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Digital Soil Mapping: Challenges and Future Prospects

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Abstract

Digital Soil Mapping (DSM) has revolutionized the field of soil science by integrating advanced statistical techniques, environmental data, and remote sensing technologies to create high-resolution soil maps. Unlike traditional soil mapping, which relies on qualitative estimates and is labor-intensive, DSM provides a more efficient and reproducible approach to soil characterization. This paper explores the advancements, applications, and challenges of DSM, highlighting its role in precision agriculture, environment management, and land-use planning. To accomplish these objectives, a narrative review approach was employed, facilitating a comprehensive exploration of the topic through the collection, summarization, and synthesis of findings from previous research. Previous research has demonstrated that Mapping DSM has significantly enhanced the accuracy and accessibility of soil data. However, several challenges persist, including data availability, model selection, and uncertainty quantification. The future trajectory of DSM is closely dependent on technological advancements, particularly in machine learning, big data analytics, and real-time soil monitoring. Overcoming these challenges requires a multidisciplinary approach involving interdisciplinary collaboration, policy support, and the development of open-source tools. These findings underscore the need for continued investment in innovative technologies and collaborative frameworks to maximize DSM’s potential in sustainable land management and agricultural decision-making.

Key words: Agriculture, Environmental covariate, Machine learning, Remote sensing, Soil properties

نقشه برداری دیجیتالی خاک: چالش ها و چشم اندازهای آینده

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خلاصه

نقشه‌برداری دیجیتلی خاک (Digital Soil Mapping) با – توحید تخنیک های احصائیوی پیشرفته، معلومات محیطی و تکنالوژی سنجش از راه دور (Remote sensing)، جهت تهیه نقشه های خاک با وضوح بالا انقلابی در خاکشناسی ایجاد کرده است. برخلاف نقشه‌برداری معمولی خاک که متکی به تخمین های کیفی بوده و نیازمند نیروی بشری زیاد است، نقشه‌برداری دیجیتلی خاک (DSM) روش کارآمدتر و قابل تکرار برای شناسایی خصوصیات خاک ارائه می‌دهد. پاراگراف جدید این مطالعه به بررسی پیشرفت‌ها، کاربردها و چالش‌های نقشه کشی دیجیتلی پرداخته و نقش آن را در زراعت دقیق، مدیریت محیط‌زیست و پلانگذاری استفاده زمین برجسته می‌سازد. برای دستیابی به این اهداف، از روش مروری روایتی استفاده شده که با جمع آوری، خلاصه‌سازی و ترکیب یافته‌های تحقیقات قبلی، امکان

بررسی جامع موضوع را فراهم می‌سازد. تحقیقات قبلی نشان داده‌اند که نقشه‌برداری دیجیتلی خاک دقت و قابل دسترسی بودن معلومات خاک را به‌طور چشمگیری افزایش داده است. با این حال، چالش‌های متعددی چون دسترسی به معلومات، انتخاب مودل مناسب و عدم اطمینان در کمی سازی موجود است. مسیر آینده نقشه‌برداری دیجیتلی خاک متکی به پیشرفت‌های تکنالوژی، بخصوص در زمینه یادگیری ماشین (machine learning)، تحلیل دینای بزرگ و نظارت بی درنگ بر وضعیت خاک (real-time soil monitoring) می باشد. غلبه بر این چالش‌ها نیازمند رویکردی چند جانبه بوده که همکاری های چند جانبه، حمایت پالیسی و توسعه وسایل قابل دسترس (open-source tools) را در بر می‌گیرد. این یافته‌ها بر ضرورت سرمایه‌گذاری مستمر در تکنالوژی های نوآورانه و چارچوب‌های همکاری مشترک تأکید دارند تا بتوان از ظرفیت کامل نقشه‌برداری دیجیتلی خاک (DSM) در مدیریت پایدار زمین و تصمیم‌گیری‌های زراعتی بهره‌برداری کرد.

کلیمات کلیدی: زراعت، متغیرهای محیطی، یادگیری ماشین، سنجش از راه دور، مشخصات خاک

Introduction

Soil is essential for both human and environmental health, playing a vital role in ecological processes. The demand for high-resolution quantitative soil data is increasing in various sectors, including agriculture, forestry, mining, land reclamation, and environmental science. To meet this demand, soil scientists are developing advanced mapping techniques that offer more precise and comprehensive soil information. By integrating soil observations with models of soil-landscape relationships, soil scientists analyze spatial variations in soil (Nelson, 2021).

Soil mapping involves compiling and distributing this information for broader applications. Traditional soil mapping depends on mental models and generates sharply defined map units with qualitative accuracy and uncertainty estimates. This approach is time-consuming, resource-intensive, and lacks reproducibility and the ability to be updated. To overcome these limitations, Digital Soil Mapping (DSM) has emerged as an innovative method that combines spatial data, environmental covariates, and statistical models to predict soil properties and classifications across various landscapes (Lagacherie and McBratney, 2008). Advances in geographic information systems (GIS), remote sensing, and computer processing have made soil mapping more quantitative (Nelson, 2021).

The main goal of DSM is to create spatial soil information systems (SSINFOS) that help users make informed decisions on agricultural and environmental matters (McBratney et al., 2003). DSM has transformed the way soil information is represented and understood. By utilizing advanced statistical techniques and integrating extensive environmental data, DSM facilitates the creation of detailed gridded soil prediction maps that can be updated dynamically as new data becomes available (Nelson, 2021). This method connects soil properties to environmental factors such as climate, topography, vegetation, and land use, greatly enhancing the accuracy of soil maps for applications in agriculture, ecological studies, and beyond (McBratney et al., 2003).

A key application of DSM Is In pre"Isio' agriculture, where It has been successfully used to predict soil properties, offering valuable insights for maximizing crop yields while reducing environmental impacts. For instance, DSM has been applied in regional precision agriculture, showcasing its ability to provide detailed soil information that promotes sustainable farming practices. The incorporation of remote sensing data, including satellite imagery and airborne sensors, has further improved DSM by delivering high-resolution, large-scale spatial information for soil mapping (Söderström et al., 2016).

Digital Soil Mapping (DSM) improves soil-mapping accuracy by integrating existing soil data with environmental variables. This method combines historical soil information with detailed environmental factors, allowing for the creation of precise soil maps, particularly in regions with limited or outdated field data. By utilizing legacy soil data and extensive spatial environmental data, DSM techniques establish quantitative relationships between soil properties and environmental covariates, enabling the production of accurate soil maps (Nussbaum et al., 2018). This integration aids in the creation of detailed soil maps, which are particularly useful in areas where traditional soil surveys are limited or not feasible. Additionally, DSM techniques like machine learning and geostatistics have played a crucial role in reducing uncertainty and improving the accuracy of soil property predictions (Padarian et al., 2019).

Several drawbacks of digital methods are evident: firstly, and most significantly, their soil geography theory relies on correlating observations with environmental covariates that are meant to represent soil-forming factors. This is much less comprehensive than a soil-geomorphic landscape analysis conducted by an experienced surveyor. If these covariates do not fully represent the factors, dissimilar soils may be grouped together. Some covariates are either absent or too coarse to be useful, particularly surficial lithology. Furthermore, the soil-forming factor of time, or the age of the landform, is difficult to represent through covariates, as it requires geomorphic analysis and estimates of past climates. Secondly, these models can only function with the profile observations they are provided, which rarely cover the entire soil-geographic space because most field sampling plans were not designed to support DSM. In fact, such plans have only recently been developed and are still in the process of being refined (Rossiter, 2021).

Looking forward, the future of DSM is closely tied to advancements in machine learning, big data analytics, and real-time soil monitoring technologies. The integration of deep learning techniques is expected to improve the predictive accuracy of DSM models, while real-time soil sensing technologies have the potential to provide dynamic soil data, allowing for more informed decision-making in land management (Padarian et al., 2019).

This article provides an in-depth analysis of the challenges and prospects of DSM. It discusses key challenges such as data quality and availability, model selection and complexity, the incorporation of pedological knowledge, uncertainty quantification, and the need for computational resources. Additionally, the article explores future opportunities, including advancements in remote sensing, the integration of machine learning and process-based models, the potential of crowdsourcing and citizen science, the development of open-source tools, and the importance of policy support and funding. By addressing these challenges and highlighting emerging prospects, this review underscores DSM's potential to transform soil science and enhance sustainable agricultural practices globally.

Methodology

This narrative review was conducted to examine the current challenges, and future prospects of Digital Soil Mapping (DSM). The review is based on an extensive analysis of peer-reviewed journal articles, books, and relevant theses from reputable sources. The literature was selected from various academic databases and publishing platforms. Additionally, a master's thesis on predictive DSM by Nelson, (2021) was reviewed to incorporate insights from prior academic research. The selection process involved identifying key publications related to DSM, focusing on studies addressing data quality, model selection, pedological knowledge integration, uncertainty quantification, and computational resources. Furthermore, literature exploring advancements in remote sensing, machine learning integration, crowdsourcing, open-source tools, and policy support was analyzed to provide a comprehensive perspective on future developments. Relevant keywords such as Digital Soil Mapping, soil prediction models, remote sensing in soil mapping, machine learning in soil science, and "uncertainty in soil mapping were used to search for pertinent studies. Preference was given to recent publications (within the last 10 years) to ensure that the review reflects the most up-to-date findings and technological advancements in DSM. Older but foundational studies were also included to provide historical context.

By synthesizing insights from multiple sources, this review aims to present a structured analysis of the challenges and opportunities in DSM, offering a foundation for further research and application in the field.

Results

Digital Soil Mapping (DSM) combines soil observations with environmental factors through numerical models, providing a more precise and efficient method than conventional approaches. Nevertheless, DSM still encounters challenges, including issues related to data accessibility, model selection, and the quantification of uncertainty. These challenges need to be overcome to fully realize its potential (McBratney et al., 2003).

Challenges and Future Prospects in Digital Soil Mapping

This article presents a comprehensive analysis of the challenges and prospects of digital soil mapping through thematic analysis. It critically examines key obstacles and potential outcomes, providing insights into current limitations and opportunities for further development.

Present Challenges

- **(i) Data Availability and Quality:** The effectiveness of DSM is highly dependent on the availability and quality of data. In numerous areas, particularly in developing nations, there is a lack of high-resolution soil data and environmental covariates, which impedes the creation of accurate digital soil maps. Furthermore, variations in data collection techniques and standards can introduce inaccuracies in DSM results (Chen et al., 2022).
- **(ii) Model Selection and Complexity*:*** Choosing the right predictive models is essential for DSM. Although machine learning algorithms are commonly used, selecting a model that strikes the right balance between complexity and interpretability presents challenges. Complex models may perform excellently on training data but struggle with new data due to overfitting. On the other hand, simpler models might fail to capture the complex interactions between soil properties and environmental factors (Wadoux et al., 2020).
- **(iii) Uncertainty Quantification:** Quantifying and communicating the uncertainty inherent in DSM outputs is essential for informed decision-making. However, many DSM studies fail to properly address uncertainty, which can result in overconfidence in the findings. Establishing standardized approaches for uncertainty assessment and effectively communicating this information to end-users continues to be a major challenge (Chen et al., 2022).
- **(iv) Incorporation of Pedological Knowledge:** Incorporating traditional pedological knowledge into DSM continues to be a challenge. Many DSM methods rely predominantly on statistical correlations, which may neglect established principles of soil science. It is crucial to bridge the gap between data-driven models and expert knowledge to create meaningful and accurate soil maps (Wadoux et al., 2020).
- **(v) Computational Resources:** DSM processes, particularly those involving large datasets and complex models, demand significant computational resources. Limited access to high-performance computing infrastructure can pose a challenge for researchers and practitioners, especially in resource-limited environments (Chen et al., 2022).
- **(vi) Low Sampling Density and Spatial Clustering:** Soil observations are often sparse and unevenly distributed, with samples clustered in accessible areas such as near roads or research stations. This biased sampling reduces the representativeness of training data and limits the accuracy of predictions, especially in remote regions (Hengl et al., 2015).
- **(vii) Scale and Resolution Mismatch:** Mismatches between the scale of environmental covariates (e.g., DEM, satellite images) and the true variability of soil properties can reduce model accuracy. Coarse-resolution data may fail to capture fine-scale soil variation, while very high-resolution data can introduce noise and increase computational demands (Arrouays et al., 2014).

(viii) **Legacy Data Integration:** Incorporating older soil survey data remains difficult due to differences in sampling depth, analytical techniques, and classification systems. Harmonizing these datasets is necessary but often resource-intensive and uncertain, especially when metadata are incomplete (Hengl et al., 2017).

(ix) **Remote Sensing Limitations:** Remote sensing data are widely used as environmental covariates in DSM, yet they face challenges such as cloud cover, atmospheric effects, and vegetation masking. Additionally, optical sensors cannot directly measure subsurface soil properties, limiting their usefulness for certain mapping goals (Mulder et al., 2011).

(x) **Model Transferability Across Regions:** DSM models often perform well in the specific area where they are trained but show limited applicability when transferred to new regions with different soil-forming factors. This lack of generalization reduces the scalability of DSM approaches (Minasny & McBratney, 2016).

Future Prospects

(i) **Advancements in Remote Sensing:** The growing availability of high-resolution remote sensing data presents significant opportunities for DSM. Future sensors with improved spectral and spatial resolutions will deliver more detailed environmental covariates, enhancing the precision of soil property predictions. Moreover, incorporating time-series remote sensing data will capture temporal changes, further refining DSM models (Richer-de-Foeges et al., 2023).

(ii) **Integration of Machine Learning and Process-Based Models:** Integrating machine learning techniques with process-based soil models can capitalize on the strengths of both approaches. While machine learning is effective at detecting patterns in large datasets, process-based models bring a mechanistic understanding of soil processes. This combined approach can enhance prediction accuracy and offer valuable insights into the underlying soil dynamics (Wadoux et al., 2020).

(iii) **Crowdsourcing and Citizen Science:** Involving the public in soil data collection through crowdsourcing initiatives can significantly improve data availability for DSM. Citizen science projects, supported by mobile technologies, can collect soil observations on an unparalleled scale. However, ensuring data quality and establishing protocols for incorporating crowd-sourced data into DSM remain important areas for further research (Thompson et al., 2020).

(iv) **Development of Open-Source Tools:** The development and distribution of open-source DSM tools can make advanced mapping techniques more accessible to a wider audience. These tools can support capacity building, particularly in resource-limited areas, and encourage standardization in DSM practices. Collaborative platforms can also promote knowledge sharing and innovation within the DSM community (Chen et al., 2022).

(v) **Policy Support and Funding:** Gaining policy support and securing funding are essential for the long-term development of DSM initiatives. Advocacy emphasizes the significance of accurate soil data for agriculture, environmental management, and climate change mitigation can help attract investment. Partnerships between government agencies, academic institutions, and international organizations can provide the necessary resources and frameworks to advance DSM (Thompson et al., 2020).

Discussion

Digital Soil Mapping (DSM) has revolutionized the collection, analysis, and application of soil data in various fields such as agriculture, environmental management, and land-use planning. However, its effectiveness depends on addressing key challenges and leveraging technological advancements to enhance accuracy and usability. One major challenge is the availability and quality of soil data, particularly in developing regions where high-resolution datasets are lacking, affecting the reliability of digital soil maps (Arrouays et al., 2014). Advancements in remote sensing and open-source soil databases can help bridge this gap, while citizen science and crowdsourced data offer potential solutions, albeit with concerns about data quality (Richer-de-Foeges et al., 2023).

The choice of predictive models also plays a crucial role, as machine learning algorithms have significantly improved mapping accuracy, but balancing complexity and interpretability remains a challenge. While deep learning techniques could enhance predictive capabilities, their success relies on computational resources and structured training datasets, necessitating a fusion of traditional pedological knowledge with data-driven models for better trust and usability (Wadoux et al., 2020).

Additionally, uncertainty in DSM predictions remains a limitation, as many studies fail to clearly quantify prediction errors, making it difficult for end-users to confidently apply results. Standardizing uncertainty quantification and incorporating probabilistic modeling can address this issue, while visual tools can improve communication of uncertainty to non-experts (McBratney et al., 2003).

The integration of remote sensing and GIS-based approaches is crucial for the future of DSM, with high-resolution satellite imagery from missions like Sentinel and Landsat providing valuable environmental covariates for improved model predictions (Richer-de-Foeges et al., 2023). Combining time-series remote sensing data with DSM can also capture temporal soil changes, enhancing accuracy. Furthermore, government policies and funding play a critical role in advancing DSM applications, with investments in national soil databases and open-source DSM tools democratizing access to high-quality soil information. Strengthening collaboration between researchers, policymakers, and local communities is essential for promoting the effective use of DSM in sustainable land management and precision agriculture (Thompson et al., 2020).

Conclusion

Digital Soil Mapping (DSM) has transformed soil science by providing high-resolution, data-driven solutions to soil mapping challenges. By integrating environmental variables, remote sensing, and advanced computational techniques, DSM has improved soil information accuracy and usability across agriculture, land-use planning, and environment management. However, challenges such as data availability, model selection, and uncertainty quantification remain. Addressing these requires advancements in remote sensing, machine learning, and process-based modeling, alongside stronger collaboration between scientists, policymakers, and local communities. Open-source DSM tools and citizen science initiatives can further enhance data accessibility and applicability. The future of DSM depends on technological innovations, interdisciplinary research, and policy support. As machine learning and big data analytics evolve, DSM models will become more accurate and efficient. Expanding government funding and policy frameworks will ensure broader access to reliable soil information.

By identifying key barriers and opportunities, this research highlights DSM’s potential to revolutionize soil science and contribute to sustainable agriculture, environmental conservation, and effective land management. To maximize its impact, governments should standardize soil data collection, increase investments in remote sensing and capacity-building programs, and promote public-private collaborations. Stakeholders, including farmers and environmental planners, should integrate DSM into decision-making, support citizen science, and invest in geospatial technologies. Future research should focus on refining machine learning models, improving uncertainty quantification, integrating multi-source data, and enhancing long-term soil monitoring. Strengthening these efforts will ensure DSM’s reliability, accessibility, and role in sustainable land and environmental management.

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