How to integrate ground-truth and satellite image to estimate surface soil moisture at the field and watershed scales?

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Abstract. Soil moisture is a key environmental variable for developing a coupled hydrological and biogeochemical modeling approach. It is recognized that a relationship does exist between water stress and emission of volatile organic compounds (VOCs) in forested areas, which may have negative effect on human health and ecosystems. Therefore it is necessary to achieve a better understanding of the land phase of the hydrological cycle, namely soil moisture estimation, which modulates surface energy balance and consequently vegetation cover patterns. This work focuses on a new methodological approach to evaluate the spatial variability of surface soil moisture at the field scale using the Bayesian kriging model jointly with TDR measurements and Landsat 8-TM remotely sensed image. The analysis looked for quantifying different deterministic sources of variability, measurement errors and also components not well understood of variability. In particular, the spatial distribution of *in situ* measurements and digital image data in a scene provided by remote sensing technology is addressed through a geostatistical framework. This technique is explored as alternative to the regression techniques currently used for modeling soil moisture mapping. Tests conducted on an extensively sampled pasture field showed significant improvement, which suggests that the methodological approach could be applied at the watershed scale for validating remotely sensed datasets.

1 Introduction

Climate models provide support to weather and climate forecasting and projections of likely climate change scenarios. These models consider numerically the behavior of components of the terrestrial climate system, such as the atmosphere, oceans, cryosphere (ice and snow areas), vegetation, biogeochemical cycles and their interactions. In addition, these models allow the simulation of probable conjunctures of climate transformation, taking into account several emission levels of Greenhouse Gases (GHG), including changes in land use and land cover. In recent years, great effort has been made to pursue the better

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understanding of the land phase of the hydrological cycle associated to biogeochemical changes through experimental work and mathematical modelling [1]. However, many issues still remain open to discussion, such as improvement of input data sources, calibration, validation, parametrization and upscaling. Complementarily, we should emphasize that studies devoted to understanding the estimated soil moisture in the root zone based on the partitioning of the energy balance in conjunction with hydrological models and remotely sensed images are being developed under different frameworks [2-4], but they are still limited. Thus, given the importance of soil moisture applications both in surface and groundwater hydrology and in modeling of weather and climate, water and geochemical cycling, there is an evident need for studies to enable a better understanding of this variable on a field scale and regional scale.

By contrast, it is also acknowledged that an important issue still remains to be addressed: how should hydrological and hydraulic variability be related to the spatial distribution of brightness values in the images provided by remote sensing technology. In particular, this work focuses on procedures to estimate soil moisture at a field scale envisaging the soil moisture mapping at the watershed scale. The spatial distribution of digital image data in a scene provided by remote sensing technology is addressed through a geostatistical analysis procedure.

2 Methodology

Initially, the analysis investigated the possible relationship between the underlying physical phenomenon of soil moisture distribution and how it relates to or translates into the image Secondly, the spatial variability in the ground-truth data set and in the image were evaluated, with special emphasis on the geostatistical approach through the construction of semivariograms and covariograms. The last part examined the feasibility of using a geostatistical model, which allows the combination of hard data (ground-truth TDR 15cm deph soil moisture data) and soft data (image) for the estimation of the surface soil moisture distribution. More specifically, we developed a methodology to join both datasets to produce a more accurate soil moisture spatial distribution at the field scale.

One Landsat8-TM image was acquired jointly with a one-day field campaign of 6-hours (June 18, 2014) for collecting surface soil moisture data from a reasonably flat vegetated field at the Piabanha river watershed in the mountainous area of Rio de Janeiro, Brazil. There were 98 soil moisture collected data points available for 112 grid points with respect to the field campaign performed (Fig.1). The overpass of satellite was approximately simultaneous when compared to the field campaign conducted along the same day.

Fig. 1. Vegetated field extensively sampled (550 m by 250 m) for TDR surface soil moisture distribution. The sampling scheme has 112 nodes for which 98 TDR samples were collected (yellow dots) plus 14 non-available data points (red dots).

First, the Landsat image (band 10) was used for determining the land surface temperature (LST – 120 m resolution) and also the spectral combinations to determine the normalized difference vegetation index (NDVI – 30 m resolution) for the whole Piabanha river watershed which covers an area of approximately 2060 km^2. Both data sets were combined to produce a soil moisture indicator (IUS - % v/v) in a similar procedure as presented by [5]. A scale of 30 m was used for the spatial structure modeling the IUS at the watershed scale. We then used the satellite derived IUS index as the initial guess and also for extracting the field variance which was used for estimating initial uncertainty. A geostatistical reference system was then adopted for evaluating the spatial correlation structures in the dataset through the construction of semivariograms and covariograms. After this stage, the Bayesian kriging method [6] was used to estimate the spatial soil moisture field and its corresponding uncertainty, taking the ground-truth TDR soil moisture data as baseline and then comparing this reference to different alternative scenarios, including those generated by simply using satellite image (IUS) and different levels of combination of hard-data (TDR soil moisture data) and soft data (satellite image).

3 Results

Under the established framework, we provide a comparison between the results obtained using the ground-truth, the IUS index derived by Landsat satellite image and the proposed geostatistical methodology. We initially develop the semivariograms for depicting the correlation structure of the ground-truth volumetric soil moisture and the IUS index. Figure 2 illustrates the normalized omnidirectional semivariograms for both datasets based on the corresponding variances. The modeling approach considered the isotropy for the characterization of both datasets. Such modeling was performed through omnidirectional semivariograms adjusted by the theoretical spherical, Gaussian and exponential models (Fig. 3). Spherical model was adopted to produce the results in this work.

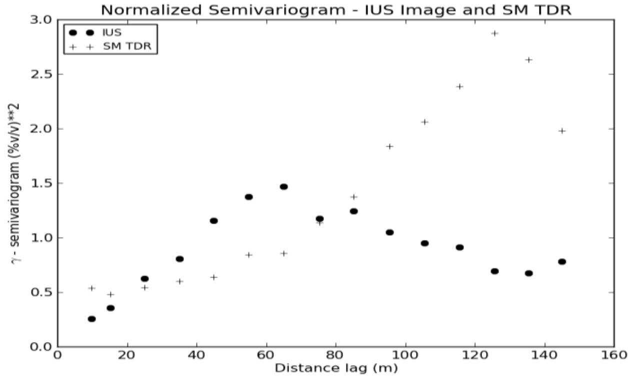

Fig. 2. Normalized semivariograms for ground-truth and image (% v/v).

The Bayesian kriging model is then evaluated assuming three different scenarios with 8, 27 and 49 points have been sampled for the calibration procedure. The other measurements are used for the validation procedure. Figures 4 and 5 demonstrate that the Bayesian Kriging model captures much better the spatial variability identified in the ground-truth soil moisture data when compared to the original IUS satellite mapping. Table 1 provides summary statistics to complement the volumetric soil moisture maps (Figures 3 and 4). The statistical measures used in Table 1 are the (a) correlation coefficient (R), (b) the mean error (ME), (c) the mean-square reduced error (MRE) (average over the sum of the differences between the observed and estimated values divided by the standard deviation of the observed values), and (d) the mean-square error (MSE).

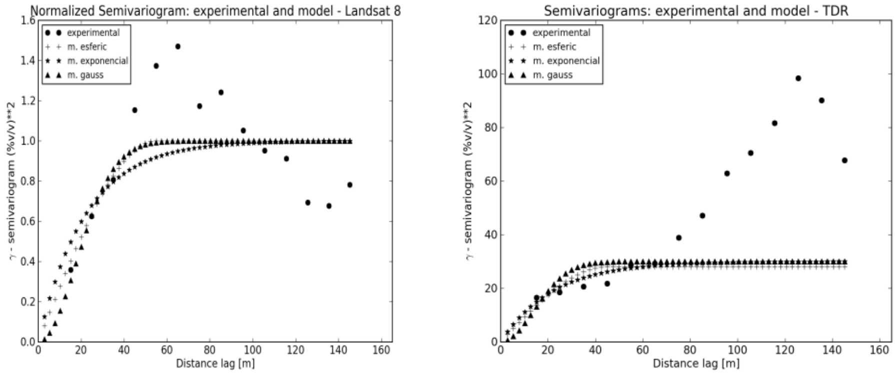

Fig. 3. Semivariograms for the IUS and for the volumetric soil moisture: (a) normalized semivariograms for the soft data (image) – experimental and model (on the left); (b) semivariograms for the hard data (ground-truth) – experimental and model (on the right).

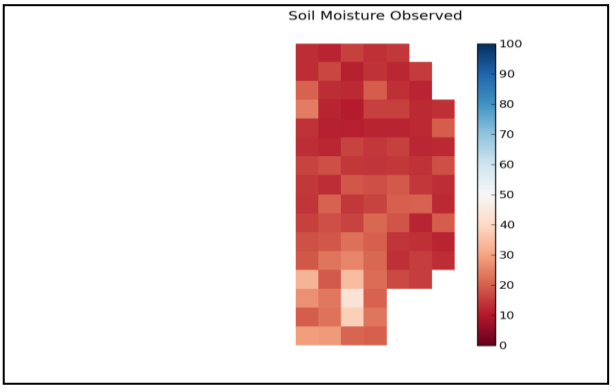

Fig. 4. Color scale map for the ground-truth volumetric soil moisture (% v/v).

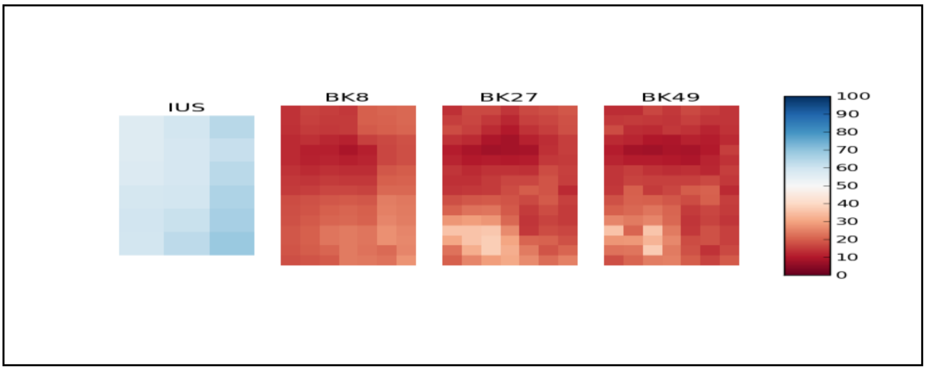

Fig. 5. Landsat 8-TM image (IUS) and Bayesian Kriging (BK) field estimated soil moisture (% v/v) – calibration sample sizes of 8, 27 and 49.

Table 1. Statistical Measures of comparison for the IUS and geostatistical methods (hard data and estimated hard data based on IUS).

Method	Average Soil Moisture (% v/v)	Std. Dev. Soil Moisture (% v/v)	R	ME	MRE	MSE
Ground-truth	17.43	5.85	-	-	-	-
IUS	60.43	2.91	-0.04	-42.53	54.06	43.01
BK 8	17.62	4.02	0.34	-0.19	0.99	5.82
BK27	18.01	7.25	0.76	-0.57	0.58	4.46
BK 49	17.00	6.05	0.84	0.43	0.33	3.37

4 Conclusion

Soil moisture plays an important role in stream flow modeling. It determines infiltration during a rainfall event and controls evaporation between storms. Geostatistical analysis showed that a similar behavior and correlation structure is present in both data sets (ground-truth and image) as well as a relationship does exist between the ground-truth and the image. In addition, it was shown that geostatistical methods such as the Bayesian kriging, which allow the combination of hard data (ground-truth) and soft data (image), can provide us with a better representation of the surface soil moisture data spatial variability at the field level when compared to the use of only satellite derived information.

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