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Estimating soil moisture at various depths from near surface ESA CCI Soil Moisture

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Soil moisture drought is a natural, reoccurring phenomenon that can affect any part of the land. It consists one of the most challenging problems for the modern agriculture as it directly affects the water, energy and food security nexus[1]*. Remote sensed soil moisture products have been proved to be valuable tools for the study of the soil moisture droughts. The European Space Agency (ESA), through the Climate Change Initiative (CCI) is currently providing nearly 4 decades of global satellite observed, fully homogenized soil moisture (SM) data for the uppermost soil layer. This data is valuable as it consists one of the most complete in time and space observed soil moisture dataset available.*

1 Grillakis, M. G. (2019). Increase in severe and extreme soil moisture droughts for Europe under climate change. Science of The Total Environment, 660, 1245-1255

Such observations are valuable for the systematic evaluation of global hydrological and land surface models that require a large number of forcing variables, in addition to precipitation and temperature, such as radiation, humidity, air pressure, and wind speed, while are usually systematically evaluated on a single or very limited data (e.g. discharge)[2].

One of the main limitations that ESA CCI SM exhibits is the limited depth at which the soil moisture is estimated (limited to approximately 5cm of soil), while the global GHMs, LSMs provide simulations for a variety of different depths, mainly between 1m to 3m.

In this work we use the ESA CCI SM data to estimate the Soil Water Index (SWI) at the global scale, which can serve as a soil moisture approximation for different depths.

2 Papadimitriou, L. V., Koutroulis, A. G., Grillakis, M. G., & Tsanis, I. K. (2017). The effect of GCM biases on global runoff simulations of a land surface model. Hydrology & Earth System Sciences, 21(9).

SWI is estimated by the equation below, using as a surface soil moisture estimation, the ESA CCI SM data.

$$SWI(t) = \frac{\sum_i m_s(t_i) e^{\frac{t-t_i}{T}}}{\sum_i e^{\frac{t-t_i}{T}}} \; for\ t_i \leq t$$

where SSM is the surface soil moisture – provided by CCI SM at time t_i.

Here, we calibrated the T parameter against soil moisture measurements of International Soil Moisture Network (ISMN) (~ 6200 calibration points). which provides a large database of homogenized soil moisture measurements.

The R^2 between SWI and soil moisture was used as the calibration objective function of T parameter.

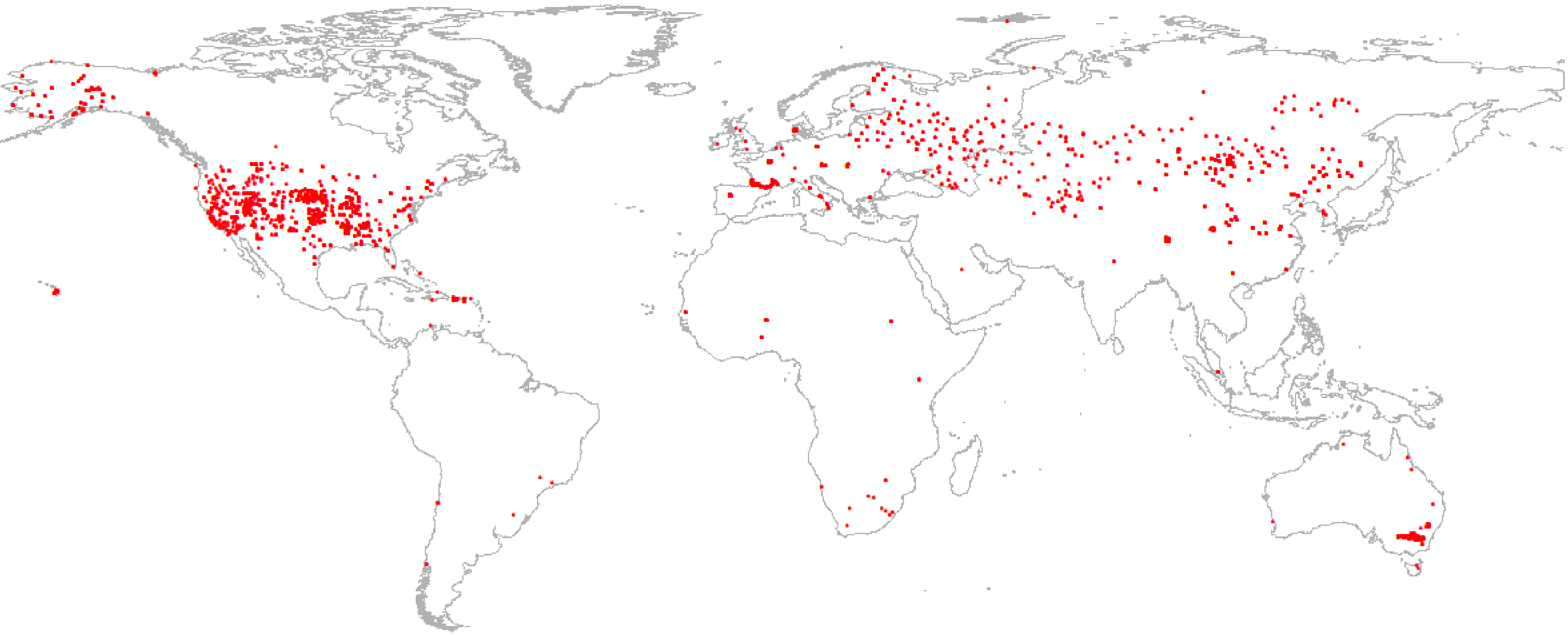

Figure: Distribution of the ~6200 ISMN points where the T parameter was calibrated

Then we extracted the properties of the Soil Grids 250m dataset for each one of the ISMN calibration locations. The different soil properties were tested for their ability to predict the previously best attained T value for each ISMN point.

Several soil properties parameters were tested:

1	AWCh1	Available soil water capacity (volumetric fraction) for h1 (pF 2.0)
2	AWCh2	Available soil water capacity (volumetric fraction) for h2 (pF 2.3)
3	AWCh3	Available soil water capacity (volumetric fraction) for h3 (pF 2.5)
4	AWCtS	Saturated water content (volumetric fraction) for tS
5	BLDFIE	Bulk density (fine earth) in kg / cubic-meter
6	CLYPPT	Clay content (0-2 micro meter) mass fraction in %
7	CRFVOL	Coarse fragments volumetric in %
8	ORCDRC	Soil organic carbon content (fine earth fraction) in g per kg
9	SLTPPT	Silt content (2-50 micro meter) mass fraction in %
10	SNDPPT	Sand content (50-2000 micro meter) mass fraction in %
11	WWP	Available soil water capacity (volumetric fraction) until wilting point

The 11 parameters were individually checked for statistical correlation to the calibrated T values. Eight of them were found to significantly correlate in terms of p-Value, and with slope 95% confidence that does not cross zero.

		Regression slope	Regression slope Lower 95	Regression slope Upper 95	SE	tStat	pValue
1	AWCh1	-3.85	-4.62	-3.08	0.39	-9.80	0.00
2	AWCh2	-4.29	-5.24	-3.35	0.48	-8.92	0.00
3	AWCh3	-4.98	-6.07	-3.88	0.56	-8.92	0.00
4	AWCtS	-1.50	-1.88	-1.12	0.19	-7.76	0.00
5	BLDFIE	0.05	0.04	0.06	0.01	9.17	0.00
6	CLYPPT	1.16	0.87	1.46	0.15	7.66	0.00
7	CRFVOL	-0.05	-0.34	0.24	0.15	-0.33	0.74
8	ORCDRC	-0.12	-0.16	-0.07	0.02	-5.10	0.00
9	SLTPPT	-0.02	-0.20	0.15	0.09	-0.28	0.78
10	SNDPPT	-0.24	-0.38	-0.10	0.07	-3.36	0.00
11	WWP	0.06	-0.40	0.52	0.24	0.26	0.80

The 8 strongly correlating parameters were then put into a generalized linear model to estimate the relative contribution to the optimal T parameter.

	Parameter	Regression slope	Regression slope Lower 95	Regression slope Upper 95	SE	tStat	pValue
1	AWCh1	-8.72	-13.34	-4.09	2.36	-3.7	0.00
2	AWCh2	7.70	1.22	14.19	3.31	2.3	0.02
3	AWCh3	-0.31	-6.16	5.55	2.99	-0.1	0.92
4	AWCtS	25.4	20.8	30.0	2.36	10.8	0.00
5	BLDFIE	0.85	0.71	0.99	0.07	12.0	0.00
6	CLYPPT	-2.69	-3.46	-1.92	0.39	-6.9	0.00
8	ORCDRC	0.14	0.02	0.25	0.06	2.4	0.02
10	SNDPPT	0.12	-0.07	0.31	0.10	1.2	0.22

Two of the parameters (Sand content and Available soil water capacity for h3) within the generalized linear model shown pValue>0.05 and were excluded the linear model.

The next step is to correlate the strong correlating SoilGrids parameters to estimate (extrapolate) the T value in global scale.

95% Confidence bounds of the T can also be created to envelop the estimation uncertainty.

The procedure is repeated for various ranges of soil depths.

The calibrated T values can be used to estimate the SWI for each CCI grid cell and for various depths.

The resulted dataset will be used for the evaluation of global hydrological models on their ability to simulate the soil moisture.

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