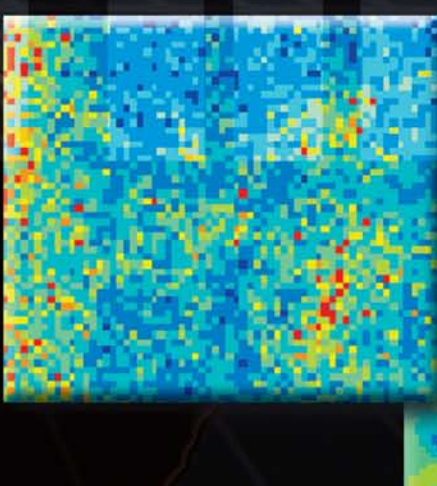
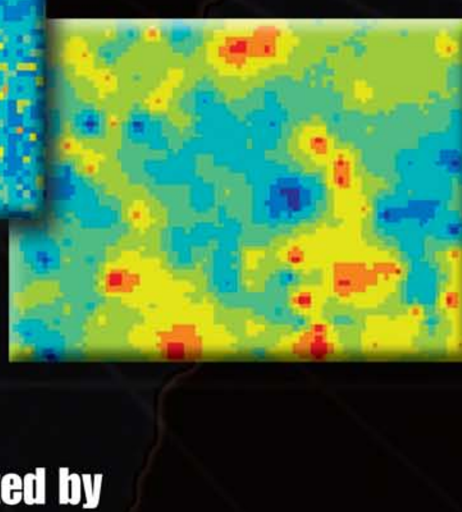
Environmental Soil-Landscape Modeling

Geographic Information Technologies and Pedometrics





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13 Three-Dimensional Reconstruction and Scientific Visualization of Soil-Landscapes

Sabine Grunwald

CONTENTS

ABSTRACT

An approach to reconstruct and visualize virtual soil-landscape models and space–time simulations based on ontological modeling comprising the physical, logic/representation, implementation, and cognitive universes were presented. The modeling process was disaggregated into conceptualization, reconstruction, and scientific visualization. The ontological modeling concept was employed to produce three- and four-dimensional virtual models integrating soil, land use, and topographic datasets for soil-landscapes in southern Wisconsin and northeastern Florida. Spatially and temporally explicit modeling of robust soil properties (e.g., bulk density) as well as dynamic soil properties (e.g., water level) was demonstrated. Ordinary kriging and cokriging were used to reconstruct the soil-landscapes, and Virtual Reality Modeling Language to render virtual objects. To engage users, interactive functions were programmed in Java and External Authoring Interfaces. Scientific visualization combined with quantitative reconstruction techniques has the potential to translate real soil-landscapes and ecosystem processes into a transparent format to enhance our understanding of real-world phenomena and complex environmental systems. Web-based virtual soil-landscape models and space–time simulation models facilitate the exploration, analysis, synthesis, and presentation of georeferenced environmental datasets. Combining multimedia elements (e.g., Internet, interactivity, three-dimensional scientific visualization) can produce insight that would not arise from use of the elements alone.

13.1 INTRODUCTION

Scientists have focused on two contrasting concepts to study soil-landscapes and ecosystem processes, which are both equally important. The reductionist approach promotes ever more detailed studies of distributions, soil classes, events, and processes, followed by their interpretation. The other approach develops and enunciates an integrative, unifying point of view encompassing and integrating previous observations and results. Both concepts have been employed for quantitative spatially explicit modeling of soil-forming factors evolving through time.

Different kinds of models have been used to translate real soil-landscapes and ecosystem processes into virtual environments. Hoosbeek and Bryant[1] provided an overview of pedogenetic models using the following criteria: (1) the relative degree of computation (qualitative vs. quantitative models), (2) complexity of the model structure (functional vs. mechanistic models), and (3) level of organization (soil region, pedon to molecular scale). Modeling is about choosing the appropriate metaphor or analogy with which to better understand a phenomenon, e.g., the spatial distribution of soils and their behavior and relationship to other environmental factors. In this sense, we create media about phenomena to bridge the gap between what we do not know and what we are trying to comprehend. Media such as slides, maps, animations, three-dimensional virtual worlds, and digital libraries are models. Although one might talk of absolutes such as reality and truth, all we have at our disposal are models, which mediate the world for us. Transcending real into virtual soil-landscapes depends on the (1) space domain, (2) time domain, (3) spatial and temporal scale, (4) ecosystem conditions, (5) spatial and temporal variability, (6) interrelationships between environmental factors and soil properties, and (7) causal linkages and behavior of the system. The modeling process itself can be disaggregated into (1) conceptualization, i.e., defining the model structure and design; (2) reconstruction, i.e., describing and quantifying underlying conditions and behavior using mathematics; and (3) scientific visualization (SciVis), i.e., abstracting real soil-landscapes into a format that we can comprehend and that helps us to understand the complexity of soil-landscapes.

Real soil-landscapes are complex, consisting of an inextricable mix of systematic and random patterns of environmental variables (e.g., soils, topography, land use) varying continuously in the space–time continuum. Soils and parent material show gradual variations in the horizontal and vertical planes, forming three-dimensional bodies that are commonly anisotropic. There is no real beginning and endpoint in real soil-landscapes because environmental conditions are dynamically changing through water flow and biogeochemical processes. In addition, human activities confound naturally occurring patterns and processes.

Transforming real into virtual soil-landscapes is based on model predictions and estimations. Estimations use sample data to make an inference about a population, whereas predictions refer to a statement about the future or reasoning about the future. Methods used in science for the derivation of predictions of unknown facts from known facts include (modified after Bunge[2]):

1. Logical inference that includes deduction, induction, and abduction, the latter one referring to the generation of hypotheses to explain observations
2. Structural laws that help predict new properties from the known properties of material or formal structures
3. Phenomenological laws that predict phenomena on the basis of known constant associations
4. Functional laws that infer functional properties of a system from knowledge of the functional role of the parts and their interconnections
5. Statistical laws that help derive collective properties of classes of events from an analysis of such classes
6. Mechanical laws that extrapolate future (or past) states on the basis of known current states and relations (e.g., Newtonian laws)

Recently, much attention has been given to transform what Egenhofer and Mark[3] called the naïve geography, a body of knowledge that captures the way people reason about geographic space and time, into complex geographic ontologies and semantics.[4] Since ontology is the means to discover the structures and generalities in reality that (metaphysical) realism predicts, ontology is a crucial part of the science world. An ontology is a formal, explicit specification of a shared conceptualization. *Conceptualization* refers to an abstract model of phenomena in the world by having identified the relevant concepts of those phenomena. *Explicit* means that the type of concepts used, and the constraints on their use, are explicitly defined. *Formal* refers to the fact that the ontology should be machine readable. *Shared* reflects that ontology should capture consensual knowledge accepted by the communities. Since most ontological schemes use spatial and temporal concepts, GIScience often serves as an ontological precursor to the design or discovery of phenomena in scientific investigations.[5] Fonseca et al.[6] proposed an ontology-driven geographic information system (ODGIS) that acts as a system integrator independently of the model. The idea is to build a next-generation GIS that entails a systematic collection and specification of geographic entities, their properties, and relations. Smith[7] suggests a terminological distinction between referent or reality-based ontology (*R-ontology*) and elicited or epistemological ontology *(E-ontology*). R-ontology is a theory about how the whole universe is organized, and corresponds to the philosopher's point of view. E-ontology, on the other hand, fits the purposes of software engineers and information scientistis, and is defined as a theory about how a given individual, group, language, or science conceptualizes a given domain.

Smyth[8] and Davis[9] suggest domain-specific ontologies that are based on the following ontological elements:

$$\{\text{content/entities} + \text{time} + \text{geometry} + \text{physics} + \text{logic}\}$$

These ontological components, in turn, can be modeled computationally as objects, spatial representation, temporal representation, numerical models, and knowledge base and inference systems, respectively. Applied to soil-landscape modeling, *content* can be modeled, e.g., as soil attributes, soil classes, or other environmental attributes. Typically, hierarchical trees can be built that represent an ontological component, e.g., a catena composed of soil types, soil attributes that distinguish soil types, soil horizons that define soil types, soil attributes that define horizons, etc. This is in analogy to a hierarchical model that allows the identity of individual trees to be subsumed by a forest; it makes sense to see either the individual trees or the forest. Similarly, we can create soil-landscape snapshot models that represent either the spatial distribution of soil horizons or one specific soil attribute (e.g., soil phosphorus content). There may be several *time* and *geometrical* representations of the same underlying entity. For example, the *geometry* to represent soil characteristics (e.g., silt content) can be a two-dimensional polygon, three-dimensional polyhedron, pixel (two-dimensional raster cell), or voxel (three-dimensional cell). According to Davis,[9] *physics* refers to the rules of interaction between or among entities typically expressed as mathematical formulas. A *logic* allows new facts to be deduced about a (soil-landscape) world for a given configuration.

To understand the role of ontologies in geographic data modeling, Gomes and Velho[10] suggested the four-universes paradigm for modeling a digital (virtual) representation. The four universes are:

1. The *physical universe*, which comprises the objects and phenomena of the real world that will be modeled and transcended into a virtual world.
2. The *mathematical universe* or *logical universe*, a formal definition of these objects and phenomena.
3. The *representation universe*, which uses metaphoric (symbolic) or mirror real-world descriptions of the elements defined in the mathematical universe. For example, a soil profile might be represented as a dot on a map (symbolic representation) attached with a label/legend, or set of multiple polyhedrons that represents soil attributes, soil horizons, and the shape of the soil profile.
4. The *implementation universe*, which is used to map the elements from the representation universe into data structures implemented in a computer language.

Fonseca et al.[6] added the *cognitive universe*, which captures what people perceive about the physical universe. Figure 13.1 characterizes the different universes for a soil-landscape in southern Wisconsin using soil horizons and soil characteristics (e.g., bulk density), crisp objects and voxels, geostatistical methods to reconstruct the soil and terrain features mathematically, and Virtual Reality Modeling Language (VRML) to visualize the soil-landscape models (Figure 13.1).

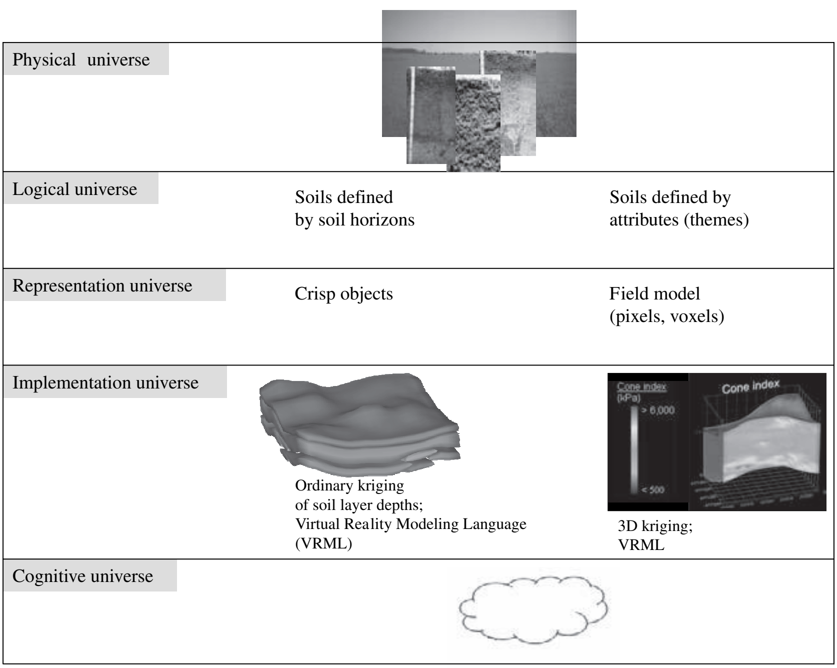

FIGURE 13.1 Schematics of universes used to model a soil-landscape in southern Wisconsin. (See color version on accompanying CD.)

13.2 SPACE AND TIME CONCEPTS

Conceptions of space and time have profoundly influenced our notion of how we observe, describe, and perceive soil-landscapes. Generally, it is necessary to divide geographical space into discrete spatial units, and the resulting tessellation is taken as a reasonable approximation of reality at the level of resolution under consideration. Peuquet,[11] Goodchild et al.,[12] and Burrough and McDonnell[13] propose two contrasting spatial discretization methods: (1) crisp irregular two-dimensionl polygons or three-dimensional polyhedrons and (2) regular-shaped pixels or voxels. In essence, both methods discretize Euclidean geographic space that has a constant zero curvature; i.e., it is a plane and has one and only one parallel to a line passing through a given point. Conceptually there is a slight difference, but computationally a large difference, between both discretization methods. This can be explained by the fact that vector and raster data types are encoded differently, where the former one encodes nodes and vertices of geographic features as well as the topology explicitly, whereas the latter one is based on a much simpler matrix representation. Many different spatial algorithms have been developed and customized to accommodate either vector or raster data in a GIS environment.

Frank[14] and Raper et al.[5] provide an overview of time models. Newtonian time is focused on a succession of phenomena along a linear time coordinate, providing the simplest time concept characterized by causal inertness. Time is viewed as a neutral framework against which independently unfolding events are projected, sorted, and measured. Newton argued that time is absolute, implying that the universe has a single universal clock capable of determining that two occurrences are simultaneous. The present moment, which is changing constantly, forms the center point. Backcasting and forecasting models predict past and future events (e.g., formation of Spodosols, land use change) with exponentially increasing prediction errors from the present moment. Other soil-landscape models are snapshot models that are limited to describe current environmental conditions. Frank[14] proposed alternative time concepts, such as cyclic time, branching time, transaction time, and event-driven time. Other time concepts remain in the phenomenological realm, such Husserl's human subjective time, Minkowski's light cone of time, and Einstein's relative time.

Almost all existing soil-landscape simulation models are based on Newtonian time that is well suited to represent physical and chemical processes. However, the modeling of anthropogenic-driven events (e.g., land use change, sometimes irrational decisions by land stewards) or chaotic climatic events modeled within a Newtonian framework poses problems. Characteristics of real time include that events are nonrepeatable, sometimes structured and at other times chaotic. Real time is relative and depends on the context of previous events and expected future. More generally, the timing of an event changes its nature to the extent that the unique context of other events within which it occurs affects its role in the determination of subsequent events. No two instants can be the same, each one relating to a different set of preceding and succeeding moments and their remembered or anticipated contents.

Space–time domains curved or warped by the presence of mass and energy within them revolutionized our thinking, unifying space and time in the general theory of relativity. Such epistemological space–time concepts have been adopted to represent reality but they are difficult to implement. Much simpler space–time models have been adopted for soil-landscape modeling. Hayes[15] proposed the concept of histories, reasoning that no two histories may overlap in space–time and that a history may be projected onto a point in space–time. Roshannejad and Kainz[16] suggested the logical data model shown in Figure 5.8. The geographic coordinates are described by x, y, and z coordinates representing easting, northing, and depth from the soil surface, respectively. Time is considered the fourth dimension, relegating attribute values to the fifth dimension. Deterministic event models describe the change of ecosystem states in a chain-like fashion according to mathematical algorithms. The result is a spatio-temporal thematic object triplet describing data evolution. Hence, data evolution is described by a sequence of records $\{(s, t, e)\}$, where s is a spatial coordinate, t is a time stamp, and e is an ecosystem function (= behavioral function, e.g., mineralization, leaching of nitrate).

The linkage between space and time conceptualization is through the *process* to be described. Conventionally, simulating ecological processes correspond to a sequence of events with an orderly structure, where one event occurs after the other (deterministic view). Each process that is in focus provides its own context and conceptual frame for the cognition of space and time. Change must be seen as a composite of processes (and interactions between those processes) that occur on a wide band of timescales in the atmospheric, biological, geological, and human domains. Chrisman[17] and others suggested treating time as an axis, a dimension of measurement similar to the spatial case — simply spatializing time.

McSweeney et al.[18] pointed out that soil-landscapes are three-dimensional systems and should be represented using geographic information technology. Burrough and McDonnell[13] argue that the term *three-dimensional* is usually (and properly) reserved for situations in which an attribute varies continuously through a three-dimensional spatial frame of reference, e.g., soil system, whereas land use, land cover, and topography are surfaces and can be represented as two-dimensional geographic features in three-dimensional view. Timeless two-dimensional space concepts will continue to be useful to represent soil-landscapes. Yet recently there have been major advances in computational capabilities, geostatistical analyses, and SciVis, resulting in striking multidimensional soil-landscape representations. Such models will revolutionize how we comprehend soil-landscape systems.

Some soil-landscape studies are limited to one specific period of data collection,[19] others to two dimensions,[20,21] and few are dynamic, addressing changes over time.[22] The development of three- and four-dimensional models has been hampered in the past by the large amount of input data required and the complexities of soil-forming and ecosystem processes. Models that are highly specialized describe the spatial distribution of one property explicitly, such as digital terrain models,[23] land cover layers,[24] or soil maps.[21] There are fewer models that infuse above- and belowground properties to reconstruct soil-landscapes and environmental systems in three-dimensional geographic space.[25–27] Numerous studies present techniques for three-dimensional visualization.[28–30] However, they do not extend their approach below the soil surface to address a three-dimensional ecosystem. Even fewer studies attempt four-dimensional space–time modeling of soil and landscape properties.[31] Since soil-landscapes are truly three-dimensional, undergoing continuous evolution of their components (e.g., due to soil formation, water table dynamics), adequate computerized techniques are needed to reconstruct and visualize these multidimensional and multicategorical environmental systems.

Currently, no universal spatio-temporal modeling and information system exists, but there are a variety of prototypes. Abraham and Roddick[32] presented a comprehensive review on conceptualizations of spatio-temporal databases. Koeppel and Ahlmer[33] distinguish between attribute-oriented spatio-temporal databases that track changes in information about spatial entities, while topology-oriented spatio-temporal databases track changes in positional information about features and their spatial relationships. Whigham[34] proposed a dual-ordered hierarchical structure where time and events are represented in their own hierarchies, placed on a spatial background reference. Hermosilla[35] argues for a temporal GIS with reasoning capabilities based on artificial intelligence. Peuquet and Duan[36] suggest an Event-Based Spatio-Temporal Data Model (ESTDM) focusing on events that are represented along a temporal vector in chain-like fashion. Yuan[37] suggests a three-domain model representing semantics, space, and time separately and providing links between them to describe geographic processes and phenomena. Many of these tools are focused on database management rather than reconstruction and scientific visualization.

13.3 RECONSTRUCTION AND SCIENTIFIC VISUALIZATION

State-of-the-art reconstruction techniques are described throughout this textbook. An overview is given in Chapter 1. Mathematical and statistical methods used to reconstruct soil-landscapes have been described by Goovaerts,[38] Chilès and Delfiner,[39] Stein,[40] McBratney et al.,[41] Webster and Oliver,[42] and Berthouex and Brown.[43] The strengths of soil-landscape modeling lie in hypothesis testing, understanding causal linkages between environmental factors, and their interrelationships within a spatial and temporal explicit context.

Scientific visualization can be implemented using programming languages such as Java, C++, or VRML. The last one is a three-dimensional open-source graphics language suitable for stand-alone or browser-based interactive viewing on the Internet and is used to render the face geometry of soil-landscape models.[44,45] Within the VRML-capable browser, the user can move around VRML worlds in three dimensions, scale and rotate objects, and view updates in real time. Capabilities of VRML include three-dimensional interactive animations, three-dimensional worlds (scenes) comprising several different three-dimensional objects, scaling of objects, material properties and texture mapping (e.g., draping of photographs or bitmap art over the face of a three-dimensional object), setting different viewpoints, and use of light sources. In short, VRML provides the technology that integrated two- and three-dimensional objects, text, and multimedia into a coherent modeling framework. When these media types are combined with scripting languages, an entirely new genre of interactive applications becomes possible. The key elements of the VRML are nodes that describe the shapes, colors, lights, viewpoints, how to position and orient shapes, animation timers, interpolators, etc., and their properties in a virtual world. Fields define attribute characteristics of a node, and every value is of a specified field type.[45] Object-oriented languages such as VRML, C++, and Java support the concept of data abstraction and modularity in program design.

Troy and Czapar[46] employed VRML to evaluate conservation practices. They generated a three-dimensional environment for the Lake Springfield watershed in order to visualize environmental factors and to direct the planning, installation, and maintenance of conservation practices. The authors found VRML useful in the promotion of properly placed best-management practices. Miller et al.[47] used VRML to model rural environments and document land use changes. They emphasized that the virtual reality environment has the potential to aid in communication, decision making, and scenario testing. Lovett et al.[48] used a VRML-based approach for sustainable agricultural management exemplified by a virtual landscape. Grunwald et al.[25] developed similar soil-landscape models implemented in VRML at four different spatial scales for sites in southern Wisconsin. Models were implemented using polyhedrons to represent soil layers that were integrated with a digital elevation model (DEM) to describe soil-landscapes. Voxels were used to create three-dimensional soil property models for bulk density, soil texture, and penetration resistance.

The Internet, geographic information technology, and SciVis provide new education and information delivery capabilities. Numerous studies have shown that SciVis is effective for enhancing rote memorization and higher-order cognitive skills.[49–51] Stibbard[52] found that information is absorbed best when using more than one human sense; i.e., 10% of the information is taken in by reading, 30% by reading and visuals, 50% by reading, visuals, and sound, and 80% by reading, visuals, sound, and interaction. Koussoulakou and Kraak[49] tested the usefulness of different SciVis methods, including static maps, series of static maps, and animated maps, and found significantly better response times for animated maps. Barraclough and Guymer[50] reported that advanced visualization techniques served to better communicate spatial information between people in different fields, such as scientists, administrators, educators, students, and the general public. Just as maps can visually enhance the spatial understanding of phenomena, interactive spatio-temporal applications can enhance our understanding of complex environmental systems and the underlying transport processes driving soil and water quality. According to Fisher and Unwin,[53] visual interfaces maximize our natural perception abilities, improve our comprehension of huge amounts of data, allow the perception of emergent properties that were not anticipated, and facilitate understanding of both large-scale and small-scale geographic features of ecosystems. According to Gordon and Pea,[54] SciVis improves learning because it supports the thought process and methodologies practiced by scientists. These include learning from observation, developing hypotheses to explain observations, and testing of hypotheses with datasets, thereby iteratively developing more detailed and sophisticated analyses. Raper[55] and Morris et al.[56] present innovative management of multivariate and multidimensional datasets and display environmental data in a three-dimensional format. The development of immersive and desktop virtual reality techniques has been instrumental to develop virtual soil-landscapes and environments. VRML models enhanced with Java and External Authoring Interfaces provide capabilities to display real soil-landscapes in three- and four-dimensional digital formats.[57] Characteristics of virtual reality include (1) immersion, (2) navigation (freedom for the user to explore), and (3) interaction.

13.4 APPLICATIONS

The following applications describe the ontological components used to implement different virtual soil-landscape models.

13.4.1 Soil-Landscape Model 1

13.4.1.1 Physical Universe

The study site, a 2.73-ha field, was located on the University of Wisconsin–Madison Agricultural Research Station, West Madison. Shallow reworked loess cover was found on the eroded soils on shoulder and backslope positions, whereas thick reworked loess deposits were found on footslope and toeslope positions. Soils were mapped as fine-loamy, mixed, mesic Typic Argiudolls. The reworked loess was underlain by sandy loam glacial till. Land use was a corn (*Zea mays*)–alfalfa (*Medicago sativa*) rotation. Climate is temperate humid. A constant-rate profile cone penetrometer (PCP), described in detail in Grunwald,[58] was used to collect cone index measurements up to a soil depth of 1.30 m at 273 locations on a 10 $\times$ 10 m grid. Bulk density (BD) measurements were collected along soil profiles in 10-cm-depth increments at 77 locations spatially distributed throughout the site. The BD sampling design targeted locations that showed heterogeneous terrain patterns. Cone index measurements were dense (n = 273), whereas bulk density measurements were sparse (n = 77). A Trimble 4600 LS differential global positioning system (dGPS) (Trimble Inc., Sunnyvale, CA) with base station and beacon differential correction was used to georeference sampling locations and collect elevation data using a dense kinematic mapping technique.

13.4.1.2 Logical and Representation Universe

The goal was to map the spatial distribution of BD across the site in southern Wisconsin adopting a voxel model. The soil and terrain data were fused to reconstruct a coherent three-dimensional model representing terrain and soil patterns.

13.4.1.3 Implementation Universe

Three-dimensional collocated cokriging was used to predict BD at unsampled locations using cone index data as the secondary variable. Cokriging is an extension of autokriging. It takes into account additional correlated information in the subsidiary variables[59] according to Equation 13.1. The dataset was partially heterotopic. A heterotopic situation can be characterized by a variable of interest known at a few points and an auxiliary variable known everywhere in the domain (or at least at all nodes of a given estimation grid and at the data locations of the variable of interest):

$$\hat{Z}(x_0) = w_0 S(x_0) + \sum_{\alpha=1}^{n} (w_Z Z(x_\alpha) + w_S S(x_\alpha)) \tag{13.1}$$

where

$\hat{Z}$ = estimated value
w = weights
$Z(x_0)$ = primary random variable Z at location x_0
$S(x_0)$ = secondary random variable S at location x_0
x_α = points used to estimate x_0; $\alpha = 1, \ldots, n$

The three-dimensional bulk density voxel model was fused with elevation data to produce a three-dimensional soil-terrain model. Virtual Reality Modeling Language was used to render face geometry of voxels. Each voxel represents one estimated BD value. Models in Figure 13.2 show the spatial distribution of BD across the study site. Cross-validation showed a mean squared estimation error of 0.05. A scientific visualization technique called slicing was employed to show the variation of BD across the site (Figure 13.3).

13.4.1.4 Cognitive Universe

Soil-landscape models are Web based and provide interactivity functions to engage users (e.g., zoom, rotate). Three-dimensional models stimulate the geographic abstraction skills. Bulk density values are viewed in concert with terrain properties, providing insight into soil-topographic relationships. Grunwald et al.[59] found that in glaciated landscapes in southern Wisconsin BD is closely related to soil materials such as glacial till and reworked loess. Commonly, large BD values ($\geq$1.6 Mg m^{-3}) are associated with sandy loam glacial till, and medium BD values ($\geq$1.3 and <1.6 Mg m^{-3}) are found in loess material. The presented

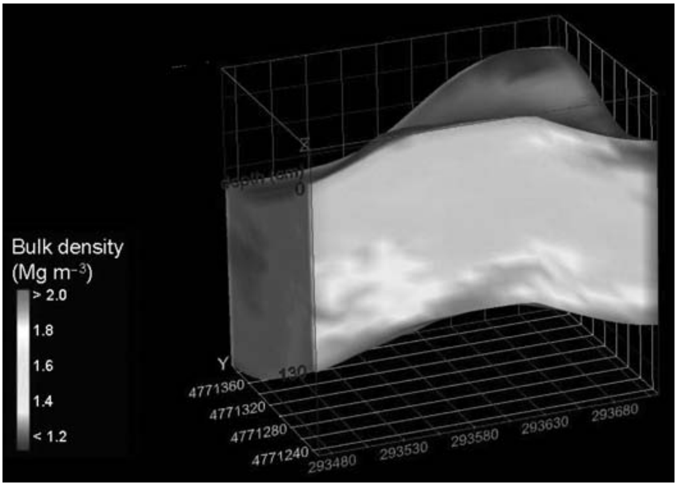

FIGURE 13.2 Three-dimensional model showing the spatial distribution of bulk density values. (See color version on accompanying CD.)

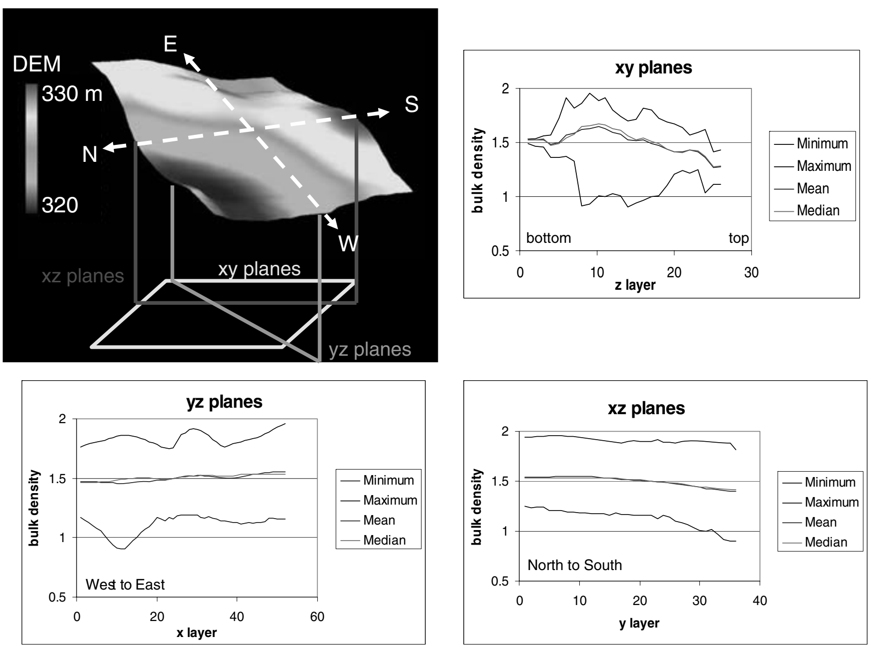

FIGURE 13.3 Bulk density values (Mg m^{-3}) along slices in different planes across the Wisconsin study site. (See color version on accompanying CD.)

models provide the foundation for sustainable land use management, optimizing crop growth while minimizing adverse effects on the environment.

13.4.2 Soil-Landscape Model 2

13.4.2.1 Physical Universe

The study area comprised a 42-ha site in northeastern Florida with hydric and nonhydric soils. About one third of the site was covered by cypress (*Taxodium distichum*) and about two thirds by slash pine (*Pinus elliottii*). In 1994, three silvicultural treatments were administered. While the southwest block was left as a control (uncut), the southeast block was clear-cut. On the northwest block only the forest on the hydric soils was cut; that on the nonhydric soils was left untouched. Morphological and taxonomic soil data were collected at 123 locations on a 100×100 m grid. Topography was characterized by laser level and ranged from 27 to 31 m. A detailed description of the study can be found in Bliss and Comerford.[60]

13.4.2.2 Logical and Representation Universe

The objective was to generate a model that displays the spatial distribution of soil horizons across the study site. The crisp object model was adopted to represent horizons focusing on soil genetic aspects of this site. The soil and terrain data were integrated to reconstruct a coherent three-dimensional model representing terrain and soil patterns.

13.4.2.3 Implementation Universe

Two-dimensional ordinary kriging[42] in the horizontal plane and linear interpolation in the vertical plane were used to create three-dimensional face geometry of soil layers. The output product was a stratigraphic model representing soil horizons as polyhedrons or volume objects (Figure 13.4a). The *IndexedFaceSet* VRML class was employed to render polyhedrons. A point-arc geographic data model was used to create *IndexFaceSets*. The appearance of volume objects was coded using the RGB (red-green-blue) color classification system. A model showing representative soil pedons across the site used VRML texture mapping, draping photographs of soil profiles over the face of cylinder objects (Figure 13.4b). Cylinders were linked to quantitative datasets using Java Script embedded into VRML. Each soil profile has a sensor node, which senses the computer mouse. Once the user selects a soil profile, an event is sent to the Java Script through the Java External Authoring Interface and attribute data are displayed in a textbox adjacent to the three-dimensional soil model. Geographic objects in VRML were created using the Environmental Visualization System software (EVS-PRO, CTech Development Corporation, Huntington Beach, CA).

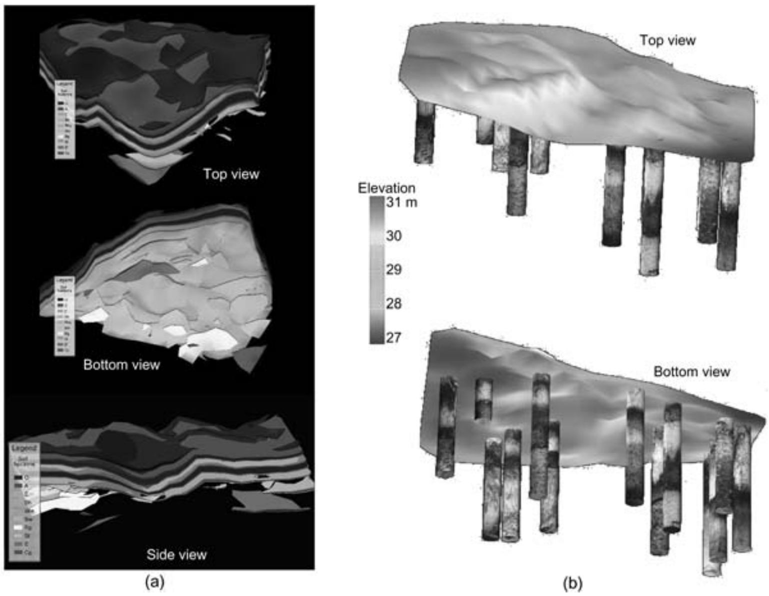

FIGURE 13.4 (a) Three-dimensional soil horizon model. (b) Soil profile model. (See color version on accompanying CD.)

13.4.2.4 Cognitive Universe

The model was implemented using desktop virtual reality and is accessible at http://3Dmodel.ifas.ufl.edu. Employing SciVis facilitated multiple views of the soil-landscape, which stimulates a greater understanding and insight of the flat-wood system. It is this synthesis of geographic datasets that distinguishes the virtual environment from conventional instructional media (e.g., two-dimensional GIS maps).

13.4.3 Space–Time Simulation of Water Table Dynamic

13.4.3.1 Physical Universe

The water table was monitored biweekly at 123 wells on the flatwood site described under Section 13.4.2 from April 1992 to March 1998. The wells were 1 to 1.4 m deep and positioned on a 100×100 m grid. Daily precipitation data were collected for the same period and aggregated to biweekly time increments.

13.4.3.2 Logical and Representation Universe

The objective was to generate models that show the spatial and temporal distributions of water table dynamics across the site. The terrain model was fused with the water model. The first representation model was based on voxels (space–time

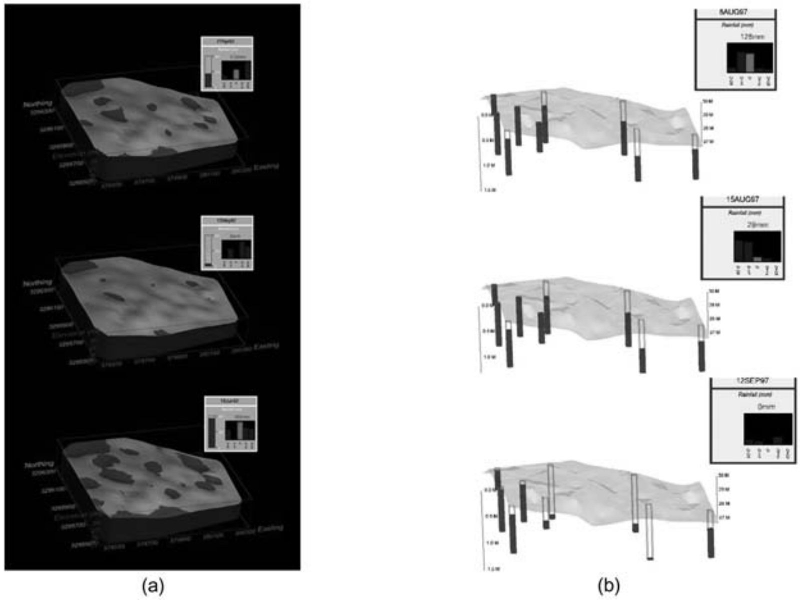

FIGURE 13.5 (a) Space–time models of inundation. (b) Space–time models show water table depth and rainfall observed for different periods. (See color version on accompanying CD.)

inundation model), and the second representation model was based on objects (space–time model of water table depth).

13.4.3.3 Implementation Universe

13.4.3.3.1 Space–Time Inundation Model (Figure 13.5a)

Hundreds of semivariograms for water table depth had to be generated, each representing one specific period between April 1992 and March 1998. Water table levels were interpolated using two-dimensional ordinary kriging. The water table surface was sliced with the digital elevation model to distinguish inundated from noninundated areas. The *CoordinateInterpolator* VRML node was used to produce a smooth display of water table depths between observation periods. The *IndexedFaceSet* VRML class was employed to render the extent of the study site.

13.4.3.3.2 Space–Time Model of Water Table Depth (Figure 13.5b)

Each well was rendered using empty cubes and positioned at observed geographic locations. After triggering the simulation, a Java program reads the measured water table levels, defined by their respective x, y, and z coordinates, at each well for a specific period. The *CoordinateInterpolator* VRML node was used to interpolate water levels across the flat-wood site. A graphical user interface was added as front end to enable users to select the wells and period they want to display. The cubes are filled with water on-the-fly according to respective observed water levels constrained to the subset of user-defined parameters. The simulation can be repeated for different well locations or periods. Java Server Pages from Sun Microsystems was used for developing this dynamic Web simulation.

13.4.3.4 Cognitive Universe

The space–time models are available at http://3Dmodel.ifas.ufl.edu. An interactive framework was used to engage users. Users can trigger an event by constraining the border conditions (e.g., time period, geographic domain) of simulations. Adaptive selective simulation stimulates experimental learning through the observation of ecosystem processes using a sequence of events: trigger an event, observe ecosystem process, interpret, assimilate. Causal linkages between terrain properties, land use, soils, precipitation, and water table dynamics within a spatially and temporally explicit context can be described and visualized. Employing SciVis facilitated multiple views of the content world, which stimulates a greater understanding and insight of the flatwood system. Desktop virtual reality, when combined with other forms of digital media, may offer great potential for a cognitive approach to research and education.

13.5 FINAL REMARKS

The use of software components extracted from ontologies is a way to share knowledge and integrate different kinds of information. Ontological component modeling is structured and facilitates transparent documentation of the modeling process. Ontologies are useful at the database, reconstruction, and visualization levels.

SciVis combined with quantitative reconstruction techniques has the potential to translate real soil-landscapes and ecosystem processes into a transparent format to enhance our understanding of real-world phenomena (e.g., water dynamics, nitrate leaching) and complex environmental systems. Limitations of the presented approach are largely those due to the availability of soil and other environmental datasets used to reconstruct models and the size of the study area. Soil-landscape models that extend over large areas are challenging to visualize because soils are typically mapped only to a depth up to 1 to 2 m. Therefore, it is necessary to use exaggeration factors to visualize soil profiles or properties across a landscape that extends over hundreds of square kilometers. Web-based virtual soil-landscape models and space–time simulation models facilitate the exploration, analysis, synthesis, and presentation of georeferenced environmental datasets. Shiffer[61] argues that users gain an improved understanding by viewing information from several different graphical perspectives. Krygier[62] notes that combining multimedia elements (e.g., Internet, interactivity, three-dimensional SciVis) can produce insight that would not arise from use of the elements alone. Virtual soil-landscape models are beneficial in disseminating georeferenced soil and landscape data to educators, researchers, government agencies, and the general public. In the realm of education, Freudenschuh and Hellevik[63] pointed out that students should be encouraged to become active participants, rather than passive learners, by appealing to their multisensory learning ability with interactive media. Training and integration of quantitative modeling and programming skills into curricula is a prerequisite to produce the next generation of interactive, virtual soil-landscape models.

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