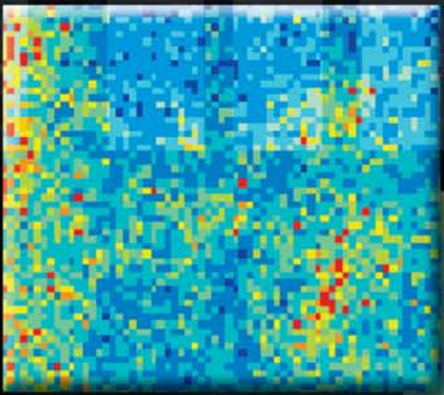
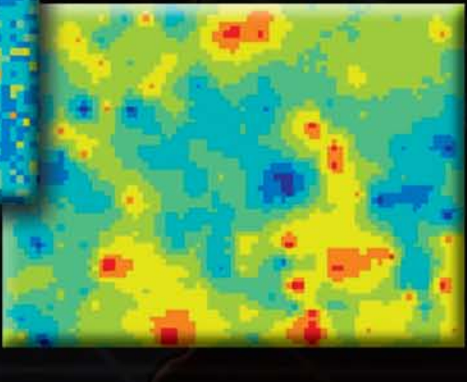
# Environmental Soil-Landscape Modeling

## Geographic Information Technologies and Pedometrics





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# 5 The Impact of Emerging Geographic Information Technology on Soil-Landscape Modeling

*Sabine Grunwald and Sanjay Lamsal*

## CONTENTS

## ABSTRACT

We provide an overview of historic and emerging soil mapping technologies, soil mapping paradigms, and data management. Geographic information technology (GIT), including the emergence of global positioning systems, geophysical mapping techniques such as electromagnetic induction and ground-penetrating radar, soil sensors such as profile cone penetrometers, soil spectroscopy, and remote sensors, are introduced and critically discussed. Special attention is given to the limitations of each emerging technology and the impact on environmental soil-landscape modeling. Geographic and soil information systems have served as integrators to manage and analyze soil and other environmental datasets. The Web-based distribution of soil-landscape data through the Internet has enabled global data sharing.

## 5.1 WHAT IS EMERGING?

### 5.1.1 Soil Mapping Technologies

Since the beginning of the systematic study of soils, various concepts have been adopted to map soils and their properties. Emerging soil mapping techniques have had a major impact on how we map and describe soils, resulting in a paradigm shift in pedology and soil science. Early soil surveyors used soil augers, spades, pencils, and notebooks. These were later complemented by laboratory measurements. The tacit knowledge of the soil surveyor to comprehend a soil-landscape was the basis for characterizing the spatial distribution of different soils. Soil surveying based on soil taxonomies has been focused on the mapping of morphological, physical, chemical, and biological properties, with less emphasis on pedogenesis. The use of aerial photographs for soil mapping, which began during the late 1920s and early 1930s, greatly increased the precision of plotting soil boundaries. Constraints on these hard-copy soil maps were imposed by the experience of the soil surveyor and available budgets. For example, in the U.S., for a standard soil survey at a map scale of 1:24,000, an average of one auger boring per 14 ha (40 acres) has been used.

The heterogeneous nature of soils across a landscape has long been recognized, and different concepts and sampling designs have been employed to model the variation. At large (field) scale, high-intensity soil surveys can be conducted. For example, Lark[1] used intensive grid sampling (20-m intervals) and mapped soil texture and soil depth to identify seven map units across a 6-ha field. At small (coarse) scale, such high-density sampling is not feasible due to limited budgets and time constraints. Alternative methods are in need to improve existing soil surveys to provide high-quality and high-resolution soil maps. With the advent of global positioning systems (GPS), geophysical soil mapping techniques, soil sensors, and soil spectroscopy, it has become possible to map larger areas rapidly with higher sampling densities, resembling more exhaustive datasets for fine-scale mapping. Recent technological advances offer new opportunities for spatially explicit mapping of heterogeneous soil patterns. However, limitations still persist in terms of accurate and precise mapping of soil properties. In this chapter we will discuss a variety of emerging geographic information technologies (GIT) and their potentials and limitations in the characterization of soil-landscapes.

### 5.1.2 Soil Mapping Paradigms

The perceptions of soils and soil mapping paradigms have changed with time. Early soil mapping was influenced by the use of soils for farming, ranching, and forestry. In recent years the effort has shifted to acquire more quantitative and accurate site-specific soil data. Bouma et al.[2] pointed out that soil data are important for precision agriculture (PA), but current soil survey data do not satisfy precision agriculture requirements, including an appropriate level of detail and soil property information. The PA industry explored various high-density soil mapping and geostatistical techniques to produce fine-scale soil property maps.[3] Likewise, environmental assessment studies require detailed information about the spatial and temporal distributions of soil properties. The U.S. Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS) and its predecessors, with local and state agencies and land grant universities, have been generating soil information in the U.S. for over 100 years. Although originally focused on the agricultural use of soil data, the mission of NRCS is now much broader, i.e., "to help people conserve, improve and sustain our natural resources and the environment."[4] Though the need for high-quality and high-resolution soil property maps has been recognized, we are still struggling to meet the demands of farmers, environmental scientists, the forest industry, and others.

In order to reduce soil information to a manageable form, soils are classified at various levels of hierarchy (taxonomic units). The crisp geographic data model is a well-adopted model for soil mapping at the landscape scale.[5] This *entity-based approach*[6] or *object view*[7,8] defines the real world as an arrangement of discrete, well-defined objects that are characterized by their geometrical and topological properties and by their nonspatial attributes (Figure 5.1). It is seldom, however, that a soilscape can be adequately described and defined from one pedon.[9] Therefore, the relationships of soils with observable landscape features (topography, vegetation, parent material, etc.) are used to infer the variability of

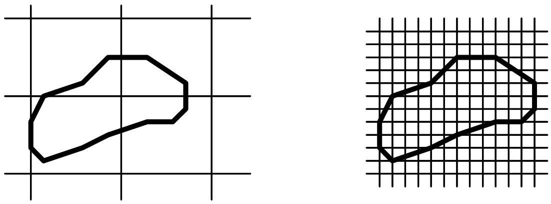

**FIGURE 5.1** Representations of soils: (1) polygon, entity or object view, and (2) raster, field view.

soil properties, thereby interpolating the individual pedon properties/observations over the study area.[10] Based on such observed properties, similar soils are grouped together and translated into soil classes.[9] Soil properties are considered homogeneous within the map unit and sharp breaks in soil properties are assumed, forming the polygon boundaries. This soil mapping concept has been questioned extensively.[11–13] Crisp soil mapping is practical; however, it ignores the continuous spatial variation in both soil-forming processes and in the resulting soils. Burrough et al.[14] consider it a double-crisp model because the identified soil groups are supposed to be crisply delineated in both taxonomic space (the space defined by the soil properties) and geographic space (defined by the map unit boundary). Bie and Beckett[15] demonstrated that even with aerial photo identification (API), different surveyors choose radically different boundary spacing, and not every important change in soil properties occurred at physiographically distinct locations.

The raster-based or *field view* geographic data model[6,7] evolved as an effort to address the digital representation of continuously varying environmental properties such as soils (Figure 5.1). Commonly, geostatistical techniques[16–18] are employed to create continuous raster-based maps that model the spatial autocorrelation of soil properties measured at georeferenced locations. Typically, deterministic or stochastic methods are employed to characterize soil variation along with the prediction uncertainty.[19,20] The spatial discretization units in continuous maps are pixels or voxels whose size depends on the underlying spatial variability, sampling density, and survey design. McBratney et al.[21] suggested three levels of resolutions that are of interest: >2 km, 2 km to 20 m, and <20 m, which correspond to global/national, catchment/landscape, and local extents, respectively.

An alternative approach to map soils, considering its continuous nature, is provided by fuzzy sets, first introduced by Zadeh.[22] Fuzziness, a concomitant of complexity, is a type of imprecision characterizing classes that for various reasons cannot or do not have sharply defined boundaries or units. Numerous authors[23–28] describe the fundamental principles, operations, and applications of fuzzy sets to soils. Fuzzy methods allow the matching of individuals to be determined on a continuous scale instead of a Boolean binary or an integer scale. Contrary to crisp sets that assign membership values of 0 and 1, a fuzzy set is a class that admits the possibility of partial membership. Hence, fuzzy sets are generalizations of crisp sets to situations where the class boundaries are not or cannot be sharply defined. Though numerous applications of fuzzy set theory to soil-landscape modeling exist,[25,27–29] it has not been widely adopted. Reasons are seen in the fact that users prefer to have one crisp output map (e.g., bulk density map), rather than complex fuzzy output maps, which are more challenging to interpret. Defuzzification has been suggested to backtransform the fuzzy output into crisp soil data.[30] However, such a procedure opposes the paradigm of fuzzy set theory, i.e., the fact that our world has many shades of gray rather than being black and white. There has been extensive criticism about the development of membership functions for fuzzy application using soft input or subjective expert knowledge.

Past studies have clearly demonstrated that there is no single, overall soil classification and mapping paradigm that can be used uncritically at all locations and at all levels of resolution.[14] Regardless of the approach employed, soil mapping must take into account prevailing processes of soil formation, differences in lithology, landform, drainage, and others for delineating soil properties or classes. Continuous maps focus on specific soil properties, contrary to crisp maps, where soil properties are lumped into soil classes. In this regard, continuous soil maps are better suited to soil investigations focusing on specific purposes (so-called technical soil surveys), while crisp maps provide an overall picture of the soil variation across the landscape. Few studies[31,32] have shown that crisp soil mapping can provide predictions that are equally as good as continuous soil maps obtained by geostatistical techniques. Rogowski[33] compared taxonomic soil survey data to continuous soil data developed using geostatistical methods at farm and watershed scales. Results showed that the variability of bulk density and hydraulic conductivity can be estimated by comparing regularized variograms of measured and published values. These findings provide avenues of incorporating crisp soil data with raster-based soil datasets, reconciling the two contrasting geographic data models.

### 5.1.3 Data Management

Historically, hard-copy soil maps were produced that show crisp soil map units as polygons and associated legends. With the advent of geographic information systems (GIS) storage, management, analysis, and display of soil data have changed tremendously. The emergence of GIS has had a pivotal impact on soil surveying. In the early 1980s, vector-based GIS emerged, which were used to represent crisp soil map units, while raster-based GIS were developed mainly for remote sensing applications. Vector and raster-based GIS eventually merged to become hybrid GIS, providing both geographic data models within one software package.

Spatial data are stored in the form of database management systems (DBMS).[6] Modern DBMS use many methods for efficiently storing and retrieving data, but all are based on three fundamental means of organizing information, which also reflect the logical models used for real-world structures known as the hierarchical, network, and relational schemata. Hierarchical systems of data organization are adopted in soil taxonomies (e.g., *U.S. Soil Taxonomy*).[106] Keys enable ease of access and retrieval of data. A disadvantage of hierarchical databases is large index files, which have to be maintained, and certain attribute values may have to be repeated many times, leading to data redundancy, which increases storage and access costs. The network database structure, though similar to the hierarchical database structure, avoids redundancy and linkage problems. Most commonly used in GIS are relational database (RDB) structures. An example of the RDB used in the Soil Survey Geographic (SSURGO) database is given in Figure 5.2. The data are stored in simple records, known as tuples, which are sets of

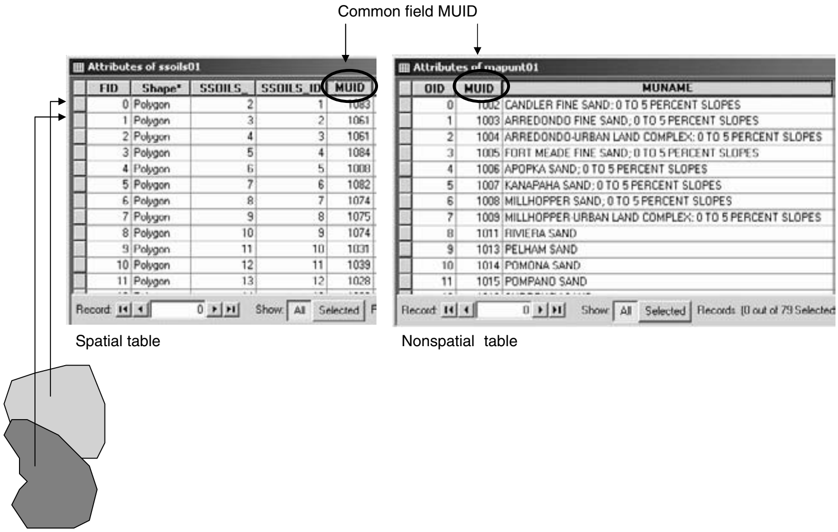


**FIGURE 5.2** Spatial and nonspatial tables from SSURGO. The tables are stored in RDB format. Attribute fields from different tables can be associated using common fields (e.g., map unit identification (MUID) attribute field).

fields each containing an attribute. Tuples are grouped together in tables known as relations. Each table or relation is usually a separate file. Identification codes are used as unique keys to identify the records in each file. Data are extracted from a relational database defining the relation that is appropriate for the query. Advantages of RDBs are their flexible structure, ease to update, and nonredundancy. Disadvantages occur where the relationships between tables are complex and a number of joins are needed to produce a soil map. Such operations are error prone. Recently, a fourth structure has been introduced to GIS, which is called object orientation structure.[6] Object database management systems (ODBMS) integrate database capabilities with object programming language capabilities. An ODBMS makes database objects appear as programming language objects in one or more existing programming languages (e.g., C++, Java). Object database management systems extend the object programming language with transparently persistent data, concurrency control, data recovery, associative queries, and other database capabilities. Object-oriented databases use abstract data types, which add flexibility to a DBMS; however, there are two constraints that limit their application. First, the market adoption of object-oriented databases has been limited, despite the availability of such products for several years. Second, the Structured Query Language (SQL) is tightly coupled with the relational database model. SQL is a declarative language where users only specify the desired result rather than the means of production.[34]

Burrough[35] argues that GIS facilitate flexible weighting of properties in accordance with a specific purpose. Hence, the boundaries in technical groupings often cut across taxonomic subdivisions. Dudal[36] points out that there is no need anymore for data aggregation into taxonomic units to efficiently manage spatial datasets. Databases that contain geo-referenced soil property data enable users to select and group clusters of relevant soil property data by function of demand.

Emerging geographic information technology enables us to integrate geospatial datasets of soils and other resources. It facilitates universal data sharing across the Internet as outlined in the National Spatial Data Infrastructure (NSDI), which is a concept defined as the technologies, policies, and people necessary to promote sharing of geospatial data throughout all levels of government, the private and nonprofit sectors, and the academic community. The Federal Geographic Data Committee (FGDC) sponsors a decentralized system of servers called the Geospatial Data Clearinghouse, which is a collection of over 250 data servers that have geographic data primarily for use in GIS, image processing systems, and other modeling software. Such a framework enables users around the globe to access and share digital soil datasets.

## 5.2 EMERGING SOIL-LANDSCAPE MAPPING TECHNOLOGIES

### 5.2.1 Global Positioning Systems

Early soil surveyors recognized the importance of mapping soils in the context of geographic space; i.e., it mattered where (at which location) a soil observation was made and how it related to adjacent soils, topography, land use, and other properties. Reference systems such as the U.S. Public Land Survey System featuring relative georeferencing based on nested grids such as townships, ranges, and sections improved the capabilities to reference a soil sample to a specified geographic location. However, the uncertainty of georeferencing was relatively high. The introduction of GPS to soil mapping was pivotal, providing accurate and precise geographic coordinates of soil observations. To characterize soil-landscapes, each soil sampling location is georeferenced using a GPS based on x (easting) and y (northing) coordinates. Global positioning systems combined with GIS provide a powerful toolset to build soil information systems (SIS).

Global positioning systems consist of a satellite segment, control segment, and user segment.[37] The GPS receiver in the user segment records the radio signals broadcasted by each satellite, which are processed to obtain its distance (range) from the satellite.[38] The distance of the receiver from a minimum of three (more is even better) satellites defines a unique position in two- and three-dimensional space, respectively. An alternative to such autonomous GPS is a differential GPS (DGPS), which entails establishing a base station with a true coordinate location determined using high-accuracy survey methods. The GPS-measured position for the base station is compared to its predetermined location to define an error vector, which is used to correct the position measured by GPS units elsewhere, either in real time (real-time DGPS) or after the data are collected (post-processing DGPS).

Each dilution of precision — positional, vertical, horizontal, timing, and geometric — and environmental conditions contribute to the overall final positional accuracy of the GPS measurement. The current Standard Performance Service (SPS) published by the U.S. government is ±37 m horizontal and 77 m vertical 95% of the time.[37] With selective availability (SA) turned off, civilian use of GPS is often much better and regularly achieves a horizontal accuracy of about 20 m, while having a vertical accuracy of about 50 m. Even handheld GPS units facilitate relatively accurate mapping of geographic coordinates, while DGPS are capable of mapping geographic locations with submeter accuracy.

### 5.2.2 Geophysical Techniques

For conservation, political, ethical, and cultural reasons, destructive auger-based soil sampling is not feasible at all sites[39] and prohibitive for spatially dense sampling.[40] The lack of sensitive tools to detect subtle shifts among soil properties limits the spatial delineation of soil variability.[41] As an alternative, geophysical methods that are noninvasive and reliable can complement the soil mapping effort.[42]

#### 5.2.2.1 Electromagnetic Induction

Electromagnetic induction (EM) facilitates mapping the electrical conductivity (EC) of soils. Electrical conductivity correlates to soil properties affecting crop productivity, including soil texture, cation exchange capacity (CEC), drainage conditions, organic matter, salinity, and other subsoil characteristics. Other applications combine EC data with sparser georeferenced point soil observations to produce thematic soil maps. Electrical conductivity surveys are also used to prescreen a soil-landscape. Maps are then used to identify heterogeneous areas that are targeted for more detailed auger-based soil mapping.

Traditionally, the soil paste method[43] has been used to assess soil EC, but more recently commercial devices have become available to measure and assess bulk soil EC rapidly and economically across sites. Georeferenced *in situ* estimates of EC are now being made at the field scale using both direct contact sensors to measure resistance and noncontact sensors based upon EM technology.[44] In EM surveys, a sensor in the device measures the electromagnetic field induced by current inserted into the soil. The strength of this secondary electromagnetic field is directly proportional to the apparent electrical conductivity (ECa) of the soil. Hartsock et al.[45] summarized the variation in soil electrical conductivity as being attributed to multiple factors: amount and connectivity of soil water, bulk density, soil structure, water potential, timing of measurement, soil aggregation (e.g., cementing agents such as clay and organic matter, soil structure), electrolytes in soil water (e.g., exchangeable ions), soil temperature, the conductivity of the mineral phase (e.g., types and quantities of minerals, degree of isomorphic substitution, exchangeable ions), and more. Despite the multiple causes of EC variability, bulk soil ECa measurements have been related to individual factors that limit soil use and productivity, such as salinity,[46] moisture, clay content, calcium and magnesium content, depth to bedrock and fragipan,[45] and soil horizons.[47] Yoder et al.[48] predicted the movement of agrochemicals, and Sudduth et al.[49] predicted depth to topsoil using EM. We like to point out that EC provides surrogate information, and often there are multiple causes generating variable fields of EC measurements. However, EM surveys facilitate rapid mapping of soil-landscapes, generating exhaustive datasets. Hence, EC is a powerful tool to map soil variation across fields. Generally, the use of EM has been most successful in areas having reasonably homogeneous subsurface properties with a minimal sequence of dissimilar subsurface layer.[50] EM mapping coupled with traditional soil sampling can provide a compromise between soft and exhaustive, and hard (quantitative) and sparse soil data, respectively. Two instruments widely used for measuring bulk soil EC *in situ* are the EM38 meter (Geonics Limited, Mississauga, Ontario) and the Veris System (Veris Technologies, Salina, KS). The EC meters respond to the average bulk soil EC between the surface and a maximum depth of about 1 m (Veris) or 1.5 m (EM38).

#### 5.2.2.2 Ground-Penetrating Radar

Ground-penetrating radar (GPR) is one of the geophysical exploration and subsurface delineation techniques that has proven to aid greatly in site characterization and mapping. The GPR method has found widespread acceptance for shallow subsurface mapping because it can detect shallow underground discontinuity and heterogeneity,[51] covering a wide area in a short period with high spatial resolution.[52]

Ground-penetrating radar information is acquired by reflecting radar waves off subsurface features. The ground-penetrating radar antenna is pulled along the ground by hand or behind a vehicle. The radio waves are propagated in distinct pulses from a surface antenna, reflected off subsurface features, and detected back at the source by a receiving antenna. The travel time of the energy pulses and the velocity change of radar waves can accurately trace the distance or depth to the subsurface feature. The electrical and magnetic properties of rocks, soils, and fluids (natural materials) control the speed of propagation of radar waves and their amplitudes. At radar frequencies, electrical properties are dominantly controlled by rock or soil density, chemistry, state (liquid/gas/solid), distribution (pore space connectivity), and content of water. Ground-penetrating radar measures differences in the dielectric constant of subsurface features. Dielectric constants range from 1 (air), 4 (dry sand), 5.5 (dry limestone), 6 (wet sandstone), 11 (till), 23.5 (wet sandy soil), 27 (wet clay), 64 (organic soil), to 81 (water). Ground-penetrating radar waves can reach depths up to 30 m in low-conductivity materials such as dry sand or granite. Clays, shale, and other high-conductivity materials may attenuate or absorb GPR signals, greatly decreasing the depth of penetration to 1 m or less. The resolution is controlled by the wavelength and polarization of the electromagnetic energy, the contrast in electromagnetic properties, and the size, shape, and orientation geometry of the target. The resolution increases with increasing frequency (decreasing wavelength), but at the expense of depth of investigation.

Although earlier GPR systems recorded the raw subsurface reflections on paper printouts, currently used GPR systems are equipped to record the reflections in digital format. Conyers and Goodman[39] discussed some of the field and post-acquisition techniques to acquire, process, and interpret GPR data. Typically, radar antennas are moved along the ground and two-dimensional profiles of a large number of periodic reflections are created, producing profiles of subsurface features and stratigraphy. In case data are acquired in a series of transects, and the reflections are correlated and processed, it is possible to create three-dimensional models of subsurface features. Ground-penetrating radar provides higher resolution of subsurface features than EM, but it is more depth restricted.[50]

Gish et al.[53] used georeferenced GPR data in concert with EM data to identify subsurface restricting layers. These data were coupled with hydrological models in a GIS to determine potential flow pathways from topographic maps of a subsurface restricting layer. Doolittle and Collins[50] compared EM and GPR techniques in areas of karst and found GPR effective in determining the thickness of surface layers and locations of buried solution features, while the presence of multiple, contrasting soil horizons and layers weakened relationships and created nonunique interpretation for EM. In Florida, GPR is used extensively to update soil surveys.[42] Ground-penetrating radar is most successful in sand-rich soils (e.g., Florida soils), but it fails in silt-rich material due to confounding impact of soil moisture and other factors. Successful applications of GPR include identification of subsurface features and cavities,[50] identification of soil layers and subsurface flow channels,[53] archaeological investigations,[39,54] fractures and faults in geological formations,[51] and more. The integrated use of GPR and EM, supported by ground truth verification, increases the confidence of subsurface feature interpretations.[50] However, many GPR applications are qualitative in nature, highlighting subsurface variability. The true nature of the variability is often confounded by many interrelated soil properties. Therefore, it is challenging to derive quantitative relationships between soil properties and GPR measurements.

### 5.2.3 Sensors

#### 5.2.3.1 Soil Sensors

Soils impose resistance to penetration by virtue of texture, structure, porosity, water content, cementing agents, and compaction.[55] A profile cone penetrometer (PCP) is an instrument in the form of a cylindrical rod with a cone-shaped tip designed for penetrating soils and for measuring penetration resistance expressed as cone index (CI). Two standards for PCP applications exist: the American Society for Testing and Materials[56] and the American Society of Agricultural Engineers[57] standards, which differ mainly in the cone apex angle of 60° and 30°, respectively. Truck or all-terrain vehicle (ATV)-mounted constant-rate PCPs provide more reliable CI data than handheld push penetrometers (Figure 5.3). Clustered cone index profiles collected on a grid with 10-m spacing on a 2.73-ha site in southern

**FIGURE 5.3** Truck-mounted PCP system. (Courtesy of Soil Science Department, University of Wisconsin, Madison.)

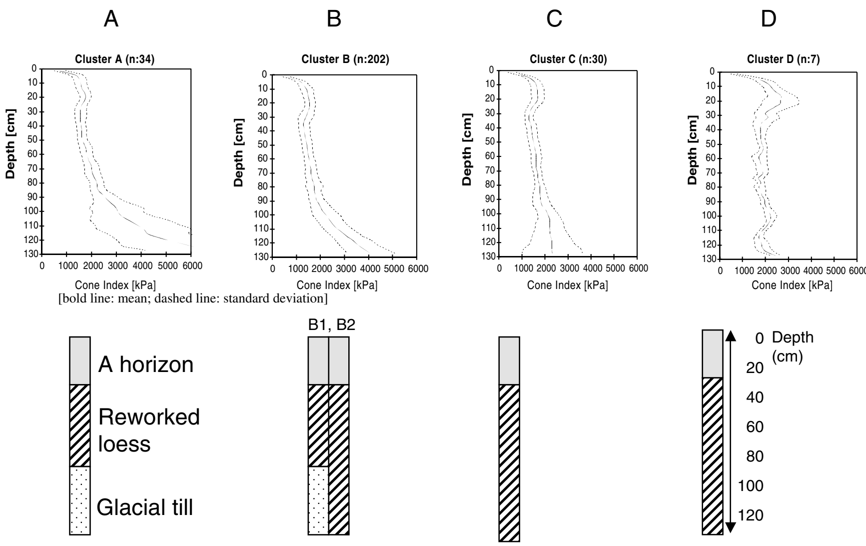


**FIGURE 5.4** Cone index curves ($n$ = 273) were clustered into four groups and related to soil horizons/materials. Data were collected at a 2.73-ha site in southern Wisconsin on a grid with 10-m spacing.

Wisconsin are shown in Figure 5.4. The identified four clusters were related to soil materials. A detailed description of the study can be found in Grunwald et al.[55]

Among the soil characteristics that influence penetration resistance are soil texture, porosity, structure, water content, cementing agents, organic matter, and compaction. Numerous authors related measured CI to soil properties. Rooney and Lowery[58] mapped soil horizons. Correlations between particle size and penetration resistance were presented by Kasim et al.,[59] Kurup et al.,[60] and Puppala et al.,[61] where coarse-textured soils showed greater penetration resistance than fine-textured soils. Water content and organic matter content are inversely related to penetration resistance,[62,63] while cementing agents like carbonate, silica, hydrous silicate, and hydrous iron oxide[61] increase penetration resistance. Lowery and Schuler[64] showed that penetration resistance and bulk density increased with increasing level of compaction. Grunwald et al.[65] derived pedotransfer functions relating cone index to soil texture, bulk density, and soil moisture content. Grunwald et al.[55] used a profile cone penetrometer to distinguish between glacial till and reworked loess soil materials in a glaciated landscape in southern Wisconsin. The CI data combined with soil property and topographic data were used to reconstruct the soil-landscape using clustering and multidimensional kriging.

The advantage of rapid nonintrusive mapping using PCP is limited by the fact that penetration resistance is the response signal to soil-factor combinations. Hence, CI represents a surrogate of soil properties such as soil moisture, soil texture, and bulk density in varying quantities. Profile cone penetrometer data can be used in combination with other soil sensors or traditional soil mapping techniques. A combination of tip and sleeve measurements and a soil moisture probe with sparse soil observations were explored by Soil and Topography Information, LLC (Madison, WI) to make inferences on soil horizons and soil texture. A color video camera was integrated in a PCP to record soil profiles while measuring CI[66] (Figure 5.5). Image processing techniques can be used to derive numerous soil properties (e.g., soil color, soil texture, soil structure). For example, Schulze et al.[67] found that soil color is closely related to soil organic matter. The integration of multiple soil sensors and traditional soil mapping techniques will provide new and exciting avenues to generate high-resolution and quality choropleth soil maps in the near future.

#### 5.2.3.2 Soil Spectroscopy

Conventional soil extraction methods of phosphorus, nitrate, carbonates, metals, and others are labor intensive, expensive, and time consuming.[68] In addition, dense sampling is required to adequately characterize spatial variability of a soil-landscape, making broad-scale quantitative evaluation difficult.[69] As reflectance and emittance behavior of soil is highly dependent on its biochemical and physical fabric,[70] the analysis of such characteristics can provide information on soil properties. Soil spectroscopy refers to the use of sensing instruments[71] to measure the absorption, emission, or scattering of electromagnetic radiation from soil to qualitatively or quantitatively study soil properties. Diffuse reflectance spectroscopy is increasingly used for the rapid nondestructive characterization of a wide range of materials.

For soils, the basic application range consists of the visible (350 to 700 nm), near-infrared (NIR) (700 to 2500 nm), and mid-infrared range (MIR) (2500 to 25,000 nm). While NIRS has developed into a major tool for analytical determinations over the past two decades, the main use of mid-infrared has been for research or qualitative analysis involving spectral interpretation.[72] A number of

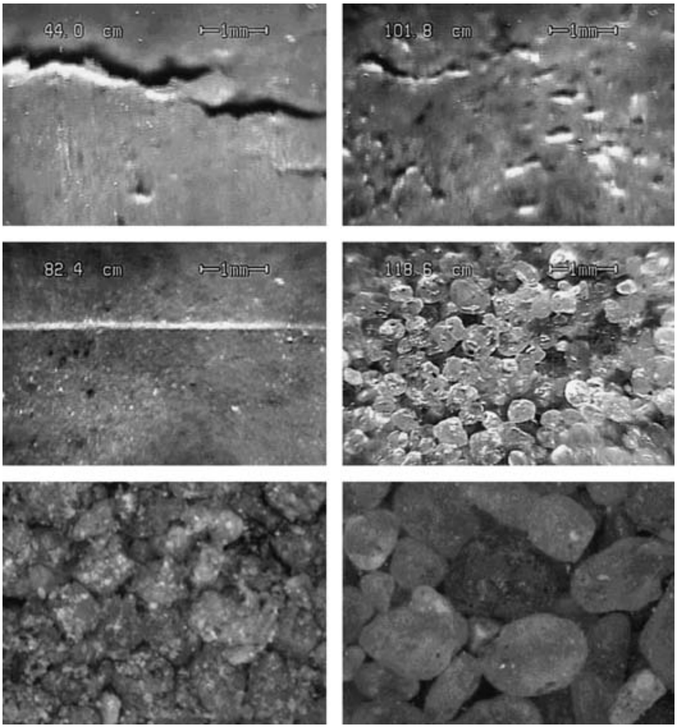


**FIGURE 5.5** Images collected with a soil imaging penetrometer. (Courtesy of Soil and Topography Information, LLC, Madison, WI.) (See color version on the accompanying CD.)

scientists[72,73] found that MIR diffuse reflectance spectroscopy can be performed with accuracy equal to or greater than that achieved using NIR spectroscopy. For example, soil organic matter is related to reflectance in the 2.5 to 25 μm range, but their overtones (at one half, one third, one fourth, etc. of the wavelength of the fundamental feature) occur in the near-infrared 0.7 to 1.0 μm and shortwave 1.0 to 2.5 μm regions.[74]

Spectral reflectance signature libraries of numerous material samples and composites have been cataloged.[74–76] From these libraries, unknown samples can be interpreted for soil properties. First, the spectral signatures of soil samples are scanned with a spectroradiometer in the field or laboratory. Soil properties are then measured, designated to sample the variation in the spectral library, and calibrated to soil reflectance. Chemometric models to predict soil properties from soil spectra can be built using classification and regression trees (CARTs), multivariate adaptive regression splines (MARSs), partial least square regression (PLSR), and other statistical methods. The resultant functions are then employed to predict the soil properties for new samples that belong to the same population as the library soils.[74] The models are evaluated using statistical tools (e.g., crossvalidation, validation, coefficient of determination). Therefore, the success of using spectral libraries to characterize soil properties depends primarily on the ability to build robust models between measured soil properties and soil reflectance spectra.

Research has demonstrated the ability of reflectance spectroscopy to provide nondestructive, rapid prediction of soil physical, chemical, and biological properties (e.g., calcium, magnesium, iron, manganese, and potassium),[77] soil texture,[78] total carbon, total nitrogen, and pH.[72] Soil structure has influence on the reflectance behavior of soil, which is probably why Daniel et al.,[70] Udelhoven et al.,[77] Couillard et al.,[78] and Sudduth and Hummel[81] found laboratory spectrometry performed better than field spectrometry.

Despite the tremendous scope of reflectance spectroscopy to characterize soils, there is need for research in the use of spectroscopy for soil characterization and mapping. Considering the problems of atmospheric interferences, shade and shadow, etc., associated with remote sensing from space-based platforms,[76] soil spectroscopy offers a reliable alternative for accurate on-the-go mapping of soil properties. Since most satellite and airborne sensors are limited to the topsoil, spectroscopy offers rapid analysis of multiple soil properties from one soil sample. Rapid assessment of soils using spectral models will dramatically cut sample processing time and cost. Reduced sample processing costs may facilitate sampling soils with much higher density and frequency. Research in data acquisition (e.g., instrument sensitivity) and data analysis (statistical chemometric modeling) remains an area of continuous research.

### 5.2.3.3 Remote Sensors

Remote sensing is a relatively cheap and rapid method of acquiring up-to-date information over large geographical areas. Although satellite and airborne images contain tremendous information in various spectral bands, data transformation techniques such as tasseled cap[80] and vegetation indices[76] (e.g., normalized difference vegetation index (NDVI)) reduce the number of bands and provide a more direct association between signal response and physical processes on the ground, highlighting users' interest. Passive remote sensing employs sensors that measure radiation naturally reflected or emitted from the ground, atmosphere, and clouds in the visible, near-infrared, and short-wave infrared range. In contrast, active remote sensing techniques employ an artificial source of radiation as a probe. The resulting signal that scatters back to the sensor characterizes the atmosphere or Earth.

Various satellite systems operating within the optical range generate data on Earth resources at different resolutions.[76] Landsat Enhanced Thematic Mapper (ETM 7+) scenes have a grid resolution of 30 m. Hyperspectral sensors have multiple bands (e.g., hundreds of bands) with spectral resolutions less than 20 nm. Hyperspectral images, such as NASA's Airborne Visible/Infrared Imaging Spectrometer (AVIRIS), with 224 contiguous spectral channels and approximately 20-m resolution, and IKONOS multispectral images, with 1-m panchromatic and 4-m multispectral resolution, provide a spatial resolution we have not seen before.

These spatial resolutions contrast readily available crisp soil survey maps derived from few auger borings per hundreds of hectares. For example, currently SSURGO soil maps derived at a map scale of 1:24,000 provide the most detailed soil data in the U.S. In Florida, the average soil map unit size in SSURGO is 605,176 $m^2$, which contrasts the resolution of remote sensing imagery.

Exhaustive pixel-based thematic maps can be derived from satellite imagery that are valuable to support soil mapping efforts (e.g., the selection of representative sites for field investigations), to provide auxiliary data to predict soil properties, assess environmental quality, and develop recommendations for land resource management. Georeferenced soil properties can be integrated with remotely sensed images and upscaled to regional scale. Remote sensing combined with GIS offers a powerful toolset to support soil mapping. Current limitations of remote sensors for mapping of soil properties have been (1) the lack of penetration depth, which is often limited to the top centimeters of the soil, and (2) vegetation cover, which obscures the mapping of soil properties. Radar and gamma radiometry have overcome these limitations. Radar sensors are noted for their ability to penetrate clouds, fog, and rain, as well as an ability to provide nighttime reflected imaging by virtue of their own active illumination. The synthetic aperture radar (SAR) aboard the European remote sensing satellites ERS-1 and ERS-2 is an imaging technology in which radiation is emitted in a beam from a moving sensor, and the backscattered component returned to the sensor from the ground is measured. These images have been used to map soil moisture and climate characteristics at landscape scale.

Remote sensing applications are manifold and include soil organic matter mapping,[80] land cover mapping,[82,83] land classification,[84] delineation of salt-affected areas,[85] change detection of land use,[86] and many more. Kasischke et al.[87] used ERS SAR imagery for monitoring surface hydrologic conditions in wetlands of southern Florida. The results showed wide variation in ERS backscatter in individual sites when they were flooded and nonflooded. Surface soil moisture was retrieved using microwave radiometry by Pardé et al.[88] using the L-band. To date, there is no space-borne sensor measuring the microwave emission of the soil surface at this frequency, although several new programs are scheduled. Hyperspectral images of AVIRIS and Hyperspectral Mapper (HyMap) were used to map expansive clay soils in Colorado, focusing on smectites, smectites/illites, and kaolinites.[89] Mapping of vegetation, geology, and soils using AVIRIS imagery was conducted by Drake et al.[90] in a semiarid shrubland/rangeland soil-landscape using short-wavelength infrared (2 to 2.5 μm).

## 5.3 GEOGRAPHIC AND SOIL INFORMATION SYSTEMS

### 5.3.1 Geographic Information Systems

Geographic information systems, which help to manipulate, analyze, and present information that is tied to a spatial location, have revolutionized the way we manage soil and other environmental datasets. Modern GIS emerged in the 1960s. The history of GIS is unique in that it was developed nearly concurrently by separate research teams at different locations with different backgrounds. One of the earliest accounts of a computerized GIS is the Canada Geographic Information System (CGIS) developed in the early 1960s. Meanwhile, the Harvard Laboratory for Computer Graphics and Spatial Analysis (HLCGSA) created an automated mapping application, SYMAP, which served as the training ground for many of the scientists that developed and created the precursors to the popular GIS packages used today. For the U.S. Census study in 1966, new methods were developed incorporating topology, i.e., spatial relationships between connecting or adjacent vector features. While the 1960s served as the decade of GIS development, the 1970s were years of lateral diffusion.[91] More universities and government agencies became interested in the technology, expanding the user base of GIS. Since the early 1970s, the Environmental Systems Research Institute, Inc. (ESRI) became one of the dominating players providing GIS software, GIS datasets, and GIS services to a worldwide audience. While hardware became cheaper, faster, and more powerful, software evolved, providing sophisticated spatial operations to users. For example, GIS enabled users to integrate soil-forming factor layers and relate them to soil data within a spatially explicit framework. Geographic information systems are versatile to provide representations in the form of crisp and raster-based soil maps. They are scalable, expandable, and provide ease to update soil and other datasets. Soil scientists were able to implement the conceptual soil-landscape models developed several decades earlier within a GIS environment. Spatial operations include overlying, extracting, and generalizing spatial data to name only a few. Complex statistical and geostatistical methods were embedded within the GIS environment providing ease of use.[92] For example, advanced geostatistical techniques within a GIS environment were used by Grunwald et al.[93] to create soil quality maps that characterize the spatial distribution of soil phosphorus. Environmental variables derived from auxiliary sources (e.g., remote sensing, GPR, EM, etc.) can be combined with primary soil data (e.g., soil texture) in a GIS to derive secondary/functional soil data (e.g., soil quality index). Spatially explicit relationships between topographic, geologic, vegetation, and soil properties can be quantified using GIS. Soil GIS scientists have been creative in developing predictive soil-landscape models with the support of GIS. Most important, GIS forced soil scientists to quantify previously descriptive soil datasets. To summarize, GIS has revolutionized how we manage, analyze, and present spatial data, including soil-landscape data. It has served as an integrator of soil and other environmental datasets, providing the platform for quantitative soil-landscape modeling. Geographic information systems are used by state and federal agencies, universities, consulting companies, and others, becoming as commonplace as a pencil to a traditional soil surveyor.

To ensure the sharing of spatial data between different user groups, agencies, applications, and platforms, a variety of spatial data standards were developed. The Spatial Data Transfer Standard (SDTS) was developed by the Federal Geographic Data Committee (FGDC). In the Open GIS Consortium (OCG), numerous private companies, government agencies, and academic institutions work side by side to develop publicly available geoprocessing specifications. For example, the Open GIS Consortium developed the Geographic Markup Language (GML), which is an open standard to enable transfer of spatial data between different vendors. The Geographic Markup Language is the geographic counterpart of the eXtensible Markup Language (XML) used for metadata documentation. GML encodes geographic information, including both the geometry and properties of geographic features. The FGDC of the U.S. has defined a Content Standard for Digital Geospatial Metadata (CSDGM) providing standardized guidelines for the documentation of spatial datasets. The CSDGM was adopted by the USDA NRCS to disseminate soil data via SIS. Besides these formalized spatial standards, a double standard based on ESRI's vector and raster data formats exists (e.g., ESRI's shapefile data format).

In recent years, the adoption of GIS technology by soil scientists resulted in dramatic changes. Geographic information systems developed from mainframe GIS to desktop GIS and WebGIS. WebGIS refers to the use of the World Wide Web (WWW, in short Web) as a primary means to integrate, disseminate, and communicate geographic information.[94,95] Spatial applications provided on the Web include (1) data services that enable users to retrieve data from Web-based geodatabases and (2) map services that provide users with online display capabilities of thematic maps. Distributed geographic information (DGI) refers to the use of Internet technologies to distribute geographic information in a variety of forms, including maps, images, datasets, spatial analysis operations, and reports.[96] DGI is the most encompassing framework, including both WebGIS and mobile GIS (e.g., pocket PCs with wireless connections). Peng and Tsou[97] suggest expanding GIS data services by including the dissemination of spatial science knowledge and GIS output, which is commonly called GIScience. Examples of state-of-the-art WebGIS applications are given by Mathiyalagan et al.,[98] who developed a WebGIS and geodatabase for Florida's wetlands, providing data and map services related to soil and vegetation data (Figure 5.6). The Florida Geographic Data Library (FGDL) (http://www.fgdl.org/) provides a repository of spatial data for Florida using the data service concept.

Only a few GIS-based representations of soil-landscapes are three-dimensional, and even less are four-dimensional, considering changes of soil-landscape properties through time. Roshannejad and Kainz[99] developed a logical data model for a space–time information system. The model considers $x$ (easting), $y$ (northing), $z$ (depth), $t$ (time), and $a$ (attributes). Time is considered the fourth dimension, relegating the attribute values to the fifth dimension (Figure 5.7). Data evolution can be 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 representing behavior (e.g., illuviation, mineralization, nitrate leaching). To maintain data consistency, spatiotemporal indexing can be used. Few prototypes of space–time information systems have been presented. Abraham and Roddick[100] presented a detailed review of spatiotemporal database concepts. Koeppel and Ahlmer[101] distinguished between attribute-oriented spatiotemporal systems that track

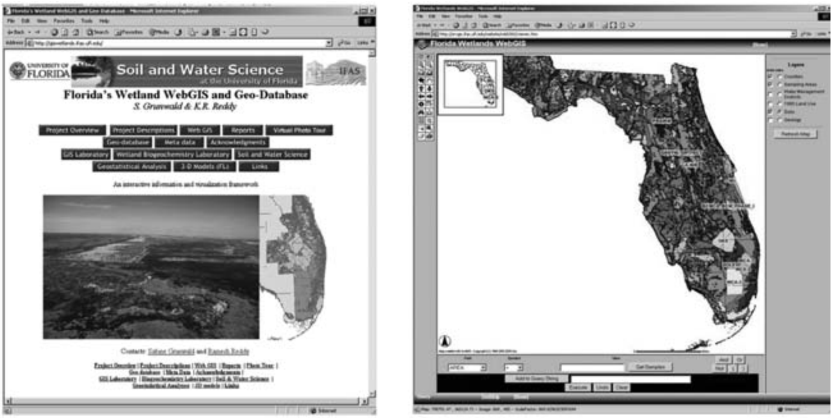


**FIGURE 5.6** WebGIS and geodatabase for Florida's wetlands, including map and data services (http://GISWetlands.ifas.ufl.edu). (See color version on the accompanying CD.)

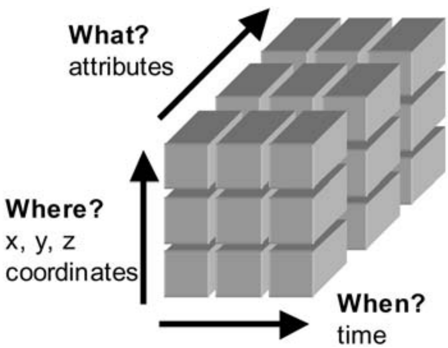


**FIGURE 5.7** Logical data model. (After Roshannejad, A.A. and Kainz, W., *ACSM/ASPRS Annu. Convention Exposition Tech. Pap.*, 4, 119–126, 1995.)

changes in spatial entities and topology-oriented spatiotemporal systems that track changes in positional information about features and their spatial relationships. Peuquet and Duan[102] suggested an Event-Based Spatio-Temporal Data Model (ESTDM) focusing on events that are represented along a temporal vector in chain-like fashion. Yuan[103] suggested a three-domain model representing semantics, space, and time separately and providing links between them to describe geographic processes and phenomena. Ramasundaram et al.[104] extended two-dimensional GIS operations to the third (space) and fourth (time) dimensions. They developed three-dimensional soil-landscape models and interactive space–time hydrologic simulations for a flatwood site in Florida that are disseminated via the WWW. Results from a space–time GIS application using nitrate–nitrogen data for a site in northern Florida are shown in Figure 5.8. The model was created using multidimensional ordinary kriging of nitrate–nitrogen

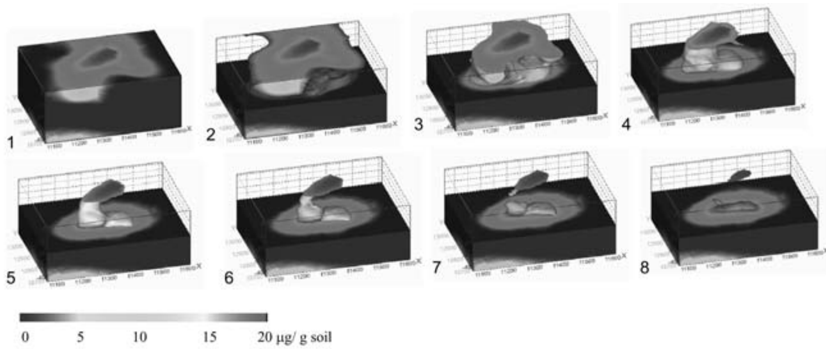


**FIGURE 5.8** Nitrate–nitrogen plume at different periods ($n = 1$ to 8) implemented within a GIS (EVS-PRO). The space–time model shows change in attribute values and geometry of the plume. (See color version on the accompanying CD.)

at eight different time periods using EVS-PRO (CTech Development Corp., Huntington Beach, CA). The Spatio-Temporal Environment Mapper (STEM), a GIS system that handles time and depth of an entity in addition to mapping the entity horizontally, was presented by Morris et al.[105] They argued to treat time and depth ($z$) as a dimension rather than an attribute, which is a prerequisite to effective multidimensional visualization and analysis. This opposes the common view of modeling three-dimensional solid objects (e.g., representation of soils as three-dimensional objects). Rather, the $x$ (easting) and $y$ (northing) coordinates are extended by time and a depth dimension. Though concepts and prototype space–time information systems exist, more research is necessary to develop a universal tool that can manage, analyze, and visualize soil-landscape data in space and through time.

### 5.3.2 Soil Information Systems

To disseminate soil data flat files, hard-copy and digital maps, geodatabases, GIS, or the WWW are used in numerous variations. Specialized geodatabases for soil data have been developed at different spatial scales, for different geographic regions and data formats. Commonly, they are referred to as soil information systems.

At the global scale the Food and Agriculture Organization of the United Nations (FAO)–United Nations Educational, Scientific and Cultural Organization (UNESCO) *Soil Map of the World* was the first attempt to cooperatively develop a standardized soil map covering all continents. A uniform legend was developed, with the main objective to obtain an inventory of the world soil resources based on integration of existing soil classification systems. The first world soil map at a scale of 1:5 million was published in 1974. Based on soil development status, material, and major geographical zones, 24 major soil groups (MSGs) and 106 soil units were distinguished. The definitions and nomenclature of the diagnostic horizons and properties were adopted from *U.S. Soil Taxonomy*,[106] but the definitions have been summarized and sometimes simplified to serve the purpose of the legend.[107] Revised versions of the FAO-UNESCO legend of the *Soil Map of the World* were issued in 1988 that distinguished 28 MSGs and 153 soil units.[108] At the global level the FAO-UNESCO *Soil Map of the World* is still the only worldwide, consistent, harmonized soil inventory that is readily available in digital format and provides a set of estimated soil properties for each mapping unit.[109] The development of the Soil Terrain (SOTER) program started in 1986 and focused on standardized mapping of areas with distinctive, often repetitive patterns of landform, morphology, slope, parent material, and soils at a 1:1 million scale. Each SOTER unit is linked through a GIS with a database containing attributes of landform, terrain, soils, climate, vegetation, and land use.[109] The World Reference Base for Soil Resources (WRB) project was initiated by the International Soil Science Society (ISSS), FAO, and the International Soil and Reference Information Center (ISRIC) to provide scientific depth and background to the 1988 *Soil Map of the World, Revised Legend*.[110] The WRB is a first step toward standardization of our global soil resources.[111] All global soil maps are based on the double-crisp paradigm lumping over geographic and taxonomic space, which is due to the lack of high-resolution soil data in many nations, the density of soil observations, and the predominance of soil classification systems around the globe.

In the U.S., three complementing soil information systems (SISs) were developed and are maintained by USDA NRCS: (1) Soil Survey Geographic Database (SSURGO, 1:15,840 to 1:31,680; typical map scale of 1:24,000; the conversion of SSURGO into a new database format called Soil Data Mart is in progress), (2) State Soil Geographic Database (STATSGO, 1:250,000), and (3) National Soil Geographic Database (NATSGO, 1:7,500,000). The SSURGO provides the most detailed digital soil data using a relational database management system (RDBMS). Data mining of hard-copy soil survey maps to produce vector GIS soil data is still ongoing across the U.S. Each map unit is assigned a unique identifier, known as the map unit identification number (MUID), which links to soil attributes stored in separate data tables. The SSURGO was intended for use by landowners, farmers, and planners at the county level. However, it lacks the capabilities for site-specific application (e.g., septic tank installation, site-specific management). The STATSGO was developed generalizing SSURGO data and is useful at the regional scale. The NATSGO was designed for national and multistate resource appraisal, planning, and monitoring. All U.S. SIS are based on the double-crisp paradigm. Many more double-crisp SIS were adopted in different nations.[112]

Soil information systems that store georeferenced soil property data are invaluable for future soil-landscape modeling projects. These data can be readily integrated with other spatial environmental layers, providing a valuable resource for various land resource applications. The U.S. National Soil Characterization Database provides morphological, chemical, physical, and biological soil properties for thousands of pedons. The Hydraulic Properties of European Soils (HYPRES) is a central database having a flexible relational structure consisting of soil pedological and hydraulic properties from different institutions in

Europe.[113] The Australian Soil Resources Information System contains over 160,000 soil profile descriptions complemented by laboratory data. The International Soil and Reference Information Center has been instrumental in developing numerous SIS, including the world inventory of soil emission potentials (WISE) international and global soil profile dataset, the International Geosphere Biosphere Programme–Data and Information System (IGBP-DIS) soil dataset for pedotransfer function development, and the ISRIC SIS, which assembles monoliths accompanied by soil profile descriptions, environmental data, soil reports, and a slide collection. These and other SIS provide a valuable resource to build soil-landscape models.

## 5.4 SIGNIFICANCE FOR FUTURE SOIL-LANDSCAPE MODELING

Previous shortcomings in soil-landscape modeling have been related to soil mapping paradigms, the labor-intensive collection of soil data, and database management. Soil survey maps have been produced extensively using the double-crisp soil mapping paradigm. Such soil polygon maps and associated datasets provide representative soil property values for map units without providing statistics about the within-unit variability and statistics such as the variance, coefficient of variation, range, and minimum and maximum values. Deficiencies of map unit boundary placement and location-specific mapping of map components have been acknowledged by soil surveyors.[114] In contrast, pixel-based soil mapping is much more data intensive and requires knowledge about quantitative spatial modeling techniques to produce accurate soil-landscape models. Our technical progress is impressive, encompassing how we collect, manage, and analyze soil and environmental datasets to characterize soil-landscapes. Yet there is still an urgent need to improve the training of the next generation of scientists and soil mappers. As pointed out by the current chair of commission of 1.5 Pedometrics of the International Union of Soil Science, Gerard Heuvelink, we must introduce pedometrics in the soil science curricula of higher education. Much more emphasis has to be placed on holistic soil-landscape modeling, integrating soil with other environmental datasets. This requires an education that is not limited to soil taxonomy and soil genesis, but includes GIS, remote sensing, quantitative methods, and more. We have to learn to grasp beyond tacit knowledge of soil surveyors to produce state-of-the-art soil-landscape models. Available geographic information technology combined with mathematical and (geo)statistical methods will produce the next generation of quantitative soil-landscape models.

Numerous studies have shown that it is possible to reconcile both soil mapping paradigms using a hybrid approach. Since the demand for pixel-based soil property maps is evident, there is no doubt that shifts from the double crisp to georeferenced soil property mapping will naturally occur. Geographic information systems have no limitation in handling hundreds of thousands of soil property data, which can be retrieved and combined with other environmental datasets on demand. Rapid soil mapping devices and techniques are finding more widespread use to generate denser soil datasets. Such dense datasets provide the input for advanced geostatistical methods to create quantitative soil-landscape models. Combinations of dense and sparse soil and environmental datasets, collected with different sensors and techniques, and model- and design-based mapping strategies are pivotal to create accurate, high-resolution soil-landscape models. Such models can be readily shared using state-of-the-art Web-based geographic information technology. We are optimistic that eventually we can satisfy the demand for quantitative georeferenced soil-landscape property data using emerging geographic information technologies.

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