CHAPTER

A new era of digital soil mapping across forested landscapes

14

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ABSTRACT

Soil maps provide essential information for forest management, and a recent transformation of the map making process through digital soil mapping (DSM) is providing much improved soil information compared to what was available through traditional mapping methods. The improvements include higher resolution soil data for greater mapping extents, and incorporating a wide range of environmental factors to predict soil classes and attributes, along with a better understanding of mapping uncertainties. In this chapter, we provide a brief introduction to the concepts and methods underlying the digital soil map, outline the current state of DSM as it relates to forestry and global change, and provide some examples of how DSM can be applied to evaluate soil changes in response to multiple stressors. Throughout the chapter, we highlight the immense potential of DSM, but also describe some of the challenges that need to be overcome to truly realize this potential. Those challenges include finding ways to provide additional field data to train models and validate results, developing a group of highly skilled people with combined abilities in computational science and pedology, as well as the ongoing need to encourage communication between the DSM community, land managers and decision makers whose work we believe can benefit from the new information provided by DSM.

Introduction

Soil maps provide essential information for forest management, and complement information on timber resources, forest ecosystems, hydrology, and other components of natural systems to support decision making by forest managers (Montigny and MacLean, 2004; Varma et al., 2000). Geographic information systems (GIS) provide a means to organize, analyze and display multiple layers of digital information about soil, topography, hydrology, vegetation and other land characteristics, and the integrated analysis of these types of information is required for effective land management (Sheppard and Meitner, 2005). Interpretations based on soil and landscape data inform operational forestry activities such as road construction, harvesting, reforestation and stand tending, as well as planning for land use, watershed management, ecosystem stability, and the collective responses of forests to global change. High resolution information is needed at the site level for operations (Murphy et al., 2011; Verbist et al., 2010), while planning activities at watershed and regional levels are often supported by maps at intermediate scale (Thompson and Kolka, 2005). National and planetary-scale information on forest soil resources and attributes (e.g., Mansuy et al., 2014; Samec et al., 2018; Hengl et al., 2017) is also needed to better understand global change as it affects biogeochemical cycles, climate and other natural processes.

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The transformation of soil maps from analog to digital

In the two decades spanning the arrival of the new millennium, scientists and specialists in diverse fields such as soil science, remote sensing, computer processing, and data analysis transformed the way soil maps were produced. The increasing use of digital techniques during this time period is shown in Fig. 14.1, which tracks the number of research articles and citations documenting the development of digital soil mapping (DSM) techniques. Prior to the widespread availability of GIS, global positioning systems (GPS), and desktop computers capable of manipulating large spatial datasets, soil mapping was carried out by teams of surveyors using their understanding of soil - landscape relationships, field descriptions of soil, and analog methods of cartography using pen and paper (Goodchild, 1988). Digital techniques including acquisition of spatial information through remote sensing, interpretation of the resulting data with computer algorithms, and GIS-based processing of vector and raster datasets represent modern day enhancements to the traditional mapping approaches. Map production methods also changed in other disciplines of earth science, environmental assessment and natural resource management during this time period, and the use of spatially-enabled geographic datasets (i.e., 'digital' maps) became widespread, so that they became an integral part of forest operations and management by 2010.

The transformation of mapping methodology from analog to digital not only aided the production of soil maps, but also allowed new types of information to be conveyed through soil mapping (Kuhn,

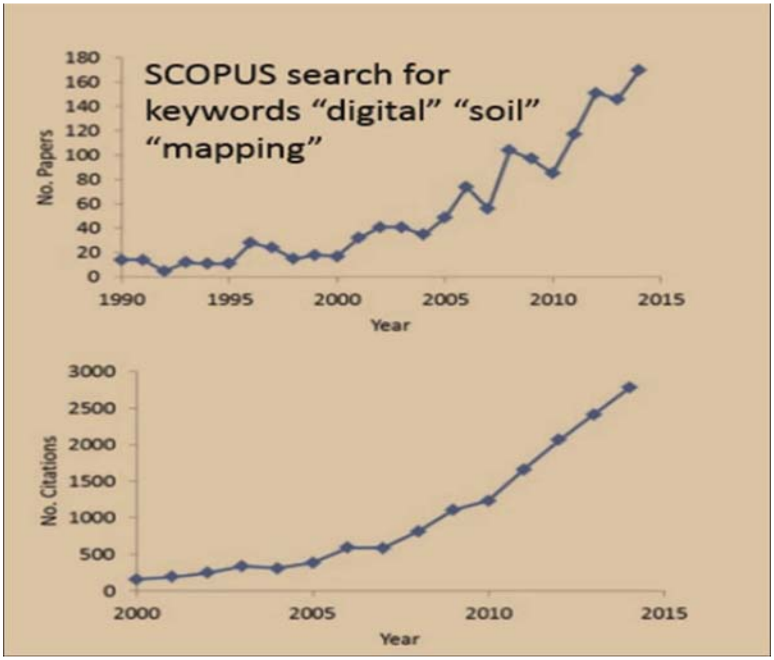


FIG. 14.1

Articles and citations on the topic of digital soil mapping, 1990–2015.

2012), and ultimately, it led to profound changes in the way soil and environmental scientists communicate with each other, with scientists in other disciplines, and with decision makers. These new ways of interacting with and analyzing geographic data are only beginning to be understood as this article is written, and the transformation of soil mapping represents a vibrant arena of forest and land management research. Some aspects of the digital transformation, and the changes to interpretation and communication of soil information are summarized in Table 14.1.

Over the past several decades, a wide variety of remote sensing information has become available to soil mappers at low or no cost, including spaceborne radar from the Shuttle Radar Topography Mission (SRTM; Farr and Kobrick, 2000), multispectral imagery from Landsat (Markham et al., 2004) and the moderate resolution imaging spectroradiometer (MODIS; Salomonson et al., 2006), and soil moisture via radiometry from the Soil Moisture Active Passive satellite (SMAP; Entekhabi et al., 2010). The availability of these data has compensated, in part, for the loss during the 1980's of government supported mapping programs for soils in many parts of the world (e.g., Ibanez et al., 1999). The ability to process the resulting deluge of data on desktop computers with open source software and cloud computing has enabled soil maps to be produced at higher resolution for less cost, and with rigorous evaluation of mapping uncertainties. As well, a broader mandate for soil mappers has opened up the map making process to a wide range of new participants who have revitalized the production and spatial representation of soil information.

Table 14.1 **Aspects of the transformation of soil mapping from analog to digital form.**

	Analog	Digital
Map content	Soil types with attributes assigned to classes	Soil types and attributes represented equally effectively; more flexible
Map format	Polygons with labels (choropleth)	Vector (geometry plus data) and raster
Consistency	More subjective; documentation of map production methods presented in a separate report	More objective; algorithms for map production can serve as full documentation of the assumptions and approaches used
Uncertainty	Difficult to calculate and represent	Calculated and represented using a wide variety of statistical methods
Update	Each edition of the map is a static snapshot	Outputs can be recalculated, and maps updated to incorporate new information
Scale	Fixed scale	Multiple scales more easily represented
Accessibility	Need to be printed, or viewed as static images	Accessible on the internet, and as interactive images and representations
Decision making	Largely carried out by humans with a small number of inputs	Multi factorial decision making is common; flexible use of soil information; decision-making rationale is better documented
Landscape and hydrologic process visualization	Inferred from contour lines and stream channel location	Explicit depiction of water accumulation and flow is made possible by digital terrain analysis

Opportunities for improving forest soil information using DSM

Digital soil mapping offers improved soil inventories, interpretations, and decision support systems compared to analog maps. The databases that form the core of a digital soil map are well suited for documenting what was learned about soil resources during the previous era of analog mapping, for extending those interpretations to new areas, and for evaluating and interpreting new environmental data. Digital soil databases also support the development of new information on soil attributes that address modern questions in resource management and environmental science (e.g., Hengl et al., 2017; see Text box 14.1). Uncertainty evaluation provides objective feedback for mappers regarding the success of alternative mapping approaches, and gives users important information on map reliability that informs investments in future monitoring and modeling. And finally, the soil interpretations themselves should improve over time owing to the rigorous nature of their development as computer encoded models, with specific values attached to the model parameters that can be adjusted to suit different scenarios and objectives.

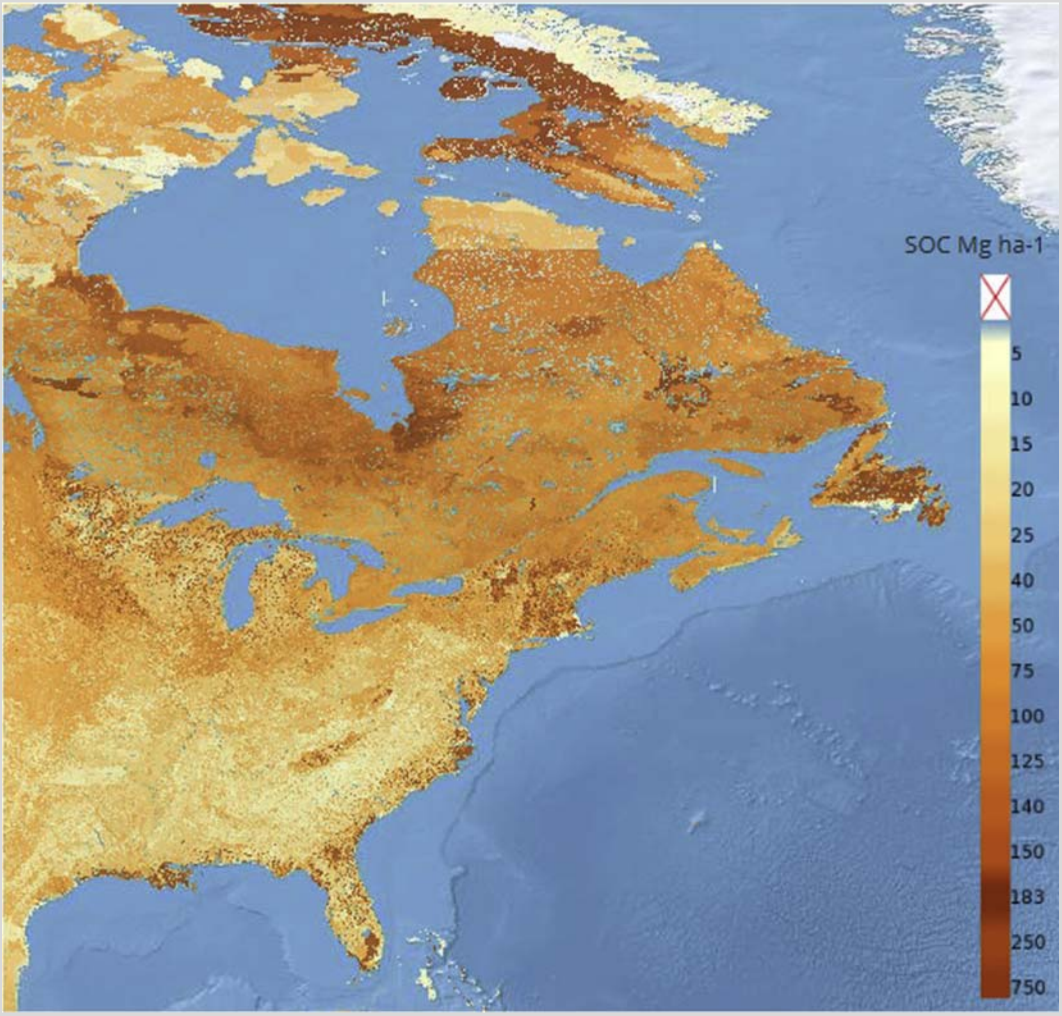
The process-based representation of water movement in landscapes is one of the most significant differences between digital soil maps and traditional (analog) soil maps. Digital terrain analysis provides an exceptionally precise and detailed depiction of water accumulation and flow, and these representations serve as a reliable description of topography as a soil forming factor. The resulting interpretations of water flow in the landscape are closely related to observed variation in soil properties that result from processes such as erosion, deposition, aeration, drainage, and accumulation of organic matter (see examples in Text box 14.2). Topographic and hydrologic analyses also inform site − level forest operations by identifying wet areas in the landscape (Murphy and Arp, 2012; Case et al., 2005), for evaluations of forest productivity (Waring et al., 2014) and for riparian management (Agren et al., 2015).

Using DSM to integrate soil information and remotely sensed data on land cover (Hansen et al., 2013) is also valuable for depicting the effect of land management or other anthropogenic activities on soil conditions. As an example, Coops et al. (2012) modeled leaf area index (LAI) using a process-based growth model and linked the result with estimated LAI obtained from satellite data (MODIS) to predict soil fertility and available water storage capacity (AWSC) for forested areas of western North America. The coupling of remotely sensed environmental information with soil

BOX 14.1 Global soil organic carbon map

The global soil organic carbon map (FAO, 2018 http://www.fao.org/global-soil-partnership/pillars-action/4-information-and-data-new/global-soil-organic-carbon-gsoc-map/en/) was produced using DSM procedures in order to create individual gridded maps at 1 km resolution for 196 countries in all areas of the world. Soil organic carbon stocks were estimated to a depth of 30 cm. The information in this map represents the most comprehensive evaluation of soil organic carbon information currently available at the global scale, and provides information to scientists participating in a wide range of activities to understand the role of soil carbon as it affects atmospheric CO_2 and climate change.

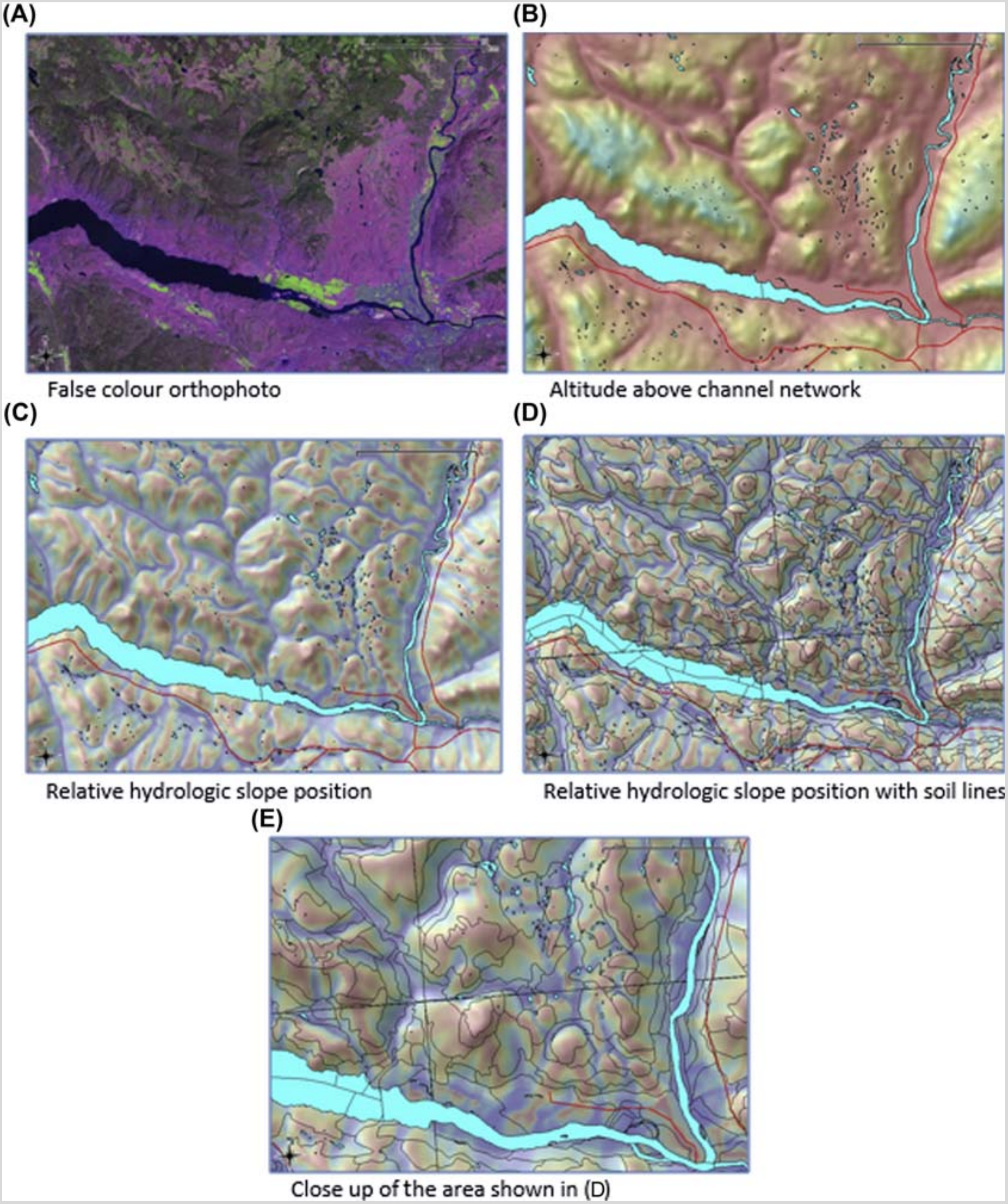
BOX 14.1 Global soil organic carbon map–cont'd



Soil organic carbon stocks in eastern North America (FAO, 2018).

BOX 14.2 Variation in topography

In the images below for an area in central British Columbia, Canada, several derived topographic variables are shown in relation to vegetation and landscape features. The close association between the topographic features and soil properties is illustrated in images (d) and (e) by the similarity between the patterns of topographic variation and the polygon boundaries of the semi-detailed soil survey map for the area (Young et al., 1992). These similarities lie at the heart of the DSM process, which essentially encodes these relationships into computer models of soil type and characteristics. Images a,b,c, and d each have an area of approximately 86,400 ha (36,000 m × 24,000 m).



properties in this way is only made possible by the accurate geo-positioning and alignment of soil data from DSM and satellite imagery.

The need for high quality input data represents a significant challenge to the full realization of DSM's potential to transform the collection, analysis and display of information on forest soils. Such data are needed to train predictive models, and for map validation. Although remote sensing can be used to collect some of that information at relatively low cost, field evaluation of soil conditions is still required. These data are expensive to obtain, and many DSM products currently rely on internal forms of map validation which can allow certain types of errors to go unnoticed. Another challenge for forest soil mapping with DSM relates to the need for mappers to have combined skills in computer science, forestry and pedology. Without a strong background in field pedology, DSM'ers run the risk of producing maps that may look good, and possibly even pass certain validation tests, but contain interpretation errors that seriously reduce their utility.

Concepts in DSM

The overall goal of creating any soil map (conventional or digital) is to portray the variation in soils across the landscape. Heuvelink and Webster (2001) discuss two broad approaches toward this end. One approach is to classify soils into distinct types and then to divide the landscape into units where those soil types are present; this *discrete* approach was the main concept guiding map development for most legacy soil surveys. A second approach recognizes the *continuous* nature of soil variation, and uses geostatistics and regression to evaluate variation in soil attributes across landscapes. Both the discrete and continuous approaches are implemented in DSM. The discrete approach typically focuses on predictive models aimed at classification, while the continuous approach can employ a range of models, but is often pursued through regression and spatial autocorrelation. The continuous approach is especially advantageous where mapped soil classes are not uniform, or where the transition from one soil type to another in the landscape is gradual, with few abrupt boundaries. Some mapping approaches have features typical of both approaches, the use of fuzzy logic to estimate the relative possibility that a particular area belongs to a defined soil type is one example; in effect, it creates a 'continuous classification' (Heuvelink and Webster, 2001).

Generally, DSM involves the production of maps of different soil types or properties that portray the quantitative relationships between field or laboratory observations of soil and comprehensive spatial representations of environmental data for the survey area. The field observations are usually provided as single points (e.g., observations from soil pits) and the environmental data is usually in raster (pixel) format, although this may not be essential. The overall mapping process is outlined in Fig. 14.2, where the geodata, including soil pit data and information for environmental covariates, are depicted as inputs to predictive models that evaluate relationships among the input data in a spatially explicit modeling environment, producing outcomes that are spatial representations of predicted soil types or properties.

The DSM process can be thought of as training a model, where the term model *calibration* is also used to describe the training process. There are many modeling approaches that can be used in DSM, and some of these were described in McBratney et al. (2003) and Heung et al. (2016). The quantitative depictions of soil variation that result from such models are used to interpolate values or extend the map to points where no soil observations were made, but they also serve as a record of the soil − environmental relationships. For example, one of the most important tasks involved with the creation of a DSM

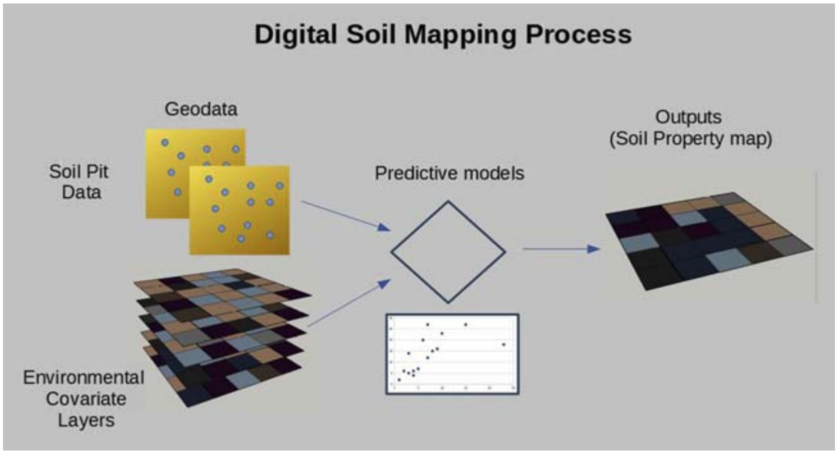


FIG. 14.2

Generic work process for digital soil mapping.

is to incorporate a soil - landscape model into a computer readable form. One way to do this is by modeling the relationships between legacy soil information (e.g., soil development, horizon sequence, carbon stocks), and environmental covariates derived from a DEM for topography (e.g., slope, elevation, curvature, flow accumulation) along a toposequence. For soil forming factors other than topography (e.g., climate, vegetation, and parent material), a similar process would be used with, for example, remotely sensed data to derive a spatial representation of soil in relation to the observed variation in the soil forming factor. One of the reasons that DSM leads to improved soil information is the way in which it compels soil scientists and mappers to rethink many of the mapping concepts that were used in the past. These include the development of map legends, the creation of maps that can be presented at more than one scale, and the representation of uncertainty for quantitative and categorical data. For example, DSMs commonly cover large areas and, therefore, more than one legacy soil map could be available as input for a single DSM covering a more extensive area. Harmonizing the data structure, units of measurement and map legends across multiple inputs is an important task that needs to be addressed at the start of a DSM project. The nature of a DSM, where the view can be made smaller or larger by a simple zoom operation, presents the map maker with many opportunities, but also some challenges. Key in this regard is the concept of mapping support, which describes the size of the soil units that are being used to train the predictive model, which is analogous to the experimental unit, a fundamental concept in statistical analysis for field experiments that rely on regression or analysis of variance. Underlying concepts in soil classification, taxonomy, and even soil description will all need to be evaluated and re-evaluated as DSMs displace traditional maps as the primary source of soil information.

Gallant et al. (2007) provide a detailed discussion of the need to match the process scale with the observation scale (support) when creating predictive models of soil properties with DSM. There is also an opportunity for the producers of DSMs to recognize and encode the characteristic dimension(s) of the landscape in relation to the detail of the map being produced, where land facets are small (c.40 m) units that represent hill slopes with attributes such as slope, aspect and drainage position. Land systems are bigger, about 600 m, and examples of their attributes include relief, modal slope, and stream pattern (Gallant et al., 2007).

DSM and predictive ecosystem mapping

In many regions, forest ecosystem mapping, or eco-site mapping is the primary guide to forest management. The Forest Service within the US Department of Agriculture uses the Terrestrial Ecological Unit Inventory (TEUI; Winthers et al., 2005) for ecosystem mapping. In British Columbia Canada, the Biogeoclimatic Ecosystem Classification system (BEC; Meidinger and Pojar, 1991) performs a similar function. Ecological classification and mapping frameworks such as the BEC and TEUI are integrated approaches for bringing together information on landscape elements including soils, climate, geology and potential natural vegetation to identify and map ecosystems as landscape units at fine scales. The separation of land units is conceptually based on soil properties, existing vegetation and potential natural vegetation, so these frameworks attempt to combine the disciplines of soil science and ecology. For example, within the TEUI, an ecological type is viewed as a distinctive combination of biotic and abiotic factors, or landscape elements. Ecological types are classified according to the relationships among those factors, so that combinations of landscape elements with similar potential natural vegetation, successional dynamics and management capabilities tend to be included in the same ecological type.

Predictive ecosystem mapping (PEM) is a semi-automated process of mapping ecological types across landscapes (Hamilton and Benton, 2010), and this mapping process shares many similarities with DSM. Both activities rely on the application of Jenny's (1941) principles to elucidate relationships between ecological (or soil) types and key environmental data for relief/topography, climate, parent material, biota and time. In DSM, soils are classified according to those same, or similar, biotic and abiotic factors as used in PEM, but the soil types themselves are thought of as distinct entities and are the object of classification based on properties like soil color, soil organic matter (amount and distribution), and sequences of soil horizons. So the current and potential vegetation on a site play key roles in both activities, but PEM relies on vegetation to a greater extent. PEM and DSM are closely related activities, both using computational methods to analyze geographic data with the aim of predicting ecosystem types (PEM) or soil types (DSM).

MacMillan et al. (2009) discussed the application of automated methods for mapping ecological entities, noting that PEM and DSM are both complex processes that integrate multiple disciplines in natural science. They both also rely heavily on techniques of digital terrain analysis for depicting topographic variation in landscapes, as demonstrated by MacMillan et al. (2007), who used a predictive mapping approach to identify site units for a large area of British Columbia, Canada at low cost and with good accuracy.

Hamilton et al. (2010) illustrated the application of techniques drawn from DSM to map land types (LT) for low relief landscapes in Michigan. In the national hierarchy of ecological sites, the LT unit is described at map scales of 1:24,000–1:60,000. Predictive ecosystem mapping (PEM) involved using the random forest algorithm trained with 4920 field plots over a 60,000 ha area. Cross validation showed an accuracy of 68%.

Soil information, therefore, can inform ecosystem interpretations (PEM) important for silviculture, harvest planning and sustainable forest management, but DSM is also valuable in its own right for other management activities such as productivity evaluations, watershed management and evaluating soil sensitivity to soil degrading processes. DSM's are also used in other fields of study including hydrology, geomorphology and global change.

From pedons to regions: the process of DSM

Information for a wide range of soil and environmental variables can be collected in the field, measured in the laboratory, and/or estimated from remotely sensed data to classify and predict soil properties across space and through time. In traditional soil mapping, the focus has often been on locating the boundary between two soils and then classifying the soils within each boundary. The classified map areas may be associated with specific soil or environmental information (e.g., soil orders), and while traditional map products are spatially continuous, the classifications seldom are. In DSM, the landscape is composed of spatially explicit population units (e.g., 'pixels') of specific resolution, and quantitative techniques are used to classify and predict soil attributes in each pixel based on the soil and environmental variables within that pixel. While measured and observed soil variables are typically not available in each pixel, there commonly is sufficient auxiliary information available in each pixel to predict its soil class and properties. These pixel-based classifications and predictions can be used to generate soil maps, facilitate soil inventory, assess risk, characterize uncertainty, and enable accuracy assessments of other map products (Carre et al., 2007; Minasny and McBratney, 2016). There are several modes of statistical inference (e.g., design-based, model-assisted, model-based, hybrid) to produce the probabilistic expressions required for inferences and each mode relies on different assumptions, data, and methods which may result in different population parameters (Webster and Oliver, 2007).

Defining the population of interest: mapping objectives

Defining the population of interest (e.g., geographic extent, soil depth, soil properties) helps to determine whether there are sufficient data for classification and/or prediction and ultimately to achieve the mapping objectives. A sample is a set of population units or individuals (e.g., soil pits, soil cores), with the whole set of individuals considered as a population. Understanding the nature of data required to classify and/or predict soil properties is an essential part of developing a map or estimating a population parameter. Typically these data come from surveys which may be extensive (e.g., national forest inventories [NFIs]) or project-specific (e.g., stands or landscapes).

For each population unit, a set of variables are measured or qualitative attributes assigned which can take on several different forms. In some cases, a variable describing a soil characteristic can take on one of two states (binary variables). In other cases, a soil characteristic may take on more than two states (multi-state variables). Finally, there are soil properties with quantitative values that fall along a continuous scale (continuous variables). Collectively, these binary, multi-state, and continuous variables are used along with auxiliary information (e.g., climate data, remotely sensed data) to classify and/or predict soil properties for a population.

In many cases, data that were collected in the field, measured in the laboratory, or observed from remote instruments were not intended to be used together. Fortunately, there are many data fusion techniques available to resample remotely sensed data, transform variables collected in the field or laboratory, and standardize units of area, volume, and/or mass so that multiple data sources can be harmonized for use in classification and prediction (Castanedo, 2013).

Soil variables for classification and prediction

Traditional soil mapping and prediction are based primarily on Jenny's (1941) mechanistic model for soil formation on the landscape defined as:

$$S = f(c, o, r, p, t) \tag{14.1}$$

where S are natural soil bodies on the landscape that develop as a function (f) of interactions between c = climate, o = organisms including humans, r = relief, p = parent material, and t = time. This model (14.1) has been used for decades as a qualitative means for understanding the factors that drive soil pattern and formation. McBratney et al. (2003) expanded Jenny's model to facilitate empirical quantitative descriptions of relationships between soil and other spatially referenced variables:

$$Sc \text{ or } Sa = f(s, c, o, r, p, a, n) + e \tag{14.2}$$

where soil classes (S_c) or attributes (S_a) can be predicted from knowledge of s = soil (other soil properties), c = climate (various climate properties), o = organisms (vegetation or fauna or human activities), r = topography (landscape attributes or landform), p = parent material or lithology, a = age, or the time factor, n = space, or spatial position, and e = spatially correlated residuals.

The variables defined by McBratney et al. (2003) in model (14.2) can be acquired from many different data sources. A given soil (s) can be represented by variables obtained from field and/or laboratory measurements (e.g., soil texture, soil organic carbon), remotely sensed data (e.g., soil moisture), or existing data products (e.g., soil order maps) which are georeferenced. Organisms (o) can be represented by field or laboratory measurements (e.g., forest types, soil microbe presence/absence), remotely sensed data (e.g., Normalized Difference Vegetation Index [NDVI] obtained from Landsat spectral data), or existing data products (e.g., National Land Cover Database). Parent material (p) can be represented by mineralogy, which is related to specific spectral bands from the Landsat TM or ETM. There are also georeferenced surficial geology maps that can be used to characterize parent material. Relief (r) can be characterized by many different terrain variables acquired from remotely sensed data sources (e.g., Light Detection and Ranging [LiDAR]) and field measurements (e.g., slope, aspect, and elevation). Climate (c) variables can be acquired from local weather stations that have sustained observations or from regional climate models (e.g., PRISM Climate Group [2016]). Finally, age (a), which is not always considered as a covariate in the model (14.2), can present a time element and be included if there are repeated survey measurements and/or information on disturbance or land use history for the population unit.

Sources of information

Given the diversity of variables identified for the classification and prediction of soil properties, and the emerging techniques for data fusion, there are many different sources of information that can be used for DSM. Two broad approaches to DSM have emerged over the last few decades (Shi et al., 2009), and while they are not mutually exclusive (Grunwald, 2006; Walter et al., 2007), differences in philosophy and technical emphasis may result in different DSM plans and strategies. The first and most common approach for DSM is described by McBratney et al. (2003) and is sometimes referred to as being *data-driven*. This approach aims to leverage statistical methods and modern computing combined with data from soil surveys, existing maps, and other empirical sources to quantitatively classify and predict soil properties over some defined space. This approach is typically data-intensive, relying on extensive empirical information, which may include analytical information from georeferenced points. The second approach, which is closely aligned with conventional soil survey and mapping frameworks, relies on soil scientist knowledge and incorporates modern techniques of fuzzy logic to reduce inconsistencies and the expense of manual processes (Zhu et al., 2001; Shi et al., 2004). This *knowledge-based* approach relies more heavily on the expertise of trained professionals and their understanding of an area of interest rather than data from intensive field campaigns. Both approaches to DSM require extensive information and this information is often collected for many different purposes, which, in turn, may influence spatial extent, variables measured, and other factors (Kerr and Ostrovsky, 2003). Care must be taken when harmonizing information for DSM to ensure it is used correctly and that the mode of inference aligns with the way the information was acquired.

Expert knowledge

Expert knowledge or judgment can take on many forms even within the context of DSM. For example, databases with empirical information collected as part of a formal soil survey may be supplemented with expert knowledge on particular soil characteristics (e.g., drainage class). In other cases, formal processes have been established to integrate expert knowledge into a DSM framework (MacMillan et al., 2007; Shi et al., 2009). In a case study from Vermont, USA, Shi et al. (2009) describe soil scientist knowledge from the perspective of scale and space. The scale refers to the geographic extent of the knowledge with some being “global”, that is, covering the entire geographic range of the dataset (e.g., “All the locations in the mapping area where environmental conditions are similar to those of this location are likely to have soil X”) compared to some being “local” and only covering limited areas within the domain (e.g., “The vicinity of this location is likely to have soil X”). The space component refers to how a scientist’s knowledge is represented in both parameter and geographic space. An expert’s knowledge in parameter space, according to Shi et al. (2009), is likely to cover the entire, or “global”, spatial extent of the project (e.g., “The optimal slope gradient for soil X in this mapping area is between 8% and 20%”) while geographical knowledge is likely to be “local”, or specific to certain areas within the project domain (e.g., “In areas of geological type A, the optimal slope gradient for soil X is between 8% and 20%”). Several studies (e.g., Ashtekar and Owens, 2013; Zhu et al., 2001; Shi et al., 2004; Skidmore et al., 1996) have highlighted examples and applications of expert knowledge in DSM. These approaches have proven particularly effective for areas with limited extent (e.g., US counties) and with relatively consistent soil-landscape relationships. For large and complex domains, relying on expert knowledge alone may not be possible.

Field and laboratory information

Observations can be collected from point samples in a soil survey over a defined (finite) population and used directly (e.g., soil texture class), or laboratory analysis may be required to obtain soil properties of interest (e.g., soil pH). Typically the population units that make up the sample are georeferenced. In the case of strategic surveys with large geographic extent, like NFIs, point samples represent an area larger than the population unit. For example, in the US NFI, soil cores are taken on permanent intensive field plots which represent an area of approximately 390 km^2 (USDA Forest Service, 2011). Databases with soil and environmental variables (e.g., International Soil Carbon Network, http://iscn.fluxdata.org/data/access-data/) from many different field surveys are growing and are increasingly being used for model training and validation. These databases often represent soil samples from purposive surveys or local studies that focus on a particular land-use type (e.g., cropland or forest land), study area, or research question and may not be representative of the overall population. In other cases, variables may come from equal-probability samples, either collected on a systematic grid or randomly located, which are representative of the populations they encompass. In both cases, it is important to understand the underlying sampling frameworks used to obtain the soil and environmental covariates so that the related data can be harmonized properly with auxiliary information (e.g., remotely sensed information) and so that an appropriate mode of inference is used for prediction.

Remotely sensed information

Remote sensing estimates are obtained from active or passive sensors that detect electromagnetic radiation from the earth's surface (Entekhabi et al., 2010). Passive sensors collect electromagnetic information produced as a result of the interaction between solar radiant energy and surface materials (such as various satellite measurements), while active sensors such as LiDAR or radar collect information returned from the earth's surface as a result of an emitted signal. In both cases, the electromagnetic radiation detected is used to *estimate* landscape characteristics that will be useful as covariates for classifying and predicting soil properties. In most cases, these data are also spatially explicit, which facilitates harmonization with other georeferenced information.

Remote sensing estimates that provide elevation and spectral response data are commonly used in DSM (Mulder et al., 2011). These data can be spatially explicit and either continuous or discontinuous. In either case, the raw data from remote sensing instruments often require substantial post-processing to convert active or passive measurements into meaningful variable estimates. The remote sensing of topography via passive sensors (e.g., aerial photographs) or active sensors (e.g., LiDAR) results in the generation of digital elevation models (DEMs), which are used extensively in soil mapping, the utility of which is well-documented because variations in relief can often be related to soil properties and classes. Spectral data from passive remote sensors (e.g., Landsat TM) provides information about the surface properties of vegetation, soil, water, and other materials. Spectral signatures obtained from passive sensors can be related to environmental covariates that drive soil development, and can therefore be used to predict other soil characteristics. Specifically, there are examples of remotely sensed data and associated products being used to map the variations in *r, c, o, p,* and indirectly, *s* (Franklin, 1995; Chen et al., 2000; Mulder et al., 2011). When considering the use of remotely sensed information in DSM, the type and methods of data collection, the spatial/temporal extent and consistency of the data, the timing of data acquisition, and the resolution of data compared to the physical properties of interest must all be considered (Kerr and Ostrovsky, 2003; McBratney et al., 2003; Mulder et al., 2011).

Comparing studies

The emergence of DSM and formal methods for obtaining, processing, modeling, and validating map products has facilitated a wide range of comparisons among digital soil maps and traditional map products. The *GlobalSoilMap.net* project (Fig. 14.3; Odeh et al., 2014) is an example of one effort by the

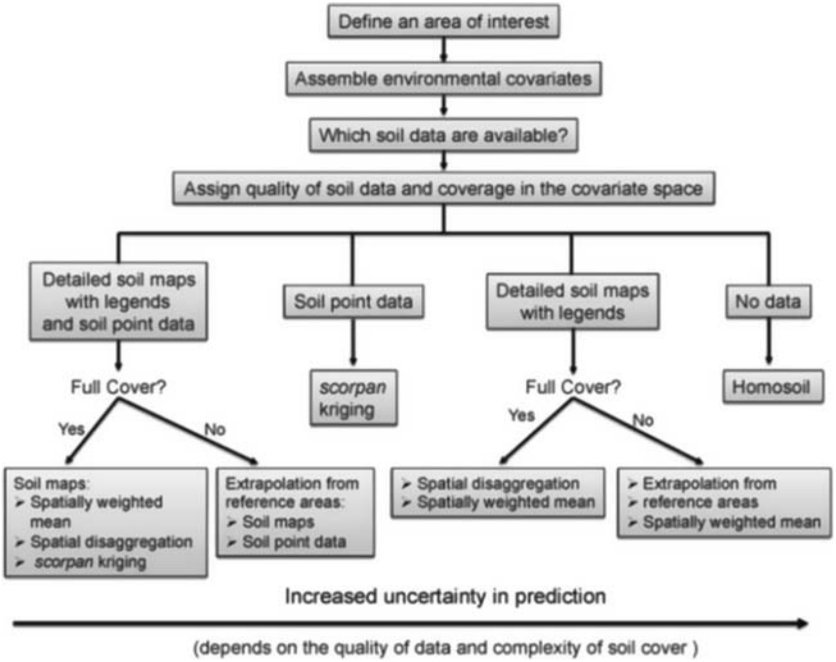


FIG. 14.3

Digital Soil Mapping process used in the GlobalSoilMap.net.

Adapted from Hempel et al. (2014).

DSM community to identify, apply, illustrate, and document different approaches to prediction that can be applied under different conditions. This effort has not only led to advances in the science of DSM but has also helped to formalize methods for making comparisons. In contrast to *GlobalSoilMap.net*, which uses a mosaic of maps produced by countries to obtain global coverage, the *SoilGrids* project (Hengl et al., 2017) uses a single model that incorporates information from soil pedons from across the world. The global soil organic carbon map (FAO, 2018: Text box 14.1) is another example of a large extent map produced by mosaicking individual contributions. Comparing different approaches such as these provides important information to improve digital soil databases and our understanding of how soils are distributed across the planet.

Using DSM to guide the adaptation of forest management to global change

Because DSMs provide maps of soil properties as well as estimates of uncertainties, they facilitate the use of forest soil information to guide land management decisions and for the modeling of ecological processes at various scales. Soils are central to the provision of the ecosystem services (ES) by forests.

The concept of ES describes the benefits people obtain from ecosystems (MEA, 2005) and is useful to the understanding of the dependence of human well-being on ecosystems. ES include the provision of clean air, clean water, flood control, productive and healthy forests as well as the conservation of gene pools. A great challenge for forest management in the future will be to maintain or enhance the provision of ES while considering the cumulative impact of human activities, including global change. Important linkages between soil and ES are detailed in Adhikari and Hartemink (2016), Grêt-Regamey et al. (2015) and Schwilch et al. (2016). Indeed, the potential of an ecosystem to provide ES depends on its biophysical structure, of which soils are a major part (de Groot et al., 2010). A framework for linking soil properties to ES is presented in Fig. 14.4.

While there can be no doubt that soil properties are fundamental to the provision of ES, recent reviews have shown that the use of soil information in ES mapping studies has been modest. Adhikari and Hartemink (2016) stated that most studies on the valuation of ES lack a soil component or the soil component is either poorly defined or too generalized. Moreover, Greiner et al. (2017) reviewed methods for quantifying the soil contribution to ES and found that only 60% of ES mapping studies used at least one soil property in their assessment. In addition, a minority of studies used more than one soil property. These results clearly highlight that, although soils are recognized as being fundamental to the provision of ES, the use of soil information in ES studies remains limited. There may be several reasons for this, an obvious one being that the linkages between soil map information and ES are not direct and require expert knowledge. For example, the translation of a soil type into a risk of nutrient depletion, erosion, or simply a map of C stock may require knowledge that is not directly provided by these maps. However, even where such knowledge may be lacking, the new ways of thinking enabled

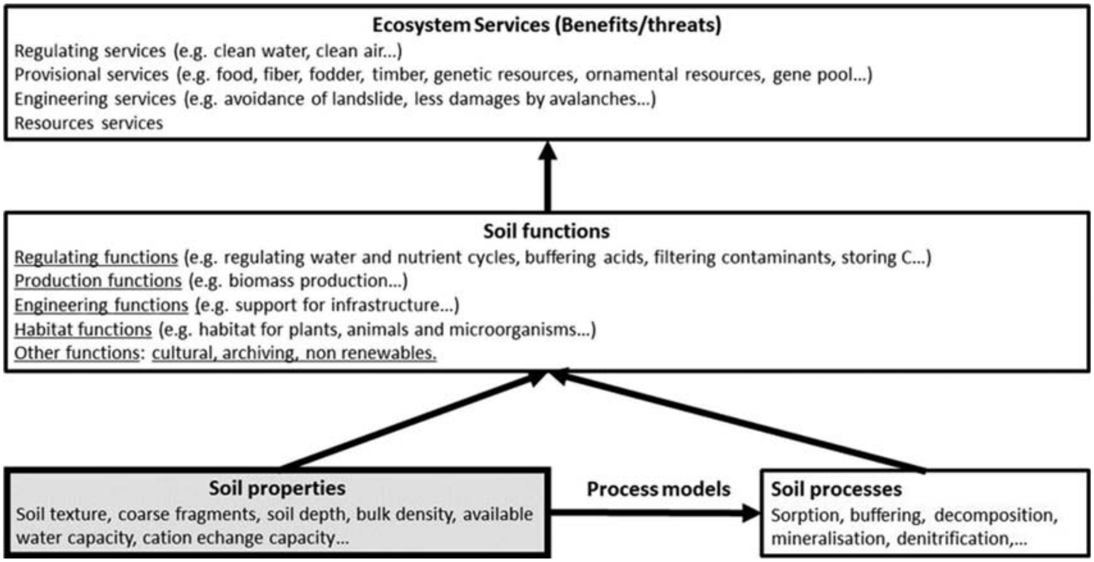


FIG. 14.4

Framework linking soil properties to ecosystem services.

Inspired from Grêt-Regamey (2016) and Adhikari and Hartemink (2016).

by DSM offer important advantages over traditional soil maps for integrating soil information into forest management and planning. Ongoing development of DSM products should translate into major benefits for forest ecosystem management and consequently human well-being.

Mapping soil properties

The availability of soil property maps greatly facilitates the uptake of soil information to the ever-increasing demand for estimating and mapping of soil functions and ES. Maps of soil properties are fundamental to developing a landscape scale understanding of ES through their role in defining soil processes and soil functions as represented in Fig. 14.4. Conventional systems for mapping and classifying soils were not designed to evaluate soil functional properties with the explicit geometry necessary for ensuring mass balance when stores and fluxes are computed (Arrouays et al., 2017). In a survey of ES mapping studies, Greiner et al. (2017) ranked the soil properties that were most frequently used. Soil organic C ranked first, followed by variables linked to water availability, soil intrinsic properties such as soil texture, bulk density and depth. A limited number of studies considered soil chemistry variables such as CEC, pH or base saturation, perhaps because of the limited availability of such data. These observations suggest that the use of soil parameters to assess ES as schematized in Fig. 14.4 is constrained by the availability of maps of soil properties with appropriate resolution. As highlighted previously, ongoing development of DSM should help to alleviate these constraints.

Considerable variability in a particular soil property may occur within a soil order and even within a soil series when individual properties are assessed (Loescher et al., 2014). Studies of the spatial variability of soil chemical and biological properties have indicated that spatial independence varies greatly with the property considered, as well as with land use (Robertson et al., 1993; Loescher et al., 2014). DSM has the potential to provide more accurate information for specific properties compared to conventional soil mapping that assign a single value for several soil properties over a mapped polygon, often with no assessment of the level of uncertainty. For example, the consideration of co-variables such as a topographical index should increase the accuracy of the spatial prediction of certain soil properties within a soil mapping unit, especially in complex terrains. When a specific need arises, for example an interest in increased accuracy in mapping soil C stocks of a given region, DSM can provide information indicating the effort needed, in terms of sampling intensity, to improve the accuracy to a given level of precision for that specific property. The terms "tailor-made map" or "map on demand" are now being used to describe such efforts. It should be recognized that even where soil properties are correlated, a map of a given property (e.g., soil C) may not show the same spatial dependence or spatial pattern as a map of another property (e.g., heavy metals) because different processes are driving the accumulation or availability of these elements independently of the main soil processes defining soil types.

Because of the interactive nature and flexible presentation options of DSM products, they are increasingly being used to predict changes in ecosystem composition and processes at various scales, making soil science more useful to other disciplines. For example, DSM products have been used to understand and predict climate change related vegetation shifts (Kuhn et al., 2016), or changes in net primary production (Maire et al., 2015). Such results would have been much more difficult to achieve with traditional soil maps.

While there are many benefits expected to arise from the increased use of DSM in environmental and global change management, Baveye and Laba (2014) sound a note of caution regarding the attraction scientists may feel for new technologies and concepts. Specifically, they provide an alternative perspective on the need for further advances in techniques of geostatistics, but in general they argue that (soil) researchers may at times focus too much on the application of new and innovative methods, sometimes at the expense of a continued search for answers to the questions for which the methods were first employed. They illustrate the concept through an alternative view that evaluating soil homogeneity may at times be a better approach for answering questions related to crop production and evaluating soils for their ability to provide ES. The selection of an appropriate measurement, sampling framework, and plot design to support area or volume estimation is a fundamental element of that requirement. In many cases, they argue, the use of a simpler approach provides answers that are just as reliable as more complex and detailed schemes.

Uncertainty in soil mapping

The assessment of fine scale uncertainty provided by DSM fills an important information need when assessing or modeling soil properties at the landscape level. The consideration of uncertainty enables a better understanding of the role of soils in sustaining processes and providing ES. For example, at the landscape level, when a relationship between a soil property and a process is being investigated it is difficult to conclude on the robustness of the relationship if the uncertainties of the soil property are not known or not reported. Considering only the average of a soil property can be misleading. For example, two mapping units may show a great difference in a soil property (e.g., pH) but if the within-site variability is large the difference may not be significant. Conversely, two soils having a much closer pH may be statistically different if the variability is low. This simple example illustrates that mapping of soil properties and reporting uncertainties at a finer scale, should make it possible to better interpret mapped soil information. Furthermore, consideration of fine scale uncertainty levels can help answer questions about model performance or the robustness of an indicator used to evaluate the sustainability of forest management.

Temporal analysis: using DSM to evaluate forest change

One of the most promising aspects of the transition from traditional soil maps to DSM is the improved representation of soil change. Heuvelink and Webster (2001) outline some of the conceptual differences involved when time is added to a spatial analysis; recognizing that (a) time consists of a single dimension, (b) it always moves forward, and (c) the laws of conservation of mass and energy must be obeyed. Time series analysis involves the evaluation of structure in a series of repeated measurements of a single property, and the analysis bears resemblance to the use of geostatistics to evaluate spatial variation.

Detailed analysis of time series data has been applied to some aspects of soil science (e.g., soil hydrology; temperature), but is less common in others (e.g., changes in soil chemical or physical properties). This is due, in part, to the type of measurements being taken. For example, the sampling effort to acquire repeated, spatially explicit measurements of attributes like soil bulk density or soil carbon over large areas represents a significant challenge as compared to measurements from, as an example, automated sensors. For repeated measurements that require collection of a sample, considerable replication is necessary to ensure the results are representative of the sample volume, and that the sampling volume is explicitly defined, especially with respect to depth. Also, the destructive nature of some types of measures precludes a true re-measurement of the same medium. Because of these considerations, some assessments lend themselves better than others to detailed time series analysis.

Soil carbon

Many DSM projects cite the need for more information on climate change as a driver of soil C stocks, and this seems justified considering that the global soil C stock (median estimate of 1450 Pg C to 1 m depth, range 504−3000; Scharlemann et al., 2014) is estimated to be nearly two times larger than the atmospheric C pool. There is much interest in evaluating changes in soil organic C stocks, and detailed discussion of methods for evaluating them have been described in the Intergovernmental Panel on Climate Change (IPCC) Good Practice Guidance for National Greenhouse Gas Inventories (IPCC, 2006), and in the IPCC Good Practice Guidance (GPG) for Land Use, Land-use Change and Forestry (LULUCF; IPCC, 2003). Two approaches for estimating change in C stocks in any pool are the *stock difference* method and the *gain-loss* method. The IPCC (2006) and Kurz et al. (2009) describe the stock difference method as “inventory change” meaning the difference in C stocks between two inventories conducted at different times (although within the same population unit), and the gain-loss method as “one inventory plus change” meaning that process-based modeling is used to evaluate the changes occurring after a single inventory. The difference between these two approaches can be illustrated by a comparison of efforts to evaluate changes in soil organic C in the United States and Canada.

Estimation of greenhouse gas fluxes from forests of the United States is based on the stock difference method and relies on results of re-measurements within the NFI every 5−10 years to estimate C stocks for all pools, including soil (US EPA, 2018). The NFI in the United States is conducted by the Forest Inventory and Analysis (FIA) Program of the USDA Forest Service. Permanent ground plots within the NFI are distributed approximately every 2400 ha across the conterminous land mass of the United States and at different spatial intensities and measurement frequencies in Alaska, Hawaii, and Territories of the United States. Tree- and site-level attributes are measured at regular temporal intervals on plots that have at least one forested condition (USDA Forest Service, 2017). Soil samples are collected adjacent to every 16th permanent plot, where at least one forested condition exists, distributed approximately every 390 km^2 (O’Neill et al., 2005).

In Canada, the Carbon Budget Model of the Canadian Forest Sector 3 (CBM-CFS3; Kurz et al., 2009) is used to estimate change in forest C stocks based on the gain-loss approach. The required modeling of changes to soil C stocks, which are based in part on field observations of soil variables, is one of the most challenging aspects of CBM-CFS3 (Shaw et al., 2014). In a comparison of modeled versus inventory data across Canada, Shaw et al. (2014) reported that almost 90% of the variation in the total ecosystem C stock error was contributed by the soil C pool. DSM approaches should improve the predictions of spatial and temporal variability in soil C stocks in the future and could lead to improved model representation, regardless of whether the stock difference or gain-loss approach is used.

Regarding the ability of repeated inventories to detect changes in soil carbon stocks, Conen et al. (2003) discussed the characteristics of a study site that would make it suitable for long term monitoring for global change research, including (1) the carbon stocks should have reached long-term equilibrium (i.e., ‘old sites’ in terms of pedogenesis were preferred), (2) the site should be free of extraneous factors affecting carbon stocks, such as land use change, flooding, erosion, (3) the spatial variability should be small, and (4) the expected change due to global warming should be large, so that measurable changes will occur over a relatively short time frame. Conen et al. (2003) evaluated the sensitivity of field based soil sampling and carbon analysis in relation to temporal change for time scales relevant to global change from two benchmark sites in steppe ecosystems in Russia. They used stratified random sampling to establish plots that were spatially referenced with high accuracy. The mean annual air temperature of the two plots differed by approximately 1.7C and the plot with warmer temperatures had higher variability and lower soil carbon concentration, so that the minimum detectable change in soil organic carbon was 0.036% and 0.048% C, respectively. They concluded that if 50 soil measurements were taken at each plot/time, a 10% decline in carbon concentration could reliably be detected in 26 years at the dry (colder) steppe plot while it would take 43 years to reliably observe a 10% decline at the (warmer) desertified steppe. This work highlights the relevance of precise spatial data in evaluating climate change effects on SOC, as well as providing insights into the types of questions that can be answered by temporal analysis within a DSM framework.

One of the challenges involved with performing temporal analysis of soil attributes is that data to support the predictions of change may not be available. Saby et al. (2008) used an innovative approach to evaluate changes in soil organic C in France during a 14-year period by comparing results from soil test samples that were previously submitted to certified analytical laboratories by farmers. These authors retrieved 329 records from a national database and sorted them into 3 time periods. Precise field locations were not available, but the data records were each attached to a canton administrative unit from which they were collected, effectively registering their spatial location to that unit (approximately 5 km^2). The data were compared against expected trends in soil organic C and elevation to confirm the assumptions about location and the distribution of soil organic C values. The results revealed a large decline in soil organic C for that area over the 14-year time period.

Efforts to optimize data collection over larger areas were discussed by Baldock and Grundy (2017), who described a program to monitor changes in soil C at the continental scale for Australia. These authors outlined the trade-offs between increased precision with fewer measurements for direct measurement of soil organic C, compared to the increased sample coverage (with less precision) for proximal sensing, remote sensing, and computer simulation as approaches for estimating soil organic C stocks. They used measurements on C estimation areas within agricultural fields to develop regression models describing the change in C stocks over time in response to agricultural management. These, coupled with baseline values, could be used to estimate C stock changes and support DSM-based evaluations of climate change and soil C.

Modeling change resulting from natural disturbance events could also greatly benefit from the improved soil information made available by DSM. Seidl et al. (2011) discuss current approaches for spatio-temporal modeling of forest disturbance by drought, wind throw and wildfire. Soil processes play an important role in each of these disturbance types, and although the modeling approaches are varied, improved soil information of the type provided by DSM would improve these efforts. In particular, reliable spatially explicit soil information would facilitate a shift from statistical models to more mechanistic approaches. It would also facilitate the spatially explicit modeling of responses across landscapes in comparison to approaches that rely on statistical (implicit) distributions of different soil conditions across landscapes. Soil factors affecting water content were identified as fundamental drivers of drought occurrence, while the effect of soil properties on wind throw was more subtle and related to site conditions, and susceptibility and the resistance to uprooting (Seidl et al., 2011). In contrast to these drivers, to evaluate the relationship of soil to fire modeling would require not only an understanding of the effects of soil properties on vegetation composition and condition as they affect fire occurrence and behavior, but also the impact of fire on soil properties, in particular soil C levels, loss of humus cover, and increased susceptibility to erosion.

DSM as a tool for quantitative evaluation of soil processes

Another type of temporal analysis that is relevant to global change effects on forests is the modeling of landscape and soil evolution. Dietrich et al. (2003) describe a process-based approach for evaluating sediment transport and erosion in landscapes. The mathematical expressions of such processes were presented as geomorphic transport laws that control the evolution of landforms over time in response to slope-dependent soil creep, soil production, landslide transport, overland flow erosion, and channel incision. Roering and Gerber (2005) used geomorphic transport laws in forested landscapes of Oregon to show that the soil erosion rate after wildfire was six times greater than the long term erosion rate, and that fire effects could be linked to as much as 50% of the overall erosion on steep hillslopes. Geomorphic transport laws have not been defined for all the processes that drive landscape evolution, and they are not intended to provide exact predictions of site specific features at given times. However, these mechanistic descriptions of landscape change are grounded in observation and experimentation, so they can provide a reference state for fine-scale prediction in the absence of other information. They also can serve as comparative measures of how landscapes differ from one another (Dietrich et al., 2003).

Quantitative landscape evolution models, such as the examples provided, share many similarities to DSM, as both represent new approaches that harness modern computing and in particular, digital elevation models, to evaluate flows of material and energy in landscapes. These quantitative evaluations of landscape and soil processes are informing a new mathematical understanding of pedogenesis and other fundamental soil functions, which can be considered as occurring in the vanguard of a new era of "quantitative pedology" that is intricately linked to the concepts and activities of DSM and its application to temporal analysis of soil. In addition to the conceptual similarities, outputs from quantitative landscape evolution models can inform DSM (e.g., by better depicting variations in regolith thickness across landscapes), while observations taken in support of DSM can be used to inform and validate landscape evolution models.

In a unique extension to the mechanistic approach exemplified by the use of geomorphic transport laws, Heung et al. (2013) used the empirically derived universal soil loss model (USLE; Wischmeier and Smith, 1978), parametrized with a full suite of soil and environmental data to drive a cellular automata model for evaluating landscape evolution in British Columbia, Canada. The cellular automata in this model provided a feedback loop to adjust the USLE parameters at each time step, which had significant effects on model output. Effectively, soil redistribution at each time step resulted in changes to the topography and flow routing, and the redistribution of soil in each subsequent step is enhanced or diminished in a way that could not be recognized by the USLE in its original (empirical) form.

Mechanistic models of soil genesis, or models of soil evolution, can also be used to evaluate and predict changes in soil properties over time. Minasny and McBratney (2008) provided an extensive review of quantitative pedogenetic modeling, and they presented a soil landscape model for soil thickness and carbon content based on a mass balance approach. In addition, efforts to extend soil landscape models to quantitative descriptions of soil profiles were discussed by Minasny and McBratney (2016). One example of a profile model is SoilGen (Finke, 2008), which considers an initial soil or parent material as a starting point, and applies boundary conditions that represent the factors of soil formation to soil forming processes that modify the original soil or material. SoilGen is a one dimensional solute transport model that simulates leaching of solutes and clay in addition to evaluating processes of heat flow, weathering, bioturbation and the uptake of water and ions. Yu et al. (2013) used the SoilGen model to evaluate controls on the cycling and accumulation of organic matter in three loess soils under long-term deciduous forests in Belgium in comparison to three pedons under recently (1970) established deciduous forest in the Ziwu Mountains, China. In the future, spatialized versions of these mechanistic profile models could potentially be developed by linking the algorithms for process based models of soil profile evolution with the georeferenced data and computing environment of DSM.

While mechanistic studies such as those described have important implications for evaluating soil forming processes and improving the theoretical basis for understanding the mechanisms of landscape change, they have had limited application so far in mandated assessment of anthropogenic change at the local, regional, or global scale. This likely reflects the difficulties associated with quantifying the reliability of assessments resulting from a purely theoretical process, particularly where anthropogenic influence is substantial, or where stochasticity plays a large role in observed spatial and temporal distribution patterns. Models invariably are simplifications of the natural processes, making calibration difficult, especially when the modeled processes operate at finer scales than can be practically reflected in field sampling programs aimed at verifying the results. A considerable amount of data would be required to verify model outputs in a way that would satisfy regulatory obligations or commitments related to climate change. If such data were available, a preferred approach might be to portray the results of measurements (or predictions of their values) in a spatial context at successive sampling times using DSM techniques.

Conclusions

Much effort has been spent over the past few decades to better describe the spatial variation of soil properties through statistical and mechanistic approaches that can be applied through DSM. This effort has been very successful in developing mapping tools that show great promise for enhancing the use of soil maps in answering a wide range of questions in forest resource management and global change. The tools include GIS software capable of manipulating large datasets and computer models employing new statistical approaches to extract soil interpretations from large databases of soil and land information. The land data are being collected on an ongoing basis from a wide range of aerial and space-borne platforms, and are subsequently distributed to users through the internet at low or no cost. The conceptual framework for this transformation of map making is stated in an updated perspective on Jenny's (1941) classic model of soil formation, involving the addition of spatial position as well as the observed soil properties at that location of soil formation (McBratney et al., 2003). Predictive techniques based on machine learning, regression, and geostatistics combine to analyze the available data in this spatial context and develop enhanced soil maps that convey soil class and attribute information at a higher resolution than previously possible. The new maps are also capable of providing a much better understanding of their reliability andnew ways of thinking about how spatially explicit soil information can be combined with other information on ecosystems and land characteristics to provide new information and interpretations to address global change needs in forest management.

There is little question that the achievements made so far in DSM are transformational, but what is less clear is whether the potential benefits of these new approaches are being realized as quickly as needed. Several constraints outlined above are summarized here:

Acquiring the soil pit data needed to train predictive models: It may seem counter-intuitive, but the development of advanced mapping techniques, with their potential to quickly provide predictions of soil type and attributes over very large areas has led to a need for more field data, rather than less. More field data is needed because (a) the higher resolution of the new map products has expanded the range of possible values for soil conditions at a given location, (b) the DSM's are being prepared for new and expanded areas including those outside of where traditional soil maps are available, and (c) evaluating uncertainties in DSM requires independent validation data. In the first case, the high resolution and specificity of pixel-based (raster) maps allows varying soil conditions that previously may have been lumped into a single average or modal value for a large area (polygon), to be explicitly depicted at each of the many thousands of pixels within a typical soil map. Soil pit data is therefore required so that this variation can be better described at each point in order to achieve the best results. In the second case of extending soil mapping into previously unmapped areas, or where soil information is highly generalized, new soil pit information is required to help understand the variation in soil properties for areas where it had not been previously evaluated. Finally, the most rigorous evaluations of uncertainty for predicted values of soil properties require validation data to be kept entirely separate from the data used to train the model. In the longer term, this need for new validation data may decline as these data can be re-used for several projects if they are of high quality.

Linking pedological knowledge with computational skills to produce high quality DSM's: What can sometimes be lost in these discussions is that the main purpose of the activity is to prepare a soil map, and the best person to prepare and evaluate the quality of that map will have a detailed understanding of pedology. There is a considerable learning curve in developing skills related to both of these activities. Ideally, this issue can be resolved by working in teams of specialists each with their own skill set. The need for effective among team members communication cannot be over-stated. The DSM community is currently growing, in part, due to growing power of modern computing and growth of interest in environmental science.

Providing land managers with information needed to make decisions in forest management and global change: The increasing application of DSM techniques to problems in forest management, ES, and global change is more than an academic exercise. McBratney et al. (2012) describe how soil assessments can be identified and structured by soil scientists or by stakeholders. Regardless where the initiative arises, it is essential that map makers and decision makers collaborate to effectively make use of the detailed soil information available through DSM.

To summarize, new mapping approaches and technologies embodied in DSM show tremendous promise to better apply soil information to problems in forest management and global change, and will likely continue undergoing constant improvement for the foreseeable future. Several examples exist where the new techniques are providing valuable information. An ongoing challenge for practitioners of DSM, forestry professionals, resource managers and decision makers, is to work together to ensure that better soil information is incorporated into decision making to better manage natural resources and improve environmental stewardship.

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