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Scaled spatial variability of soil moisture fields

Minha Choi,[1] Jennifer M. Jacobs,[2] and Michael H. Cosh[2]

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[1] This study identifies soil moisture spatial variability patterns using measurements across different extents (i.e., field, watershed, and basin) and depths (i.e., from surface to root zone profile) from 18 different soil moisture field experiments. The spatial variability patterns are well represented by negative exponential functions between the mean and the coefficient of variation of soil moisture. Principal component analysis demonstrates that rainfall and topography explain surface soil moisture variability changes as soils dry, while soil parameters control the maximum relative variability. Soil moisture's relative variability typically decreases as sampling extent increases, supporting the power law decay function proposed by Rodriquez-Iturbe et al. (1995). The finding that soil moisture relative variability increases as soil depth increases is consistent with an earlier study (Choi and Jacobs, 2006). These common soil moisture variability patterns can provide a feasible methodology to validate land surface models and to estimate variability across extents from mean soil moisture values. **Citation:** Choi, M., J. M. Jacobs, and M. H. Cosh (2007), Scaled spatial variability of soil moisture fields, *Geophys. Res. Lett.*, *34*, L01401, doi:10.1029/2006GL028247.

1. Introduction

[2] Knowledge of spatial soil moisture variability may provide the blueprint for future ground-based experiments and networks [*Famiglietti et al.*, 1999]. Moreover, its variability information is very crucial to understand and improve the parameterization for land surface hydrologic modeling [*Giorgi and Avissar*, 1997]. However, soil moisture variability is not well understood over a range of areal extents and depths or across sites [*Famiglietti et al.*, 1999; *Martinez-Fernandez and Ceballos*, 2003; *Jacobs et al.*, 2004]. Although numerous studies have characterized soil moisture, there is no agreement as to whether soil moisture variability is positively [*Famiglietti et al.*, 1998; *Martinez-Fernandez and Ceballos*, 2003] or negatively [*Famiglietti et al.*, 1999; *Hupet and Vanclooster*, 2002] correlated to mean soil moisture content.

[3] The spatial soil moisture variability is mainly affected by physical properties such as climate, soil texture, vegetation, and topography in natural catchment or agricultural land [*Mohanty and Skaggs*, 2001]. *Jacobs et al.* [2004] and *Mohanty and Skaggs* [2001] concluded that topography is a crucial physical factor to understand surface soil moisture variability. *Teuling and Troch* [2005] pointed out that soil and vegetation may be important factors that increase or decrease soil moisture spatial variance. They concluded that a simple soil moisture model provides a preliminary link between physical processes and statistical variability patterns. *Choi and Jacobs* [2006] also concluded that a simple physical model provides insight to statistical relationships necessary to disaggregate physical land surface model predictions. Additionally, soil moisture variability may differ by spatial extent or scale [*Crow and Wood*, 1999].

[4] The objective of this study is to identify common patterns among soil moisture statistics across a variety of landscapes. Specifically, the relationships between mean soil moisture and spatial variability of soil moisture measurements are quantified. Spatial variability patterns are examined in light of local physical properties including climate, soil, topography, extent, and vegetation. This study differs from previous studies in that it 1) brings together measurements from 18 different experiments across the world, 2) includes both surface and root zone soil moisture, and 3) uses multivariate statistics to identify the effect of physical properties on soil moisture spatial variability.

2. Study Region

[5] Table 1 identifies the 18 data sets (from 9 distinct field experiments) used in this study and provides detailed information for each study region and experiment. Additional information is available from the references listed in Table 1. Thirteen of the soil moisture data sets were obtained from the Southern Great Plains 1997 (SGP97) experiment and Soil Moisture Experiments 2002 (SMEX02), 2003 (SMEX03), 2004 (SMEX04), and 2005 (SMEX05) [*Crow and Wood*, 1999; *Jacobs et al.*, 2004; *Bosch et al.*, 2005; *Cosh et al.*, 2006; *Choi et al.*, 2005]. SMEX are a series of soil moisture field experiment conducted annually from 2002 to 2005 (SMEX02 – SMEX05) in Iowa, Georgia, Alabama, Oklahoma, and Arizona. Additional data sets are from Florida, Belgium [*Hupet and Vanclooster*, 2002], and Spain [*Martinez-Fernandez and Ceballos*, 2003]. The sites are predominantly agricultural lands with some forests, pastures, and clear cuts. Eleven data sets have only surface soil moisture measurements from approximately 0–6 cm. The remaining data sets include a profile of measurements in the root zone. All locations have regular sampling spaces determined by each field experiment plan and were sampled using in-situ devices, except the Iowa basin (Data ID E) which uses Polarimetric Scanning Radiometer (PSR) instrument. The sampling data of Data ID B, E, J, and Q have field scales (~800 m). In each field, fourteen soil moisture sampling were averaged. With these four exceptions, the sample sizes or scales (i.e., point scale) are comparable. However, the extent of sampling ranges from field to basin. The extent of

[1] Department of Civil Engineering, University of New Hampshire, Durham, New Hampshire, USA.
[2] Hydrology and Remote Sensing Laboratory, USDA ARS, Beltsville, Maryland, USA.

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Table 1. Summary of Field Characteristics and Data[a]

		Sampling Approach					Site Description										
Locations	ID	Extent,[b] km^2	# of Points	Date	Frequency	Depth	Soil	θ_{wp}[b,c]	θ_{fc}[b,c]	ϕ[b,d]	Sand[b,e] %	Relief	Max. Diff Elev.[b,f]	Land Use	LAI[b]	Annual Rainfall,[b] mm	Reference
Iowa, US (SMEX02)	A[g]	Basin (5000)	48	6/02–7/02	Daily	Surface	Loam	0.12	0.31	0.46	22	Low	138	Agriculture	2.19	835	SMEX02Data set
	B[g]	Watershed (100)	33	6/02–7/02	Daily	Surface	Loam	0.12	0.31	0.46	33	Low	47	Agriculture	2.65	835	SMEX02Data set
	C[g]	Field 11 (0.64)	25	6/02–7/02	Daily	Profile	Loam	0.15	0.35	0.48	29	Rolling	3.7	Corn	2.96	835	*Choi and Jacobs* [2006]
	D[g]	Field 13 (0.64)	31	6/02–7/02	Daily	Profile	Loam	0.15	0.35	0.48	29	Rolling	6.1	Soybeans	1.09	835	*Choi and Jacobs* [2006]
	E	Basin (5000)	10080	6/02–7/02	Daily	Surface	Loam	0.12	0.31	0.46	-	Low	-	Agriculture	-	835	SMEX02Data set
Georgia, US (SMEX03)	F[g]	Basin (3750)	49	6/03–7/03	Daily	Surface	Sand	0.05	0.10	0.40	75	Gently sloping	58	Forest, Pasture, Agriculture	1.89	1160	*Bosch et al.* [2005]
	G[g]	Watershed (334)	17	6/03–7/03	Continuous	Profile	Loam	0.09	0.27	0.45	78	Gently sloping	32	Forest, Pasture, Agriculture	2.07	1160	*Bosch et al.* [2005]
Arizona, US (SMEX04)	H[g]	Basin (3750)	40	8/04–8/04	Daily	Surface	Loam, Rock	0.09	0.27	0.45	41	Flat	568	Brush, Rangeland	0.44	350	SMEX04Data set
	I[g]	Watershed (150)	64	8/04–8/04	Daily	Surface	Loam, Rock	0.09	0.27	0.45	45	Flat	335	Brush, Rangeland	0.43	350	*Cosh et al.* [2006]
Iowa, US (SMEX05)	J	Watershed (100)	32	6/05–7/05	Daily	Surface	Loam	0.12	0.31	0.46	33	Low	47	Agriculture	-	835	SMEX05Data set
	K	Watershed (100)	10	6/05–7/05	Daily	Profile	Loam	0.12	0.31	0.46	33	Low	47	Agriculture	-	835	*Choi et al.* [2005]
Florida, US	L	Field (0.01)	40	2/98–3/98	Daily	Surface	Sand	0.05	0.10	0.40	92	Flat	5	Clear-cut	-	1315	*Fischer* [1998]
	M	Field (2.5×10^{-5})	72	2/98–3/98	Daily	Surface	Sand	0.05	0.10	0.40	92	Flat	5	Slash pine forest	-	1315	*Fischer* [1998]
Boone County, Iowa, US	N	Field (2×10^{-3})	30	5/00–9/00	Weekly	Profile	Loam	0.15	0.33	0.47	37	Low	3.1	Agriculture	-	800	*Irmak et al.* [2002]
Louvain-la-Neuve, Belgium	O	Field (6.3×10^{-3})	28	5/99–9/99	Daily	Profile	Silty loam	0.13	0.33	0.49	6	Low	3.5	Agriculture	3.63	780	*Hupet and Vanclooster* [2002]
Duero, Spain	P	Basin (1285)	23	6/99–5/02	Fortnightly	Profile	Sandy loam	0.05	0.15	0.44	71	Flat	200	Agriculture	-	385	*Martinez-Fernandez and Ceballos* [2003]
Oklahoma, US (SGP97)	Q[g]	Watershed (610)	23	6/97–7/97	Daily	Surface	Silt, Loam	0.09	0.22	0.44	58	Rolling	200	Rangeland, Pasture	2.30	750	*Crow and Wood* [1999]
	R	Field 21 (0.64)	49	6/97–7/97	Daily	Surface	Silty loam	0.13	0.33	0.49	35	Flat	-	Wheat, Grass	1.10	750	*Crow and Wood* [1999]

[a] Soil parameters are soil type, wilting point (θ_{wp}), field capacity (θ_{fc}), and porosity (ϕ).
[b]Physical properties used for PCA.)
[c]*Dunne and Leopold* [1978].
[d]*Clapp and Hornberger* [1978].
[e]STATSGO (http://www.ncgc.nrcs.usda.gov/products/data sets/statsgo/).
[f]GTOPO30 (http://edc.usgs.gov/products/elevation/gtopo30/gtopo30.html).
[g]Sites used for PCA analysis.

scale triplet is defined as overall sampling domain [*Bloschl*, 1996].

3. Methods

[6] Statistical moments of soil moisture measurements, mean and coefficient of variation, were calculated by site, soil depth, and time. *Jacobs et al.* [2004] quantified the negative relationship between the surface mean soil moisture content and the coefficient of variation using an exponential fit for four fields from SMEX02. The coefficients of variations were calculated by the ratio of standard deviation of soil moisture to mean soil moisture. Exponential fits $CV = Ae^{B\theta}$ between mean soil moisture and coefficient of variation were conducted using observed standard deviation of soil moisture and temporal average standard deviation of soil moisture by site and soil depth. Comparisons between paired exponential fits using observed standard deviation of soil moisture and temporal average standard deviation of soil moisture at each site allow us to examine how fitting parameters, A and B, are significantly different from fitting parameters, A and B, using constant standard deviations.

[7] A principal component analysis (PCA) was used to identify which physical properties were significant to understand hydrologic variability and how major principal components were related to surface soil moisture fitting parameters, A and B. The PCA is a multivariate statistics technique for data reduction and deciphering patterns within large sets of data [*Farnham et al.*, 2003; *Syed et al.*, 2004]. It describes the variance-covariance structure of a number of variables by a few linear combinations of given variables [*Johnson and Wichern*, 2002]. The maximum quantity of variance is explained by the first principal component (1st PC). Detailed descriptions for the PCA can be found in *Johnson and Wichern* [2002].

[8] For this study, the PCA was applied using standardized variables to ensure the same weight of each different physical parameter. Normalized extent, annual rainfall, soil porosity, wilting point, field capacity, percentage sand, leaf area index (LAI), and maximum difference of elevation for nine sites having sufficient physical parameters were used to conduct the PCA analysis (Table 1).

[9] Correlation coefficients between the first three principal components and the physical properties were calculated to quantify the physical variables' importance for the principal components. Correlation coefficients between the first three principal components and the fitting parameters, A and B, were also conducted to identify how the principal components are related to fitting parameters.

4. Results and Discussion

[10] Figure 1 shows the relationships between the mean soil moisture and the coefficient of variation of soil moisture by data sets and measurement depth. Figure 1 also shows superimposed lines derived from a postulation that soil moisture has constant standard deviations (i.e., standard deviation values range from 1 to 13). The coefficient of variation exponentially decreases as the mean soil moisture increases for all data sources except the Duero surface data. This result is consistent with the previous studies at individual sites [*Famiglietti et al.*, 1999; *Choi and Jacobs*, 2006].

[11] Table 2 lists the exponential fit $CV = Ae^{B\theta}$ including parameters A, B, and the correlation. The exponential fit is recognized as an efficient way to explain soil moisture variability patterns as function of mean soil moisture. The fitting parameters A and B describe the relative variability range and the variability change as related to mean soil moisture contents, respectively. Thus, the parameter A is related to the maximum relative variability, while the parameter B is related to the slope of the relative variability. The fitting parameters, A and B, vary by site and depth. The average values of A, B, and R^2 for all regions were 1.690, −0.061, and 0.656, respectively. All sites showed very strong correlations except Arizona (SMEX04), Boone County, and Duero. The magnitudes of A and B typically increase as the spatial extent decreases. For example, B values for surface measurement range from −0.091 to −0.061 for fields (0.64 km^2) and from −0.037 to −0.001 at watershed (100 km^2) and basins (5000 km^2), respectively in SMEX02. This result complements *Rodriquez-Iturbe et al.*'s [1995] finding that the soil moisture variance decreases, according to a power function, as the aggregation sampling scale increases. Here, we found that extent also follows the power decay function. *Crow and Wood* [1999] found that soil moisture variability differed by extent and scale during the SGP97. This result is consistent with our finding that spatial extent and scale influence relative variability changes because the SGP97 fields (i.e., point scale) have a greater relative decrease in variability than the watersheds (i.e., field scale (~800 m)) (Table 2). Similarly, the PSR observations (Data ID E) had extremely low variability as compared to other data sets (Table 2). This is likely due to the relatively coarse scale and large extent.

[12] The absolute values of A and B also increase as soil depth increases. The surface has the least negative relationship (i.e., A and B parameters closest to zero). These results extend *Choi and Jacobs'* [2006] finding that the surface has a smaller decrease in variability per change in soil moisture than the deeper layers.

[13] Matched pair *t*-tests, commonly used to identify differences in paired observations, were conducted to determine if the exponential models using site specific constant standard deviation values differed from models derived from the observations. The null hypothesis, H_o was that the mean differences between a fitting parameter, A or B, from observational derived exponential model and that determining by fitting the average standard deviation were identical. Separate analyses were performed for each parameter, first using the 16 surface models parameters, then the 30 root zone models parameters (Table 2). At the surface, there was no significant difference for either A, or B (p values are 0.194 and 0.086, respectively). However, for the root zone, there was a significant difference for both the A and B parameters (p values are 0.002 and 0.007, respectively). These results indicate that root zone soil moisture spatial variability is more heterogeneous than surface soil moisture spatial variability and its variability across extents cannot be captured by the average standard deviation of soil moisture. That the p value of B at surface comparison also indicates the average standard deviation

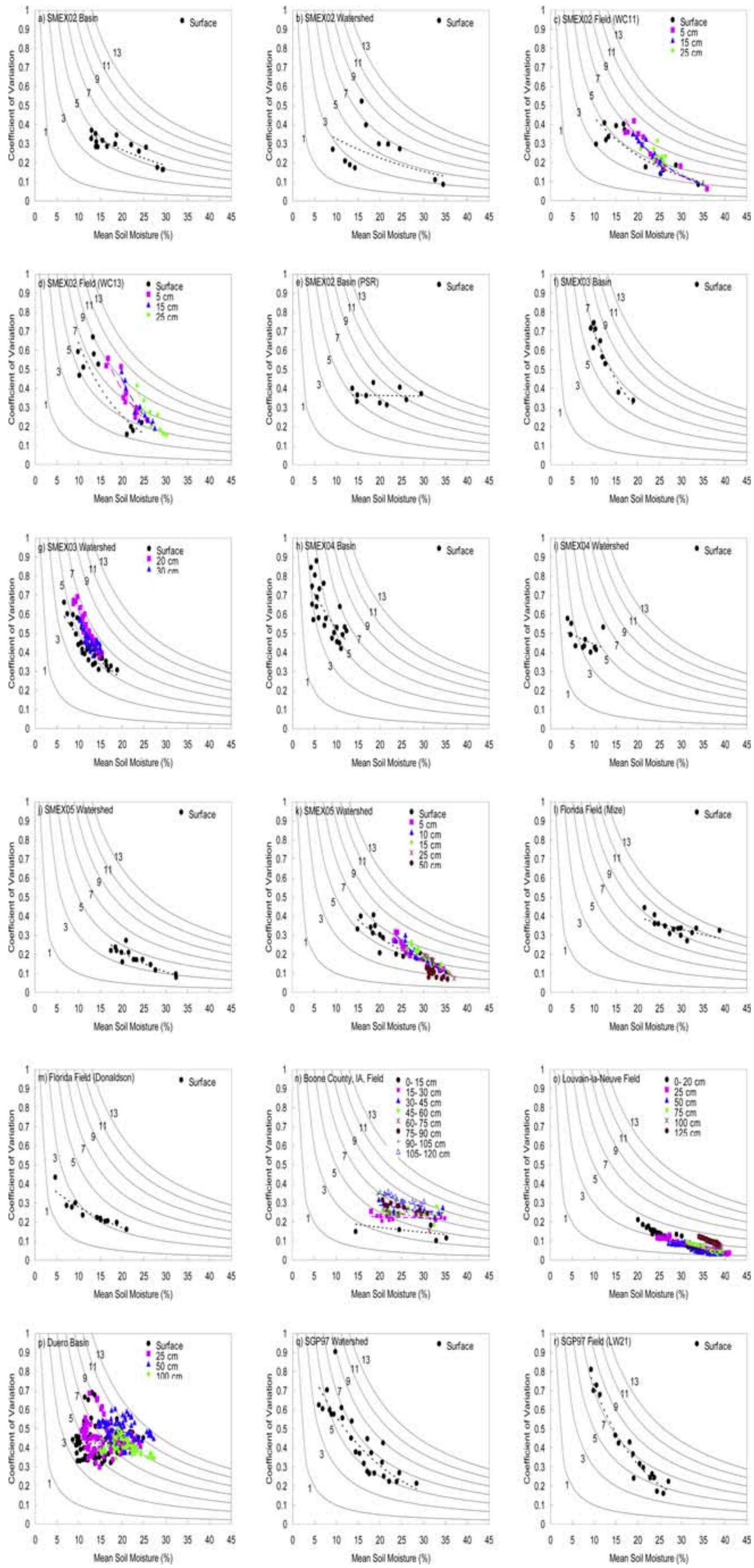

Figure 1. Relationship between mean soil moisture and coefficient of variation (a) SMEX02 Basin ~ (r) SGP97 Field (LW21) (Note: Superimposed lines are derived from constant standard deviation values, 1, 3, 5, 7, 9, 11, and 13).

Table 2. Regression Relationship Between the Coefficient of Variation and the Mean Soil Moisture Where $CV = Ae^{B\theta}$

Sites	Data ID	Extent (km^2)	Depth	A	B	R^2
SMEX02	A	Basin (5000)	surface	0.555	−0.036	0.729
	B	Watershed (100)	surface	0.474	−0.037	0.341
	C	Field WC11 (0.64)	surface	0.800	−0.061	0.801
			5 cm	2.066	−0.092	0.914
			15 cm	1.841	−0.087	0.904
			25 cm	1.918	−0.086	0.815
	D	Field WC13 (0.64)	surface	1.581	−0.091	0.811
			5 cm	2.858	−0.100	0.870
			15 cm	4.019	−0.110	0.881
			25 cm	9.751	−0.138	0.851
	E	Basin (5000)	surface	0.372	−0.001	0.003
SMEX03	F	Basin (3750)	surface	1.637	−0.087	0.924
	G	Watershed (334)	surface	0.885	−0.061	0.807
			20 cm	1.539	−0.091	0.921
			30 cm	0.914	−0.054	0.585
SMEX04	H	Basin (3750)	surface	0.943	−0.058	0.569
	I	Watershed (150)	surface	0.548	−0.021	0.202
SMEX05	J	Watershed (100)	surface	0.795	−0.066	0.845
	K	Watershed (100)	surface	0.873	−0.055	0.795
			5 cm	2.077	−0.085	0.927
			10 cm	2.445	−0.089	0.921
			15 cm	2.863	−0.091	0.914
			25 cm	8.152	−0.124	0.896
			50 cm	3.069	−0.108	0.619
Florida	L	Field Mize (0.01)	surface	0.563	−0.018	0.423
	M	Field Donaldson (2.5×10^{-5})	surface	0.456	−0.049	0.897
Boone County, Iowa	N	Field (2×10^{-3})	0–15 cm	0.240	−0.017	0.172
			15–30 cm	0.242	−0.003	0.090
			30–45 cm	0.359	−0.011	0.378
			45–60 cm	0.271	−0.004	0.028
			60–75 cm	0.381	−0.018	0.304
			75–90 cm	0.473	−0.021	0.868
			90–105 cm	0.563	−0.024	0.820
			105–120 cm	0.619	−0.027	0.703
Louvain-la-Neuve (Belgium)	O	Field (6.3×10^{-3})	0–20 cm	1.436	−0.094	0.956
			25 cm	0.925	−0.079	0.967
			50 cm	1.511	−0.100	0.917
			75 cm	4.618	−0.123	0.937
			100 cm	5.136	−0.109	0.951
			125 cm	2.206	−0.085	0.949
Duero (Spain)	P	Basin (1285)	surface	0.423	0.000	0.000
			25 cm	0.497	−0.007	0.023
			50 cm	0.590	−0.010	0.070
			100 cm	0.557	−0.014	0.180
Oklahoma, US	Q	Watershed (610)	surface	1.035	−0.061	0.789
(SGP97)	R	Field LW21 (0.64)	surface	1.681	−0.084	0.921

may be problematic to represent soil moisture variability at surface and root zone.

[14] Differences of soil moisture variability among sites are quantified as the standard deviation of soil moisture. The PCA was used to characterize these differences related to physical properties including climate, soil, and vegetation and to identify how the fitting parameters are related to physical properties. The first three PCs, collectively, accounted for 93.15% of the total variance (Table 3), capturing most of physical properties' variability. Table 3 also shows that the most important controlling parameters for the first PC are porosity, wilting point, and field capacity, all soil factors. The second PC was equally well correlated with annual rainfall and the maximum difference of elevation. The third PC, highly correlated with extent, explains less of the variability. *Famiglietti et al.* [1995] and *Syed et al.* [2004] found that precipitation and potential evaporation were the major principal component to under-

Table 3. Correlation Coefficients Among the Principal Components, Physical Property, and Fitting Parameters, A and B, Where $CV = Ae^{B\theta}$

		Correlation by Physical Property								Correlation by Fitting Parameter	
Principal Component	Variance Explained	Extent	Porosity	Rainfall	Wilting point	Field Capacity	Sand	LAI	Max Diff Elevation	A	B
1st PC	50.33	−0.613	**0.978**	−0.203	**0.982**	**0.964**	−0.802	0.203	−0.277	**−0.348**	0.178
2nd PC	32.60	−0.265	−0.097	**0.934**	0.088	−0.130	0.326	0.818	**−0.925**	0.235	**−0.389**
3rd PC	10.21	**0.718**	−0.036	0.097	0.089	0.012	−0.424	0.319	0.035	−0.168	0.101

stand the spatial variability of hydrologic cycle in regional scale. Our results are consistent with these previous studies in that precipitation is one of the major principal components. In addition, our results provide another insight that soil related factors may be one of the most significant physical factors to understand hydrological variability.

[15] The correlation between the major PCs and the surface soil moisture model fitting parameters shows that the A fitting parameter was most highly correlated with the first PC (Table 3). This indicates that soil parameters control the maximum coefficient of variation. The B fitting parameter was most strongly correlated with the second PC. The relative change in the soil moisture coefficient of variation with respect to mean moisture is better explained by rainfall and topography. Our results can provide additional insight to *Jacobs et al.* [2004] and *Mohanty and Skaggs* [2001] findings that topography was the most important factor to understand surface soil moisture structure for the SMEX02 and SGP97 experiment. That they found soil related factors to be significant during inter-storm periods is supported by the correlation between soil properties and the A parameter, which controls the relative variance under dry conditions.

[16] While the correlation of fitting parameters with average physical parameters across fields is likely significant, the correlation coefficient values is relatively low. Future studies should consider the within extent variability of spatially-distributed physical parameters to refine the current findings.

5. Conclusion

[17] The relationships between mean soil moisture and coefficient of variation are clearly explained by an exponential fit for a profile of soil moisture measurements. The magnitude of variability is dominated by soil factors. Rainfall and topography characterize how variability changes with mean surface soil moisture. Our statistical variability information is essential to identify appropriate statistical distributions and physical parameters for land surface hydrologic modeling over a range of areal extents (i.e., from sub-grid to whole grid). Further, the information on proper statistical distributions and parameter values can be used to validate land surface models' ability to characterize heterogeneity effects by extent, scale, and soil depth. Specifically, the statistical information about the fitting parameters A and B can be used to refine probability density function (PDF) approaches for SVAT (Soil-Vegetation-Atmosphere Transfer) modeling efforts to represent surface heterogeneity.

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M. Choi and J. M. Jacobs, Department of Civil Engineering, University of New Hampshire, Durham, NH 03824, USA. (mchoi@unh.edu)

M. H. Cosh, Hydrology and Remote Sensing Laboratory, USDA ARS, Beltsville, MD 20705, USA.