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Editorial

Digital Soil Mapping for Agri-Environmental Management and Sustainability

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Abstract

This Special Issue, entitled "Digital Soil Mapping for Agri-Environmental Management and Sustainability", gathers nine studies from around the globe that illustrate how digital soil mapping (DSM) is being applied to support agri-environmental management and sustainability. Field- and farm-scale studies are emphasized, where informed decisions are essential for efficient day-to-day management and profitability. The articles highlight the integration of remote/proximal sensing, along with modern machine learning techniques, to produce high-resolution soil maps, soil fertility and nutrient management zoning, and to monitor salinity and soil moisture to inform irrigation and land management. Another key focus is improving sampling strategies and assessing prediction uncertainty and model interpretability. This collection sets future DSM priorities, including cost-effective sampling, robust uncertainty assessments, and reliable cost–benefit and risk assessment approaches that link map accuracy/uncertainty to management outcomes and economic performance.

1. Introduction

Since its introduction in the 1990s, digital soil mapping (DSM) has evolved into a mature soil science discipline and has become a major tool for soil surveyors and mappers globally. However, significant challenges remain, particularly in improving the DSM toolsets and aligning DSM products with user needs. Addressing these challenges involves incorporating cost-effective sampling, applying machine learning and deep learning algorithms to enable reliable predictions and robust uncertainty assessments, and enhancing the interpretation and utilization of DSM products. These advancements can support sustainable land management at the farm level and inform policy decisions at the regional and national levels. Furthermore, new challenges are emerging, especially in relating the uncertainty in mapping soil functions and interpretations to their management and beneficial uses, requiring robust cost–benefit and risk assessment and analysis.

The purpose of this Special Issue entitled "Digital Soil Mapping for Agri-environmental Management and Sustainability" is to describe the applicability of DSM in supporting management decisions at various scales, with an emphasis on field and farm levels, where the day-to-day decisions are made. The topics featured in this Special Issue focus on the use of DSM and remote sensing for precision agriculture, uncertainty assessments, and

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cost–benefit and risk assessment analysis applications. Other topics include sampling approaches for DSM, interpreting maps to create soil functional management units, and using novel technologies such as UAVs for high-resolution soil mapping. This Editorial highlights the topics addressed by the papers while pointing out a few shortcomings that, although not fully addressed, should be the focus of future DSM research.

2. Overview of the Papers in This Special Issue

This Special Issue contains nine papers grouped by major topics. Almost all the researchers used DSM approaches to collect and analyze data for various uses from study sites in Africa, Asia, Europe, and North America. More than 50 authors representing research institutions and universities from the USA, the United Kingdom, China, Russia, India, Portugal, Bangladesh, Egypt, Saudi Arabia, South Africa, and Tunisia contributed to this Special Issue.

Synergetic Use of Bare Soil Composite Imagery and Multitemporal Vegetation Remote Sensing for Soil Mapping (A Case Study from Samara Region's Upland) Chinilin et al. (2024) aimed to develop a detailed soil class probability map for a research center by integrating synthetic composite imagery of bare soil with long-term remote sensing vegetation data and soil survey data using logistic regression (LR) and to assess the accuracy of the method based on leave-one-out cross-validation (List of Contributions, 1). With an emphasis on the management of soils for preventing land degradation, the authors identified lithological heterogeneity and contrasting topography to infer the indurated impermeable horizons that affect soil functions such as root support and development, plant growth, and crop production.

Dash et al. (2024) focused on regional soil fertility efforts while addressing one of the most important issues in DSM—the optimum sampling density (List of Contributions, 2). The authors show that sampling density affects prediction accuracy, depending on the soil properties, and that the rate of increase in prediction accuracy is not proportional to the increase in sampling density.

Also focusing on soil fertility, Swafo and Dlamini (2023) used regression kriging to generate high-resolutions maps of fertility-related soil properties and develop soil management zones to support precision agriculture on a small farm in South Africa (List of Contributions, 3).

Machine learning (ML), a part of artificial intelligence development, has gained widespread use by the DSM community. The next three papers focus on ML approaches with multiple applications.

The study "Using Automated Machine Learning for Spatial Prediction—The Heshan Soil Subgroups Case Study" by Liang et al. (2024) addressed the use of an automated ML (AutoML) approach for determining the appropriate ML method from multiple alternatives (List of Contributions, 4). The authors found AutoML to be effective for producing accurate maps of soil classes when multiple ML models are available, thus reducing the dependence on user expertise. However, they caution that more robust frameworks that incorporate methods such as spatial statistics should be developed rather than focusing solely on ML.

Salas and Kumaran (2023) developed a new bare soil index based on high-spectral-resolution AVIRIS-NG and Sentinel-2 multispectral images using ensemble ML consisting of random forest (RF) and support vector machine (SVM) (List of Contributions, 5). The approach generated high-resolution (~10 m) maps of bare soil with accuracies over 90%, which are needed for better land-use planning against urban expansion in high-population-density areas.

Kumaraperumal et al. (2022) achieved a complex DSM undertaking, where six quantitative ML and six qualitative ML algorithms were tested for predicting soil properties

and classes at a 30 m grid size (List of Contributions, 6). In addition, different sampling designs and densities were tested. The prediction accuracy results demonstrate the need for using multiple methods, depending on the property type (quantitative vs. qualitative) and due to differences in assumptions from each method. The produced high-resolution maps will support farmers and policymakers in adopting precision agriculture practices at the farm level.

Using a random forest (RF) algorithm, Jena et al. (2023) increased the accuracy of predicted maps for sand, silt, and clay fractions, which are important physical properties for determining available water holding capacity and irrigation scheduling (List of Contributions, 7). The authors generated maps using standard depth increments (0–5, 5–15, 30–60, 60–100, and 100–200 cm) based on the GlobalSoilMap initiative (Arrouays et al., 2018), contributing to this important international initiative of the soil science community [1]. Monitoring soil salinity is important, especially in dry areas at risk of salinization.

Eltarabily et al. (2024) used apparent electric conductivity (EC_a) measurements with the low-frequency electromagnetic induction (EMI) technique at specified locations in an agricultural field to develop spatial–temporal maps of salinity to support irrigation practices that help farmers save water and income (List of Contributions, 8). Accurate field soil moisture measurements are important for determining water demands and irrigation scheduling, yet soil moisture is only measured at a few locations, which is expensive and logistically challenging.

Winzeler et al. (2022) developed an effective and inexpensive method for mapping soil moisture at high resolution (List of Contributions, 9). Multiple flow-based algorithms for calculating the topographic wetness index (TWI) from available digital elevation models at different spatial resolutions were tested against the measured volumetric water content from sensors in the field at specified locations. The correlations between the TWI and measured soil moisture were more sensitive to spatial patterns than to the algorithm used to calculate TWI, and during transitions from wet to dry and vice versa, thus increasing the usefulness of the TWI, especially for topographically responsive areas. The TWI, which is easy to derive from available DEM worldwide, could guide management decisions such as schedules for fertilizer application, planting, and machinery use, especially in rainfed agriculture on sloping areas around the world.

3. Key Gaps and Future Priorities

This Special Issue demonstrates a persistent gap between DSM outputs and their real-world applications. None of the nine articles explicitly addressed the cost–benefit analysis of DSM products, underscoring the difficulty of linking DSM accuracy metrics to economic performance measures. Future work should therefore evaluate DSM as a decision support system, linking maps and uncertainty to practical outcomes such as input savings, yield stability, water- and nutrient-use efficiency, or reduced land degradation. Considering map uncertainty as a quantitative diagnostic for prioritizing resampling efforts can substantially enhance the cost-efficiency of data acquisition and model refinement. Additionally, using uncertainty information to guide precision conservation practices and develop spatially explicit, variable-rate management prescriptions strengthens the reliability of zoning decisions and supports continuous soil monitoring to advance agro-environmental sustainability.

Another set of gaps relates to operational DSM and methodological robustness, as DSM products meet user needs at the farm scale while also informing border policy decisions. Farmers and decision makers need maps that can answer their questions and are easily explainable, spatially explicit, and maintainable over time, not just statistically robust in a single study area. Although ML/automated ML approaches are valuable in

advancing DSM further, this Editorial also cautions against relying too heavily on statistical relationships alone and argues for more robust frameworks that incorporate process-based information, expert knowledge, and strong interpretability to ensure system credibility, model transferability, and successful implementation.

4. Conclusions

This Special Issue, "Digital Soil Mapping for Agri-Environmental Management and Sustainability", gathers studies on multiple DSM approaches that uses advanced ML, and remote/proximal sensing for precision agriculture and other agri-environmental applications. Most of the papers addressed various DSM challenges related to Pedometrics applications, as articulated by Wadoux et al. (2021) [2]. However, none of the studies addressed the challenge of risk assessment and cost–benefit analysis of DSM products for farm management decisions, particularly emphasizing the difficulty of linking prediction accuracy metrics from DSM with metrics of economic analysis and performance. Future DSM research would benefit from decision-focused evaluations that quantify the economic and environmental benefits of targeted sampling, and from reliable, more accurate outputs that guide precision prescriptions, which highlight future DSM needs and priorities.

Conflicts of Interest: The authors declare no conflict of interest.

List of Contributions

1. Chinilin, A.; Lozbenev, N.; Shilov, P.; Fil, P.; Levchenko, E.; Kozlov, D. Synergetic Use of Bare Soil Composite Imagery and Multitemporal Vegetation Remote Sensing for Soil Mapping (A Case Study from Samara Region's Upland). *Land* **2024**, *13*, 2229. https://doi.org/10.3390/land13122229.
2. Dash, P.; Miller, B.; Panigrahi, N.; Mishra, A. Exploring the Effect of Sampling Density on Spatial Prediction with Spatial Interpolation of Multiple Soil Nutrients at a Regional Scale. *Land* **2024**, *13*, 1615. https://doi.org/10.3390/land13101615.
3. Swafo, S.; Dlamini, P. Utilisation of Intrinsic and Extrinsic Soil Information to Derive Soil Nutrient Management Zones for Banana Production in a Smallholder Farm. *Land* **2023**, *12*, 1651. https://doi.org/10.3390/land12091651.
4. Liang, P.; Qin, C.; Zhu, A. Using Automated Machine Learning for Spatial Prediction—The Heshan Soil Subgroups Case Study. *Land* **2024**, *13*, 551. https://doi.org/10.3390/land13040551.
5. Salas, E.; Kumaran, S. Hyperspectral Bare Soil Index (HBSI): Mapping Soil Using an Ensemble of Spectral Indices in Machine Learning Environment. *Land* **2023**, *12*, 1375. https://doi.org/10.3390/land12071375.
6. Kumaraperumal, R.; Pazhanivelan, S.; Geethalakshmi, V.; Nivas Raj, M.; Muthumanickam, D.; Kaliaperumal, R.; Shankar, V.; Nair, A.; Yadav, M.; Tarun Kshatriya, T. Comparison of Machine Learning-Based Prediction of Qualitative and Quantitative Digital Soil-Mapping Approaches for Eastern Districts of Tamil Nadu, India. *Land* **2022**, *11*, 2279. https://doi.org/10.3390/land11122279.
7. Jena, R.; Moharana, P.; Dharumarajan, S.; Sharma, G.; Ray, P.; Deb Roy, P.; Ghosh, D.; Das, B.; Alsuhaibani, A.; Gaber, A.; Hossain, A. Spatial Prediction of Soil Particle-Size Fractions Using Digital Soil Mapping in the North Eastern Region of India. *Land* **2023**, *12*, 1295. https://doi.org/10.3390/land12071295.
8. Eltarabily, M.; Amer, A.; Farzamian, M.; Bouksila, F.; Elkiki, M.; Selim, T. Time-Lapse Electromagnetic Conductivity Imaging for Soil Salinity Monitoring in Salt-Affected Agricultural Regions. *Land* **2024**, *13*, 225. https://doi.org/10.3390/land13020225.
9. Winzeler, H.; Owens, P.; Read, Q.; Libohova, Z.; Ashworth, A.; Sauer, T. Topographic Wetness Index as a Proxy for Soil Moisture in a Hillslope Catena: Flow Algorithms and Map Generalization. *Land* **2022**, *11*, 2018. https://doi.org/10.3390/land11112018.

References

1. Arrouays, D.; Savin, I.Y.; Leenaars, J.G.B.; McBratney, A.B. (Eds.) *GlobalSoilMap. Digital Soil Mapping from Country to Globe*; Taylor & Francis CRC Press: London, UK, 2018; 174 p.
2. Wadoux, A.M.J.-C.; Heuvelink, G.B.M.; Lark, R.M.; Lagacherie, P.; Bouma, J.; Mulder, V.L.; Libohova, Z.; Yang, L.; McBratney, A.B. Ten challenges for the future of pedometrics. *Geoderma* **2021**, *401*, 115155. [CrossRef]

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