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Topsoil thickness mapping at watershed scale by integration of field survey, geophysics and remote sensing methods

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The adequate parameterisation of near subsurface is a critical issue due to the large spatial variability of soil properties. Direct observations made by common invasive field sampling procedures through drilling and trench excavations can be complemented in an efficient way by non-invasive geophysical methods, improving spatial data coverage in cost and time efficient way. The geophysical methods measure a physical property of subsurface that is convertible into the parameter or variable of interest. Such conversion requires development of data integration method.

In this study, we present a methodology of data integration to assess spatially the topsoil thickness at the watershed scale. To integrate the spatial variability of the soil characteristics, we used a combination of field survey, ground-geophysics, satellite and aerial imagery processing and statistical estimation techniques. The ground-geophysics was used to complement and extend the direct field observations of the topsoil thickness. The conversion of the geophysical data in topsoil thickness and the estimation of the topsoil thickness over the catchment were done through statistical methods that integrated auxiliary variables derived from the remote sensing imagery (soil and geomorphology classifications and terrain attributes). A simple and expedite soil classification based on multi-resolution segmentation of image objects and fuzzy logic was derived from a high-resolution multispectral QuickBird image combined with aerial photograph. Landform classes and terrain attributes were computed from the Global Digital Elevation Model (GDEM) of the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) satellite. We applied this methodology to the Pisões catchment ($\sim$19 km2, Portugal) where the AB horizon, following the standard pedologic classification, is characterized by its high concentration in swelling clay.

In the first step, we elaborated the sampling schema of the geophysical survey using a dataset compiled from previous studies of 48 observations of the topsoil thickness made through augering, profiling and drilling. We opted to measure the soil apparent electrical conductivity (ECa) using a GeonicsTM ground conductivity meter EM-31 because: i) the AB horizon thickness was within the range of penetration depth of this instrument; ii) a significant contrast between the electrical conductivities of the AB and C horizons was expected and confirmed by measurements. We assumed that the spatial variation of ECa over the study area was mainly controlled by the high clay content and the thickness of the AB horizon. The influence of the soil moisture content was minimized by taking the ECa measurements at the end of the dry season. We executed 6 transects, perpendicular to the main streams, which constituted 424 survey locations separated by a median distance of 21 m. Complementary direct observations were also made by using percussion drilling and digging at 22 locations along the geophysical transects.

The second step was to convert the ECa measurements into topsoil thickness using a linear regression (LR) model. The obtained dataset was used in the third and last step to estimate the topsoil thickness over the catchment selecting the appropriate geostatistical mixed linear model (MLM). In these two last steps, the remote sensing derived auxiliary variables were tested and integrated in the models to improve the relationship. To avoid collinearity effects in the models, the auxiliary predictors were selected using principal component analysis. The selection of the appropriate geostatistical MLM was done by testing the normality and the spatial correlation of the residuals (respectively Shapiro-Wilk and Moran tests). The error propagation in the models was considered and integrated in the results. Final assessment of the estimation was made by computing the root mean square error (RMSE) at 61 locations of the observed dataset.