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EVALUATION OF PARAMETER TRANSFERABILITY FOR LAND-SURFACE MODELS ACROSS SEMI-ARID ENVIRONMENTS

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1. INTRODUCTION AND SCOPE

Multi-criteria methods have been useful in identifying realistic parameters sets that significantly improve model performance at specific locations. Hydrological synthesis is required to generalize findings obtained at data rich locations to regions that are data sparse or where no studies have been carried out. Under the hypothesis that land surface model parameters have strong relationships with physical characteristics that can be recognized by means of multi-objective optimization techniques, we evaluate the similarity of model sensitivity between locations that are physically similar and between optimal parameter sets. We expect to answer the following questions:

- To what extent land-surface exchanges are adequately represented in different LSM across different dominant biomes in semi-arid environments?
- Under what conditions can model parameters obtained at one site behave and have similar values to those obtained at a physically similar location?
- Can an 'optimal' set of model parameters be obtained to represent regions with similar physical characteristics?

This analysis of parameter behavior allows exploring site-to-site differences for two dominant biomes in the semi-arid environment: shrub and grass. We evaluate the extent to which distinct dominant vegetation types and model parameterizations affect the behavior of 'physically meaningful' LSM parameters. We drive the Noah land-surface model (Ek et al., 2003) offline and perform several multi-criteria sensitivity analysis and parameter estimations using quality-controlled flux tower data from a grass and a shrub sites in Arizona (USDA Walnut Gulch Experimental Watershed) and two similar sites in New Mexico (Sevilleta, LTER). We cross-validate estimated optimal parameter sets and their sensitivity by comparing parameters obtained at one site against those obtained at other sites.

2. BACKGROUND

LSM are simplified conceptual representations of a complex natural system into different soil-vegetation-atmosphere transfer schemes, and each parameterization contains many functional coefficients that usually cannot be measured directly or extensively in time and space and therefore cannot be specified a priori and have to be estimated by constraining the model with observations. The goal of this constraining process is to efficiently extract the information contained in the observational data, rendering a reduction in the modeling uncertainty. The information extraction process should result in identification of a smaller parameter region within the feasible parameter space. Due to the multi-output nature of LSMs, multi-criteria model sensitivity analysis and calibration methods have proven to be especially suitable to effectively provide optimal parameter estimates, which are consistent with actual land-surface characteristics (e.g. Gupta et al., 1999; Bastidas et al., 2001; Demarty et al., 2004; Hogue et al, 2005, 2006; Bastidas et al., 2006a,b). Flux measurements embody an integrated response of the land surface providing with an objective way of examine model soundness at a specific location (Bastidas et al, 2001). Bastidas et al. (2003) recognized the necessity to develop methodologies to transfer the knowledge gained by means of calibration to places were data is not available. Similarly, as a result of the MOPEX, Duan et al. (2005) concluded that "…much research has to be done to understand how model parameters relate to basin characteristic especially considering that modelers are not sure that 'observable' characteristics (mostly land surface) are the most relevant descriptors of the factors that control the hydrologic behavior" and recommend that the scientific community collects data from different climatic regions for much-needed transferability studies.

This study is a pilot for one of the constituents of the PILPS Semi-arid experiment, also known as PILPS San Pedro (Bastidas et al., 2003). This experiment not only allows for assessing the ability of the models to reproduce the complex water and energy exchanges in semi-arid environments, but also provides with the opportunity to test two different vegetation covers (shrub and grass) under the 'same' climatic conditions but hundred of kilometers apart.

3. SITES, MODELS AND DATA

3.1. SAN PEDRO SITES: Lucky Hills and Kendall

The experiment has been carried out at two sites within the Walnut Gulch Experimental Watershed in southeastern Arizona, a sub-basin of the Upper San Pedro River.

The Kendall site (109°56'28'' W, 31°44'10'' N) is in the eastern part of the watershed covered mainly by perennial C_4 grasses. (see Fig.1). The elevation is 1526 masl. Soils consist mainly of very gravelly sandy loams

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which contain limestone rock fragments. Canopy height is estimated 0.4 -0.7 m. Slopes are 4-9%. Average temperature is 19.3 °C. Average precipitation 340 mm/year.

The Lucky Hills site (110°03'05'' W, 31°44'37'' N) is located in the lower (1372 masl) shrub dominated part of the basin. (s.Fig.2). The vegetation consists mainly of the C_3 species. Soils are mostly loamy sand or very gravelly sandy loams. Canopy height is estimated at 1 m. Slopes are 3-8%. Average temperature is 18.6 °C.

Figure.1 Kendall grassland site.

Figure.2 Lucky Hills shrub site.

3.2. SEVILLETA SITES: Lucky Hills and Kendall

Data collected in the McKenzie Flats area of the Sevilleta National Wildlife Refuge, central New Mexico from two sites separated by 2 km are also used in this study.

The Sevilleta grassland site (106°43'30'' W, 34°20'30'' N) is dominated by black grama. (s. Fig.3). The elevation is 1730 masl. Slopes are less than 2%. Average temperature is 17.2 °C.

The Sevilleta shrub site (106°44'39'' W, 34°20'05'' N) is covered by creosotebush. (s. Fig.4). The elevation is 1776 masl. Slopes are smaller than 2%. Average temperature is 16.9 °C. Average annual precipitation is 270 mm.

Figure.3 Sevilleta grassland site.

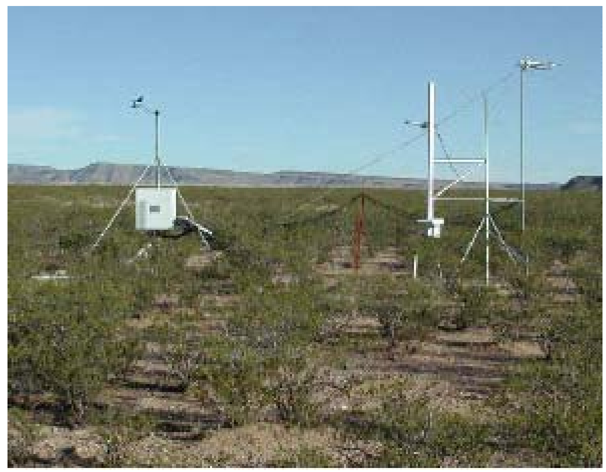

Figure.4 Sevilleta shrubland site

3.3. *Data*

Precipitation and weather data (net radiation, ground heat flux, wind speed, wind direction, air temperature, and relative humidity) has been collected continuously by the USDA-ARS Tucson for the San Pedro Sites in 20-minute intervals using a Bowen ratio system with a tower height of 3 m (Emmerich et al., 2003). It includes measurements of sensible and latent heat fluxes, and soil temperature. We use data from May to December 2000. The data at the Sevilleta sites was collected by Eric Small of the University of Colorado using tower with a 3m height at 30-minute intervals. Measurements include sensible and latent heat fluxes, and soil temperature at 2.5 cm. We use data from May to December 2001.

3.4. Noah 2.5 Land-surface Model

Near-surface atmospheric forcing data (e.g., precipitation, radiation, wind speed, temperature, humidity) is required as input for Noah in order to simulate soil moisture (both liquid and frozen), soil temperature, skin temperature, snowpack depth, snowpack water equivalent, canopy water content, and the energy flux and water flux terms of the surface energy balance and surface water balance. The model applies finite-difference spatial discretization methods and a Crank-Nicholson time integration scheme to numerically integrate the governing equations of the physical processes of the soil vegetation-snowpack medium, including the surface energy balance equation, Richards' (1931) equation for soil hydraulics, the diffusion equation for soil heat transfer, the energy-mass balance equation for the snowpack, and the Jarvis (1976) equation for the conductance of canopy transpiration.

4. METHODS

The Multi-Objective Generalized Sensitivity Analysis Procedure serves to identify sensitive parameters that merit calibration. The MOGSA (Bastidas et al., 1999) algorithm is a multi-objective extension of the Generalized Sensitivity Analysis of Hornberger and Spear. It involves a Monte Carlo search of the feasible space and the notion of Pareto ranking for separating into behavioral and non-behavioral model outputs (as opposed to a single time series error function). The two sets, behavioral and non-behavioral, are then tested to check if the they are drawn from the same joint multivariate distribution using the Kolmogorov-Smirnov (K-S) statistic. If the two samples are statistically different, the parameters are considered to be sensitive, otherwise they are considered to be insensitive. Statistical robustness is ensured by means of bootstrapping (sampling with replacement) and the use of the median of the K-S. Further, the sample size is increased until the number of sensitive parameter stabilizes. Although this algorithm was originally developed to determine the model sensitivity to input parameters, it is also a useful tool for retrieving quantitative information about influential parameters. In this study, the MOGSA algorithm is also used to identify "reasonable ranges" for parameter estimation.

The Multi-Objective Shuffled Complex Evolution Metropolis MOSCEM (Vrugt et al., 2003) is an automated method that uses a multi-objective optimization approach based on a Markov Chain/Monte Carlo Sampling strategy to evolve an initial population, randomly selected within a pre-established feasible range, towards a sample which approximates the optimal Pareto region. The goal is to identify a reasonable small parameter range, the most likely parameter set and its underlying posterior distribution, which guarantees "optimal" model performance in terms of reproducing observations.

The algorithm evaluates a multi-objective vector in order to rank and sort each of the members of the initial population, using a fitness assignment after Zitzler and Thiele (1999). The population is partitioned into groups or complexes, within which parallel evolution sequences are launched to find new candidate points that depend on the sequence structure and the complex. In order to replace the worst point, acceptance or rejection of candidates is defined by the Metropolis-Hastings algorithm. After a number of iterations, the complexes are combined and through a process of shuffling new complexes are formed. Until the Gelman-Rubin (1992) convergence criteria is reached the process continues.

5. ANALYSIS RESULTS AND DISCUSSION

5.1. Sensitivity Analysis

Using 20.000 Monte Carlo simulations at each site, MOGSA is used to identify the level of sensitivity of the 26 model parameters and 8 initial states to sensible heat, latent heat, ground temperature and the global Pareto when considering simultaneously the 3 criteria. The error function of choice is root mean squared error (RMSE).The global sensitivity index for the vegetation and soil parameters is presented in Fig.5. for each of the sites: San Pedro grass in blue, San Pedro shrub in cyan, Sevilleta Grass red and Sevilleta Shrub in magenta. The farther away from the center, the more sensitive the parameter. The dotted and dashed circles represent the 0.05 and 0.01 significance levels, respectively, corresponding to the thresholds for moderate and high sensitivity.

It is observed that some parameter sensitivities behave similarly by site and others do so by vegetation type. Parameters that fall in the same level according to site are: quartz, topt and z0. Parameters that fall in the same level according to type of vegetation cover are: cfactr and psisat. Parameters that are sensitive in all sites are: sbet, rcmin, lai, fxexp, czil, and maxsmc. Insensitive parameters in all sites are: satdw, satdk, drysmc, rsmax, and hs. Parameters b and csoil present similar sensitivity for different vegetation types at distant locations.

As a result of the sensitivity analysis, 20 parameters are chosen for estimation; thus reducing the dimensionality of the optimization problem.

In order to evaluate whether the sensitivities found at a particular location are more similar to its corresponding vegetation site in the other location or to the closest one despite not sharing the same cover, we use the Hausdorff norm as similarity index. (Bastidas and Li, 2006) In Fig.6 the result of comparing the sensitivity of vegetation parameters when using global, H or LE against the one obtained at other locations is shown. On Fig. 7 the comparison of the sensitivity of soil parameters is presented. The smaller the Hausdorff value, the more similar the sensitivities.

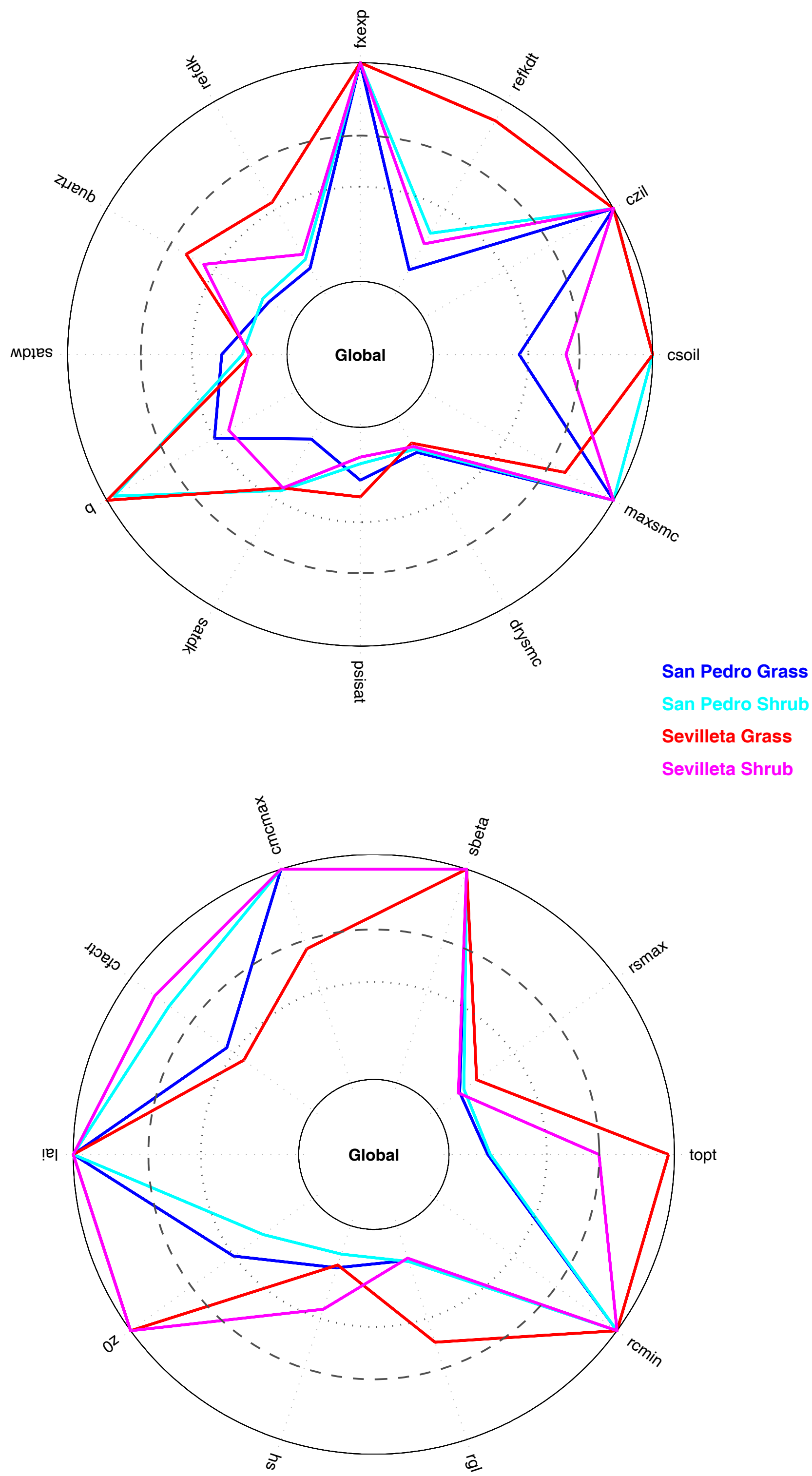

Figure 5. Parameter sensitivity using the multicriteria 'global' index (combined sensitivity to sensible heat, latent heat and ground temperature) for each of the sites. a) Soil Parameters b) Vegetation Parameters. The farther away from the center, the more sensitive the parameter. The dotted and dashed circles represent the 0.05 and 0.01 significance levels, respectively, corresponding to the thresholds for moderate and high sensitivity.

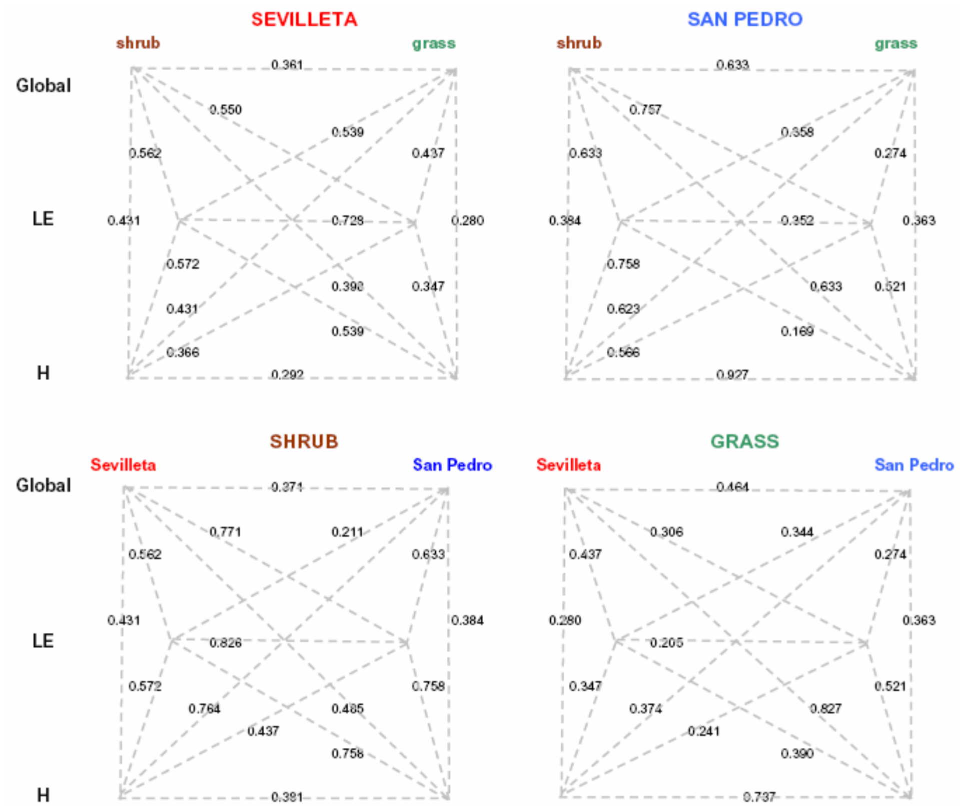

Figure 6. Intercomparison of sensitivity of vegetation parameters to multicriteria 'global' index, to latent heat and to sensible heat flux among fluxes and sites. The comparison uses the Hausdorff norm as a similarity index.

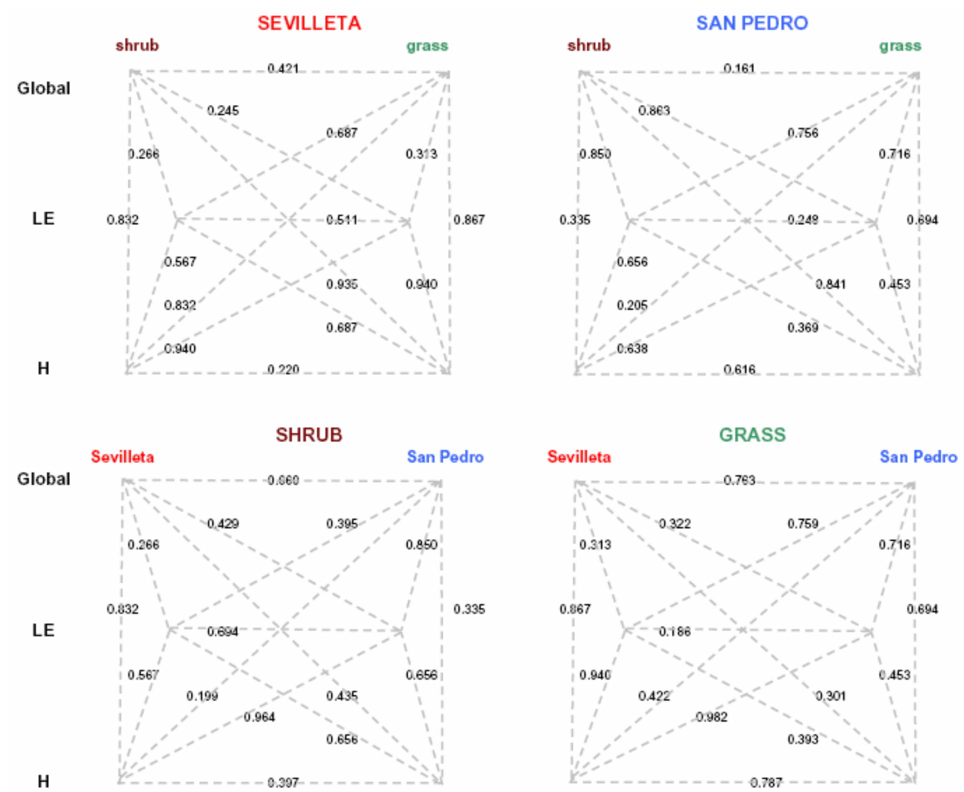

Figure 7. Intercomparison of sensitivity of soil parameters to multicriteria 'global' index, to latent heat and to sensible heat flux among fluxes and sites. The comparison uses the Hausdorff norm as a similarity index.

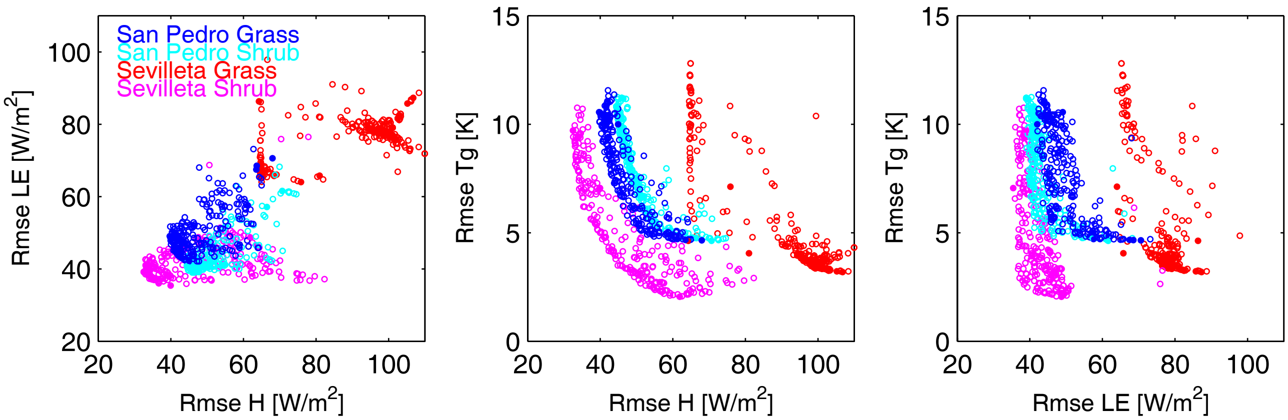

Figure 8. Model performance in error function space. Each of the dots corresponds to a single parameter set.

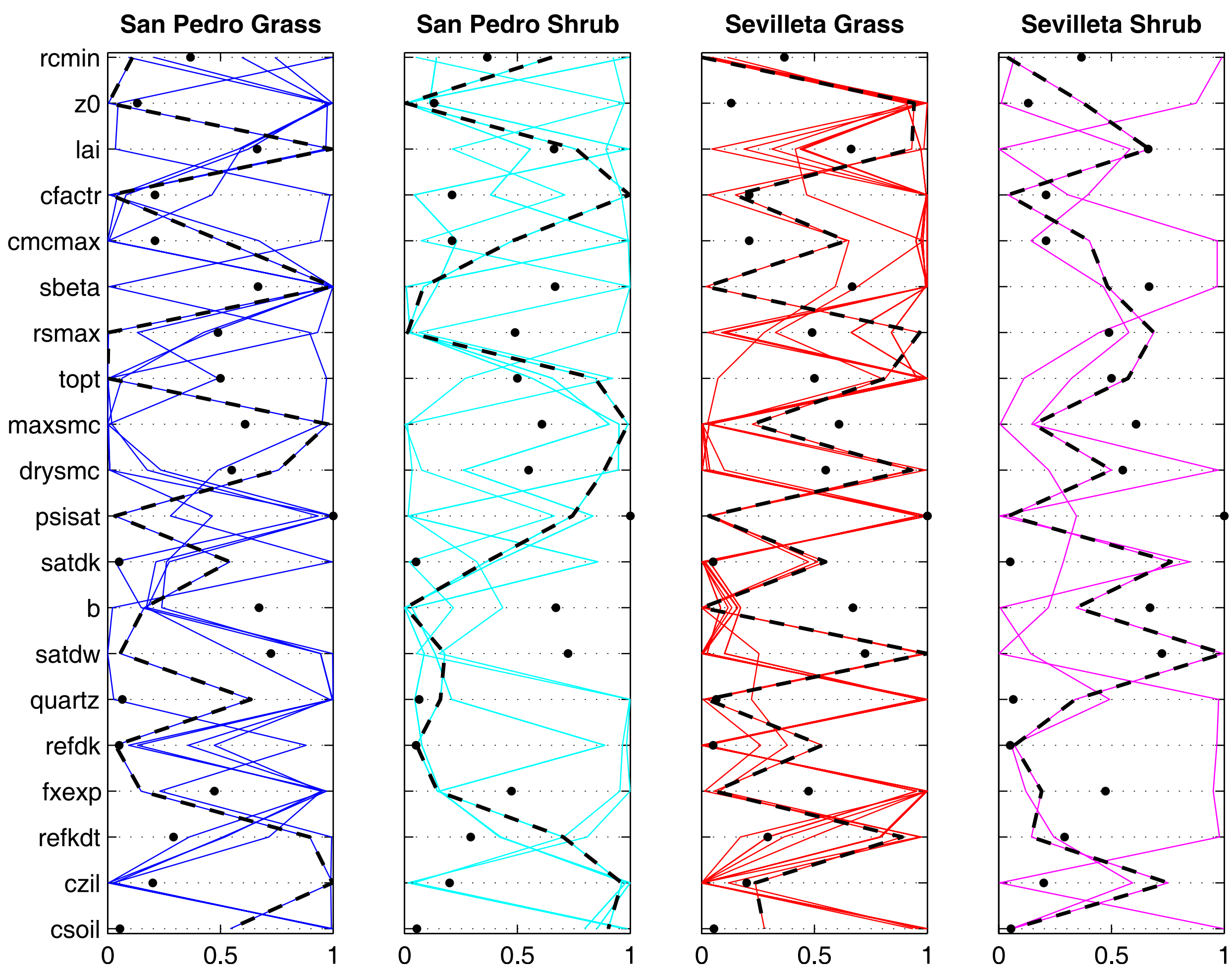

Figure 9. Normalized parameter space for each site. Each of the lines corresponds to a set of preferred solutions from the Pareto front. The black dashed lines represent a single 'preferred' set, chosen by using a L2 norm. Black dots represent the default parameter set.

No.	Parameter name	Preferred optimal values				Default	Range		Optim flag	Description
		Sev. Shrub	Sev. Grass	SP. shrub	SP. grass		Lower	Upper		
1	rcmin	19.981	5.142	263.16	48.616	150	5	1000	OPT	minimum stomatal resistance
2	rgl					100	30	150	FIX	used in solar rad term of canopy resist. fnctn.
3	hs					36.35	30	54.53	FIX	used in vapor pressure deficit term of canopy res. func.
4	z0	0.081	0.189	0.011	0.011	0.035	0.01	0.2	OPT	roughness length
5	lai	3.023	4.195	3.435	4.466	3	0.05	4.5	OPT	leaf area index
6	cfactr	0.177	0.385	1.993	0.125	0.5	0.1	2	OPT	canopy water parameter
7	cmcmax	0.864	1.319	1.010	1.059	0.5	0.1	2	OPT	*E-3 second canopy water parameter [m]
8	sbeta	-2.55	-3.94	-3.75	-1.0	-2	-4	-1	OPT	to calculate vegetation effect on soil heat flux
9	rsmax	6945.5	9682.2	338.5	244.0	5000	200	10000	OPT	max stomatal resistance
10	topt	298.7	301.1	301.4	293.0	298	293	303	OPT	optimum transpiration air temperature
11	maxsmc	0.364	0.379	0.548	0.545	0.464	0.33	0.55	OPT	max soil moisture content (porosity)
12	drysmc	0.11	0.187	0.179	0.156	0.119	0.02	0.2	OPT	air dry soil moist content limits
13	psisat	0.066	0.058	0.472	0.058	0.62	0.04	0.62	OPT	saturated soil potential
14	satdk	2.306	1.673	1.119	1.650	0.2	0.05	3	OPT	*E-5 saturated soil hydraulic conductivity
15	b	6.008	3.501	3.546	4.687	8.4	3.5	10.8	OPT	the 'b' parameter
16	satdw	2.987	2.999	1.004	0.707	2.33	0.571	3	OPT	*E-5 saturated soil diffusivity
17	quartz	0.312	0.068	0.172	0.539	0.1	0.05	0.82	OPT	soil quartz content
18	nroot					4	2	4	FIX	number of root layers < nsoil < nsold
19	refdk	0.255	1.626	0.210	0.152	0.2	0.05	3	OPT	*E-5 Reference value for sat.hyd.cond.
20	fxexp	0.924	0.417	0.754	0.763	2	0.2	4	OPT	bare soil evaporation exponent used in DEVAP
21	refkdt	1.541	8.901	7.065	8.973	3	0.1	10	OPT	Reference value for surface infiltration parameter
22	czil	0.613	0.228	0.772	0.798	0.2	0.05	0.8	OPT	to calculate roughness length of heat
23	csoil	1.271	1.790	3.27	2.419	1.26	1.13	3.5	OPT	*E+6 soil heat capacity for mineral soil component
24	zbot					8	3	20	FIX	depth of lower boundary soil temp. [m]
25	frzk					0.15	0.1	0.25	FIX	ice content threshold above which frozen soil is impemeable
26	snup					0.04	0.025	0.08	FIX	threshold snowdepth - implies 100% snow cover [m]
27	snoalb					0.75	0.3	0.75	FIX	max albedo over deep snow
28	salp					2.6	2.6	2.6	FIX	shape of dist function of snow cover
29	slope					0.1	0.1	1	FIX	slope
30	t1					299	265	265	FIX	initial skin temperature
31	cmc					5.00E-04	0	0.001	FIX	initial canopy water content [m]
32	snowh					0	0	0.1	FIX	initial actual snow depth [m]
33	sneqv					0	0	0.1	FIX	initial water equivalent snow depth [m]
34	sldpt1	0.05	0.05	0.05	0.05	0.1	0.1	0.1	FIX	soil depth
35	sldpt2					0.2	0.2	0.2	FIX	soil depth
36	sldpt3					0.6	0.6	0.6	FIX	soil depth
37	sldpt4					1.1	1.1	1.1	FIX	soil depth
38	stc1	294	294	294	294	297	260	290	FIX	initial soil temp [K]
39	stc2	292.7	292.7	292.7	292.7	293.7	260	290	FIX	initial soil temp [K]
40	stc3	291	291	291	291	291.5	260	290	FIX	initial soil temp [K]
41	stc4	290	290	290	290	290.4	260	290	FIX	initial soil temp [K]
42	smc1					0.05	0.025	0.56	OPT	initial soil total moisture
43	smc2					0.05	0.025	0.56	OPT	initial soil total moisture
44	smc3					0.05	0.025	0.56	OPT	initial soil total moisture
45	smc4					0.05	0.025	0.56	OPT	initial soil total moisture
46	sh2o1					0.05	0.025	0.56	OPT	initial soil liquid moisture
47	sh2o2					0.05	0.025	0.56	OPT	initial soil liquid moisture
48	sh2o3					0.05	0.025	0.56	OPT	initial soil liquid moisture
49	sh2o4					0.05	0.025	0.56	OPT	initial soil liquid moisture

Table 1. Noah parameters, ranges, default and preferred optimal values for Sevilleta and San Pedro sites.

5.2. Parameter Estimation

The range of feasible model parameters (adjusted in the previous step) is sampled and residuals between simulations and observations of sensible heat, latent heat and ground temperature are evaluated using RMSE as the objective function. The optimization algorithm is designed to find parameter sets that simultaneously minimize all objective functions and therefore reduce the output residual. By doing so, and due to measurement errors and deficiencies in the model physics (model errors), the methodology finds several compromise, non-dominated solutions when converges to a fair representation of the Pareto set, (Gupta et al., 1999; Vrugt et al., 2003) (see Fig.8) in which, each parameter set is no superior than other in a multi-objective sense despite of being better in a particular objective. In Fig. 8, site to site comparison in the bi-dimensional projection of the multidimensional objective space is presented. Each of the dots represents a parameter set. It is evident that the quality of the data from the Sevilleta Grassland site is inferior to the other sites, and therefore it is not considered in this analysis. The performance of the San Pedro sites is similar, obtaining the same residual. The Sevilleta Shrub site has the better performance.

To differentiate among parameter sets we follow Das, 1999, and rank the sets in a subdimensional space. The points that are simultaneously in the Pareto frontier in at least two of the projections are selected. Those sets are shown in Fig.9, using the normalized parameter range. The default parameter set for semi-arid environments is also represented using black dots. The dashed line corresponds to a parameter set whose objective function value minimizes a L2 norm, called 'preferred' set for each location. The values of the preferred optimal sets for each site, the optimization ranges used, the default values and the description of the parameters are presented in Tab. 1.

A comparison of the similarity between 'preferred' optimal sets across the locations using the Hausdorff norm is presented in Tab. 2. We observe that the preferred sets are more similar between the San Pedro sites than between the shrub sites. The sets are less similar when comparing Sevilleta shrub against Kendall.

	Sev. Grass	SP. shrub	SP. grass
Sev. Shrub	1.537	1.994	2.347
Sev. Grass	0.0	2.450	2.505
SP. Shrub	2.450	0.0	1.964

Table 2. Hausdorff norm values for comparison between 'preferred' optimal parameter sets across sites.

In order to establish whether the parameter sets found in the estimation procedure relate in any way among sites and/or vegetation covers, we compute cumulative densities and use the K-S test to determine if they come from the same underlying distribution. The distributions for several parameters for each site, including the preferred and default values are presented in Fig. 10. The result of that comparison is presented in Tab. 3. At significance level 0.05, the null hypothesis of both empirical distributions being equal or drawn from the same underlying distribution against the alternative of being unequal is rejected for 1 and not to be rejected for 0 (shaded).

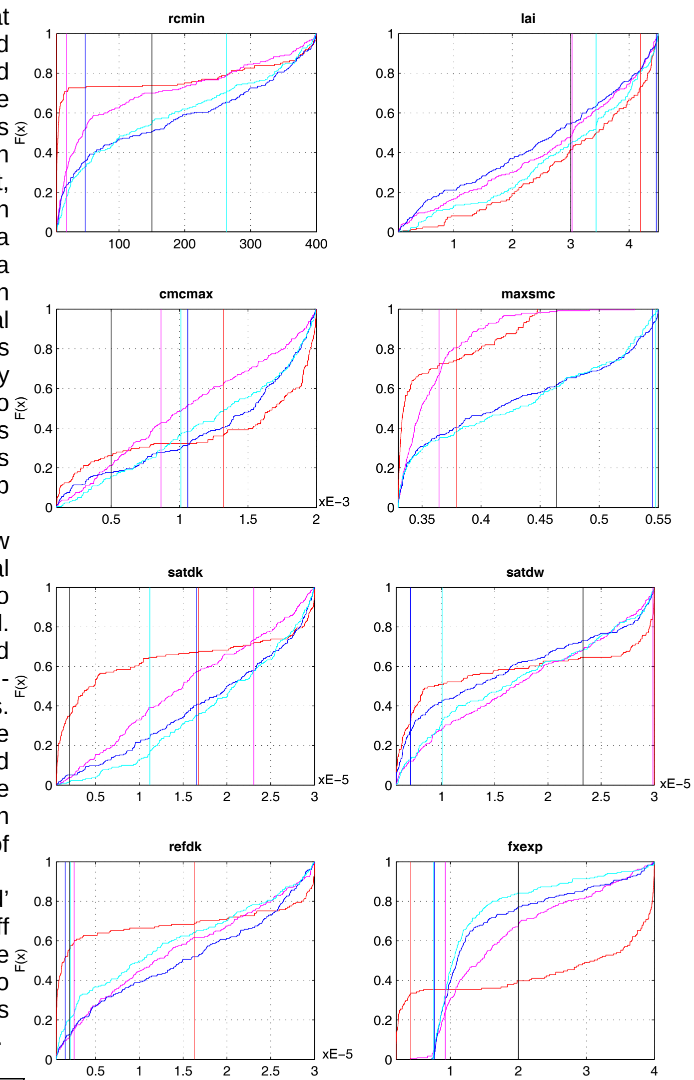

Figure 10. Cumulative distributions of parameter values for each site. The preferred values are shown as vertical lines for each site: Sevilleta Grass (red), Sevilleta Shrub (magenta), San Pedro grass (blue) and San Pedro shrub (cyan). Default value in black.

From the 3 vegetation parameters shown above, rcmin and cmcmax are found to come from the same distribution for the San Pedro sites. The LAI of Sevilleta shrub shares the same distribution with both San Pedro sites, however those two do not fall within the same distribution. For the case of the soil parameters, maxsmc, satdk and fxexp in the San Pedro sites have the same distribution. The shrub sites share the same distribution for satdw. For refdk no association has been found.

	rcmin			**lai**		
	SevS	SPg	SPs	SevS	SPg	SPs
SevG	1	1	1	0	1	0
SevS		1	1		0	0
SPg			0			1
	cmcmax			**maxsmc**		
	SevS	SPg	SPs	SevS	SPg	SPs
SevG	1	1	1	1	1	1
SevS		1	1		1	1
SPg			0			0
	satdk			**satdw**		
	SevS	SPg	SPs	SevS	SPg	SPs
SevG	1	1	1	1	1	1
SevS		1	1		1	0
SPg			0			1
	refdk			**fxexp**		
	SevS	SPg	SPs	SevS	SPg	SPs
SevG	1	1	1	1	1	1
SevS		1	1		1	1
SPg			1			0

Table 3. K-S test results. At significance level 0.05, the null hypothesis of both coming from the same distribution is rejected for 1 and not to be rejected for 0.

6. SUMMARY AND CONCLUSIONS

The work carried out here shows that semi-arid environments cannot be lumped into a single functional type classification, as is customary in the land surface community. It constitutes a preliminary step towards identifying parameter sets that can be safely transferred between locations with similar physical characteristics, thus providing parameter estimates that can be considered truly regional based on a consistent behavior across semi-arid biomes.

Further cross validation studies are needed to establish which parameters can be transferable. We found that some parameters share similar characteristics by site while others do so by vegetation cover, being not always the vegetation parameters. It can be said that for some parameters geographical proximity is more important than functional type.

7. ACKNOWLEDGEMENTS

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