



Dsm: The Digital Revolution in Soil Mapping

Parismita Dutta^{1*},
B S Bhole²,
Talwinder Singh¹,
Nikita¹ and Ankit Rana¹

¹Department of Soil Science,
Punjab Agricultural University,
Ludhiana

² RRS Ballowal Saunkhri,
Punjab Agricultural University,
Ludhiana



*Corresponding Author
Parismita Dutta*

Article History

Received: 1.11.2025

Revised: 5.11.2025

Accepted: 10.11.2025

This article is published under the
terms of the [Creative Commons
Attribution License 4.0](#).

INTRODUCTION

With the tremendous growth in computer and information technology, large volumes of data and tools have been made possible in every sector of endeavour. Soil science is no exception. Regional, national, continental, and global databases are constantly being created in the field of soil research. The challenge of comprehending these massive data sets has prompted the creation of new statistical methods and given rise to new fields like data mining, remote sensing, and machine learning. Furthermore, the growing capabilities of instruments like GPS, remote and proximal sensors, geographic information systems (GIS), and data sources like digital elevation models (DEMs) have suggested new directions in soil science studies.

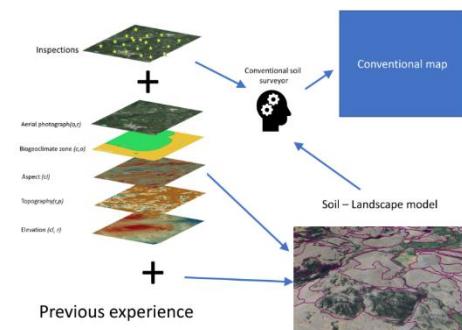
As a result, researchers throughout the world are looking into the potential of using the modern spanners and screwdrivers of science and information technology to replace the old techniques of soil survey. So begins the creation of digitized soil property and class maps. Digital soil mapping (DSM) has revolutionized the field of soil science by fusing conventional soil survey methods with cutting-edge computer technologies.

Digital soil mapping is often described as “predictive” or “pedometric” soil mapping because it predicts soil properties across landscapes from a limited set of measurements. Instead of mapping only boundaries between soil units, DSM represents soil as a continuous surface, where every pixel in a grid carries information such as texture, organic carbon, pH, or nutrient levels. In practice, DSM combines three ingredients: field and laboratory observations, environmental data (like topography, climate, vegetation indices, and parent material), and quantitative models that link the two. This approach allows scientists to translate what is known at sampled points into wall-to-wall maps at resolutions useful for farmers, planners, and researchers. Overall, Digital Soil mapping (DSM) has been recognized as the best approach in delivering spatial estimation of soil properties and associated prediction uncertainties.

From traditional to digital mapping

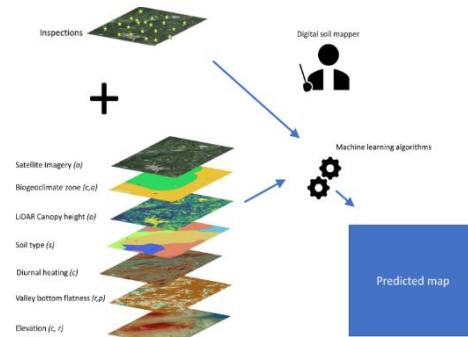
Traditional soil mapping relied heavily on expert field surveyors who drew boundaries between soil types based on visual observations, simple

measurements, and landscape knowledge. These maps were extremely valuable but could be generalized, time-consuming to produce, and difficult to update frequently over large regions.



Digital soil mapping does not replace expert knowledge but complements it with much larger datasets and computational power. By working with gridded data and automated models, DSM

can handle far more information (for example, multiple satellite time series and detailed elevation models) than would be practical with purely manual methods.



How digital soil mapping works

The technical heart of DSM is a suite of statistical and machine-learning models that relate soil measurements to “covariates” such as elevation, slope, rainfall, temperature, and satellite-derived indices of vegetation or moisture. Common tools include regression models, geostatistics (like kriging and variograms), and algorithms such as random forests, neural networks, and other machine-learning methods.

The workflow usually follows a consistent pattern: collect soil samples at selected locations, analyse them in the lab, gather spatial covariate layers in a geographic information system (GIS), and then train models to predict soil properties across all pixels in the area. The output is a stack of raster layers, each representing a soil variable and often accompanied by uncertainty estimates that show how confident the model is in different places.

Key technologies behind DSM

Several technologies have made DSM possible and increasingly popular in recent years. These include:

- **Remote sensing:** Satellite and airborne imagery provide repeated measurements of vegetation, surface moisture, and land cover, which are used as proxies for underlying soil conditions.
- **Geographic information systems (GIS):** GIS platforms store, integrate, and analyse spatial data layers, enabling soil predictions to be generated and visualized over entire regions.
- **Digital elevation models (DEMs):** Terrain attributes derived from DEMs—such as slope, curvature, and wetness indices—capture how water and materials move across landscapes and strongly influence soil formation.

- **Proximal and laboratory sensors:** Instruments such as portable X-ray fluorescence (PXRF) and spectroscopy devices speed up the measurement of soil properties in the field and lab, feeding richer data into DSM models.
- **Machine learning and deep learning:** Advanced algorithms can detect complex, non-linear relationships between soil and environment, improving prediction accuracy in many cases.

These tools together allow DSM projects to cover anything from a single farm to entire countries at resolutions tailored to the decision being made.

Need for Digital Soil Mapping in natural resource management

Farmers, land use planners, researchers, and policy makers are the major stakeholders of digital soil maps. DSM-generated maps can be used as a baseline layer for soil properties (texture, SOC, pH) without sampling every field, useful for large-scale assessments or modelling soil-landscape relationships. Especially for heterogeneous terrain (plains vs hills, irrigated vs rainfed zones, different agroclimatic zones), DSM helps to highlight spatial variability, enabling targeted soil sampling, site-specific recommendations, soil health monitoring etc. Integration of DSM outputs with other environmental, land-use, crop and climate related data can support land use planning, crop suitability analysis, carbon sequestration & climate-resilience assessments, soil, and water degradation risk mapping. For example, soil carbon studies are becoming increasingly crucial for environmental reasons to understand not just the amount of carbon stored at a given time but also how it evolves or trends over time. Because digital elevation data and other DEM features are widely available, mapping soil organic carbon (SOC) at a greater resolution is possible.

Thus, for a researcher, DSM offers a pathway to scale up soil-quality assessment, combining remote sensing, GIS and limited ground truthing, which might reduce effort and increase coverage.

The Future: Smarter, Faster, Deeper

With the rise of AI, drones, IoT sensors, and big data, DSM is becoming more advanced. AI can extract complex non-linear patterns, improving prediction accuracy for soil nutrients, texture, organic carbon, salinity, and moisture. Soil sensors placed in fields can supply

continuous data on moisture, pH, EC, and nutrient fluxes. Combining these data streams with DSM models will refine predictions and support precision agriculture. With increasing availability of high-temporal remote sensing data (e.g., Sentinel-2, PlanetScope), DSM will shift toward near real-time monitoring. Soon, farmers may receive real-time soil maps on their phones. This will help track seasonal soil dynamics such as moisture, temperature, and crop residue patterns. Researchers may predict soil changes years into the future.

Challenges in Digital Soil Mapping

There are several limitations which restricts the application of DSM in soil science studies. Many regions, especially in developing countries, lack dense and reliable soil sampling networks. Sparse data result in biased or uncertain predictions. Variability in Remote Sensing Data due to cloud cover, atmospheric correction issues, and varying spatial/temporal resolution can also limit reliable extraction of soil signals, especially under vegetation cover. Sometimes DSM models built in one region often fail in another due to different soil-forming factors. Thus, lack of standardized modelling frameworks may serve as another limitation. In addition, processing big datasets and running machine learning models requires strong computational infrastructure, which may not be available everywhere. Lastly, DSM demands knowledge of soil science, geoinformatics, statistics, remote sensing, and coding. Many institutions still lack training programs that combine these disciplines.

CONCLUSION

Digital Soil Mapping is reshaping soil science by making soil information more accessible, accurate, and actionable. While the future is promising, with advancements in AI, cloud computing, IoT, and global datasets, the field still faces barriers related to data availability, model uncertainty, and interdisciplinary capacity. Addressing these challenges will be crucial for achieving sustainable agriculture, climate resilience, and informed land management.

REFERENCES

Adeniyi O. D., Bature H. and Mearker M. 2024. A Systematic Review on Digital Soil Mapping Approaches in Lowland Areas. *Land* 13, 379.

Arrouays D., Grundy M. G., Hartemink A. E., Hempel J. W., Heuvelink G. B. M. S., Young Hong Y. S., Lagacherie P., Lelyk G., McBratney A. B., McKenzie N. J., MdL M. S., Minasny B., Montanarella L., Odeh I. O., Sanchez P. A., Thompson J. A. and Zhang G. L. 2014. Chapter three – Globalsoilmap: toward a fine-resolution global grid of soil properties. *Adv. Agron.* 93–134.

Biological Science Center. Digital Soil Mapping: New Tools for Modern Land Management Decisions.

Dharumaranjan S., Hegde R., Janani N. and Singh S. K. 2019. The need for digital soil mapping in India. *Geoderma Regional* 15, e00204.

Wadoux A. M. C., Minasny B., McBratney A. B. 2020. Machine Learning for digital soil mapping: Applications, challenges and suggested solutions. *Earth-Science Rev.* 210, 103359.