## Digital Soil Mapping: A review of techniques, Applications and Emerging Trends

**ABSTRACT**

Digital Soil Mapping is a method of digital evaluation of soil. It consisting of numerous processes such as creation of soil information system, maintenance of digital data base etc. it involves the generating digital soil maps with the help of Geographic information System and Remote Sensing. Digital Soil mapping system embedded with the computer enabled techniques to produce detailed and accurate information. Digital Soil Mapping is an integral part of the Soil information System. It is emerged as a new methodology to describe the soil physical and spatial properties efficiently. It helps in providing information related to soil organic matter other physical properties. Digital soil mapping system is consisting of various models which provide spatial information. The integration of deep learning and AI has revolutionized the way to increase the soil and crop sustainability, helps in enhancing productivity and minimizing environmental hazards. Different AI-ML technologies enable precision agriculture optimizing resource use, improving soil health, and facilitating real-time crop monitoring. AI Based soil information systems helps in precise analysis of soil properties, early detection of degradation, and optimization of irrigation practices, contributing to more sustainable land use.

**Keywords:** Digital soil mapping; remote sensing; deep learning .

**Introduction**

Soil mapping originated from the need to understand the spatial distribution and characteristics of soils to support key sectors such as agriculture, environmental conservation, land use planning, and civil engineering (reference). In recent decades, this need has intensified due to growing environmental pressures and the urgency of sustainable development. Challenges such as soil degradation, climate change, and the demand for sustainable food production have highlighted the importance of comprehensive soil assessment and monitoring (reference).

Meeting these challenges requires robust regulatory, mitigation, and adaptation strategies. Central to these efforts is access to high-resolution, accurate soil data. Richer soil information enables more informed decisions, reduces environmental risks, and enhances land productivity. Again, please add references. For example, soil maps can help farmers optimize fertilizer use, improve crop yields, and minimize environmental harm (reference). In this context, effective soil resource management is vital to sustaining the ecosystem services that soils provide.

The growing strategic importance of soil intelligence is reflected in market trends. According to a Tech Sci Research report titled “Digital Soil Mapping Market - Global Industry Size, Share, Trends, Opportunity, and Forecast, 2019–2029F,” the global digital soil mapping (DSM) market was valued at USD 146.38 million in 2023 and is projected to grow at a CAGR of 7.66% through 2029. This projected growth underscores the increasing reliance on data-driven solutions in environmental and agricultural decision-making.

This article explores the evolution of soil mapping, from traditional techniques to digital innovations, and highlights its critical role in sustainable land management, agricultural optimization, and climate resilience.

Historically, soil mapping relied on direct field observation and laboratory analysis (reference), and while foundational to soil science, these methods face several limitations in addressing modern demands for scalability, precision, and cost-effectiveness. Figure 1 represents the key soil parameter and Figure 2 represents the core techniques about soil mapping.

(Figure 1 : Key Soil Parameter)

Figure 2: Core Techniques of Soil Mapping

Digital Soil Mapping (DSM) integrates several key components to produce accurate and detailed soil information (reference). It begins with the use of soil data, which includes information from soil surveys such as soil profiles, sample analyses, and existing maps. Complementing this are various forms of spatial data, which represent environmental factors influencing soil formation such as climate data, digital elevation models (DEMs), satellite imagery, and vegetation maps. To link these datasets, DSM employs numerical models, including statistical and geo-statistical techniques, to establish relationships between soil properties and environmental covariates, allowing for spatial prediction across landscapes.

Typical DSM involves a series of steps. Firstly, it starts with data collection, involving field-based soil observations and sampling, as well as the acquisition of relevant spatial environmental data. This is followed by data preparation, where soil and spatial datasets are harmonized and processed, and often using techniques such as principal component analysis or geo-statistical interpolation, which includes Ordinary Kriging, Universal Kriging and Regression Kriging (reference). Afterwards, a predictive model or algorithm is selected for calibrating the sampled soil properties. These predictive models include regression analysis, classification trees, or neural networks. Using the outputs of these models, digital soil maps are then produced. The process concludes with validation and uncertainty assessment, where the accuracy of the maps is evaluated and the uncertainty of predictions is then quantified (reference).

DSM serves a wide range of applications, including (i) the enhancement of soil inventories, (ii) agricultural planning and management, (iii) assessment of land degradation and erosion, (iv) monitoring of soil carbon and nutrients, (v) evaluation of ecosystem health and biodiversity, and (vi) the formulation of sustainable land management strategies. This approach offers several benefits over traditional soil mapping methods, including (i) higher spatial resolution and detail, (ii) reduced time and cost for mapping large areas, (iii) the ability to generate predictions in data-sparse regions, and (iv) the provision of uncertainty estimates to support informed decision-making.

DSM also represents a powerful and modern approach to understanding and managing soil resources. By integrating diverse data sources and advanced modeling techniques, it offers an efficient, scalable, and precise alternative to traditional soil mapping, particularly valuable in the context of rapidly changing environmental and land-use conditions.

DSM has revolutionized how soil data is collected, interpreted, and applied. DSM integrates field data with environmental covariates such as climate, topography, vegetation indices (such as NDVI), and geologythrough spatial modeling techniques. This allows for more continuous, standardized, and cost-effective soil maps.

1. **1 Advantages Over Traditional Methods:**

Standardization: DSM uses consistent data sources and modeling frameworks, minimizing human bias.

Continuity: Instead of defining fixed soil boundaries, DSM models soil attributes as continuous surfaces—better reflecting real-world variability.

Scalability: It extends predictions over large or hard-to-reach areas with fewer physical samples.

Cost Efficiency: Reduces reliance on expensive field and lab work through the use of remote sensing and predictive algorithms.

**1.2 Key Concepts in Digital Soil Mapping**

1. Predictive Soil Mapping (PSM)

PSM lies at the heart of DSM. It employs statistical and machine learning models to extrapolate soil properties across landscapes. By using limited sample data and combining it with environmental variables, PSM generates high-resolution, continuous soil maps that provide more accurate representations of spatial variability.

2. Prediction of Soil Properties

DSM facilitates the estimation of various soil characteristics such as texture, moisture, and organic carbon at unsampled locations. These predictions are informed by a combination of terrain data, climate records, satellite imagery, and other covariates. Algorithms analyze these inputs to model spatial trends, enhancing the detail and precision of soil data.

3. Geographical Information Systems (GIS)

GIS plays a central role in DSM by integrating and visualizing diverse datasets. It enables researchers to overlay and analyze topography, land use, vegetation, and soil samples within a spatial framework. Combined with remote sensing, GIS provides near-real-time mapping capabilities, supporting ongoing monitoring and decision-making.

1.3 **Digital Soil Mapping Techniques**

DSM employs a range of modeling techniques typically divided into: Classification: Predicts discrete soil types or classes. Regression: Estimates continuous variables like pH, organic matter, or moisture. Supporting Technologies: Satellite Imagery: Captures large-scale spectral data for surface and vegetation analysis. Drones: Provide high-resolution, site-specific imagery and sensor data. Kriging: A geostatistical method that interpolates soil properties using known data points and spatial correlations. Variogram Analysis: Quantifies how soil properties change over distance, supporting model accuracy. Open Data & Crowd sourcing: Platforms such as government soil databases and citizen science initiatives help fill data gaps and improve model reliability.

1.4 **Applications of Digital Soil Mapping Techniques**

Agricultural Optimization

DSM enables precision agriculture by tailoring resource use to the specific needs of soil in different areas. In Australia's grain belt, it supports efficient nutrient and moisture management. In Iowa, USA, it enhances soil fertility mapping for more targeted phosphorus and potassium application. In Africa, it guides irrigation planning by identifying moisture-retaining soils—vital for adapting to climate stress.

**Environmental Management**

DSM helps identify erosion-prone regions, directing conservation efforts efficiently. In the Amazon, it assists in mapping deforestation risk zones. In Europe, DSM supports carbon sequestration strategies by identifying soils with high storage potential—helping combat climate change.

**Urban and Land Use Planning**

City planners and engineers use DSM to assess soil stability and inform safe construction. In China, DSM aids in landslide prevention by highlighting unstable soils. In New Zealand, it helps balance agricultural expansion with environmental conservation.

2. **Selected Experimental Findings**

Digital Soil Mapping plays an important role in crop and soil sustainability. Digital Soil mapping system utilizes statistical and numerical models to predict soil properties. It integrates the laboratory data with climate, soil and other topographical data. Soil plays a crucial role in supporting agriculture and biodiversity (Montanarella and Panagos, 2021).Real time, accurate soil information is provided by the Digital Soil Mapping. Traditional soil mapping involved labour-intensive process (Behrens and Scholten, 2006). Computer mediated digital mapping system used the innovative and sustainable ways for the soil mapping technologies with the integration of data science and Remote sensing ( Mulder et al. 2011). With the integration of traditional mapping techniques and modern AI driven technology, Digital soil mapping techniques gaining popularity (wadoux et al 2020).

**Digital Soil Mapping (DSM)** involves the development and population of spatial soil information systems by integrating field and laboratory observations with both spatial and non-spatial inference techniques (IUSS, 2016). It brings together principles from soil science, geographic information science, statistical modeling, and cartography within a framework that leverages environmental data to predict soil properties and classifications ( Bratney et al 2003). In recent years, DSM has experienced significant growth, driven by several key factors:
a growing demand for spatially explicit, quantitative soil information, advancements in statistical modeling and artificial intelligence, supported by improved computational and data storage capabilities, and the increasing availability of high-resolution environmental datasets that enable rapid generation of soil maps (Grunwald, 2012). The foundational framework for DSM was introduced by McBratney et al. (2003) building upon Jenny’s classic soil formation model, expressed as **S = CLORPT** ,where S represents soil and CLORPT denotes climate, organisms, relief, parent material, and time (Pendleton and Jenny 1945). These are recognized as the primary soil-forming factors. McBratney and colleagues extended this model by incorporating the spatial position factor “n,” resulting in the **SCORPAN** model. This enhanced formulation enables a spatially explicit, quantitative relationship between soil attributes (such as properties or classes) and environmental variables at specific locations. Grounded in the first law of geography and theories of soil genesis, Digital Soil Mapping increasingly employs geo statistical and soil-landscape modeling techniques at local, regional, and global scales.

Digital Soil Mapping (DSM) captures patterns of soil formation and development through spatial analysis and mathematical modeling, offering a predictive approach for mapping soil properties. The core of DSM relies on field-collected soil sample points, which serve as key inputs to quantify the spatial autocorrelation of soil attributes and their relationships with environmental covariates. The conventional method of DSM involves linking soil properties with environmental variables through quantitative models. To predict soil spatial patterns, DSM employs a variety of statistical and machine learning methods, including both linear and nonlinear regression techniques such as artificial neural networks (ANN) (Guo et al., 2013) support vector machines (SVM) (Heung et al., 2016) and regression tree models (Wang et al 2017). Among these, Random Forest (RF) has emerged as one of the most widely used techniques for soil prediction in DSM (Wiesmeier et al., 2011) However, as researchers have emphasized, it is not sufficient to consider only the environmental covariates spatial information embedded within sampling points also plays a critical role. Advanced interpolation methods like co-kriging and regression kriging have been developed to incorporate spatial dependencies. Co-kriging models spatial covariance between target and auxiliary variables, while regression kriging combines regression predictions with kriged residuals to produce refined spatial estimates (Yang et al., 2016 and Mondal et al., 2017). Other spatially adaptive models, such as Geographically Weighted Regression (GWR), assign location-specific weights based on distances from the regression centroid, allowing for spatial variation in model coefficients ( Wang et al. 2013, Song et al., 2016, Zeng et al. 2016). Despite their strengths, these models face limitations, including data requirements, complexity in modeling nonlinear relationships, and challenges in data preprocessing, especially when assumptions such as second-order smoothness are not met (Wadoux et al., 2020, Hengl et al., 2004, Hengl et al., 2007)

Advancing/Latest DSM techniques

With the rise of big data and computational power, deep learning (DL) has emerged as a powerful tool in DSM. Unlike conventional models that depend on predefined parameters, DL automatically extracts features from data, enabling it to better capture complex, nonlinear relationships among environmental variables (Zhu et al., 2017,Mahdianpari et al., 2018). In particular, Convolutional Neural Networks (CNNs) have shown promise in DSM by learning distributed spatial features from image-like environmental inputs. CNNs apply a sliding window approach to extract local patterns, effectively using both spatial structure and covariate values to predict soil properties (Zhang et al 2019). Their utility has been demonstrated in several domains Krizhevsky et al., 2012 and Veres et al. 2015 used CNNs for soil spectral classification, and (Volpi et al., 2016) applied them to land cover classification from high-resolution imagery. In DSM-specific studies, Behrens et al. 2018, and Wadoux et al. 2-18 demonstrated CNNs' superiority over standard ML models in predicting properties such as soil organic carbon (SOC). Tsakiridis et al. Tsakiridis et al., 2020 introduced a local multichannel 1D CNN for continuous soil property estimation, outperforming RF models in particle size fraction prediction

A notable advancement in deep learning is Residual Networks (ResNet), which address the degradation problem in very deep networks by introducing shortcut connections that facilitate residual learning (Wu et al 2019, He et al., 2016) This architecture has achieved strong performance in tasks like image recognition (Long et al. 2015) and semantic segmentation (Wang et al 2017, Song et al 2018).

Building on these developments, this study introduces a novel lightweight deep learning model, LSM-ResNet, tailored for DSM. Designed as an end-to-end network for predicting Soil Organic Matter (SOM), the model integrates multisource environmental covariates using fused RGB imagery. SOM was chosen due to its importance as a soil health indicator and its role in ecosystem modeling and climate policy. The model's sensitivity to pre-frame size was evaluated, and its performance was compared to the widely used RF algorithm. Results suggest that LSM-ResNet offers improved accuracy and predictive power, demonstrating its potential for producing high-resolution SOM maps critical for land use planning, agricultural management, and environmental conservation (Chen et al. 2019)

**Conclusion**

Digital Soil Mapping represents a transformative shift in how we understand and manage one of the planet's most critical resources. By combining traditional knowledge with cutting-edge technologies like GIS, remote sensing, and machine learning, DSM offers a scalable, efficient, and precise approach to soil assessment. As environmental pressures and food security challenges grow, the value of accurate, dynamic soil information becomes increasingly apparent. DSM not only meets the demands of modern agriculture and land management but also equips policymakers, researchers, and communities with the tools to build more sustainable and resilient landscape.

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