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Review on The Digital Soil Mapping: A Polygon to Pixel Approach

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Abstract
DSM plays a crucial role in addressing the challenges posed by soil degradation, land-use change, and global food security. By providing detailed spatial information on soil properties such as texture, organic matter content, pH, and nutrient levels, DSM enables more precise land management decisions. Farmers can optimize crop selection, irrigation, and fertilization practices based on soil maps generated through DSM, leading to improved agricultural productivity and reduced environmental impact. Moreover, DSM supports ecosystem management and conservation efforts by facilitating the identification of areas vulnerable to erosion, desertification, or pollution. Conservationists can use DSM outputs to design targeted interventions for soil restoration and biodiversity conservation. Overall, the integration of DSM into soil science and land management practices offers numerous benefits, including enhanced resource efficiency, improved decision-making, and better resilience to environmental challenges. However, challenges such as data availability, model validation, and uncertainty quantification remain significant hurdles in realizing the full potential of DSM. Addressing these challenges requires interdisciplinary collaboration among soil scientists, geographers, remote sensing specialists, and policymakers to advance the field and harness its potential for sustainable development.

Keywords: Digital soil map, machine learning algorithms, environmental covariates

Introduction
Soil stands as a vital natural asset, serving as the foundation of human agriculture. Civilizations flourish in areas endowed with fertile soil, but falter when proper soil stewardship is neglected. Additionally, soil plays a pivotal role in the biophysical and biogeochemical dynamics of our planet. Across continents, soil acts as a permeable interface facilitating interactions among the biosphere, hydrosphere, lithosphere, and atmosphere. Grasping the spatial distribution and proper handling of soil is imperative for sustaining a thriving society and comprehending the intricate equilibrium of chemical and physical processes crucial for life on Earth. Precise mapping of soil characteristics is indispensable for effective management, both globally and locally.

In recent decades, advancements in technology have opened up significant possibilities for enhancing the production of soil maps (McKensie *et al*., 2000) [27]. Utilizing remote sensing and photogrammetric methods, we can now generate detailed digital representations of the Earth's surface, which, when integrated with digitized paper maps within geographic information systems (GIS), facilitate the efficient characterization and analysis of extensive datasets. The future direction of soil surveying involves harnessing GIS capabilities to model spatial soil variations based on easily mappable environmental factors. Predictive soil mapping (PSM) involves constructing numerical or statistical models that correlate environmental variables with soil properties, which are then applied to geographic databases to generate predictive maps (Franklin, 1995) [11]. PSM aims to achieve three primary objectives: (1) optimizing the collection of soil data by leveraging environmental variables; (2) creating more accurate representations of soil landscape continuity; and (3) incorporating expert knowledge into model development. Furthermore, PSM holds potential for advancing pedology and soil geography by offering insights into soil formation processes.

Conventional soil mapping

Pedologists typically utilize the conceptual framework of the clorpt principle in traditional soil mapping endeavors, incorporating factors of soil formation and landscape relationships. Soil surveying is regarded as a scientific approach and a system of knowledge, integrating these factors and their distribution across the studied region, along with observed soil-landscape dynamics, to create maps. However, translating this knowledge into maps often presents challenges, resulting in maps that serve as structured representations reflecting the mental models of pedologists but may lack detailed spatial information and accuracy assessment. Jenny's clorpt model, on the other hand, offers a quantitative approach, allowing the isolation of individual factors for study, thereby influencing the development of empirical models describing soil formation mathematically. These models, which consider climate, organisms, topography, parent material, and time, facilitate a deeper understanding of soil formation processes. Nevertheless, traditional soil mapping techniques reliant on ground surveys are limited in providing spatial information at desired resolutions, especially on larger scales, and are costly and time-consuming. Hence, there's a need for robust predictive methods and models to estimate soil properties effectively across various scales and locations (Zeraatpisheh *et al*., 2017) [47].

Digital soil mapping

Conventional soil survey methods traditionally rely on the subjective interpretation of soil features by surveyors, using tools such as aerial photographs, Landsat images, and digital elevation models (DEMs) to identify geological, landform, and vegetative characteristics. These interpretations are then validated through on-site field observations. The resulting soil maps, although containing a legend of soil types, often prove challenging to interpret and utilize due to their subjective nature and potential for errors. Recognizing these limitations, there's been a push towards modernizing soil mapping techniques through digital soil mapping. This approach involves the utilization of contemporary quantitative methods, including field and laboratory observations, along with spatial and non-spatial soil inference systems (Fig 1.). Digital soil mapping encompasses various methodologies, such as computer-assisted soil cartography and predictive soil mapping, aimed at creating spatial soil information systems (Lagacherie, 2008) [22]. However, it's important to note that digital soil mapping is not solely about computerized mapping; it involves three core components: input (gathered through field observations and sampling techniques), process (using mathematical or statistical models to relate soil observations with environmental factors), and output (providing spatial soil information with prediction uncertainty). One commonly used method in digital soil mapping is the spatial soil prediction function with autocorrelated error (SSPFe),

$$S_c \text{ or } S_a = f\,(s, c, o, r, p, a, n) + e$$

This equation helps to predict soil classes or attributes based on factors like soil properties, climate, organisms, relief, parent material, age, and spatial position, while accounting for spatially correlated residuals. Unlike other models, such as Jenny's factorial model, the scorpan model focuses on empirical observations for quantitative prediction rather than explaining soil formation factors. Additionally, soil properties can be used as predictive factors, allowing for reciprocal predictions between soil classes and properties. The second most common factor in DSM research is the 's' factor (McBratney *et al*., 2003) [26]. This factor relies on the idea that soils can predict other soils, drawing from various sources: traditional soil surveys, proximal soil sensors, and remote sensors.

Conventional soil survey

These maps contain a wealth of information collected over years of fieldwork by previous soil scientists. Despite the shift to digital methods, traditional maps remain valuable for predicting soil variables within DSM.

Remote sensors

These instruments, mounted on aircraft or satellites, collect data without physical contact. Spectral sensors, particularly multispectral and hyperspectral ones, are commonly used in DSM. For instance, Landsat 8 measures visible and infrared light. Spectral sensors can also be mounted on aircraft or remotely piloted aerial systems for higher resolution data. Using spectral sensors for DSM has challenges, including vegetation obstruction, atmospheric effects, and topographic distortions. Consideration must also be given to the timing and conditions of imagery capture. Additionally, remote sensors typically capture data only from surface soils (5–6 cm). Despite these challenges, spectral measurements under bare-soil conditions have shown good correspondence with soil properties such as mineralogy, texture, organic matter, moisture, and others (Mulder *et al*., 2011) [31].

Proximal soil sensors

Unlike distant sensors which operate from above, proximal sensors are a set of ground-based tools designed for gauging soil traits potentially linked to other soil features. Since they operate at ground level, proximal soil sensors can detail soil diversity more finely than remote data, making them ideal for field-scale soil mapping. Among these sensors, electromagnetic induction (EMI) sensors have been crucial for DSM and precision farming studies (Doolittle and Brevik, 2014) [10]. The EMI sensor measures soil's apparent electrical conductivity (ECa) across various depths. EMI surveys often predict soil attributes like salinity, clay content, and moisture; additionally, secondary traits like soil density and organic carbon can be inferred from ECa readings. EMI sensors are just one kind of proximal sensor-others may include gamma radiometric sensors, ground-penetrating radar, and electrical resistivity sensors.

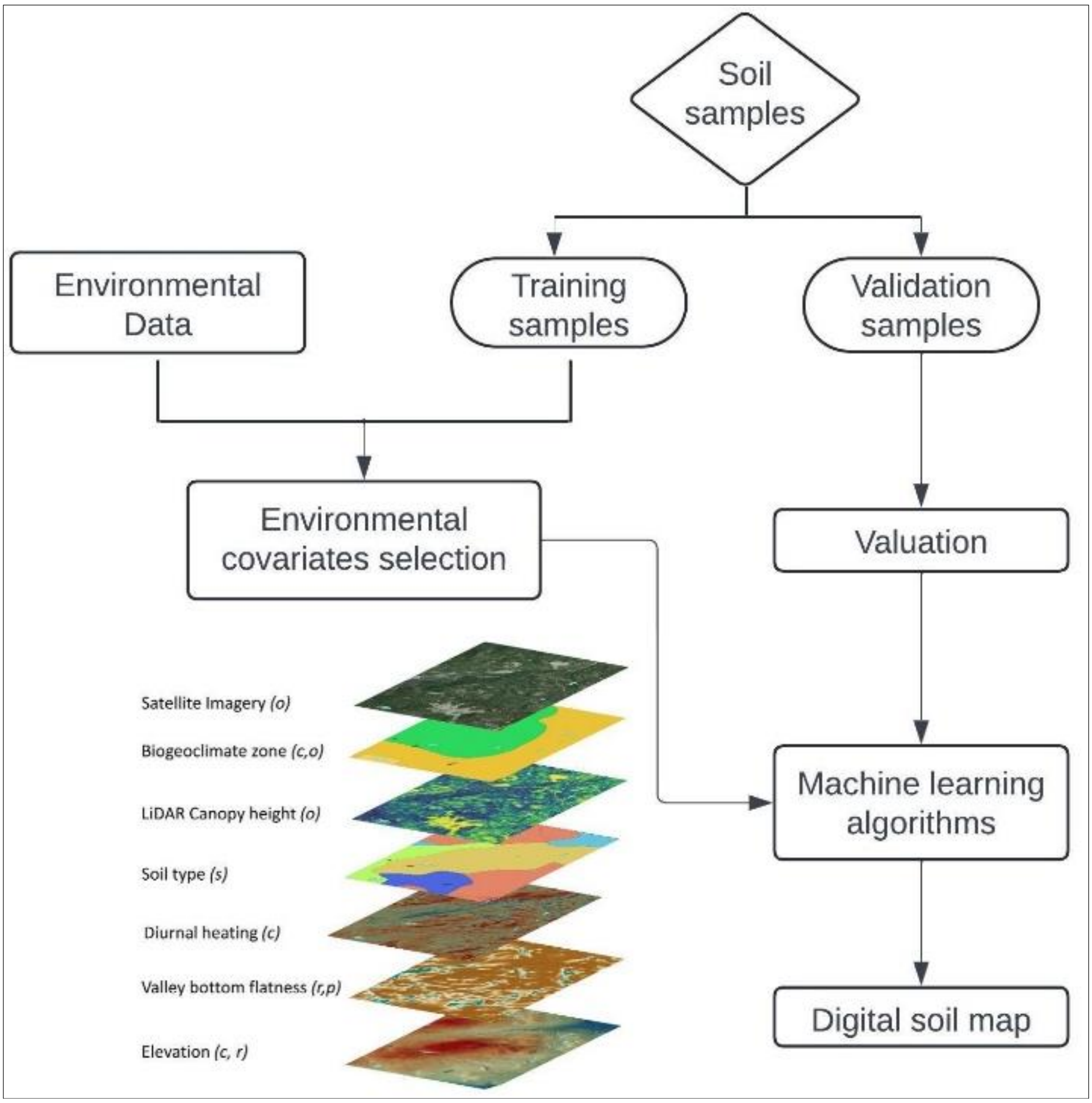

Fig 1: Workflow of Digital soil mapping

Climate (c)

This aspect is among the less utilized scorpan aspects (McBratney *et al*., 2003) [26]. Initially, local weather is greatly shaped by topography, and thus, topographic indices like height and direction could stand in for a weather factor. Nevertheless, as the study area expands to national and global levels, significant climatic trends have been found to significantly affect various soil attributes-as seen in the global SoilGrids250m product (Hengl *et al*., 2017) [16]. Regarding weather data, typical factors include average yearly temperature, yearly precipitation, and evapotranspiration (McBratney *et al*., 2003) [26]. These datasets might originate from sensors aboard satellites; nevertheless, weather model data, often sourced from weather stations, (for instance, WorldClim, ClimateNA) could also be utilized. Besides incorporating present weather conditions into a model, historical and anticipated future conditions might also be employed to replicate the impacts of shifting weather conditions in terms of comprehending the spatial and temporal trends of soil attributes.

Organism (o)

Satellite imagery provides a wealth of vegetation data crucial for Digital Surface Model (DSM) development. Various vegetative indices, like the normalized difference vegetation index (NDVI), are derived from satellite band ratios, offering insights into vegetative greenness based on near-infrared and red wavelengths. Alongside NDVI, other indices such as the Soil Adjusted Vegetation Index (SAVI), Transformed SAVI (TSAVI), Modified SAVI (MSAVI), and the Global Environment Monitoring Index (GEMI) are utilized (Maynard and Levi, 2017) [25]. These indices, along with remotely sensed data like thermal imagery, prove effective in predicting soil moisture, color, texture, and water holding capacity, as well as assessing plant growth. Researchers also leverage processed satellite imagery to create landcover maps and integrate crop data as a covariate for spatial prediction. Crop yield, a product of soil-plant-atmosphere interaction, can serve as an indicator for soil properties such as clay, moisture, and nutrient content, influencing plant growth.

Relief (r)

The r factor's importance in DSM is widely acknowledged (McBratney *et al*., 2003) [26]. A fundamental aspect of DSM studies involves utilizing a digital elevation model (DEM), which comprises elevation data arranged in a raster format. DEMs can originate from various sources, including digitized contour maps, interpolated ground measurements, or data obtained through remote sensing via satellites or RPAS-mounted sensors. Their widespread availability and typically cost-free accessibility make DEMs highly advantageous. Their usefulness lies in their adaptability for computing a diverse range of topographic parameters. For instance, DEMs facilitate the characterization of morphometric features at local scales (e.g., slope, aspect, curvature), landscape scales (e.g., relative slope position), and hydrological patterns (e.g., topographic wetness index), all of which significantly influence soil distribution.

Parent material (p)
Soil parent material data is often obtained from digital geological maps. It's crucial to acknowledge the origin of soil materials when utilizing these maps. For instance, a bedrock geology map is more valuable in regions without glaciers, where soil primarily originates from weathered bedrock.

Age (a)
The age aspect can define the duration of pedogenesis and can be approximated by the age of the substrate or material from which the soil forms (McBratney *et al*., 2003) [26]. In DSM, there's limited application of this data due to challenges in assessing soil age in a GIS-friendly format. A potential solution for integrating this aspect into DSM could involve considering human-induced landscape modifications that affect soil characteristics and types.

Spatial Position (n)
The n factor can be integrated in various ways: by utilizing the spatial coordinates of soil sample spots or employing a raster layer showing the proximity to a geographical feature. Waldo Tobler’s First Law of Geography (Tobler, 1970) [43] articulates: "Everything is related to everything else, but near things are more related than distant things." When applied to DSM, this implies that neighboring soil samples are more likely to exhibit similar properties compared to distant ones. Thus, the correlation between sampling location, its corresponding soil value, and its proximity to nearby sampling locations can be utilized to forecast (interpolate) soil values between those points using geostatistical methods. Spatial position details can also be included by measuring the distance or closeness of each pixel in the study area to specific geographical features or reference points, thereby capturing contextual landscape information. For instance, a distance-to-nearest-stream layer can be calculated using a stream network; likewise, similar distance-based layers can be computed for proximity to the ocean, lakes, rivers, geomorphic formations, and other features (Lagacherie and Mcbratney, 2006) [12].

Prediction of soil property
Environmental factors and soil characteristics are analyzed using appropriate models to estimate soil properties in unknown areas. These methods can predict both qualitative and quantitative outcomes (Kidd *et al*., 2014) [20]. Various models were evaluated for predicting soil properties. Common models include Multiple linear regression (Thompson *et al*., 2006; Triantafilis *et al*., 2009) [42, 46], neural networks (Malone *et al*., 2009; Mosleh *et al*., 2016) [24, 30], generalized linear models (McKenzie and Ryan, 1999) [28], ordinary Kriging (Santra *et al*., 2017) [37], kriging with external drift (Santra *et al*., 2017) [37], regression Kriging (Hengl *et al*., 2004) [15], classification and regression trees (Breiman *et al*., 1984) [4], k-nearest neighbor (Mehrjardi *et al*., 2015) [41], multinomial logistic regression (Kempen *et al*., 2009) [19], logistic model trees (Giasson *et al*., 2006) [13], Support vector machine (Priori *et al*., 2014) [34], and Random Forest model (Dharumarajan *et al*., 2017; Sreenivas *et al*., 2016) [9, 39].

Digital soil mapping relies on math models to depict soil distribution spatially. These models approximate reality and face uncertainty. Due to their quantitative nature, they offer quantitative assessments of accuracy and uncertainty for soil properties or classes. These estimates, along with soil spatial predictions, are integral to any mapping program. Prediction performance is evaluated by comparing predicted and observed values. Ideal models show minimal differences between the two. Evaluation metrics include coefficient of determination, root mean squared error, mean error, and Lin's concordance correlation coefficient for soil properties. For soil classes, accuracy is assessed using overall accuracy rate and kappa index. A good model typically exhibits values close to 1 for these metrics (Congalton, 1991) [7].

To quantify uncertainty in soil property predictions, digital soil mapping employs prediction intervals. These intervals delineate the likely range of values wherein the true value may lie. Typically, digital soil mapping employs 90% prediction intervals, indicating the range where a new measurement will typically fall 9 times out of 10 (Arrouays *et al*., 2017) [1]. Prediction Interval coverage percentage (PICP) serves as an indicator of uncertainty within uncertainty. In the context of soil class predictions, the confusion index is utilized to measure prediction uncertainty (Burrough *et al*., 1997; Odgers *et al*., 2014) [5, 32], which is grounded in the similarity of soil class occurrences in each grid cell.

Soil sampling
Soil sampling plays a crucial role in DSM, significantly impacting its accuracy and cost. Over the past decade, considerable advancements have been achieved in soil sampling techniques, aiming to enhance soil mapping performance while minimizing the number of samples required. Strategies such as design-based sampling (including simple random sampling, stratified random sampling, systematic random sampling, etc.) and model-based sampling (like geostatistical sampling and centered grid sampling) are commonly employed in soil mapping endeavors. Additionally, the conditioned Latin hypercube sampling method has gained popularity for soil mapping due to its ability to accurately capture environmental covariate variability in feature space. However, various potential access constraints may hinder sampling at desired locations.

Scientists have suggested a flexible Latin hypercube sampling method to address operational sampling challenges in vast and remote areas, including constraints such as land use, land cover, rugged terrain, and unforeseen roadblocks. It is anticipated that more adaptable and effective soil sampling techniques will be devised for DSM.

Application of DSM
Initially, DSM primarily focused on modeling soil landscapes, analyzing the links between soil characteristics and environmental factors. Over time, the emphasis of soil mapping has shifted from merely studying soil variation and predictive techniques to its application across diverse fields. Agriculture management (Ji and Peters 2003; Srinivasan *et al*. 2010) [18, 40], evaluation of ecosystem services (Tóth *et al*. 2013) [45], and land assessment (Bouma 1989) [3] have been

the primary beneficiaries. These applications are largely grounded in soil functions, encompassing biomass production, nutrient and water storage and filtration, biodiversity support, provision of raw materials, carbon storage, and preservation of geological and archaeological heritage (Tóth *et al*. 2013) [45], all of which directly or indirectly benefit humanity. However, conventional soil mapping based solely on general attributes or soil type is inadequate. Additional parameters such as soil salinity (Li *et al*. 2015) [23], trace elements, horizon thickness (Chaplot *et al*. 2010) [6], water holding capacity (Piedallu *et al*. 2011) [33], and electrical conductivity (Gasch *et al*. 2015) [12] should be considered. Soil maps must be integrated hierarchically with quantitative parameters like water potential and soil shrinkage curves (Salahat *et al*. 2012) [35] to effectively support agronomic models and other systems. Recent studies have expanded to include predictive aspects such as soil quality (Moncada *et al*. 2014) [29], soil parent material (Heung *et al*. 2014) [17], soil biological indicators (Shahbazi *et al*. 2013) [38], and hydro-functional mapping (Tóth *et al*. 2017) [44].

Advances in DSM

In short, over the past decade, digital soil mapping has seen four key shifts. Initially, studies focused on small areas, driven by exploration and experimentation. However, advancements have led to a transition towards examining relatively larger areas to assess the effectiveness of various mapping methods and meet spatial information needs. Simultaneously, models have evolved from simple to complex, mirroring the shift from straightforward to intricate landscapes. Simple landscapes, governed by few environmental factors, exhibit a mostly linear soil-environment relationship, while complex ones involve multiple factors with a nonlinear and nonstationary relationship. While linear regression suffices for the former, geographically weighted regression or tree-models become necessary for the latter. Additionally, there's been a progression from 2D to 3D mapping to offer comprehensive soil pattern data. Lastly, the scope of applications has broadened from agricultural management to encompass ecosystem services (Arrouays *et al*., 2020) [2].

Conclusion

The resurgence in soil science and growing interest are placing soils back on the global agenda, spanning ecosystems, climate change, and agriculture (Hartemink and McBratney 2008) [14]. Advanced technologies are required to model soil properties and processes accurately at fine scales, but pinpointing the optimal prediction methods is challenging due to varying soil-landscape relationships across different terrains. The forthcoming DSM framework aims to surpass existing paradigms by integrating soil forming factors differently for prediction. According to Sanchez *et al*. (2009) [36], DSM involves only three steps, with spatial prediction being just one aspect. Recommendations for evidence-based soil management are crucial for diverse end users, connecting soil mapping, function analysis, legacy data, and social factors. Thus, conceptual soil mapping models must expand with a thorough grasp of surface processes. Traditional polygonal soil maps, including two-dimensional ones, may prove inadequate for conveying soil details. Further advancements in virtual reality techniques are necessary for modeling soil characteristics such as color, texture, spectrum, temperature, and moisture. Additionally, notable progress in soil science involves generating global soil maps that can directly convey soil functions.

In forthcoming times, it is imperative to align regional and national soil maps to address global concerns. Identifying potential biases and uncertainties during prediction is crucial, necessitating a focused approach on soil variation. Numerous hurdles lie ahead in soil mapping endeavors, including simulating regional-scale soil heterogeneity, mapping in flat terrains, and integrating soil mapping with spectroscopy. Urbanization triggers rapid land use changes, resulting in substantial spatial soil variations challenging traditional models. Similarly, intense human activities amplify uncertainties in accurate soil mapping, particularly in transitioning areas like villages, suburbs, and urban-rural interfaces due to modern agricultural practices. (Dash *et al*., 2022) [8].

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