

Editorial

Editorial for Special Issue “Digital Mapping in Dynamic Environments”

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Abstract: It is widely acknowledged that the global stock of soil and environmental resources are diminishing and under threat. This issue stems from current and historical unsustainable management practices, leading to degraded landscapes, which is further compounded by increased pressures upon them from ever-increasing anthropogenic activities. To curb the trajectory toward a collapse of our ecosystems, systematic ways are needed to assess the condition of our natural resources, how much they might have changed, and to what extent this might impact on the life sustaining functions we derive from our environment and the extent of our food producing systems. Some solutions to these issues come in the form of measurement, mapping and monitoring technology, which facilitates powerful ways in which to be informed about and to understand and assess the condition of our landscapes so that they can be managed strategically or simply improved. This Special Issue showcases from several locations across the globe, detailed examples of what is achievable at the convergence of big data brought about by remote and proximal sensing platforms, advanced statistical modelling and computing infrastructure to understand and monitor our ecosystems better. These utilities not only provide high-resolution abilities to map the extent and changes to our food producing systems, they also have yielded new ways to determine land-use and climate effects on the fate of soil carbon across living generations and to identify hydrological risk strategies in otherwise data-poor urban environments. Leveraging the availability of remote sensing data is telling, but the papers in this Special Issue also highlight the sophistication of modelling capabilities to deliver not only highly detailed maps of temporal dynamic soil phenomena but ways to draw new inferences from sparse and disparate model input data. The challenges of restoring our ecosystems are immense and sobering. However, we are well equipped and capable of confronting these pervasive issues in objective and data-informed ways that have previously never been possible.

1. Introduction

Anthropogenic activities on the earth system to fulfill increasing demands for food and clean water for the world's population have accelerated changes in the soil and ecosystem. We need to efficiently map functions of the terrestrial ecosystem so we can manage it strategically. Digital soil and environment mapping have achieved excellent results in the prediction of soil properties at local, regional, continental, and global scales. The convergence of big data, advanced statistical modelling and computing infrastructure have now made large scale digital mapping much more feasible. Field observation data coupled with earth observing remote and proximal sensors, provide exciting new opportunities to extract new knowledge. This special issue looks for application of rich remote sensing time series data in combination with statistical models that enable space and time mapping of soil and the environment.

For this Special Issue we asked for contributions on mapping applications in agriculture, and terrestrial environments that investigated but were not limited to:

- Evaluating climate impacts on the terrestrial ecosystem functioning
- Multisource and multitemporal application of remote sensing data for digital mapping
- The use of big data analytics for spatiotemporal prediction, including deep learning.
- Incorporating process-based models for mapping dynamic soil functions.
- Spatial forecasting and/or simulation experiments of environmental resource change.
- Data fusion of various proximal and remote sensing products or model ensemble to combine outputs of several models.
- Uncertainty analysis of environmental resources.

We received, reviewed, and published 7 articles from around the world that provide new insight and approaches to leverage big data and advanced statistical modelling algorithms to better understand and monitor our ecosystems. These studies demonstrate capabilities in high-resolution mapping of the extent and phenology of high value cropping enterprises. They have yielded ways to determine land-use and climate effects on the fate of soil carbon stocks spatially and across human generations, and ways to identify hydrological risk strategies in otherwise data-poor urban environments. Importantly, papers in this Special Issue deploy sophisticated modelling workflows to deliver not only highly detailed maps of temporal dynamic soil phenomena but ways to draw new inferences from sparse and disparate model input data that will enable more informed and nuanced management of our degraded and threaten ecosystems.

2. Overview of Contributions

2.1. Landuse and Climate Affects the Fate of Soil Carbon Stocks

Soil organic carbon is an indicator variable for the functioning status of landscapes given its role in the provisioning of numerous ecosystem services. Knowing how much carbon is currently stored in soils is incredibly important, but probably more important is an understanding of the potential storage capacity. And equal to this is an understanding of how much carbon soils have been lost over time as a result of climate and land management impacts. These sorts of questions need answering in order to respond to global challenges around anthropogenically induced climate change as a result of increased emissions of greenhouse gases, including CO₂ into the atmosphere. Soils are one part of the solution whereby in places where there is a large potential to store carbon either restoratively or through the uptake of beneficial land management practices, some of the excess atmospheric carbon can be drawn down and sequestered into soils. The benefits of this are two-fold in that atmospheric carbon can potentially be reduced, and increased soil carbon promotes improved soil function in terms of nutrient cycling, water storage, gaseous exchanges, and improvements in soil structure. As [1] quite rightly state, initiatives such as the international 4 per mille effort have really mobilised efforts to better understand the status of soil carbon in soils and to what extent they can contribute to climate change solutions.

In their study across Wisconsin, USA, [1] wanted to determine to what extent did a changing climate, land cover, and agricultural activities influence soil organic carbon stocks (SOCS) across this area dating back to 1850 through to 2002. They utilised legacy soil datasets and maps together with time series of climate and landcover mapping in addition to landform and topographic data to develop a machine learning informed space-for time substitution model, for first estimating near present day carbon stocks and then hindcasting for the period from 1850–1980. While one might expect perhaps a linear trend of decreased soil carbon stocks from 1850, which was found partly to be true (due to land cover change), their models detected an increase from 1980 to 2002 which is determined to be the result of improved soil management practices. This study showcases the value of time series data analysis in order to investigate the influences of location-specific carbon management practices and

climate change on soil carbon stock changes. Moreover, the approach is general in nature and could be extended to other areas where similar historical climate and land use data exist.

2.2. Time Series Analysis of Crops

Both [2,3] exploit the use of time series remote sensing data compiled and delivered through such platforms as the Google Earth Engine (GEE). The commonality in these studies is the need to identify cropping patterns and growth stages of high-value commodities which here included rice in southeast Asia and Macadamias in Australia.

One of the difficulties of using remote sensing data is the prevalence of cloud cover that renders temporal data analytics a difficult pursuit. This is clearly the case in tropical and sub-tropical environments where there numerous and extended periods where there is substantial cloud coverage. The work by [2] navigates this issue by examining relatively new radar satellite technology from the Sentinel-1 platform. The authors were able to demonstrate that integrating these data captured over regular intervals over 2 years, coupled with rice phenology understanding and GEE cloud computing, the ability to map and monitor rice extent, cropping patterns, and growth stages. Based on the trained models, the authors can deploy a GEE App that provides the current status of paddy fields at a 10 m resolution throughout a large region. Based on this work, the authors of the article recently won the GEE and the Group on Earth Observations award for developing the world's first real-time monitoring platform for rice fields. This is clearly an achievement and impactful work in consideration that much of the world population consumes rice daily, and therefore strategic management and monitoring of these intensive cropping regions is needed now and into the future.

In Australia, the Macadamia industry is growing rapidly, given global interest in the food product itself together with associated products derived from this high-value commodity. Because the industry is growing fast, efficient tools are needed to understand and measure tree crop orchard age and historical crop area in order to develop yield prediction algorithms and facilitate improving accuracy in ongoing crop forecasts. [3] used Landsat multispectral data from all available platforms to construct time series stacks (1988–2019) across selected macadamia orchards. From several normalised difference spectral indices, an algorithm was developed which attempts to find the most recent year that an NDSI crosses a fixed threshold, due to the growth of newly planted trees. This information is used to establish year of planting of an orchard. Naturally, this approach is scalable and will augment well as the Australian macadamia industry expands its reach to international and discerning marketplaces where quality and provenance of product earn a premium price. Together both the studies here demonstrate impactful and insightful research that exploits the use of relatively low-cost data but will improve how commodity crops are managed and monitored in a more sustainable way.

2.3. High Resolution Digital Soil Mapping

When it comes to dynamic soil properties, soil carbon, nitrogen, pH, and soil hydraulic properties come to mind immediately. In addition to the [1] investigation about temporal changes in carbon stocks, [4] sort to understand and determine the contributing factors controlling soil carbon spatial variability across two contrasting climatic regions in Iran. This study is interesting from a topical standpoint of the widespread deployment of machine learning algorithms to uncover complex relationships between target and predictor variables. In addition to side-by-side comparisons of different machine learning algorithms in elucidating relationships, this study sort to combine these with innovative ensemble modelling approaches. In this study, we learn to appreciate the black-box nature of machine learning models, but this study, given the fact it is carried out in two contrasting environments, highlights the value and varied contribution of climatic and remote sensing data to better understanding soil carbon spatial variability.

National scale digital soil mapping was pursued by both [5] for mapping total nitrogen across China, and [6] for mapping soil pH across New Zealand. These studies contribute to the amassing efforts of nations around the world operationalising digital soil mapping. Both these articles not

only communicate the general need for detailed soil mapping, but also identify end-user applications specific to each nation.

From a technical standpoint, both studies exemplify the deployment of machine learning algorithms to learn the complex relationships between soil variable and covariates. Moreover, these articles are keen to implement and point out the importance of quantifying prediction uncertainties, which is a distinguishing feature of most digital soil mapping studies relative to the mapping of other environmental phenomena. Ultimately soil scientists acknowledge that spatial modelling is not without error, and therefore are quite open about communicating the reliability of the maps that are produced and illustrating specific locations where maps and their underpinning models perform well and where they do not perform so well. This has important downstream opportunities and consequences for how to improve subsequent modelling and for identifying potential use cases and applications of the mapping given the existing quantifications of uncertainty.

Collectively, each of the digital soil mapping studies in this Special Issue clearly demonstrate the selection of a diverse range of environmental variables to understand the status and behaviour of dynamic soil phenomena. There is not only the exploitation of available remote sensing imagery, but other key variables pertinent to understanding soil spatial variability including climate, parent materials and topography are also used.

Another important feature of articles presented in this Special Issue, particularly from [7] who sort to understand hydrological characteristics of soils within an urban environment for engineering and human safety purposes, and [6] with pH mapping across New Zealand, is the value of digital soil mapping to create readily-accessible information from seemingly disparate and scarce input data, in this case from legacy soil survey data. In the urban environmental setting in South Africa, [7] were able to deploy their hydrological outputs into a process-based modelling framework (HYDRUS model) from which they were able to determine the source and magnitude of soil water causing structural damage. This is an encouraging application for digital soil mapping and more particularly for the use if these outputs for detailed digital soil assessments. Also innovative was the [6] approach to dealing with legacy soil data to output 3D soil maps of pH across New Zealand. 3D mapping usually necessitates not only good spatial coverage of data points but also relatively high granular representation of soil information with depth too. Legacy soil data is often lacking in the later specification, and the authors sort to deal with this via data augmentation approaches which are relatively common in other machine learning contexts but has not yet been explored for digital soil mapping. With comparative analysis to existing 3D soil mapping approaches, the data augmentation provided encouraging results and only yielded unique opportunities in terms of creating on the go user specified end products rather than static representation of soil spatial variability.

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