



Digital Soil Mapping: A Modern Tool for Assessing Soil Health

Dr. Monika Vijay Kamble¹, *Dr. Namrata Kashyap², Amarpreet Singh³ and
Dr. Dhiraj Kumar Yadav⁴

¹PhD Scholar, Agronomy, Punjab Agricultural University, Ludhiana, Punjab, India

²SMS (Soil Science) KVK, Kamrup Assam Agricultural University,
Kahikuchi Campus, India

³Senior Scientist, ICAR-CICR, Regional Station, Sirsa, Haryana, India

⁴Senior Assistant Professor, UTD Farm Forestry, Sant Gahira Guru Vishwavidyalaya
Sarguja, Ambikapur, Chhattisgarh, India

*Corresponding Author's email: namratakashyap54@gmail.com

Soil supports global agriculture, ecological balance, and food security. However, climate change, unsustainable farming, and overexploitation have increased soil deterioration, emphasising the need for effective and scalable soil health assessment methodologies. Traditional soil survey methods, while accurate, are time-consuming, expensive, and inadequate for the accuracy required in current farming systems. Digital Soil Mapping (DSM) has evolved as a novel technique that combines soil science, remote sensing, geostatistics, GIS, and machine learning to produce high-resolution maps of soil properties. DSM can continually monitor factors like as fertility, organic carbon, texture, pH, and pollutant loads, allowing for more informed decisions in precision agriculture, natural resource governance, and environmental protection. This article investigates DSM's guiding concepts, technological underpinnings, practical applications in soil health, current constraints, and prospective future paths. DSM, with its combination of big data, open platforms, and participatory research, has the potential to alter sustainable soil management and climate-resilient farming systems.

Keywords: digital soil mapping, soil fertility, soil quality assessment, remote sensing, machine learning, GIS and geostatistics.

Introduction

Soil is the foundation of agricultural production, water control, biodiversity conservation, and carbon storage. Despite this, soils all around the world are quickly degrading as a result of human activities like as intensive farming, erosion, nutrient mining, and pollution. To address this deterioration, accurate and large-scale techniques of soil health monitoring are required. Historically, soils have been assessed by field sampling and laboratory tests. While dependable, these systems require time and resources and fail to provide the spatial information required for modern land management. Digital Soil Mapping (DSM), which was formalized in the late twentieth century, uses predictive models, environmental variables, and modern computation to characterize soil characteristics across landscapes. Since then, DSM has evolved into a key tool for precision agriculture, environmental monitoring, and land-use planning.

Principles of Digital Soil Mapping

DSM is based on the SCORPAN framework (McBratney et al., 2003), which links soil characteristics with environmental variables:

- S (Soil): Observed soil data.
- C (Climate): Rainfall and temperature.

- O (Organisms): vegetative cover, biological activity, and land usage.
- R (Relief): topographic and topographical data.
- P (parent material): lithology and geological variables.
- A (Age): The level of soil development over time.
- N (spatial position): Geographic coordinates.

By combining ground-truth soil data with variables derived from remote sensing, DEMs, and climate datasets, DSM may generate spatially continuous projections of soil conditions at local to global scales.

Technologies for Digital Soil Mapping:

1. Remote Sensing

- Satellite platforms (e.g., Landsat, Sentinel): Record vegetation indices and reflectance associated with soil quality.
- Hyperspectral data may detect soil organic carbon, mineral composition, and salinity.
- Drones and UAVs can provide ultra-high resolution photos for site-specific surveillance.

2. Geographic Information Systems (GIS)

GIS serves as the foundation of DSM, allowing for the integration, geographical analysis, and visualisation of soil and environmental information. It enables scientists to combine soil parameters with climate, vegetation, and land use maps.

3. AI & Machine Learning

Advanced algorithms (Random Forests, Support Vector Machines, and Neural Networks) improve prediction performance by modelling complicated, nonlinear connections between soil and its variables.

4. Big Data & Cloud Platforms

Google Earth Engine and worldwide projects like SoilGrids have democratised access to global, high-resolution soil resources, propelling DSM forward significantly.

5. Geostatistics

Kriging, cokriging, and regression kriging are common interpolation methods for estimating soil parameters between observed sampling locations.

Applications of DSM in Soil Health

1. Monitoring the Soil Organic Carbon (SOC)

DSM enables reliable assessment of SOC stocks across scales, which is critical for both soil fertility and climate change mitigation.

2. Soil Fertility Mapping

DSM creates nutrient distribution maps (N, P, K, and micronutrients), allowing for site-specific fertiliser delivery and avoiding misuse.

3. Land Degradation Assessment

DSM identifies erosion-prone and degraded areas, directing conservation efforts.

4. Climate Change Mitigation

DSM facilitates carbon accounting and soil involvement in climate financing mechanisms by tracking SOC dynamics.

5. Salinity and Sodicity Detection

Remote sensing and prediction models can identify salt-affected soils, which aids in reclamation and irrigation planning.

6. pH and Acidity Mapping

DSM offers pH maps to assist evaluate lime requirements and manage acid soils.

7. Precision agriculture

Farmers may reduce costs and environmental impact by integrating DSM outputs to variable rate technology (VRT) for fertiliser, irrigation, and pesticide use.

Barriers to Implementation

1. Adoption through Farmers

Low digital literacy and awareness restrict widespread adoption. Bridging the gap between high-end models and farmer-friendly recommendations is critical.

2. Data Gaps

Many nations have sparse sample networks, which limit DSM accuracy; harmonization between data sources is another issue.

3. Predictive Uncertainty

The dependability of DSM results is strongly dependent on the quality of the variables and models. Transferability across areas is restricted.

4. Technical and financial constraints.

High-resolution datasets and computing resources can be expensive, and expertise in soil informatics is limited in underdeveloped nations.

Future Directions

1. AI and deep learning: Improving model accuracy and automating soil health evaluations.

2. IoT and Sensors: Use low-cost soil sensors linked to DSM for real-time monitoring.

3. Open-Source Platforms: Extending datasets such as GlobalSoilMap to make soil data more widely available.

4. Policy Applications: Using DSM results to make evidence-based decisions in agriculture, land management, and climate action.

5. Citizen Science: Farmer-led data collecting using mobile applications to enhance coverage.

Conclusion

Digital Soil Mapping offers a paradigm shift in soil health assessment, providing precise, scalable, and data-driven insights much beyond what traditional surveys can deliver. DSM promotes sustainable soil management, precision farming, and climate resilience through the integration of GIS, remote sensing, geostatistics, AI, and cloud computing. Despite constraints like as data shortages, forecast uncertainty, and acceptance issues, DSM is quickly becoming a vital tool in contemporary agriculture. Its future lies in integration with IoT, AI, open platforms, and participatory tools, which will allow farmers, academics, and policymakers to fully realise its promise. In an era of climate stress and food security issues, DSM provides a pathway to resilient soils and sustainable agroecosystems.

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