Chapter 21

Digital Soil Mapping: Interactions with and Applications for Hydropedology

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ABSTRACT

Spatial information on soils, particularly hydrologic and hydromorphic soil properties, is used to understand and assess soil water retention, flooding potential, erosion hazard, and depth to seasonal high water table. These properties influence soil use and management interpretations for construction, waste disposal, plant production, and water management. Observed soil characteristics (soil horizons and soil properties) serve as both evidence of past processes and an indicator of present processes. As such, hydrologic and hydropedologic factors are useful for understanding and predicting soil variability. Conversely, spatial information on soils can be a critical input to hydrologic and hydropedologic models. Digital soil mapping (DSM) has evolved from traditional soil survey to take advantage of advances in computing and geographic data handling, as well as increased availability of environmental covariate data from digital elevation models and remotely sensed imagery. Digital elevation models can be used to enhance the input to hydrologic and hydropedologic models and extrapolate outputs from these models.

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1. SOIL MAPPING, SOIL SURVEY, AND THE VALUE OF SPATIAL SOIL INFORMATION

1.1. Pedology: Hydropedology and Pedometrics

Hydropedology is an integrative field of soil science, which incorporates the concepts of pedology, soil physics, and hydrology to understand soil–water interactions at various scales (Lin, 2003; Lin et al., 2005, 2006). Another integrative field that is rooted in pedology is pedometrics, which by contrast incorporates soil science, geographic information science, and statistics (Grunwald, 2006). Defined as "*the application of mathematical and statistical methods for the study of the distribution and genesis of soils*" (Heuvelink, 2003), pedometrics is concerned with quantifying soil variation in terms of its deterministic, stochastic, and semantic components. A subset of pedometrics is digital soil mapping (DSM), also referred to as predictive soil modeling (Scull et al., 2003) and quantitative soil survey (McKenzie and Ryan, 1999). Lagacherie (2008) has defined DSM as "*the creation and population of spatial soil information systems by numerical models inferring the spatial and temporal variations of soil types and soil properties from soil observations and knowledge and from related environmental variables*." The explicit geographic nature of DSM aligns it with hydropedology because hydropedology has been advocated as a means to study the relationships between soils, landscapes, and hydrology (Lin et al., 2006). Therefore, DSM can provide effective linkages for the integration of pedology and hydrology. Lin (2011) referred to the development of such linkages between hydropedology and digital soil mapping as "*an exciting research area, which can improve the connection between spatial soil mapping and process-based modeling*."

This chapter will examine the importance of hydropedology to advances in DSM through the expansion of our knowledge of pedogenesis and vertical and lateral soil variability at various scales; how DSM can support further advances in hydropedology through improved representation of spatial soil information; and how coevolution of these two fields may foster a greater understanding of – and sustainable use of – the Earth's Critical Zone.

1.2. Spatial Soil Information and Soil Survey

The perceived need for, as well as the demand for, spatial soil information is growing (McBratney et al., 2003, 2006; Lagacherie and McBratney, 2007; Hartemink and McBratney, 2008). Increasingly, detailed soil data from multiple counties and states are being viewed and analyzed together. To address resource issues ranging from local to global scales, environmental scientists and policy-makers are seeking soil information that is more specific (soil properties) and more detailed (spatially explicit). These user's needs represent a challenge for soil scientists to provide new spatial soil information, particularly in a digital format that is readily incorporated into geographic information systems (GIS) and can be analyzed with other spatial data (Lagacherie and McBratney, 2007).

Soil surveys have been conducted to meet user needs by creating an inventory of local soil resources, and by educating the public about the role of soils in their environment (Brown and Miller, 1989). The primary objective of soil survey programs is relatively consistent: to delineate uniform management areas (i.e. map unit polygons) across the landscape and provide users with information on soil properties and soil interpretations for these map units to support generalized soil use and management decision making. Alternatively, as the Chief of the US Soil Survey Division put it, the role of the soil survey is "to get the facts about soils, to classify them, and to map them in ways that would furnish a sound basis for interpretation by other people" (Durana, 2002). However, more recently, users of soil survey information are asking questions of soil survey for which it was not intended to answer (Sanchez et al., 2009; Hartemink et al., 2010), such as calculation of C stocks, distributed hydrologic modeling, nutrient cycling and nutrient depletion, and examination of climate change.

Legacy soil maps (and associated tabular data) have been digitized to produce digital map products that represent the spatial extent of soil classes and soil properties (Grunwald et al., 2011). Most of these digitized maps use a vector format to represent polygons that consist of one or more soil types or classes (e.g. soil series or soil taxa), although some digitized soil maps utilize a raster format where each grid cell is assigned a soil class or a soil property value (Grunwald et al., 2011). Whether explicit (soil properties) or implicit (soil classes), these digital databases can be used to represent the spatial variability of hydrologic and hydromorphic properties. For example, the Soil Survey Geographic (SSURGO) database, which is the most detailed soil map data for the US, provides polygon soil class maps at scales of 1:12,000 to 1:125,000, and is 86% complete for the land area of the conterminous US (Soil Survey Staff, 2009). The map units represent one or more soil classes and are linked to tables of estimated property data for each component soil. The SSURGO data are most readily available through the USDA-NRCS Web Soil Survey (WSS). Summary statistics on WSS usage, particularly which properties and interpretations are most commonly requested (Table 1), indicate that soil–water properties are some of the most popular ones. Soil properties and soil ratings in the top 20 over a single year (January–December 2011) related to potential hydropedology applications or interpretations include the top three most requested ratings (hydrologic soil group, depth to water table, and drainage class) and eight of the top 20. If counting soil characteristics that are related to hydrologic properties or processes (e.g. percent sand, silt, and clay; soil organic matter content) this number of requested ratings is 12.

1.3. Use of Spatial Soil Information in Hydrology and Hydropedology

Legacy soil data are frequently used to visualize, analyze, or model the linkages between soil properties and hydrologic processes, or between soil variability

TABLE 1 Summary of Web Soil Survey (WSS) Usage for All of the Year 2011, Indicating the Rank of the Top 20 Queries Based on the Number of Individual Requests for Reporting of Each Property or Rating. Also Shown is the Number of Months Between January 2011 and December 2011 in which that Rating Appeared in the Top 50 of All Queries

Rank	Ratings	Count	Months in Top 50
1	Hydrologic Soil Group	12,2572	12
2	Depth to Water Table	93,514	12
3	Drainage Class	84,697	12
4	pH (1−1 Water)	80,581	12
5	K Factor, Whole Soil	77,317	12
6	Percent Clay	76,822	12
7	Flooding Frequency Class	76,453	12
8	Organic Matter	74,960	12
9	Corrosion of Concrete	73,209	12
10	Depth to Any Soil Restrictive Layer	73,067	12
11	Available Water Capacity	72,396	12
12	Saturated Hydraulic Conductivity (Ksat)	71,449	12
13	Percent Sand	71,429	12
14	Ponding Frequency Class	68,268	12
15	Plasticity Index	67,686	12
16	Percent Silt	67,641	12
17	T Factor	67,467	11
18	K Factor, Rock Free	66,898	10
19	Cation-Exchange Capacity (CEC-7)	66,693	9
20	Map Unit Name	66,383	11

and hydropedologic properties. For example, Turk and Graham (2011) used SSURGO and the smaller-scale State Soil Geographic (STATSGO) database to examine the extent and spatial distribution of vesicular horizons in the western US. Vesicular horizons are found at or near the soil surface, where the characteristic bubble-like vesicular pores influence surface hydrology by restricting infiltration, often encouraging surface runoff and ponding (Turk and Graham, 2011). As another example, Vepraskas et al. (2009) also used SSURGO data to examine hydromorphic properties and soil-use interpretations. Starting with measured soil water-table fluctuations for multiple soil series, which were combined with other historic climate data in a hydrologic model to compute long-term water-table fluctuations, Vepraskas et al. (2009) used the SSURGO data to extrapolate hydrologic modeling results and soil use and management interpretations (soil suitability for septic systems and the presence of wetland hydrology) across larger land areas. Vepraskas et al. (2009) went on to use these data and models to consider climate-change impacts on soil drainage class and, therefore, changes in soil use and management interpretations.

For hydrologic modeling, soil properties are one of the most fundamental input parameters of these models. For local-scale and watershed-scale modeling using models such as watershed modeling system (WMS) (Nelson et al., 1994), Soil Water Assessment Tool (SWAT) (Arnold and Allen, 1996), and TOPMODEL (Beven and Kirkby, 1979), SSURGO data are most commonly used as soil input parameters. Most of the hydrologic models are written so that input can be taken directly from the SSURGO data with minimal processing (Ogden et al., 2001). For continental and regional-scale climate, hydrology, and ecosystem modeling using models such as Variable Infiltration Capacity (VIC) (Liang et al., 1994, 1996), Noah Land Surface Model (Noah), and Common Land Model (CLM) (Bonan, 1998; Dai and Zeng, 1997; Dickinson et al., 1993), the 1-km data from the CONUS-Soil database for the Conterminous United States (Miller and White, 1998) are commonly used. This database is based on STATSGO, and it includes parameters such as soil texture class, depth to bedrock, bulk density, porosity, permeability, available water capacity, soil-hydrologic group, and curve numbers.

Land-surface climate models are used as large-scale hydrology models by parametrizing the land-surface schemes for water balance (Wood et al., 1998). The global land-surface models, such as CLM, MOSIAC model (Koster and Suarez, 1996), and VIC, use soil data from the Global Land Data Assimilation System (GLDAS). The soil data used in the GLDAS were derived from a global soil data set that includes fractions of sand, silt, and clay, and porosity, among other fields (Reynolds et al., 2000). These properties are spatially represented based on the FAO Soil Map of the World, which is correlated to a global database of over 1300 soil pedons. The spatial resolution of the GLDAS data is 1/4 or 1 degree. Soil properties drive much of the exchanges in the land-surface system and the global data sets are increasing the understanding of atmospheric feedbacks (Zaitchik et al., 2009).

1.4. The Case for DSM

While digitized soil maps are available for most of the world (Grunwald et al., 2011); for many areas those data are at a very small scale (1:1 million or coarser) and do not adequately represent soil variability in a format that is useful to non-pedologists (Sanchez et al., 2009). The majority of currently available digital soil maps are actually compilations of multiple legacy soil maps, which were initially produced as hard-copy maps and subsequently digitized (Grunwald et al., 2011). For example, although SSURGO and STATSGO are digital products, they are based on paper maps that were later converted to vector-based polygon maps. For SSURGO, the soil maps were originally produced as part of approximately 3,000 independent soil surveys, and these individual maps are of different vintages and different scales, they were created using different mapping concepts, and they often use different soil components and different estimated property data to represent the same soil–landscape features. Consequently, there are frequently artificial boundaries in the data associated with geopolitical boundaries caused by discontinuities in map unit composition and in estimated soil property data, which produce discontinuities in mapped soil properties and in soil use and management interpretations. All these emphasize the point that digitizing existing paper maps is not DSM.

Hartemink et al. (2010) listed the following limitations of most existing digitized soil survey maps: (i) they are static, (ii) they aggregate soil information into soil classes that are not readily compatible with quantitative applications, (iii) the information content has been overly generalized relative to the information on the regional soil resources that was collected to create the soil survey, (iv) they are improperly scaled, and (v) they represent the information as polygons that are not as readily combined with most other natural resource data, which are raster-based. Similarly, Zhu (2006) emphasized that the spatial and attribute generalization of soil spatial variation into discrete classes makes soil survey information incompatible with other forms of continuous spatial data for environmental modeling. All things considered, there is a tremendous potential for the DSM community to capitalize on the demand for better soil information by improving the quality of existing digital soil maps and directly creating raster-based soil data of functional soil properties for hydropedologic investigations and hydrologic modeling.

2. DIGITAL SOIL MAPPING—SPATIAL PREDICTION OF SOIL PROPERTIES AND TYPES

2.1. Review of Approaches to Soil Spatial Prediction

2.1.1. State Factor or clorpt Model

For the latter half of the 20th century, the scientific rationale for soil mapping has been the state factor, or *clorpt* model (Jenny, 1941, 1980), which was originally proposed by Dokucheav and Hiligard, and later fully articulated by

Hans Jenny (Hudson, 1992). The state factor model is expressed by the following equation:

$$S = f(\mathrm{cl},\ \mathrm{o},\ \mathrm{r},\ \mathrm{p},\ t, \ldots), \tag{1}$$

where soil (S) is considered to be a function of climate (cl), organisms (o), relief (r), and parent material (p) acting through time (t) (Jenny, 1941, 1980). The ellipsis (…) in the model is reserved for additional unique factors that may be locally significant, such as atmospheric deposition. The *clorpt* equation illustrates that by correlating soil attributes with observable differences in one or more of the state factors, a function (f) or model can be developed that explains the relationship between the two, which can be used to predict soil attributes at new locations when the state factors are known. An important distinction of the *clorpt* model is that "The factors are not formers, or creators, or forces; they are variables (state factors) that define the state of a soil system" (Jenny, 1961). This means that the factors do not constitute pedogenic processes, but are factors of the environmental system which condition processes. In order to bridge the gap between factors and processes, the *clorpt* model is supplemented by additional models that are useful at explaining various processes at different scales. A notable example is the catena concept (Milne, 1936), which attributes soil variation along a hillslope sequence to erosion and deposition, hydrology, and stratigraphy.

While Jenny developed quantitative relationships between soil attributes and the state factors one at a time (e.g. climofunctions), in conventional soil survey, soil scientists have to rationalize the local complexity of soil-landscapes in their entirety, and therefore develop conceptual models of the soil–landscape relationships. Soil scientists' derive their tacit knowledge of soil–landscape relationships by viewing the soil continuum at a number of opportune and purposive locations (McKenzie and Austin, 1993). To segment the soil continuum, soil scientists use natural boundaries, such as "topographic divides, contacts between different rocks or sediment, inflections in slope gradient or shape, and contacts between different landforms of different age, origin, and internal structure" (Wysocki et al., 2011). Other common boundaries used in soil survey include different vegetative communities, or predefined breaks in slope gradient that are deemed significant to land management. In order to articulate the landscape position of unique soil components within map units (e.g. soil delineations), soil scientists use stringently defined geomorphic descriptors (Schoenberger and Wysocki, 2008; USDA-NRCS, 2012). Due to the fact that soil components may only correspond with a portion of a given landform, there are numerous soil-geomorphic descriptors that are unique to soil science.

2.1.1.1. Hydrologic Processes of Soil Formation

While hydrology is not explicitly named as a state factor in the *clorpt* model, water movement and storage within pedons and across landscapes form the driving force of most pedogenesis (Buol et al., 2003). For this reason, Runge (1973) named water as one of the three factors in his alternative soil factorial model, in addition to organic matter production and time. In contrast to Jenny's (1941) state factor model, Runge incorporated elements of Simonson's (1959, 1978) process-systems model. Within the *clorpt* model, hydrologic factors – including atmospheric (precipitation amount and timing) and terrestrial (evapotranspiration, water-table fluctuations or lateral water flow, hydraulic gradient, or proximity to surface water) – have been considered to be represented by climate and relief, respectively (Jenny, 1941; Buol et al., 2003). This distinction is useful for separating regional and local influences on soil hydrology.

Therefore, hydrology is considered indirectly related to each of the state factors. Climatic variations in precipitation and evapotranspiration control the amount and timing of water additions to the land surface. Relief affects the redistribution of precipitation, either due to orographic effects or by concentrating runoff, and variation in evapotranspiration, due to differences in solar radiation. Organisms, particularly vegetation, not only respond to differences in available water (due to the effect of climate and relief), but also directly influence the amount of water through interception and consumptive water use. Overall, hydrology is not an independent state factor, but a collection of processes that are influenced by the state factors.

2.1.2. scorpan *Model – The Digital Soil Mapping Formula*

Recently, McBratney et al. (2003) have offered a revised formalization of the state factor model. This revised formula is expressed by the following equation:

$$S = f(s, c, o, r, p, a, n), \tag{2}$$

where S, a set of soil attributes (S_a) or classes (S_c), is considered a function of other known soil attributes or classes (s), climate (c), organisms (o), relief (r), parent materials (p), age or time (a), and spatial location or position (n). The *scorpan* equation also explicitly incorporates space (x,y coordinates) and time ($\sim t$). Thus, the *scorpan* equation can be expanded as follows:

$$\begin{aligned} S[x, y, \sim t] = f(&S[x, y, \sim t], c[x, y, \sim t], o[x, y, \sim t], r[x, y, \sim t], \\ &p[x, y, \sim t], a[x, y], [x, y]). \end{aligned} \tag{3}$$

This expansion indicates that *scorpan* is a geographic model, where the soil and factors are spatial layers that can be represented in a geographic information system.

The *scorpan* model deviates from *clorpt* in that it is intended for quantitative spatial prediction, rather than explanation (McBratney et al., 2003). This distinction justifies the inclusion of soil and space as factors, because soil attributes can be predicted from other soil attributes and spatial information. For example, many soil attributes are correlated and can thus be reasonably predicted from each other. Also, Tobler's first law of geography (Tobler, 1970) tells us that near things are spatially correlated, and can thus be predicted by their distance from their neighbors. To account for the soil factor, prior soil information can come from either published soil maps or the expert knowledge of soil surveyors. The space factors can come from indices of relative position, or by incorporating spatial autocorrelation (e.g. cokriging or regression kriging). While prior soil information is undoubtedly not an independent factor, the independence of spatial information is dubious. In most situations, spatial information likely accounts for relationships not captured by other factors (McBratney et al., 2003). Otherwise, from a metaphysical perspective, spatial information accounts for the random diffusion of particles trying to achieve a uniform state within a system (Hengl, 2009). The addition of space is not a new idea, as Jenny himself spent a great deal of time validating spatial soil relationships (Hudson, 1992). However, the revised formulation of *scorpan* recognizes the importance of prior soil information and spatial relationships to help explain soil spatial variation.

2.1.3. STEP-AWBH Model – A Space–Time Modeling Framework

Given the importance of anthropogenic forcings in determining observed soil properties, Grunwald et al. (2011) have proposed a new conceptual model for understanding soil properties for a pixel (p_x) of size x (width = length = x) at a specific location on Earth, at a given depth (z), and at the current time (t_c):

$$\begin{aligned} SA(z, p_x, t_c) &= f\left\{ \sum_j^n [S_j((z, p_x, t_c), T_j(p_x, t_c), E_j(p_x, t_c), P_j(p_x, t_c)] \right\}; \\ &\int_{i=0}^{m} \left\{ \sum_j^n [A_j(p_x, t_i), W_j(p_x, t_i), B_j(p_x, t_i), H_j(p_x, t_i)] \right\}, \end{aligned} \quad (4)$$

where the soil property of interest (SA) is a function of a number ($j = 0$, 1, 2, …, n) of relatively static environmental factors (only at t_c): ancillary soil properties (S), topographic properties (T), ecological properties (E), and parent material properties (P), as well as a number ($j = 0$, 1, 2, …, n) of dynamic environmental conditions (with values representing dynamics through time t_i with $i = 0, 1, 2, \ldots$, m): atmospheric properties (A), water properties (W), biotic properties (B), and human-induced forcings (H). The model is spatially explicit because it constrains all properties included in equation (4) to a specific pixel location. The model is temporally explicit as indicated by the inclusion of t (time) in equation (4). This recognizes the spatial variation and temporal evolution of STEP-AWBH properties that covary and coevolve with the target soil property SA. Similar to the *scorpan* model, the STEP-AWBH model reflects the new emphasis on existing soil information and spatial location as key attributes capable of providing predictive power in soil models.

The STEP-AWBH model separates hydrologic properties (W) from topographic (T) and climatic (A) factors, and formally includes anthropogenic properties (H). In previous factorial soil models, topography (relief) indirectly expressed the effects of hydrology on soil genesis. Yet, this is a simplification of reality that the STEP-AWBH model tries to overcome, where *T* represents topographic properties (e.g. elevation, slope gradient, slope curvature, and compound topographic index) that have been shown to be correlated with soil properties (see Grunwald, 2009). However, water flow and transport processes in soil depend on the interplay of *A* (atmospheric properties, such as precipitation arriving at the soil surface); soil surface conditions (e.g. salt crusts, residues, and density and composition of vegetation cover); internal soil characteristics that determine infiltration, percolation, and lateral flow processes (such as soil texture and soil organic matter); parent material (geologic formations) that control flow into the surface and deep aquifer; and topographic properties that enhance or subdue water flow at or close to the soil surface. Thus, in the STEP-AWBH model the hydrologic properties (*W*) are captured separately from *T*. Hydrologic properties can be measured using common physically based methods (e.g. to measure infiltration and soil moisture), assessed empirically (e.g. average water capacity or long-term upper and lower water table), or remotely (e.g. using soil moisture sensors such as those derived from the European Space Agency (ESA) Soil Moisture Ocean Salinity (SMOS) Earth Explorer mission or radar-derived soil moisture using RADARSAT). Specifically, satellite-derived hydrologic properties have emerged as a direct measurement set that provides pixel-specific values covering large regions. Since hydrologic properties vary in the space and time domain, they can be expressed as (i) a series of spatially and temporally explicit data inputs into equation (4), for example, soil moisture derived in monthly intervals over a 2- or 3-year time period for all pixels within a region or (ii) temporally aggregated sets (e.g. average, minimum, and peak soil moisture over a 5-year period) for all pixels within a region. Likewise, other AWBH variables can be entered into equation (4) using spatially and temporally explicit sets (e.g. temperatures at a discrete time, e.g. Jan. 1, 2011) or condensed/aggregated data over a period of time (e.g. mean annual temperatures 2000–2010). The *H* factor represents different anthropogenic forcings that can act across shorter or longer periods of time on $SA(z,p_x,t_c)$ to shift SA into a different state, such as greenhouse gas emissions, contamination (e.g. an oil spill), disturbances, overgrazing, and others.

2.2. Digital Soil Mapping

The generic digital soil mapping approach takes the form of the *scorpan* model or STEP-AWBH. This approach is similar to that practiced in conventional soil mapping, except that the functional relationships between the soil attributes or classes and model factors are formulated using mathematical (e.g. expert rule-based or fuzzy logic models) or statistical models, rather than conceptual models (Ryan et al., 2000). These mathematical or statistical models are fitted or trained using geo-referenced soil data, expert knowledge, or preexisting soil maps.

The model factors (also known as environmental covariates and ancillary data) are represented by environmental layers contained in a GIS. Typically, preference is given to raster-based geographic data sets, such as derivatives of digital elevation models (DEM) and remotely sensed imagery (RSI), as they provide a dense grid of measured or interpolated values with which to correlate to soil attributes. Developing DSM models by correlating soil and environmental factors is an efficient quantitative spatial prediction approach if the factors are more easily attainable than the soil observations, and have a strong physical connection to soil attributes or classes (Gessler et al., 1995). McKenzie and Ryan (1999) cited the impetus for this approach due to the need to develop quantitative soil spatial prediction methods applicable at smaller scales, as opposed to methods based purely on spatial interpolation between soil observations.

2.2.1. Mathematical and Statistical Models

In order to predict the spatial distribution of soil properties or classes, various mathematical and statistical models can be used. A comprehensive review of their application in DSM is provided by McBratney et al. (2003). A similar review has taken place in ecological modeling (Guisan and Zimmermann, 2000). Regardless of the variety of models available, Austin et al. (2006) have stressed that in ecological modeling the most important consideration is not the statistical model employed, but the ecological knowledge and statistical skill of the analyst. Minasny and McBratney (2007) have likewise concluded that improved spatial prediction of soil characteristics will result from accumulating better soil data, rather than more sophisticated statistical models. Some of the most common mathematical and statistical methods applied in DSM are discussed here, such as kriging, generalized liner models, tree-based models, and fuzzy logic models.

2.2.2. Kriging

Kriging is a special case of the *scorpan* model, where only the *n* factor is considered. Like other standard forms of spatial interpolation, kriging develops predictions at new locations by modeling the spatial dependence between neighboring observations as a function of their distance. Therefore, by taking into account the distance between neighboring observations a locally weighted average is taken to estimate values at new points. However, unlike other forms of spatial interpolation, with kriging the spatial weights are estimated objectively with a statistical model, the variogram, rather than by an arbitrary mathematical function. In addition to interpolating predictions, kriging is able to estimate the variance at each point, which can be used to judge the spatial accuracy of the interpolation.

Kriging is a suitable method in the presence of spatial dependence. However, in many cases, soil properties are the result of environmental covariates. In such cases, it is beneficial to model the deterministic component of soil spatial variation as a function of the environmental covariates, and any residual stochastic component by kriging. Variants of kriging, which incorporates both deterministic and stochastic components, include cokriging and regression kriging. In comparison to other statistical and geostatistical models, Bishop and McBratney (2001) have demonstrated regression kriging to be superior. However, at the landscape scale, when the soil is not sampled at distances closer than the average range of spatial dependence, Scull et al. (2005) found multiple linear regression to be superior to regression kriging.

2.2.3. Generalized Linear Models

One of the most commonly used groups of regression and classification models are generalized linear models (GLM), which are a modified form of the classical linear model designed to handle situations in which the linear model's main assumptions are not met, with these assumptions being that the response is normally distributed with a constant variance and that the predictors combine additively on the response. Lane (2002) has advocated the use of GLM in soil science as opposed to transforming the linear model when these assumptions are not met, such as for binomial (presence/absence) and Poisson (counts) distributions. Transformations are typically used to modify the linear model to handle alternative distributions, but can affect the interpretation of additivity on the transformed scale, where statistics such as standard errors and variance ratios values should be used with caution (Webster, 2001). Like linear models, GLM have similar fitting procedures and diagnostics, so they can be likewise interpreted:

$$g(\mu) = \beta_0 + \beta x_1 + \ldots + \varepsilon. \tag{5}$$

To modify the classical linear model, GLM allow the response to belong to a wide range of exponential family distributions (e.g. Gaussian, binominal, Poisson, and gamma), and relate the response's mean to the model on scale where the effects combine additively through the link function, $g(\mu)$. The effect of the link function transforms the model to linearity, and maintains the response's range of values. More simply put, this transforms the model, rather than transforming the data to fit the model's assumptions. A consequence of modifying the linear model requires that the parameters be estimated iteratively by maximum likelihood, as opposed to being derived analytically as with least squares. Another consequence eliminates the ability to employ the analysis of variance. Instead, the analysis of deviance is used, which is a measure of the difference between the observations and the fitted model, which for Gaussian distributions equates to the residual sum of squares.

Aside from being able to handle multiple distributions, GLM have additional benefits, such as being able to use both categorical and continuous predictor variables. Also as with linear models, they allow interactions between the predictors and polynomial terms, so as to model more complex data structures. To identify such interactions, exploratory techniques such as tree-based models (Guisan et al., 2002) and coplots (McKenzie and Jacquier, 1997) may be used. The use of interactions however can increase colinearity within the model at the expense of identifying meaningful relationships between variables (Park and Vlek, 2002).

2.2.4. Tree-Based and Forest Models

Tree-based models or decision trees differ from GLM in that they do not make assumptions about the form of the data. Instead, they are often referred to as data driven, whereby the resulting model's structure is based on the data itself, rather than some assumed distribution. This can be seen as both an advantage and a disadvantage. For example, given a sizable data set trees can easily identify complex data structure. In the absence of a sizable data set, other parametric models (Maindonald and Braun, 2007) such as GLM are likely to provide better estimates, given that they make assumptions about the structure of the data.

To understand tree-based models it is best to discuss how they are grown. The standard method of tree construction develops a set of decision rules using binary partitioning, which repeatedly subdivides the response into two sets of increasingly more homogeneous groups until no further purity within the groups can be gained by splitting them. When plotted these decision rules resemble a tree. During each step of the tree's growth the partition of the response is based upon whatever split among the predictors creates the best fit. For continuous responses (e.g. regression trees) the splitting criteria used are the residual sum of squares, while for categorical responses (e.g. classification trees) there are a choice of three splitting criteria, all of which seek to optimize the proportion of correctly classified observations. After the tree is grown the final groups or leaves are labeled with the mean (e.g. regression trees) or majority (e.g. classification trees) response within the leaves. While growing a tree following this procedure can be simply automated, the decision of when to stop its growth requires the subjective intervention of the analyst. Ultimately, the process could continue until each observation is correctly classified. While this would accurately describe the given data set, it would overfit the existing data set, and therefore poorly predict new data. The idea is that as the tree grows, less and less reduction in deviance is gained with each split. So, the tree's overall accuracy would suffer little if it were pruned to a smaller number of leaves. To determine an optimum stopping point, cross-validation is used. This pruning method produces a plot of the number of leaves against the amount of deviance explained. The optimal stopping point is the location on the plot where the slope flattens out, or falls below one standard deviation of the minimum cross-validated error.

Because of the automated nature by which trees are grown, they are often useful for exploratory data analysis (Guisan et al., 2002), so as to indicate the relative importance and potential interaction between predictors. In addition, the results of a tree-based model are easily interpretable if the number of binary splits is small, and they allow a mixture of both continuous and categorical predictors. Despite the relative ease with which trees are constructed, Hastie et al. (2009) list three notable limitations. The first is that trees are inherently unstable due to their data-driven nature of construction. As such, any change in the data may produce a different tree. For this reason, research in DSM (Park and Vlek, 2001; Scull et al., 2005) has shown tree-based models to perform less well than parametric models when validated by an independent data set. A second limitation of trees is that for continuous responses they do not produce continuous predictions, but rather unrealistic stepped predictions. Still for noisy data sets, McKenzie and Ryan (1999) have suggested that this is not a problem. Lastly, Hastie et al. (2009) cite tree's inability to capture additive structure. Hastie et al. (2009) state that it is possible for trees to capture such structure with sufficient data, but that tree-based model construction process does not readily exploit such structure within data.

In an effort to overcome tree-based model's limitations, a number of alterations to the construction of trees have been proposed, such as boosting (Freund and Schapire, 1997), bagging (Breiman, 1996), and random forests (Breiman, 2001). Each distinct alteration creates a model comprised of multiple trees, generally termed an ensemble, or continuing with the use of tree metaphors a forest. By growing a forest rather than a single tree it is possible to take a majority or weighted vote among the trees, thereby increasing the accuracy and decreasing the sensitivity of the model. In boosting, a forest is grown by repeatedly reweighing the misclassified and correctly classified observations in the data set. In bagging, a forest is grown by taking repeated bootstrap samples of the observations in the data set. In random forest, a forest is grown by taking repeated bootstrap samples of the observations and predictors in the data set. While each of these ensemble methods typically generates better estimates than a single tree, they also come at the expense of their interpretability.

2.2.5. Fuzzy Logic

Fuzzy logic is an alternative to Boolean logic that determines the membership to a given class by either a 0 (no) or a 1 (yes). Fuzzy logic deals with the ambiguity of defining the soil–landscape continuum by allowing a soil to have partial membership to more than one class, on a scale between 0 and 1. Unlike kriging, regression, or classification, fuzzy logic is not truly a statistical model, because "it does not assess the accuracy of its predictions" (Heuvelink and Webster, 2001). The distinction between fuzzy logic and Boolean logic is that fuzzy logic is based on possibility theory, while Boolean logic is based on probability theory. In this way, fuzzy logic is a measure of a soil's similarity to a class, rather than its chance of belonging to it (Zhu, 2006). Zhu (2006) asserts that "soil classification is based on possibility, not probability", and, as such, fuzzy logic is a more appropriate approach for defining soil classes.

The advantage of fuzzy logic is that it allows for representing the continuous nature of the soil's both geographic distribution and attribute distinctness.

The most prominent application of fuzzy logic in DSM has been the SoLIM (Soil–Landscape Inference Model) model, developed by Zhu and Band (1994), Zhu (1997a,b), and Zhu et al. (1996, 1997). This approach uses the expert knowledge of an experienced soil scientist to formalize the relationship between soil characteristics and environmental covariates. The incorporation of soil scientists' expert knowledge though can be seen as both an advantage and a disadvantage (Scull et al., 2003). The advantage is that it can explicitly summarize a soil scientist's expert knowledge, which has been accumulated at great expense. The disadvantage is that a soil scientist's expert knowledge is subjective and lacks statistical grounds for inference.

2.3. State Factor Proxies

Historically, the *scorpan* or *clorpt* factors have been interpreted from aerial photography and topographic and geological maps. Recent advances in remote sensing and geomorphometry have made the quantification of such ancillary information more readily accessible in formats that can be manipulated with GIS. Perhaps the most easily quantified and directly correlated state factors are relief, as DEM derivatives have been the most popular predictor (McBratney et al., 2003). This is to be expected given that many soil-geomorphic and hydrologic landscape models are based on relief (Schaetzl and Anderson, 2005). However, in some cases, all the relevant state factor proxies may not exist for a given area, and therefore thematic (or vector-based) layers may need to be manually interpreted and digitized (MacMillan et al., 2010). In addition, not all state factors have predictors that are directly related to the factor they are trying to quantify; some are indirect. For example, direct estimates of age (or time) are typically absent from predictive models, unless manually incorporated (Noller, 2010). Instead, age has typically been indirectly inferred from parent material, relative landscape position (e.g. according to the principle of superposition), or by surface reflectance (e.g. dark surfaces indicate desert varnish). Below is a discussion of some of the most common environmental covariates derived from DEM and RSI.

2.3.1. Digital Elevation Models

Topography is seen to have a primary influence on local soil differentiation over time. Following the Simonson model (1959), topography is the surrogate for redistribution of water which provides energy for transfer, inputs, and outputs in the soil. In steeper terrain, topography also influences solar radiation and orographic effects. Along a hillslope, systematic soil variation is most commonly the result of the soil hydrology and erosion. This soil pattern was recognized by Milne (1936), and termed a catena. Others (Ruhe, 1975; Conacher and Dalrymple, 1977) have used this concept to segment or classify landforms into elements where different hillslope processes are dominant, which typically correspond with soil patterns. As such, hillslope models are meant to be universal, but in reality not all hillslope elements (e.g. shoulders, footslopes, or free faces) necessarily exist along any given hillslope. The measures used to differentiate hillslope elements are typically based on a land surface geometry (e.g. slope gradient and slope curvature) and relative position (e.g. slope length or contributing area). In other cases, neighborhood statistics (e.g. standard deviation or range within a moving window) have been used, particularly when discriminating macro-landforms (Dikau, 1989; Dobos et al., 2005). Thanks to advances in geomorphometry (or digital terrain analysis), such measures termed terrain attributes, land-surface parameters, or geomorphometric parameters can be readily calculated from a DEM. When included in predictive models, terrain attributes are used to infer hydrologic phenomena such as runoff potential, flow convergence or divergence, or the redistribution of soil material (Table 2). While some of these relationships are explicit, others are more implicit. For a detailed summary of soil-geomorphic processes associated with relief, see Schaetzl and Anderson (2005). What continues here is a brief summary of common DEM-derived parameters used within DSM that are relevant to hydropedology. For a detailed summary of geomorphometry, see Hengl and Reuter (2009).

2.3.1.1. Slope Gradient

The maximum rate of change in elevation (e.g. first derivative) is readily calculated from gridded DEM and is used to represent the hydraulic gradient acting upon overland and subsurface water flow through the influence of gravity (Gallant and Wilson, 2000) (Fig. 1a). A steeper slope gradient is associated with greater velocity of surface and subsurface flow, as well as greater potential of erosion and other translocation processes. Slope gradient is also a factor in several regional terrain attributes (Table 2), particularly those with hydrologic interpretations (e.g. topographic wetness index, stream power index, and sediment transport capacity index).

2.3.1.2. Slope Aspect, Solar Radiation, and Flow Direction

Slope aspect, or the compass direction that a point on the surface faces (up–down slope), is related to soil hydrology in two ways. Slope aspect is related to the amount of solar radiation received at a location, particularly when combined with slope gradient values (Wilson and Gallant, 2000; Böhner and Antionić, 2009). Insolation influences soil temperature and soil moisture content (Franzmeier et al., 1969; Chamran et al., 2002), which in turn can influence plant productivity (Hutchins et al., 1976), soil microbial activity (Abnee et al., 2004a and 2004b), and soil properties such as organic carbon content (Thompson and Kolka, 2005). When slope aspect is incorporated in predictive models, it is usually when the spatial extent of prediction encompasses large land areas with multiple hillslopes and a diversity of slope aspects. Despite this influence of slope aspect on soil processes and properties, it is not often used in predictive modeling because of the numerical

TABLE 2 Summary of Important DEM-Derived Terrain Attributes

Terrain attributes	Definition	Hydropedologic significance	References
Local – Geometric			
Slope gradient (degrees) (sg)	Maximum rate of change (degrees)	Flow velocity	Olaya, 2009
Slope aspect (sa)	Direction of slope gradient (degrees)	Flow direction	Olaya, 2009
Profile curvature (kp)	Curvature of slope gradient (radians)	Flow acceleration	Olaya, 2009
Tangential curvature (radians) (kt)	Curvature perpendicular to slope gradient (radians)	Flow convergence	Olaya, 2009
Slope shape	Classification of sg, kp, and kt into nine units	Segmentation of hillslope processes	Pennock et al., 1987
Multiresolution valley bottom flatness index	Measure of flatness and l owness	Depositional environments	Gallant and Dowling, 2003
Multiresolution ridge top flatness index	Measure of flatness and upness	Stable uplands settings	Gallant and Dowling, 2003
Local – statistical			
Standard deviation		Surface roughness or complexity	Wilson and Gallant, 2000
Range or relief		Potential energy	Wilson and Gallant, 2000
Percentile or rank		Landscape position	Wilson and Gallant, 2000
Regional			
Contributing area (ca)	Upslope area (meters^2)	Effective precipitation	Moore et al., 1991
Specific contributing area (sca)	ca/grid size (meters)	Effective precipitation	Moore et al., 1991
Topographic wetness index (twi)	ln (sca/sg)	Water accumulation or soil saturation	Moore et al., 1991

(*Continued*)

TABLE 2 Summary of Important DEM-Derived Terrain Attributes—cont'd

Terrain attributes	Definition	Hydropedologic significance	References
Stream power index (spi)	ln (sca*sg)	Soil erosion	Moore et al., 1991
Catchment height	Average upslope height	Potential energy	Moore et al., 1991
Catchment slope	Average upslope gradient	Flow velocity	Moore et al., 1991
Overland flow distance to stream	Relative topographic position (meters)	Potential energy	Tesfa et al., 2011
Vertical distance to channels	Relative topographic position (meters)	Cold air drainage	Bohner and Antonic, 2009
Normalized height	Relative topographic position (percent)	Cold air drainage	Bohner and Antonic, 2009
Solar radiation or insolation	Amount of incoming solar energy (kWh/mA^2)	Soil temperature and evapotranspiration	Bohner and Antonic, 2009

difficulties associated with slope aspect being a circular variable. As such, it is necessary to transform slope aspect to a linear scale, categorize slope aspect into classes, or instead use solar radiation. Estimation of solar radiation is more sophisticated, and therefore requires user inputs such as latitude, atmospheric properties, and temporal frequency (Fig. 1d). This extra effort is likely to be worthwhile, because solar radiation accounts for differences in topographic shadowing (from adjacent hills) and slope gradient (Hunckler and Schaetzl, 1997; Beaudette and O'Geen, 2009).

Slope aspect is also significant because it defines the flow direction of water and sediment movement through the landscape under the influence of gravity. Therefore, it is used to determine contributing area, which is a highly significant terrain attribute discussed below. While slope aspect is easily calculated, flow direction is more difficult as it must partition the proportion of flow between square grid cells. Various algorithms exist for determining flow direction, and they are classified simply as either a single flow direction (SFD) method (e.g. deterministic 8 or D8) (O'Callaghan and Mark, 1984) or a multiple flow direction (MFD) method (e.g. FD8 (Freeman, 1991), deterministic infinity or D∞ (Tarboton, 1997), and multiple deterministic infinity or MD∞ (Seibert and McGlynn, 2007)). For soil–landscape studies, MFD

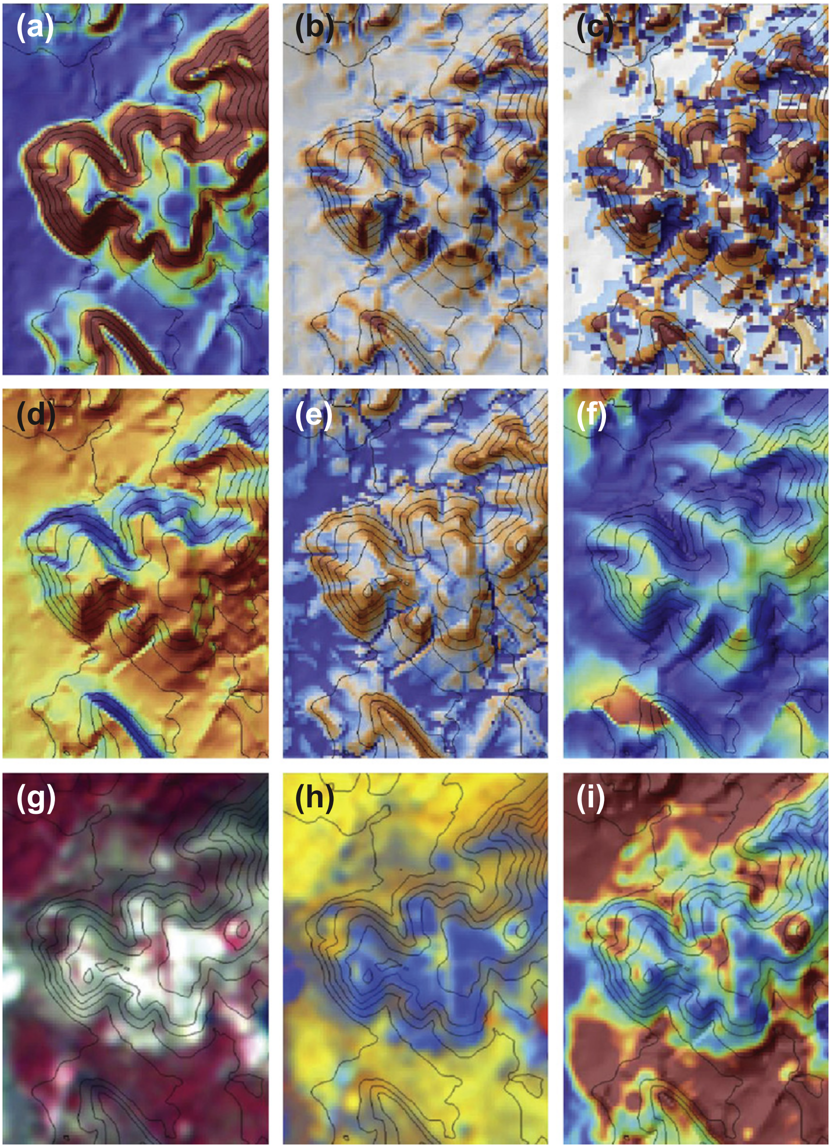

FIGURE 1 Example of common environmental covariates derived from DEM and RSI, with hillshade and 30 meter contour interval for affect. (a) Slope gradient, (b) Tangential curvature, (c) Slope shape, (d) Solar radiation, (e) Topographic wetness index, (f) Overland flow distance of channels, (g) False color composite (green, red, near infrared), (h) False color composite of tasseled cap components (brightness, greenness, wetness), (i) Normalized difference vegetation index. *(Color version online and in color plate)*

methods should be preferred to the SFD method, as they allow the modeling of flow dispersion along hillslopes. The SFD method is sufficient for determining river networks and watershed boundaries, but is inadequate on slopes because it cannot model flow divergence, and it therefore produces parallel flow lines. The MFD methods listed above produce largely similar results, but noticeable differences in flow dispersion due to each MFD-unique computation (and therefore assumptions of surface flow). For example, the FD8 algorithm is known to produce overdispersion, while the D∞ algorithm produces under-dispersion (Seibert and McGlynn, 2007). The MD∞ algorithm was shown by Seibert and McGlynn (2007) to be intermediary between FD8 and D∞. Regardless of the different theoretical approaches of each MFD to modeling surface flow, the hydropedogenic response to contributing area may vary due to soil horizonation, surface properties, or the inherent nature of the DEM.

2.3.1.3. Slope Curvature and Shape

Slope curvature measures are important because they influence local water flow in terms of convergence or divergence (tangential curvature) and acceleration or deceleration (profile curvature). There are various forms of slope curvature (e.g. second derivatives) that can be calculated from the land surface (Shary et al., 2002; Schmidt et al., 2003; Olaya, 2009), with only mean, unsphericity, and difference curvature being independent (Shary, 1995). Still the most common are profile and tangential curvature. Profile curvature is the curvature in the direction of the steepest slope (up–down slope) and normal (e.g. orthogonal or perpendicular, not vertical) to the land surface. Tangential curvature is perpendicular (across slope) to profile curvature and normal to the land surface (Fig. 1b). It should be preferred to contour curvature, with which is it often confused (Schmidt et al., 2003), because it is less sensitive to DEM errors. In many cases, the term plan curvature has been used for both tangential and contour curvatures (Schmidt et al., 2003).

Typically, profile and tangential curvature are classified into nine slope shapes, formed by the intersection of convex, linear, and concave surfaces (Ruhe, 1975) (Fig. 1c). This classification is useful for interpreting hillslope processes, such as soil and water redistribution, throughflow, and vertical infiltration. If recognizable, these forms can be used for communicating surface form, transferring research results, and serving as manageable land units. Many DEM-based approaches to soil and land classification have attempted to automate the production of these slope forms (Pennock et al., 1987; Florinsky et al., 2002; Schmidt and Hewitt, 2004), and others still produce classifications that largely resemble them (Burrough et al., 2000; Zhu et al., 2001). Still, any land classification is subjective and should correspond with recognizable ecological phenomena and environmental properties.

2.3.1.4. Contributing Area and Hydrologic Indices

Contributing area (CA), upslope area, or flow accumulation represents the area of land upslope of a specific contour length (e.g. grid size). As mentioned above, it is a product of flow direction. The value of this parameter has many process-based interpretations. Foremost, it can be used to estimate the amount of effective precipitation an area receives from upslope (assuming no infiltration or wind redistribution of snow). Second, it estimates the spatial connectivity of different positions within a watershed, and therefore can be used to infer landscape position (Gessler et al., 1995). Lastly, CA may be used to quantify flow convergence and divergence, irrespective of curvature. Given the multiple interpretations associated with CA, it is typically used for DSM applications, either alone or – more commonly – combined with other terrain attributes as an index related to soil wetness or erosion.

There are several hydrologic indices that are products of CA and other terrain attributes, including slope gradient and slope curvature (Table 2). The most widely utilized hydrologic index for both sampling design and model development is the topographic wetness index (TWI) or compound topographic index (Fig. 1e). The TWI is calculated as the natural logarithm of the ratio of specific contributing area (CA/grid size) (SCA) to slope gradient (Wilson and Gallant, 2000), and is an index of the likelihood of a cell to collect water. High values of TWI coincide with locations where larger amounts of water accumulate from upslope, but where this water is less likely to runoff because of flatter slope gradients, i.e. areas where water accumulates in the landscape. Consequently, TWI is considered a predictor of zones of soil saturation.

The stream power index (SPI), a measure of runoff erosivity, is the natural logarithm of the product of SCA and slope gradient (Wilson and Gallant, 2000). High values of SPI coincide with locations with high specific contributing area values and high slope gradient values, or areas where larger amounts of water flow in from upslope, and where this water is expected to continue to flow because of steeper slope gradients. Locations with higher SPI values are considered to be areas where water flows with higher energy and, consequently, where erosion and related landscape processes are more likely to occur.

2.3.1.5. Proximity to Drainage (Depression)

From a hydropedologic perspective, the flow path information used to calculate contributing area can also be used to calculate contextual variables. While most terrain attributes quantify the topographic conditions in the immediate vicinity (usually a 3×3 window of a gridded DEM), a number of terrain attributes have been derived that represent either a statistical summary of conditions upslope of a cell (e.g. mean upslope slope gradient or mean upslope plan curvature) (Gallant and Wilson, 2000) or an indicator of the spatial configuration between a cell and local peaks or pits (e.g. distance to the closest channel and elevation above the closest depression) (Olaya, 2009; Gruber and Peckham, 2009) (Table 2). The distance to the local drainage/depression can be calculated using either the Euclidean distance or the flow distance (Fig. 1f). Values of elevation above local drainage/depression and distance to local drainage/depression can be combined to calculate the slope gradient to the nearest drainage/depression. Such contextual terrain attributes are used in predictive modeling to quantify regional influence on soil processes and soil properties, particularly the regional gradient acting upon soil water and surface runoff. Bell et al. (1992, 1994) used these proximity measures to predict soil drainage class, while Arrouays et al. (1995) and Thompson and Kolka (2005) used such contextual terrain attributes to model soil organic C. One or more of these terrain attributes have also proven useful for predicting hydromorphic soil properties (Thompson et al., 1997; Chaplot et al., 2000) and soil classes (Lagacherie and Holmes, 1997; Moran and Bui, 2002).

2.3.2. Remotely Sensed Imagery

Remote sensing involves the use of sensors to measure the reflectance or emission of energy from a distance (Jensen, 2005). Historically within soil mapping, this has centered on the use of aerial photography, which captures images of reflected sunlight within the visible to near-infrared portion of the electromagnetic spectrum. Today, numerous sources of imagery (Fig. 1g) are available from various platforms, the most common being Earth-orbiting satellites. These satellites measure reflectance and emissions from a wide swath of the electromagnetic spectrum, with each having unique spectral and spatial resolutions tailored to their field and scale of interest, be it observing weather, oceans, or land. In principle, remote sensing is valuable because different earth-surface features have unique spectral signatures, as a result of their unique physical and chemical properties. The uniqueness of a given features spectral signature determines its ability to be identified correctly from afar.

Remote sensing can provide direct information on various *scorpan* or STEP-AWBH factors, including soil, organisms, and parent material. Also, indirect relationships can be established with other factors, such as climate and time. In humid environments, reflectance provides information primarily on vegetation, whereas in arid and agricultural environments where the soil surface is typically exposed, information on parent material and the soil can be inferred. In particular, in arid and agricultural environments some surface soil properties, such as mineralogy, texture, moisture, organic carbon, iron content, salinity, and carbonates, can be associated with specific adsorption features (Mulder et al., 2011). Due to the multitemporal frequency of satellites, they also offer further possibilities to observe changes in the land-surface over time, which is usually associated with the senescence of vegetation.

The wide array of potential information within RSI makes it an attractive, but complicated environmental covariate. For example, in many cases, it can be difficult to separate specific spectral signatures from the confounding effects of vegetation, topographic shadowing, or other factors. To compensate for these factors various image processing techniques have been developed. In the event that such techniques are insufficient, it is typically necessary to incorporate ancillary data, such as DEM derivatives, to distinguish seemly similar spectral signatures. One of the greatest difficulties is mapping human-modified landscapes, which contain a mosaic of patterns dominated by the effects of land use and cover rather than native vegetation. Therefore, in human-modified settings DEM derivatives are likely to provide better predictors of static soil properties (e.g. soil texture), unless predictions are constrained to similar land-use and cover types. Within human-modified landscapes, land use and cover may be used to develop conditional rules for inferring dynamic soil properties (e.g. organic matter).

The intent in the following section is to review derivatives of RSI that are commonly used as environmental covariates. For a thorough discussion of the application of RSI in DSM, see Boettinger et al. (2008) and Boettinger (2010). In contrast, Mulder et al. (2011) provides an exhaustive discussion of soil attributes that can be estimated using proximal and remote sensing for DSM. Full-length treatments on the subject of image processing can be found in Jensen (2005) and Schowengerdt (2007).

2.3.2.1. Spectral Transformations

Individual satellite bands can be used directly to infer soil characteristics, but commonly derivatives of RSI or spectral transformations are used. In contrast to spatial transforms, spectral transforms affect the multivariate or feature space, rather than the image space (e.g. x,y coordinates). Spectral transforms are applied to enhance specific spectral signatures and reduce data redundancy in the original bands. Common examples are band ratios, principal components, or tasseled-cap components.

Band ratios are image ratios where one band is divided by another. This is a nonlinear transformation that has the benefit of the reducing topographic shadowing inherent in the original bands, while enhancing absorption features contained in the denominator relative to the numerator, at the expense of increasing noise inherent in the original bands (Schowengerdt, 2007). Modulation or normalized difference ratios are a modification of simple ratios, which scale the ratio values between –1 and 1, and enhance the contrast of lower ratio values (Schowengerdt, 2007):

$$\text{Simple ratio} = \frac{\text{Band 1}}{\text{Band 2}}, \tag{6}$$

$$\text{Modulation or normalized difference ratio} = \frac{\text{Band 1} - \text{Band 2}}{\text{Band 1} + \text{Band 2}}. \tag{7}$$

One of the most common ratios is the normalized difference vegetation index (NDVI), which is a ratio of near infrared to red (Fig. 1i). This normalized ratio is used to assess the amount of healthy green vegetation on the land surface. Numerous other ratios have been utilized for enhancing various soil adsorption features in arid and semi-arid environments, such as carbonates, clay, iron content, organic matter, and grain size. An important caveat is that the physical interpretation of band ratios may not translate to different environments compared to those for which they were developed, due to the complex interaction of land-surface characteristics (e.g. vegetation and soils).

Principal components (PCs) are linear combinations of the original bands, designed to remove the collinearity (e.g. data redundancy) between them. PC analysis (PCA) involves rotating the original coordinate axes of the data to new orthogonal (e.g. perpendicular) axes that contain the maximum amount of information for each dimension. Because PCA is simply a mathematical rotation of the original bands, it is data dependent. Therefore, the physical interpretation of PC is unique to each particular satellite scene, and any correlation between the PC and soil characteristics is fortuitous. However, typically the first PC (e.g. PC 1) is typically dominated by the overall image brightness of the original bands, while the last PC is typically dominated by random noise.

Tasseled-cap components (TC) are similar to PC, a linear combination of the original bands (Fig. 1h). They differ from PC in that their rotation is fixed, rather than data dependent, which allows PC to maximize the variation in any given scene. Also, the TC rotation has been primarily developed for the Landsat satellites, and a handful of other satellites, whereas PC can be generated from any combination of DEM derivatives or RSI. The TC transform was originally developed by Kauth and Thomas (1976) in order to develop standardized components which have a common physical interpretation (Table 3).

3. DIGITAL SOIL MAPPING FOR HYDROPEDOLOGIC APPLICATIONS

Lin et al. (2006) describe how hydropedology provides a framework for "understanding, measurement, modeling, and prediction of water fluxes across the landscape." The key issues that require attention are structure, function, and scale. In the context of DSM, structure may be manifested in the prediction of the spatial arrangement of soil characteristics that influence hydrology (e.g. pixels or map units that represent soil properties, such as subsurface hydraulic conductivity; soil horizons, such as the depth to impermeable fragipan or bedrock; and soil classes, such as soil series with root-restricting layers or low available water-holding capacity). Observed structures are the result of the fluxes and processes that have occurred over time within the soil–landscape system, and therefore provide clues to current functions. DSM products provide a means to fully extend hydropedologic concepts and understanding in the spatial domain. In particular, such digital soil survey data may be used to derive hydromorphic properties and hydrologic processes suitable for (i) land-use and soil management decisions, (ii) input into hydrologic, ecological, or other earth-surface models, and (iii) estimates of soil characteristics at unsampled or unobserved locations.

3.1. Mapping Soil Properties that Influence Hydrology

Observed spatial and temporal variability in hydrologic response is attributable to landscape heterogeneity (Troch et al., 2009). McDonnell et al. (2007) have

TABLE 3 Summary of Common Spectral Transformations of Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper (TM+)

Spectral tranformations	Definition	Interpretation	Scorpan factors	References
Image ratios				
Normalized difference vegetation index (NDVI)	(NIR − R)/ (NIR + R)	Vegetation abundance	Organisms, climate	
Soil adjusted vegetation index (SAVI)	(1 + L) ((NIR − R)/ (NIR + R + L))	Vegetation abundance in arid and semi-arid environments	Organisms, climate	Huete, 1988
Carbonate index	R/G	Carbonate radicals	Soil, parent material, age	Amen and Blaszczynski, 2001
Iron index	R/MIR_2	Ferrous iron	Soil, parent material, age	Amen and Blaszczynski, 2001
Clay index	MIR_1/MIR_2	Hydroxyl radical (e.g. clay)	Soil, parent material, age	Amen and Blaszczynski, 2001
Gypsic index	$(MIR_1 - MIR2)/(MIR1 + MIR2)$	Gypsic soils	Soil, parent material, age	Nield et al., 2007
Natric index	$(MIR_1 - NIR)/(MIR1 + NIR)$	Natric soils	Soil, parent material, age	Nield et al., 2007
Grain size index (GSI)	(R − B) (R + G + B)	Surface texture	Soil, parent material, age	Xiao et al., 2006
Principal components (PC)	**Mathematical rotation**			
PC_1		Image brightness		
$PC_{2\text{-}n}$		Variable		
PC_n		Random noise		
Tassel cap components (TC)	Fixed mathematical rotation			Crist et al., 1986; Huang et al., 2002

(*Continued*)

TABLE 3 Summary of Common Spectral Transformations of Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper (TM+)—cont'd

Spectral tranformations	Definition	Interpretation	Scorpan factors	References
TC_1		Soil brightness	Soil, parent material	
TC_2		Greenness	Organisms, climate	
TC_3		Wetness (moisture)	Soil	
TC_4		Haze		

(B = Blue; G = Green; R = Red; NIR = Near infrared; MIR_1 = Mid-infrared 1; MIR_2 = Mid-infrared 2; L = Constant).

indicated that poor characterization of this landscape heterogeneity, including soil properties, has hindered the field of hydrology. Consequently, improving our understanding of the nature of soil variability across hillslopes and watersheds is expected to enhance our ability to model and predict hydrologic response (Troch et al., 2009). The role of spatial structures in hydrologic response and hydrologic modeling is discussed by Grayson and Bloshl (2000). In particular, Houser et al. (2000), Vertessy et al. (2000), and Western and Grayson (2000) illustrate the use of soil spatial data on modeling watershed-scale hydrologic response, and discuss the limitations of available soil data.

The spatial variability of soils and soil properties is recognized as having a significant influence on (i) the partitioning of precipitation between rainfall and runoff, (ii) lateral and vertical redistribution of subsurface water, and (iii) the spatial distribution of soil moisture at hillslope and catchment scales (Guntner and Bronstert, 2004). Both vertical and lateral variability in soil properties can influence hydrologic response, particularly at hillslope and catchment scales. Vertical changes in soil characteristics, particularly the presence of discontinuities and abrupt boundaries, will influence infiltration, percolation, and evapotranspiration. Furthermore, vertical heterogeneity (e.g. clay lenses; textural discontinuities, cemented horizons, or dense layers) can also promote lateral redistribution of soil water. Grayson and Bloshl (2000) provide a thorough examination of spatial patterns and spatial processes in hydrologic systems.

3.1.1. Soil Horizons

Certain soil horizons or horizon sequences are the result of hydrologic processes within the soil and serve as evidence of the magnitude and direction of water movement within the soil. Eluvial and illuvial processes translocate silicate clay minerals, iron oxides, humus, carbonates, and other soil constituents. It is because of these linkages between hydrology and pedogenesis that allow for the successful application of DSM approaches to predict the spatial distribution of soil horizons (Table 4), such as albic, argillic, spodic, and fragipan horizons. Conversely, the presence of these and other soil horizons (e.g. cemented layers) can influence soil–water–plant interactions and hydrologic processes by restricting root growth, storing more (or less) plant available water, promoting lateral water flow, or producing perched water tables.

There are a number of examples of the successful application of DSM to predict the occurrence of soil horizonation. Many have focused on the mapping of topsoil thickness (Pennock et al., 1987; Moore et al., 1993; Gessler et al., 1995; Zhu, 2000; Park et al., 2001; Hengl et al., 2004). Another common target property, and one that is important hydrologically relative to water-storage capacity and plant available water, is soil depth or depth to limiting layer (Odeh et al., 1994, 1995; McKenzie and Ryan, 1999; Sinowski and Aureswald, 1999; Ryan et al., 2000). Gessler et al. (1995) also developed models for the spatial prediction of the presence or absence of an albic horizon.

3.1.2. Soil Properties

Soil property maps developed using DSM efforts may have particular value in hydropedology as well as the environmental modeling community as input into models, or input into pedotransfer functions (PTFs) to develop the necessary property maps that can be used in such models. Texture and the related particle-size distribution greatly influence the rate of water flow through soils. This soil property is a key input parameter in all hydrologic models. Numerous DSM efforts have produced maps of soil textural properties (e.g. McKenzie and Austin, 1993; Moore et al., 1993; Arrouays et al., 1995; de Bruin and Stein, 1998; Oberthur et al., 1999; McBratney et al., 2000; Park and Vlek, 2002; Scull et al., 2005). For other important hydropedologic properties, such as soil structure, bulk density, and saturated hydraulic conductivity (Ksat), there are few examples of DSM approaches to mapping these properties.

Whole-profile soil properties integrate several soil properties to provide information on soil–water relationships and soil use and management interpretations. For example, soil water storage is a fundamental ecosystem service that is commonly determined from measured or estimated properties, including horizon thickness, soil texture, rock fragment content, and depth to root-limiting layer (if present). Quantifying soil water storage is crucial for understanding water transport. Commonly, runoff is predicted when the storage capacity for a given soil is exceeded. For climate modeling, information on soil water storage is needed to predict the amount of water available for evapotranspiration. The available water-holding capacity is influenced by depth to bedrock or depth to a hydraulically limiting layer. DSM products can improve the ability to represent these soil properties and deliver better information to

TABLE 4 Selected Examples of Studies Using DSM Approaches to Predict Soil Properties of Hydropedologic Significance

		Predictive factors			
Authors	Soil attribute or class	Terrain attributes	Remotely sensed imagery	Other	Spatial extent[a]
Soil Horizon and Profile Characteristics					
Moore et al. (1993)	Horizon thickness	X			Field
Zhu and Band (1994)	Horizon thickness	X	X		Local
Gessler et al. (1995)	Horizon thickness	X			Local
Boer et al. (1996)	Soil thickness	X			Local
McKenzie and Ryan (1999)	Soil thickness	X	X	Climate, geology	Local
Sinowski and Auerswald (1999)	Soil thickness	X			Local
Ryan et al. (2000)	Soil thickness	X	X	Climate	Local
Park et al. (2001)	Horizon thickness	X			Local
Hydromorphic Soil Properties					
Bell et al. (1992, 1994)	Soil drainage class	X			Local
Cialella et al. (1997)	Soil drainage class	X	X		Local
Thompson et al. (1997)	Hydromorphic index	X			Field
Chaplot et al. (2000)	Hydromorphic index	X			Field
Campling et al. (2002)	Soil drainage class	X	X		Local
Chaplot and Walter (2002)	Hydromorphic index	X			Regional
Peng et al. (2003)	Soil drainage class	X	X		Local

TABLE 4 Selected Examples of Studies Using DSM Approaches to Predict Soil Properties of Hydropedologic Significance—cont'd

Authors	Soil attribute or class	Predictive factors: Terrain attributes	Remotely sensed imagery	Other	Spatial extent[a]
Liu et al. (2008)	Soil drainage class	X	X	Proximal sensing	Field
Lemercier et al. (2012)	Soil drainage class	X	X	Geology	Local
Hydropedologic Properties					
McKenzie and Austin (1993)	Soil water content (−10 kPa, −1.5 Mpa	X	X		Local
Zheng et al. (1996)	Available water capacity	X			Local
Lark (1999)	Soil water content	X			Field
Ryan et al. (2000)	Available water capacity	X	X	Climate	Local
Pachepsky et al. (2001)	Soil water retention	X			Field
Romano and Palladino (2002)	Soil water retention	X			Local
Malone et al. (2009)	Available water capacity	X	X		Local
Other Soil Properties					
McKenzie and Austin (1993)	Bulk density; clay content	X	X		Local
Moore et al. (1993)	Organic matter; silt content; sand content	X			Field
Arrouays et al. (1995)	Organic matter content; clay content	X		Climate	Local
de Bruin and Stein (1998)	Clay content	X			Field

[a]Spatial extents include: Field = <0.25 km^2, Local = 0.25–10^4 km^2, and Regional = 10^4–107 km^2.

hydrologists. Examples of DSM efforts that have yielded predictions of soil water availability include McKenzie and Austin (1993), Zheng et al. (1996), Voltz et al. (1997), Lark (1999), Lagacherie and Voltz (2000), Ryan et al. (2000), Pachepsky et al. (2001), and Sommer et al. (2003).

3.2. Mapping Soil Properties Influenced by Hydrology

Hydropedologic properties have been a common product of pedometric modeling and DSM activities (Table 4) because (i) hydropedologic properties such as drainage class, available water content, and hydromorphic features are important for developing soil use and management interpretations and making land-use decisions and (ii) hydropedologic properties are strongly influenced by hillslope hydrologic processes, which are readily modeled with DEM-derived terrain attributes because of the relationship between topography and hillslope hydrologic processes. In fact, the earliest example of quantitative prediction of soil classes or properties noted by McBratney et al. (2003) in their comprehensive review of DSM is work by Troeh (1964) on the prediction of soil drainage classes using slope gradient and slope curvature. Bell et al. (1992, 1994), Campling et al. (2002), and Peng et al. (2003) also developed terrain-based statistical models to predict soil drainage classes. Similar soil–landscape modeling approaches have been used to predict soil hydromorphological properties (Thompson et al., 1997; Chaplot et al., 2000; Park et al., 2001), water content (McKenzie and Austin, 1993; Lark, 1999), available water capacity (Ryan et al., 2000), and water retention curve characteristics (Romano and Palladino, 2002).

The accumulation of SOC is often a function of hydrology, either local or regional, and is driven by climatic and topographic factors (Collins and Kuehl, 2001). Consequently, the spatial distribution of SOC is related to moisture availability for biomass production and/or soil saturation, which limits organic matter decomposition. Mapping SOC (or soil organic matter) using DSM approaches has been demonstrated on various scales by Arrouays et al. (1995, 1998), McKenzie and Ryan (1999), Bell et al. (2000), Gessler et al. (2000), Ryan et al. (2000), Chaplot et al. (2001), Hengl et al. (2004), Terra et al. (2004), Thompson and Kolka (2005), and Vasques et al. (2010).

There are many observed physical, chemical, and morphological properties that are the result of hydrologic conditions or processes within the soil. From the standpoint of soil use and management, soil hydromorphology is a primary factor in evaluating soil suitabilities and limitations. Redoximorphic features such as iron and manganese concentrations, iron depletions, and depleted matrix are directly related to the depth to and duration of saturated and reducing conditions in the soil, and provide evidence of where in the soil or landscape water accumulates and persists that had aggregated over long periods of time. The presence of redoximorphic features (kind, quantity, size, color, shape, and location) is used to establish soil drainage class and determine the occurrence of aquic conditions (Soil Survey Staff, 1999) and hydric soil conditions (USDA-NRCS, 2010). There are many examples of landscape-scale studies of soil wetness and hillslope hydrology that have scrutinized the relationship between hydrologic regimes (e.g. depth to and duration of observed water tables) and soil morphological features (e.g. Vepraskas and Wilding, 1983a,b; Thompson and Bell, 1996, 1998; Reuter and Bell, 2001, 2003; Jenkinson et al., 2002; D'Amore et al., 2004). As illustrated by McDaniel et al. (1992), Thompson et al. (1998), Noguchi et al. (1999), D'Amore et al. (2000), Lin (2006), and others, observed soil morphological properties – redoximorphic features, ped surface features, and pore architecture – at hillslope and catchment scales can be useful for interpreting the nature of water movement and areas of water storage. However, iron and manganese are not the only soil constituents that are influenced by hydrology. The distribution of carbon, nitrogen, calcium, phosphorus, and other elements can be related to hydrologic conditions and processes (Vasques et al., 2010). Thompson et al. (1997), Chaplot et al. (2000), and Chaplot and Walter (2002) have demonstrated that soil color indices that combine multiple soil color characteristics from a soil profile (e.g. color and thickness of the surface horizons and relative thickness of horizons with RMF) can be developed and, using DSM methods, used to map the extent of hydromorphic soils.

4. RESEARCH NEEDS AND FUTURE CONSIDERATIONS

As technology has become more accessible, allowing the common use of mathematical and statistical methods, a considerable degree of overlap between hydropedology and DSM has developed. Indeed, this trend is likely to continue as hydropedology seeks to analyze more sophisticated data sets. From this perspective, hydropedology, like other subdisciplines of soil science, can be seen as an application-oriented example of DSM that focuses on examining soil and water functions rather than methodological issues. Research needs and future considerations where hydropedology can benefit from DSM include capitalizing on existing soil databases, development of PTF, estimation of dynamic soil–water properties (including genoform and phenoform), estimation of model uncertainty, incorporation of depth (i.e. vertical anisotropy), examination of scaling of soil–water functions, and integration of computer software. As such, DSM products should reflect the input requirements for environmental models, such as those used in hydrology and hydropedology.

There are numerous opportunities for developments in DSM and hydropedology that will promote even greater interactions between these two fields. These needs are driven by the data and interpretation requirements both within the soil science community and among the external users of soil data, information, and knowledge. For example, DSM products must reflect the requirements for input into hydrologic models in terms of scale, spatial resolution, and representation of the soil–water continua. An immediate need is for

DSM approaches that capitalize on existing soil data (often referred to as legacy data), including maps, pedon data (characterization data and morphological descriptions), and point measurement data. A complement to the use of legacy data is the use of sensors for mapping soil properties at field scales as well as continental scales using proximal and remote-sensing systems. For both of these data sources, as well as traditional environmental covariate data, there is a need for development and refinement of mapping and modeling techniques.

In many developed countries, there is already a wealth of legacy soil information available. As such, there is increased effort to exploit existing point data (pedon characterization data and morphological descriptions), thematic maps, and expert knowledge to produce digital soil maps that represent soil properties and classes at scales (or resolutions) that meet the needs of the growing user community for soil geographic information (Mayr et al., 2010; Dobos et al., 2010). Although legacy data are readily available, their analyses are complicated because they were typically collected for different purposes, and therefore may be of inconsistent quality due to changing conventions, missing data, and limited geographic and environmental coverage. Therefore, significant effort is necessary to harmonize them for new purposes. It is difficult to estimate the bias in existing data, but preference is generally given to point data as they represent direct observations and measurements rather than aggregated data. Whatever format of legacy data is used, its source should be evaluated, and any subsequent results scrutinized according to current standards and assessed with independent data. Properly utilized legacy data can help answer new questions.

Due to the limited scope of legacy data, its primary utility may be serving as a covariate for *scorpan* or STEP-AWBH models. This approach is already commonplace. In a recent review, Grunwald (2009) found existing soil information used to develop PTF and soil spatial prediction functions (SSPF) in over 36 percent of DSM studies. PTF and taxotransfer functions (TTF) are one method that has been and is expected to continue to be a valuable tool for extending the utility of legacy data, particularly for hydropedology.

Scale and resolution are also critical issues, including the effects on predictions and the utility of these predictions. Most available soil map products are vector soil class maps, which depict polygons that represent one or more soil classes. The component soils of these map units, while not mapped spatially, often occur in specific landscape positions. These individual soil types within the delineated map units often have differing physical, chemical, biological, or morphological properties that produce different hydrologic responses. Knowledge of the location and extent of these contrasting soil classes or properties is important for accurately representing hydropedologic properties and soil-hydrologic responses. Hively et al. (2005) demonstrated that small undifferentiated areas within soil map unit delineations can be important areas of runoff generation and P loss processes. Furthermore, DSM products should also help bridge scales from pores to pedons, and from catenas to catchments.

Aggregation (generalization) of geographic space (e.g. to delineate soil map units) and/or attributes (e.g. to derive soil classes) have been used extensively in soil surveys, which is inherently ingrained in legacy data sets. Trends in DSM are evident to disaggregate larger map units into fine-grained pixels (coarse scale to fine scale) and to map continuous soil properties rather than soil classes or categorical properties. These trends are facilitated by geographic information technologies, soil and remote sensors, and advanced computational power which allow to develop soil prediction models with ancillary environmental data. Constraints imposed by data availability to characterize the spatial distribution and variability of soil properties has led to aggregation (lumping) of modeling hydrologic processes within subbasins, basins, or larger hydrologic units. Soil map units and hydrologic units often do not coincide and impose ambiguities on modeling the soil–water continuum. Considerations with regard to appropriate spatial and attribute scales are needed for successful future applications in hydropedology. This will require collaboration on characterizing spatial and attribute variability of parameters that characterize the soil–water continuum and joint investigation of scaling behavior. To match the map scale and resolution of space and attributes will be critical to interlink both disciplines – DSM and hydrology – to conjoin hydropedology.

DSM has put much emphasis on mapping the long-term responses (e.g. redoximorphic features, SOC) from natural and anthropogenic forcings through factorial models (e.g. *clorpt* and *scorpan*), often not explicitly accounting for the time component. In addition, assessment of spatial variability and distribution of stable soil properties has received much attention. In contrast, the main focus of hydrology has been on continuous measurements and/or simulations of hydrologic parameters to model water flux within the soil–landscape continuum. Thus, the time component has played a much more prominent role in hydrology than in soil mapping. Hydropedology is poised to bridge these space–time gaps and promote the harmonization of approaches and models accounting equally for both hydrologic and pedogenic factors and processes, e.g. spatial and temporal distribution and evolution of soil-hydrologic properties which drive processes, and vice versa. In particular, in the context of increasing concerns about how anthropogenic-induced forcings, such as global climate change and land-use shifts, will alter soil and water resources, more research on short- and long-term impacts are needed. The STEP-AWBH model proposed by Grunwald et al. (2011) is one such effort to explicitly address the importance of the temporal component in soil variability and soil mapping. Temporal databases, such as RSI from Earth-orbiting satellites, are expected to have useful applications for DSM and hydropedology. In particular, data from passive microwave sensors have been used to map the temporal variability in soil moisture (Hollenbeck et al., 1996; Jackson and Le Vine, 1996).

Whereas empirical and stochastic models to predict soil properties or classes are predominant in DSM, a mix of stochastic–deterministic (process-based) models is used to model hydrologic processes. Pedogenic simulation models are still sparse and difficult to validate due to the long time frames over which pedogenic processes operate, whereas hydrologic processes occur over shorter time intervals (e.g. rainfall–runoff events). This disparity in modeling approaches has led to separation rather than integration among soil science and hydrology disciplines. However, enhanced monitoring capabilities through sensors and long-term soil-hydrologic monitoring networks could facilitate to overcome these constraints. This will require concerted efforts and an investment in monitoring infrastructure. Establishing linkages between pedogenesis and hydrologic properties and processes (Lohse and Dietrich, 2005; Lin, 2010) and the development of quantitative models of pedogenesis (Rasmussen and Tabor, 2007; Minasny et al., 2008; Rasmussen et al., 2010) are important contributions that hydropedology can make to DSM.

An understanding of hydropedologic processes and relationships is expected to improve our ability to map and model soil–water spatial and temporal variability. Additionally, precise and accurate maps of soil properties and soil classes provide a means to both understand hydropedologic processes and functions at landscape and watershed scales (e.g. Lin, 2006), and extrapolate that knowledge across scales. The explicit consideration of hydropedology in DSM may encourage the development and adoption of quantitative maps and models of soil cover, soil structure, and soil horizonation such that modern soil map data can be more readily incorporated into water flow and transport models (Lin et al., 2006).

As soil scientists begin creating different soil data products, hydrologic models will be developed to use these products. In a study conducted by Basu et al. (2010), the researchers created the Threshold Exceedence LaGrangian Model (TELM) to predict stream discharge and peak flow in a tile-drained engineered landscape. This parsimonious model utilized basic soil input data to characterize a 700-km^2 watershed. This simple model based on soil filling and exceeding capacity performed as well as SWAT (Soil Water Assessment Tool) at characterizing stream flow. The setup time and calculation time for TELM were minimal compared to SWAT. Soil scientists working in DSM can play a significant role in the research area of stream flow prediction by working more closely with hydrologists.

Collaboration among DSM scientists and hydropedologists is expected to further our understanding of the complexities of the soil–water continuum within and across soil-landscapes. Digital soil maps and spatio-temporal databases are an important means by which DSM scientists and hydropedologists will communicate our knowledge with each other and with the greater scientific community. It will also be important that we have an understanding of modeler needs for input into hydrologic models. The linkage between hydropedology and pedometrics will be further strengthened as efforts advance from DSM to digital soil assessment (Carre et al., 2007).

5. SUMMARY

Creating synergies between hydropedology and DSM will promote new research endeavors and is expected to foster further advances in geospatial soil database development and process-based modeling (Lin, 2011). A primary linkage between hydropedology and DSM is the role of water in pedogenesis and soil–landscape processes that strongly influence spatial variability in soil properties. Hydrology influences pedology through soil-forming processes (additions, losses, transformations, and translocations), which led to the development of genetic horizons and features. However, soil properties, especially heterogeneity of soil properties, influence hydrology through soil–water interactions at the pore, pedon, and hillslope scales.

Many of the scientific questions regarding the Earth's Critical Zone require information on soils and soil variability. With the current technology, providing explicit spatial data has become possible. There is a tremendous research need to develop a greater understanding of the feedback between water redistribution on the landscape and the impact this has on soil properties. The deeper understanding of the feedback will provide scientists with tools to understand fundamental ecosystem relationships. DSM approaches seek to maximize information delivery from existing soils databases (including spatial and tabular, point and polygon) and develop new geospatial soil data products. These DSM products are expected to enhance spatial detail and to represent depth variation. Quantitative linkages between soil processes (hydropedology) and soil geography (DSM) are expected to yield more accurate and more precise soil maps, which will provide support for discovery-driven applications of hydropedology and contribute to resolving issues related to forcing, coupling, interfacing, and scaling (Lin, 2011).

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