume that differences in the two vegetation cover types (both rangelands with characteristics of sparse vegetation density) are too small to cause a significant effect which would explain the high variability of Ks values.

### 3.5 Ks and Rainfall-Soil Moisture Response

In order to investigate if the spatial distribution of our measured Ks values can be explainedby the pattern of rainfall-soil moisture responses, we analyzed the correlation between rainfall intensities and soil moisture increase and examined the time lag between the occurrence of the rainfall event and the course of the soil moisture increase. We expected to find a strong rainfall-soil moisture response for locations with high surface Ks values and weak responses for stations showing low surface infiltration rates.Furthermore we expected the saturated hydraulic conductivity to influence the response time until the maximum soil moisture response is reached.

Quicker responses (shorter time until maximumsoil moisture content is reached) would be likely for locations showing high surface conductivities, and longer time steps would be likely for areas with reduced surface Ks.

For this analysis we used 30min rainfall and soil moisture data from 2010-2015 from the permanent USDA-ARS soil moisture probes and rain gauge stations, which coincide with our measurement sites (accessible under http://www.tucson.ars.ag.gov/dap/).For each station we selectedrainfall events with dry antecedent soil moisture conditions, to ensure that the increase in soil moisture content can be attributed to the selected rain events. We then computed the time from the onset of the rain event until the maximum increase in soil moisture is reached. An example of a course of a soil moisture increase (VWC = Volumetric Water Content) for a selected rainfall event and a selected station is given in Figure 10.

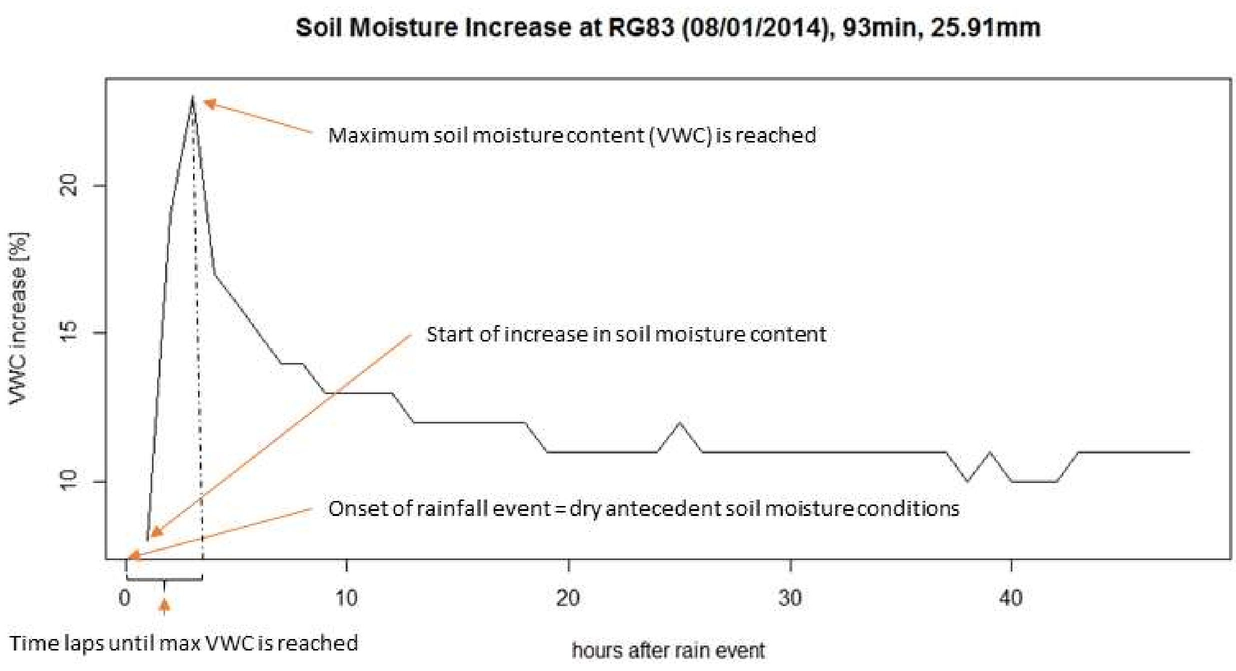


*Figure 10: Example of the course of a rainfall-soil moisture response for a selected storm event (93min duration and 25.91mm rainfall rate) for station RG83.*

A comparison of the rainfall-soil moisture response pattern with the collected Ks data, shows that a faster (1.5h) response can be found for the station with highest surface Ks values (RG100) than for station RG46 where particularly low surface Ks wasmeasured (response time 2.5h). This proves our hypothesis that strong rainfall-soil moisture responses can be related to locations with high surface Ks and weak responses to locations with low surface Ks. However maximum and minimum Ks values don't coincide with maximum and minimum response intensities and response delays. Therefore no explicit relationship between Ks values and rainfall-soil moisture response patterns can be defined which would be valid for the entire data set.

### 3.6 Comparison of Ks from Field Measurements and PTFs

As stated in the introduction section, PTFs are typically used in estimating Ks, which are then used in hydrologic and land surface modelling. In this section, we evaluate the accuracy of such estimates in our semi-arid study area. We selected four widely-used PTFs: *Wösten et al*., [1999] (for surface and subsurface Ks), *Cosby et al*.[1984] and *Ferrer-Julia et al*.[2004] (for subsurface Ks). These PTFs estimate Ks based on soil texture classes and bulk density. In Figure 11, we compare the Ks values estimated using the PTFs against our field measurements, at each sampling site.

With regard to surface Ks (Fig. 11a), the PTF gives reasonable values for smaller Ks values (~< 2 cm/h), but underestimates all Ks values higher than 2 cm/h with increasing underestimation for higher Ks values. The PTF estimates give a much smaller range (0.19-1.92 cm/h) than the field measurements (0.41-5.56 cm/h). This is primarily because the field measurements give larger ranges of values for a given soil texture class (e.g., fine sandy loam: 0.55-4.29 cm/h; sandy loam:

0.41-5.56 cm/h) than the corresponding PTF estimates (fine sandy loam: 0.14-1.22 cm/h; sandy loam: 0.25-1.14 cm/h). The overall variability in the PTF Ks estimates across all soil texture classes is much smaller than the variability in the field measurements of Ks within a given soil texture class, indicating that site specific land surface characteristics (such as crust formation) is much more important than just soil texture class and bulk density information in determining

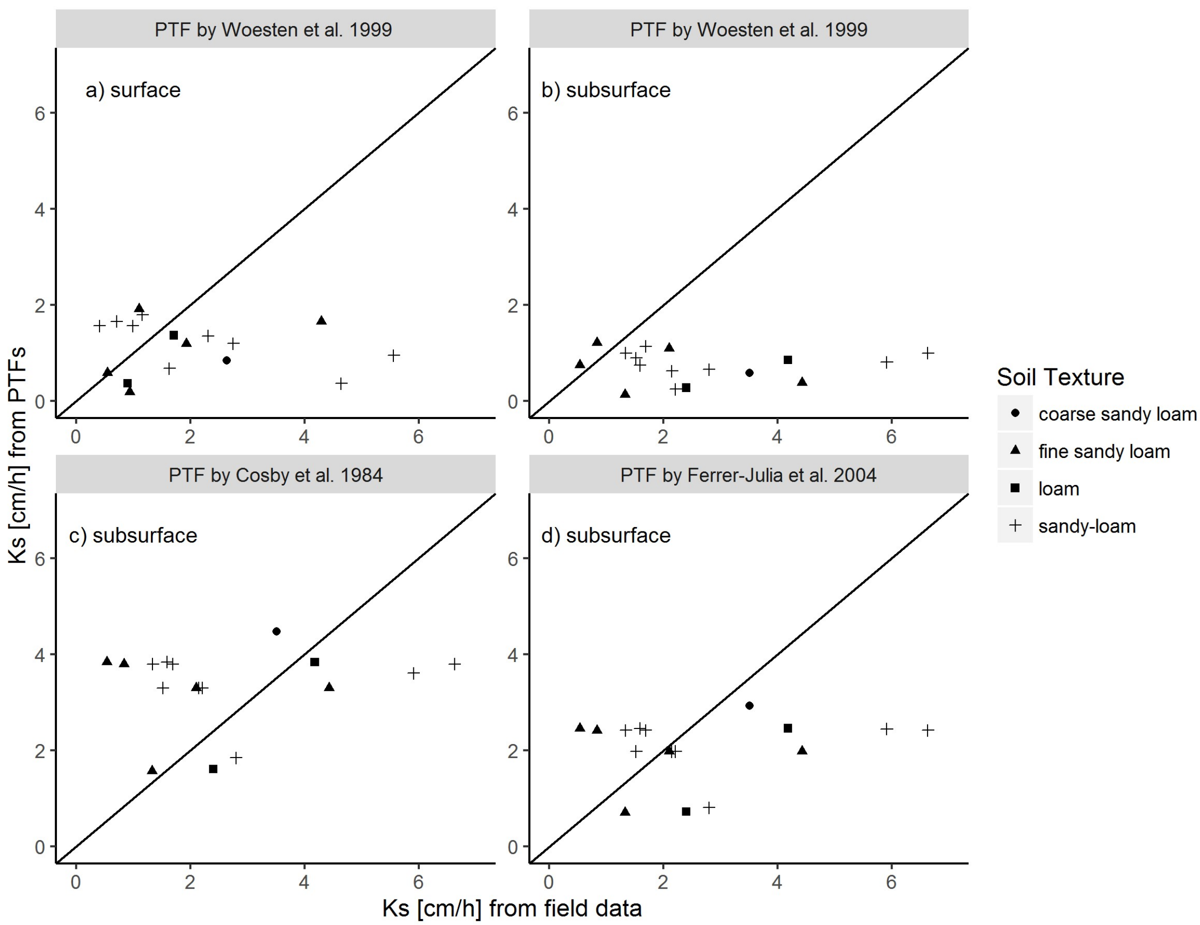


*Figure 11: Comparison of Ks values estimated from four PTFs against field measurements of Ks*

surface Ks.

With regard to subsurface Ks (Fig.11 b-d), similar stories can be drawn of the accuracy of the PTF estimates: the PTF estimates have a smaller range than measured values; the variability in the PTF estimates across all soil texture classes is smaller than the variability in the field measurements within a given soil texture class; and PTFs underestimate high values of Ks with increasing underestimation for higher Ks values. The accuracy of the PTF subsurface Ks estimates depends on the magnitude of the Ks and the PTFs. For high Ks values, all PTFs underestimate field measurements. For low Ks values, two of the PTFs [*Cosby et al*., 1984; *Ferrer-Julia et al*. 2004] overestimate Ks while the PTF by *Wösten et al.*[1999] gives reasonable values.

### 3.7 Ks estimations from remote sensing data

The comparison of the in-situ Ks data with commonly used method for Ks estimationrevealed their limitations and demonstrated the need for an alternative method to obtain spatially distributed Ks data. Following, the use of remote sensing imagery is tested, with the aim to delineate crusted surface conditions and relate them to specific Ks-characteristics in order to obtain spatially distributed Ks information. We test the derivation of crusted soil surface conditions from hyperspectral and high resolution multispectral data and compare the results with our field data to examine if in-situ Ks patterns coincide with the remote sensing derived soil surface patterns.

#### 3.7.1 Crust delineation from hyperspectral Hyperion images

First,the derivation of soil surface characteristics fromhyperspectral Hyperion images is tested. The reason for choosing a hyperspectral data set lays in the capability of the image to resolve the full spectral signatures of specific surface materials. Increasing studies exist about the use of remote sensing data for estimating soil minerals and soil properties such as soil crusts[*Ben-Dor* *et al*., 2009; *Dutkiewicz et al*., 2009; *Summers et al*., 2011]. The data can freely be obtained throughthe USGS Earth Explorer tool (http://earthexplorer.usgs.gov/). Hyperion data provides images with a spatial resolution of 7.7 x 100km and its hyperspectral sensor is able to resolve 220 spectral bands, ranging from 0.4-2.5µm. We selected the Hyperion image from July, 10$^{th}$, 2009, as it showed the best spatial coverage of the study area as well as the best image quality with respect to atmospheric conditions. Selecting a summer image ensures that environmental setting meets the conditions found during our field campaign (i.e. summer monsoon time).

After conducting initial image enhancement (exclusion of bad bands and stripe removal) we assigned training areas for each land cover type (urban area, sparse vegetation cover, dense vegetation cover, crust on slopes and plains (crust 1) and crustin riverbeds (crust2)). A separation into two crust classes was made due to the differences in their genesis and differences in their material composition, which is reflected in their spectral characteristics. The unique spectral signatures of each of the assigned land cover types let us separate the classes based on their characteristics in each spectral band (i.e. in each wavelength interval) (Fig. 12a). Based on these spectral differences a decision tree was elaborated to define the membership of each image pixel to the appropriate land use class (Fig. 12b). The decision tree was then used as constraint for the land use classification.

The final classification reveals unsatisfactory result (Fig. 12c). It shows a significant overestimation of crust 1 areas and a poor classification performance for crust 2.Crust 1 reveals a producer accuracy of 80.2%, but shows an error of commission of 56.9%, meaning that 59.9% of the classified crust 1 pixel where erroneously assigned to this class.Crust 2 shows a low error of commission (17.43%) but could only be classified with aproducer accuracy of 27.2%. Hence the classification based on the spectral signatures of the crusts turns out to be difficult.

Even though a more detailed examination of the use of Hyperion images for crust delineation

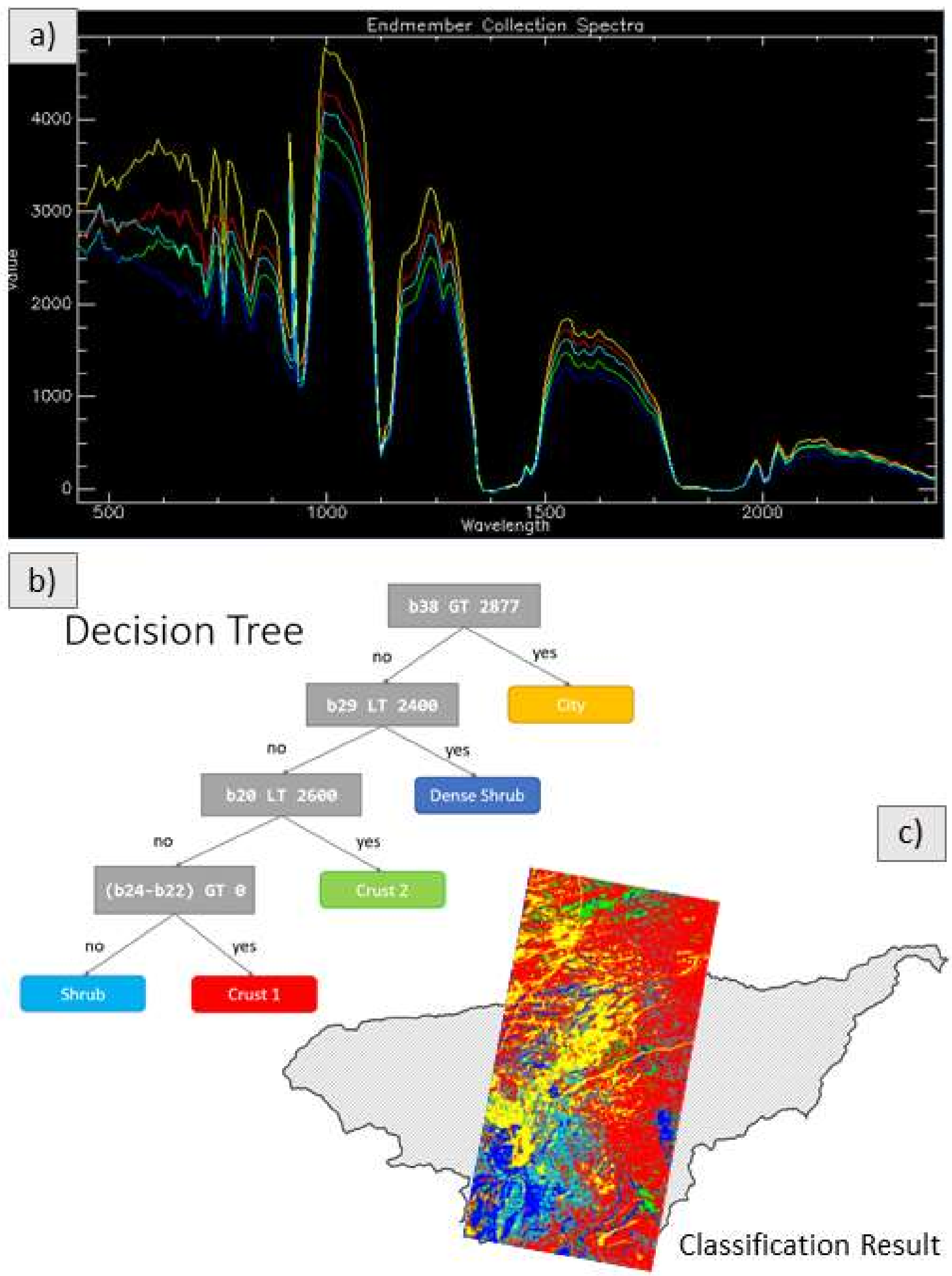


*Figure 12: Classification procedure from hyperspectral Hyperion data. a) Spectral signatures of selected land use classes. b) Decision tree based on spectral differences and c) Classification results.*

should be madeand more constraints could be included in the decision tree to reach a sound supposition, we conclude the following: the analysis showsthat crusts cannot easily be distinguished through their spectral characteristics. Spectral differences seem too small to clearly distinguish single land use classes. Also, no significant differences in spectral signatures could be found in the region of "clay"-bands (around 2200nm), which are commonly used to identify clay content in order to detect crusted surface. Hence the application of hyperspectral remote sensing images for the delineation of crusted surfaces seems limited. This conclusion aligns with finding of other authors [*de Jong et al*., 2011] who found, that the derivation of soil surface properties such as crust, cannot easily be accomplished by hyperspectral data sets.

### 3.7.2 Crust delineation from high resolution QuickBird images

An alternative way of using remote sensing imagery for the estimation of soil surface characteristics is the use of high resolution images, such as QuickBird. Based on our field observations we select crusted training areas and run a supervised maximum-likelihood classification using 2 multispectral, high resolution QuickBird images from spring and summer 2006. The images cover the basin between -110°7'0''W and -109°53'0''W, with a spatial resolution of 2.4m (Fig. 13).

The results (Fig.14a) show that this basic classification procedure presents reasonable results with respect to creating a spatially distributed crust map for our semi-arid region. Areas classified as crust are located in low lying and flash-flood prone areas where surface water retention occurs, which coincides well with our field observations. The accuracy assessment reveals the following statistics: Crusts could be classified with a small error of commission

(6.8%) and likewise a small error of omission (18.4%), showing only a small amount of erroneously included and excluded crust pixels. The resulting producer accuracy is 81.6% and producer accuracy is 93.2%.

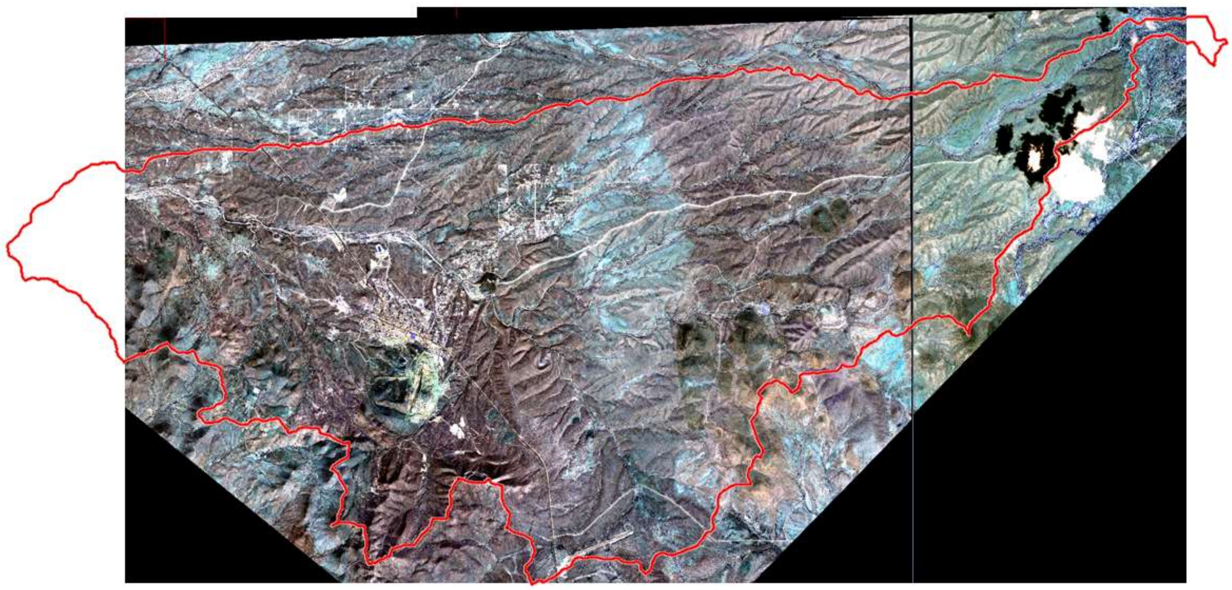

*Figure 13: QuickBird Images covering the WGEW between -110°7'0''W and -109°53'0''W with a spatial resolution of 2.4m.*

A comparison of the derived crust map with our field measurements of Ks (Fig.14b) shows, that as expected, the sample sites which are located on areas classified as crust show particular low surface and high subsurface Ks values, whereas non-crusted locations show higher surface Ks and lower subsurface Ks. The averagesurface Ks of sample sites on crusted areas is 1.19 cm/h, while the average surface Ks on non-crusted surfaces is 2.75 cm/h. Hence the delineated crust map shows a crust pattern which aligns well with our in-situ measurements.

Only the three locations RG20, RG14 and RG57 reveal an inconsistency withthe crust map classification. Possible reasons for this discrepancy might lay in small classification uncertainties e.g. due to the time lag between the date the image was taken (year 2006) and the conduction of the field measurements (year 2015). Once structural soil crusts are formed they are persistent in the environmentunless they are mechanically removed, whichjustifies the use of older images. However, during this period, land-use changes and land cover degradation have takenplace [*Ritchie et al., 2005*].RG20 and RG14 are located in close vicinity of crusted areas, which mighthave extended during the last years, revealing now characteristics of crusted surfaces. Local crust appearances of small extent, due to particular soil and runoff characteristics at a small scale, might be too small to be captured by satellite imagery and might be the reason why RG57 could not be classified as crusted area. More field data and a more recent satellite image are necessary to test this hypothesis. Nevertheless the analysis shows encouraging results. Despite the small sample size and the high spatial variability of the in-situ Ks measurements, the remote sensing derived crust map showsreasonable crust patterns which match our in-situ measurements. Based on this analysis we conclude that despite its simplicity, this approach shows promising results for an improved spatially distributed estimation of Ks values which could be incorporated into hydrological models.

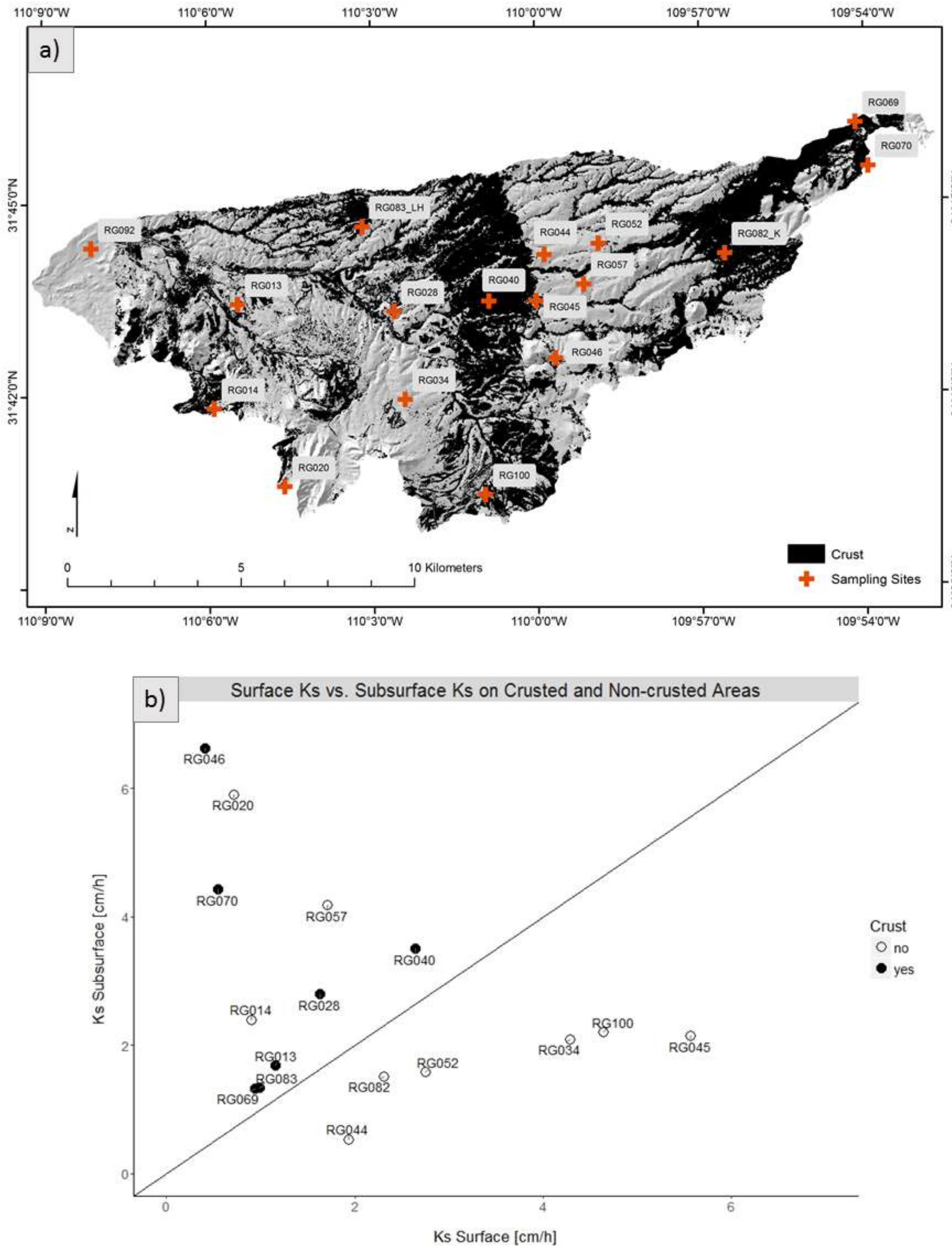


*Figure 14: a) Crusted areas (black) in the Walnut Gulch Watershed. Delineated based on high resolution satellite imagery. b) Comparison of surface and subsurface Ks on delineated crusted and non-crusted areas.*

# 4 Conclusions

Estimation of surface and subsurface Ks is critical in hydrological and land surface modeling, among other applications. The typical approach of estimating surface Ks is through the pedo-transfer function whose primary input is soil texture information. Subsurface Ks is estimated either through a similar pedo-transfer function or an exponential decay function where Ks decreases with increasing soil depth. Semiarid regions have significant presence of soil crust formations that reduce the surface Ks, and therefore the validity of such approaches for estimating Ks are questionable. In this study, we undertook field measurements to study the relationship between surface and subsurface KS in a semi-arid region with significant crust formation. The study region is the Walnut Gulch Experimental Watershed (WGEW), a semi-arid region that was the site of NASA's SMAP Validation Experiment in 2015 dubbed as "SMAPVEX-15". Our results reveal the following:

- The assumption that Ks decreases with increasing soil depth is not necessarily true in semi-arid regions with significant presence of crust formation. In areas where the surface Ks values are very high (> 4 cm/hr), the subsurface Ks values are lower (< 3 cm/hr). However, in areas where the surface Ks values are very low (< 0.8 cm/hr), the subsurface Ks values are very high (> 4 cm/hr).
- The expected relationship between soil texture and surface Ks does not necessarily hold true in semi-arid regions with significant presence of crust formation. Soils with coarse-grained texture (Sandy loam) have higher subsurface Ks values compared to relatively fine-grained texture (fine sandy loam), as expected. However, the surface Ks values for

the coarse-grained soils are strikingly lower compared to the fine-grained soils, which may be due to more crust formation over the coarse-grained soils.

- The pedo-transfer functions typically used to estimate surface and subsurface Ks are not reliable methods for semi-arid regions with significant presence of crust formation. The PTFs generally underestimate higher values of surface and subsurface Ks estimates. The range of Ks estimates obtained through the PTFs across all soil texture classes is much smaller than the range of field measurements of Ks in the same soil texture class, indicating that the site specific land surface characteristics (such as crust formation) are much more important than just soil texture class in estimating Ks.
- The use of remote sensing data for Ks estimation gives an outlook to potential improvement of Ks estimation, taking into account its high spatial variability. The identification of soil surface properties from a hyperspectral satellite image revealed significant difficulties and no satisfactory classification results could be achieved. A derivation of a crust map from high resolution remote sensing products however showed promising results for a spatially distributed estimation of Ks. The derived crust map showed reasonable crust patterns which coincide well with the collected in-situ measurements. For future applications this means that if Ks can be accurately related to specific surface characteristics, such as crusts, the derivation of crust maps from remote sensing images presents a way to obtain Ks data at the resolution needed for a detailed spatially distributed hydrological model and could help to improve the performance of hydrological simulations.

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