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The Digital Soil Mapping: Advancing the Knowledge Frontiers

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Abstract
Soils are essential for supporting food production and providing ecosystem services but are under pressure due to population growth, higher food demand, and land use competition. Because of the effort to ensure the sustainable use of soil resources, demand for current, updatable soil information capable of supporting decisions across scales is increasing. Digital soil mapping (DSM) addresses the drawbacks of conventional soil mapping and has been increasingly used for delivering soil information in a time- and cost-efficient manner with higher spatial resolution, better map accuracy, and quantified uncertainty estimates.

Keywords: Soil Information, *GlobalSoilMap*, Digital Soil Mapping, Predictive Models

Overview
The biggest carbon reservoir in terrestrial ecosystems is found in the soil. Soil carbon is essential to soil fertility for the survival of plants, animals, and people. In addition to aiding in the determination of soil organic carbon (SOC) content and stock across areas, the spatial distribution of soil carbon also supports Earth system modelling and sustainable land management. However, accurate measurement of the global soil carbon pool is still difficult due to a lack of soil observations worldwide, particularly at deep depths, which also contributes to the high degree of uncertainty in estimates of the terrestrial carbon stock. Because of this, it's critical to create efficient techniques for measuring and tracking the spatially precise information of soil carbon, particularly in light of the small sample sizes.

12% of the area that is free of ice on Earth is covered with crops. Degradation of soil quality is a problem affecting arable soils that are under significant threat in many areas. There is evidence that, starting with the first furrow of human agriculture, the soil carbon store began to drop over time, contributing 116 Pg of carbon (as CO_2) to the atmosphere and less organic carbon to hydrographic environmental sediments. International attention has been focused on worries about increased greenhouse gas emissions from degraded agriculture. The global programme '4 per 1000' places significant emphasis on managed agricultural areas due to their ability to increase the stock of SOC. The FAO-launched RECSOIL effort was one of several international projects aimed at increasing carbon sequestration in prospective soils, such as degraded and cropped soils. Effective management techniques can help crop potential for sequestering carbon. In order to preserve soil fertility, make informed decisions about land management, and enable a realistic estimate of carbon sequestration capability, it is helpful to evaluate the current status and change of agricultural carbon content and stock.

Traditional techniques for examining soil carbon that rely on field experiments take a lot of time and work. Digital soil mapping (DSM) has emerged as an essential method for obtaining spatial data on soil carbon in the last several decades. The "scorpan" model, a conceptual DSM paradigm that describes the empirical quantitative interactions between soil and environmental variables, in accordance with the soil formation theory.

Models and environmental variables of digital soil carbon mapping in agricultural settings

In order to uncover advanced existing knowledge and to highlight areas where future DSM investigations in agriculture might be conducted, we focus on prediction models and environmental variables in digital mapping of soil carbon in cropland in this part.

Models

Techniques for linear statistics: Because linear statistical approaches are more widely available and easier to apply, they are frequently used in digital mapping of soil carbon. Between a response variable and a set of dependant variables ,they create a particular model. The linear statistical techniques mostly involve regression models that make use of generalised and ordinary least squares. Specifically, partial least squares regression (PLSR) and multiple linear regression (MLR) are the two most widely used models.

Geostatistical techniques: Geostatistical techniques have been widely used in the mapping of soil properties. They are effective in quantifying and modelling the spatial variation of the variable of interest, assuming that samples close together, on average, are valued more similarly than those that are farther apart. However, in order to produce accurate semivariograms, these methods require rather dense point data, and geostatistical methods hardly account for the relative importance of the various drivers of soil carbon dynamics. Only the geostatistical methods that include environmental covariates into the kriging system are covered in the review. As an extension of OK, CoK takes into account correlations with the primary variable (Z1) and uses one or more covariables (Z2) in the estimation at unsampled sites. A linear model of coregionalization can be used to calculate and model the semivariogram and cross-semivariogram of all Z1 and Z2. DSM contains numerous instances of CoK uses.

Techniques for Machine Learning: In contrast to geostatistical models, machine learning techniques do not necessitate stringent statistical assumptions regarding the input data distribution. The intricate and non-linear link between soil carbon and environmental variables, also referred to as "SCORPAN" factors, may be worked with by them in an efficient manner. In the article, "ML methods" are defined as a broad category of techniques that use data mining to identify patterns and then apply those patterns to regression or classification tasks. This article identifies cubist, RF, SVM, and artificial neural network (ANN) as the models that are employed more commonly.

Combined techniques: The combination of two or more distinct algorithms, such as RK, RF plus spatially weighted regression, and random forest plus residuals kriging (RFRK), is known as a hybrid approach. In general, these algorithms outperform linear statistical approaches or basic geostatistical algorithms in terms of prediction performance.

By combining regression between the primary (target) variable and secondary variable(s) using kriging residuals produced from the regression, RK, a popular hybrid method, includes environmental factors into the kriging models. The use of multivariate, independently measured secondary data in RK methods to map SOC stock. The effectiveness of RK in conjunction with cropping methods and natural variables was assessed. RK's validity is heavily dependent on the choice of environmental factors, despite the fact that it has been demonstrated to offer the benefits of simple implementation, thorough results, and good prediction accuracy.

Lately, a number of research works have concentrated on hybrid geostatistical processes, primarily combining ML techniques with geostatistics. For instance, used remote sensing data to conduct ANN-OK and ANN-SK for the geographic variability of SOM content. The outcome shown that the hybrid geostatistical approaches outperformed the basic geostatistical approaches, such as SK, OK, and CoK, in terms of prediction reliability.

Alternative techniques: Other creative approaches to soil mapping have been put forth that do not fit within the previously mentioned categories. This method permits the building of the depth function of SOM content for each soil type at each prediction site by using general pedological knowledge to define depth function structures with geostatistical modelling. Nevertheless, the approach necessitates a substantial quantity of current soil records, which could not be relevant in regions with a scarcity of samples. A novel technique called "individual predictive soil mapping" was introduced. Based on the representativeness of the soil samples, this method may effectively utilise a small number of soil samples. This method computes similarities between environmental covariates of the unvisited points and the sampling points, assuming similar soil attribute characteristics under similar environmental conditions. A similarity weighted average method is then used to calculate the target attributes of the entire area.

An overview of the models used for digital soil mapping

It is evident from the study results above that no model consistently performs better than any other. According to a number of recent research, machine learning (ML) approaches appear to be more effective than linear statistical methods at incorporating non-linear correlations between soil carbon and environmental covariates throughout the model-construction process. ML techniques might meet the needs of moderating requirements on the number of sample points and indicating the relative value of each environmental covariate. However, machine learning techniques rely heavily on data, and the amount and quality of the input training observations greatly influence the outcomes of the predictions. Sometimes, using ML techniques could even produce less accurate results than using straightforward models. In a spatial downscaling study that when faced with a limited number of training samples, simpler methods like linear statistical methods or general additive model outperformed RF and cubist to capture the essential variables. Furthermore, the same model performs differently at different soil depths. Predictive model performance declined with depth, according to research on four standardised depths: 0–15, 15–30, 30–60, and 60–100 cm. The lowest estimation accuracy was found for the 60–100 cm depth interval, with much larger root mean square errors (RMSEs) than the first two layers (0–30 cm of soil profiles). The best performance of SVR in estimating SOC content was observed in the 0–15 cm depth of soil profiles.

Various sets of environmental covariates and goal soil qualities may be better suited by different predictive models. Some research indicates that when choosing which models to use a priori, the target variable's correlation strength with environmental covariates may be a crucial factor. Furthermore, although some predictive models can simply provide predictions, others can also provide correlations between the soil and its surroundings. Research indicates that RFRK performs well when modelling intricate relationships between variables, and that RT and the generalised additive mixed model are useful for evaluating relationships between variables. Consequently, it is possible to obtain better forecasts by utilising many complementing methods than when employing these models alone.

Future horizons

We identify some challenges in the current use of agricultural information and models for digital mapping of soil carbon, then we want to outline several promising solutions to our interwoven request and application challenges. Moving forward, we should not be locked into a single approach *a priori*, whether it be efficient sampling strategies, model modification, or suitable agricultural information. A holistic conceptual framework is proposed for better monitoring spatial and temporal variation of soil carbon to support food production, soil protection, carbon sequestration, and emissions mitigation.

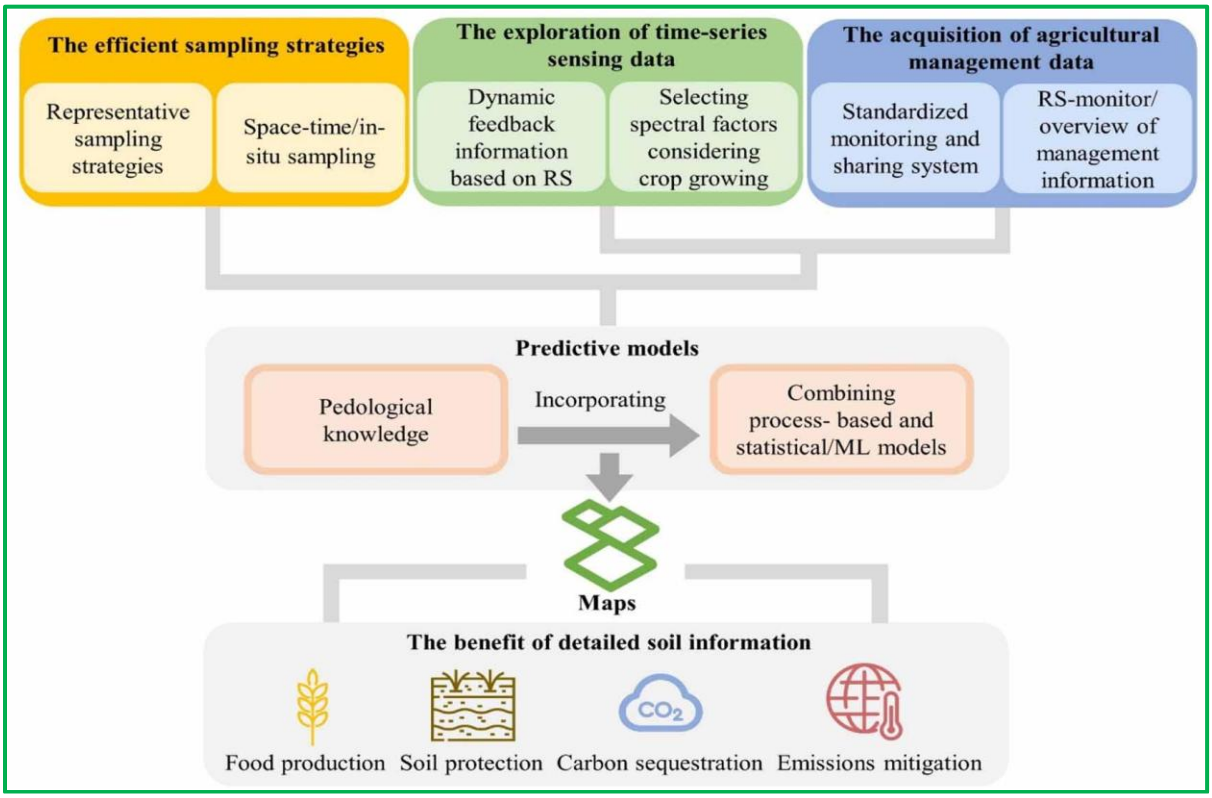

Fig: An integrated framework illustrating the promising solutions for digital mapping of soil carbon in cropland

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