remote sensing

Editorial

Estimation and Mapping of Soil Properties Based on Multi-Source Data Fusion

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Recent advances in remote and proximal sensing technologies provide a valuable source of information for enriching our geo-datasets, which are necessary for soil management and the precision application of farming input resources. This is because of the advantages of these modern technologies in that they provide a high sampling density enabling the exploration of the within-field spatial and temporal variability of soil characteristics, and being fast and cost-effective, compared to the traditional laboratory analysis methods. However, soils are complex in nature, and measurements of key soil properties or processes in soils might not be achievable by the use of a single sensor [1,2]. This necessitates innovative solutions beyond the single-sensor approach, which should be implementable not only under laboratory conditions but in situ in either stationary or on-line measurement modes. In the past few years, several studies on the implementation of multi-sensor (remote and proximal) and data fusion approaches in soil science have been reported in the literature, although this research area is still at its early stages of development. The aim of such integration is twofold: (1) improves the detection accuracy of a soil property or a list of soil properties [3–5], and (2) improves the quality of soil maps, management zone maps [1] and the resulting decision support for variable rate applications in precision agriculture [6–8]. The integration of different data layers has greatly benefited many other applications in agriculture and environmental soil modeling that require more extensive temporal and spatial information than that contained in any individual dataset provided by a single sensor. At the same time, the major progress that has been made in different aspects of digital soil mapping (DSM) make DSM more mature and operable than ever before. The integration of multi-sensor source data fusion with the DSM technique is foreseen to provide a better understanding of soil processes and enable a more accurate estimation of soil properties at various spatial and temporal scales. It will also provide new insights into processes occurring in soils and sources of variabilities linked to soil dynamics in different scenarios of land management practices, precision agriculture, environmental pollution, and climate change.

This Special Issue was proposed to gather scientific contributions on new methods and applications in soil science, based on multi-source spatio-temporal data fusion techniques. The proposed key target themes included: (1) the use of proximal and remote sensing techniques for the measurement and mapping of biological, physical, and chemical soil properties, soil contaminants, and soil processes; (2) modeling approaches for deriving new indices, understanding soil processes, and the estimation of soil-related yield limiting factors; and (3) improving recommendations for precision agriculture applications. In total, 12 papers were accepted for publication on topics indirectly or closely related to the topics proposed. Out of these 12 papers, five papers combine multi-source remote sensing data, four papers combine proximal sensing data, and a third category consists of three papers that do not implement data fusion.

Under the first category, one paper combines remotely sensed optical and radar data for the estimation and mapping of soil clay using support vector machine (SVM) and

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random forest [9], reporting a moderate accuracy of 63–65%. Another study, using satellite-based data, deals with the prediction of soil organic carbon using time series analysis of a monthly (over 12 months) collected normalized difference vegetation index (NDVI) from Landsat 8 imageries. All four tested multivariate regression and machine learning models resulted in moderate to poor prediction results [10], although the time series model provided much better results, compared to the single- and two-month NDVI prediction models. Remote sensing Landsat 8 data were fused with moderate resolution imaging spectroscopy (MODIS) high temporal resolution data for DSM of soil texture [11]. Results showed that the mapping accuracy based on Landsat 8 data (if subjected to successful soil spectral dynamic feedback to account for multiple drying after rainfall) was higher than that obtained with the fusion of Landsat 8 and MODIS. In another paper [12], theassess the use of a non-invasive electromagnetic induction (EMI) technique as an augmentation to a traditional peat coring survey that provides localized and discrete measurements. spatial distribution of soil texture was measured successfully using the fusion of airborne microwave remote sensing data and topographic indices in a hybrid geostatistical approach. Optical, near-infrared, and thermal infrared data from the Landsat 8 satellite and the Advanced spaceborne thermal emission and reflection radiometer (ASTER) global digital elevation model (GDEM) were fused for soil moisture mapping under sparse sampling conditions, based on the Bayesian maximum entropy (BME) framework [13].

The fusion of proximal sensing data under the second category is demonstrated by four studies in this Special Issue. In one paper, the authors fused spectral data in the visible and near-infrared (vis-NIR) range collected at two modes, e.g., laboratory and on-line in field (tractor-based) for the on-line prediction of secondary soil properties [14]. The authors concluded that the fusion of spectra provided the best results for on-line prediction and these were comparable to the corresponding models using on-line spectra only. A second paper compares the predictive ability of vis-NIR spectra, mid-infrared (MIR) spectra, and their fused spectra for soil classification [15]. Results showed the prediction accuracy of the data fusion using a multiple objectives mixed SVM model (i.e., vis-NIR-MIR spectra) to deteriorate, compared to the individual vis-NIR or MIR model performance. However, when combined with outer product analysis, spectra fusion resulted in improved classification accuracy reaching 68.4%, compared to the SVM data fusion model (61.1%). Another work fused spectral data of eight soil layers collected with a vis-NIR spectrometer for the analysis of a coastal soil chronosequence using 16 soil profiles [16]. A combination of the DUALEM-421S instrument to measure apparent electrical conductivity (ECa) with a traditional soil coring survey and light detection and ranging radar (LiDAR) to measure alleviation and derive terrain attributes was used to measure and map the depth of a peat soil based on a multiple linear regression analysis [17]. Results showed that while the combinations of ECa data (both single- and multiple-coil) with elevation generally provided slightly higher accuracies, the uncertainty estimates for single-core DUALEM-421S predictions were smaller.

Out of the 12 papers accepted into this Special Issue, three studies have not attempted to fuse data. One study compares the performance of three commercially available X-ray fluorescence spectrophotometers for the estimation of multiple soil geochemical properties using a diverse dataset collected from 10 different countries across three continents, namely, Europe, Africa, and Asia [18]. The second paper assesses the performance of a portable x-ray fluorescence (XRF) sensor set up with two different X-ray tube configurations (combinations of voltage and current) to predict nine key soil fertility attributes: clay, organic matter (OM), cation exchange capacity (CEC), pH, base saturation (V), and extractable nutrients (P, K, Ca, and Mg) [19]. A portable XRF sensor was used to successfully measure and map potentially toxic elements (PTEs) in soils in Fuyang County in southeast China. Then maps of soil PTEs were further improved using a model averaging approach, which combined multiple maps created by different geostatistical methods, using measurements from both laboratory chemical analysis and portable XRF sensor predictions [20]. Although these three papers did not apply a multi-sensor data fusion approach in their analyses, the knowledge and results reported could be of indirect influence on the understanding of technical restrictions or advantageous for use in future multi-sensor data fusion analyses.

The analysis of the 12 papers published in this Special Issue confirms that the multi-sensor data fusion topic is still in its infancy stage, as hypothesized in the introduction above. This is due to the low number of papers submitted, with three of the accepted papers having an indirect link to the topic of the Special Issue. Even when papers linked closely with the project topic, the fusion was sometimes implemented on data collected from the same sensor over time [10,12], space [16], or using different measurement modes [14]. However, the topic holds great potential for application in different domains in soil science, environment, and agriculture. It is worth noting that the assumption that a multi-sensor data fusion approach should result in the improved prediction accuracy of a soil property is not always valid, and this will depend on synergies between data coming from different sensors. Poor synergies could lead to the deterioration of results; hence, this approach should be recommended with caution after thorough investigations and validation using several datasets.

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