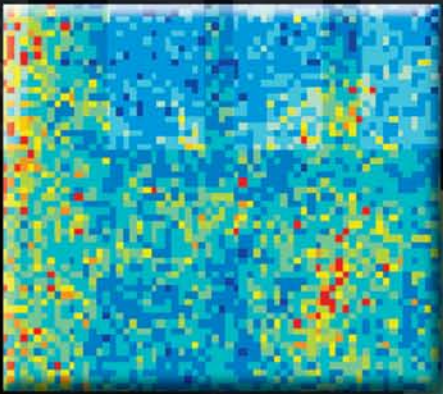
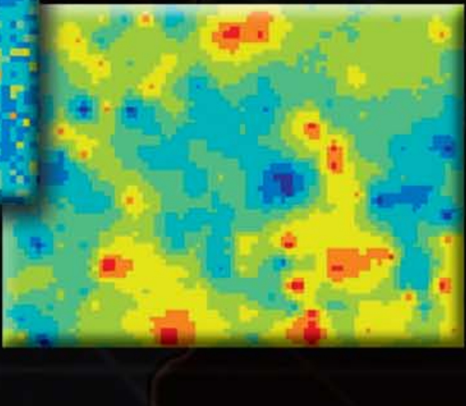
Environmental Soil-Landscape Modeling

Geographic Information Technologies and Pedometrics





edited by

Sabine Grunwald

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1 What Do We Really Know about the Space–Time Continuum of Soil-Landscapes?

Sabine Grunwald

CONTENTS

ABSTRACT

Growing concerns about environmental quality, degradation of ecosystems, aforestation, and human-induced erosion and pollution lead to the necessity of a holistic perception of soil-landscapes. From this viewpoint, soils are viewed as part of an ecosystem, stressing their important functions as buffers interfacing land use activities and water resources. Numerous qualitative and quantitative methods have been proposed to study the distribution, behavior, and genesis of soils. Environmental soil-landscape modeling is a science devoted to understanding the spatial distribution of soils and coevolving landscapes as part of ecosystems that change dynamically through time. There are slow but persistent shifts from qualitative to quantitative soil-landscape modeling providing digital, accurate, precise, and nonbiased information about soils. The philosophical soil-landscape paradigms rooted in empiricism, which emerged in the early 20th century, are still valid, and in fact, they form the cornerstone to reconstructing soil-landscapes with pedometrics. In this chapter an overview of holistic soil-landscape modeling techniques is given that integrates numerous environmental factors.

1.1 INTRODUCTION

Soils vary in geographic space and through time. They are complex and difficult to observe. Yaloon[1] asked a provoking question: "Is soil just dirt, too commonplace to study?" This textbook proves the opposite is true. There has been a multitude of research resulting in a variety of conceptual, qualitative, and quantitative soil-landscape models. This textbook covers the history and concepts of soil-landscape modeling. Emerging geographic information technologies and their impact on soil-landscape modeling are given special attention. We introduce numerous pedometrical techniques to study the distribution, behavior, and genesis of soils. In this chapter relevant terminology is introduced and an overview of soil-landscape methodology provided.

Soils are interrelated with surface attributes (e.g., topographic attributes) and aboveground attributes (e.g., land cover and land use), and they interact dynamically with the lithosphere, atmosphere, hydrosphere, and biosphere, collectively forming the pedosphere. The functions and relevance of soils include (1) production of food and fiber, (2) absorbance, storage, and release of water, (3) geomembrance filtering and buffering solutes, (4) habitat for biota, (5) foundations for housing, transportation, and engineering structures, and (6) cultural and aesthetic pleasure. Soils can be viewed as functional units that are used for multiple purposes (e.g., precision agriculture, urban development, recreation, etc.) by multiple users. Understanding the spatial and temporal distribution of soils and soil characteristics is a prerequisite for optimizing economic profits while minimizing adverse impacts on soil and water quality. Environmental soil-landscape modeling is a science devoted to understanding the spatial distribution of soils and coevolving landscapes as part of ecosystems that change dynamically through time.

1.2 PHILOSOPHICAL PERSPECTIVES OF SOIL-LANDSCAPES

Perspectives of soil-landscapes are diverse and change over time. Passmore[2] discussed the contrasting attitudes of man toward nature and soils. Early Stoic (Greek)-Christian doctrine assumed that "everything is made for man's sake." Aristotle argues that "plants are created for the sake of animals and the animals for the sake of men" and that "nature is at its best when it fulfills men's needs. So to perfect nature is to humanize it — to make it more useful for men's purposes."[3] Kant points out that "man's relationship with nature is not subject to moral census."[4] Descartes' radical philosophy suggests that "men should render themselves the masters and possessors of nature."[2] There is a strong Judeo-Christian Western tradition that man is free to deal with nature as he pleases, since it exists only for his sake. Soils are viewed as substrate to produce food and are perceived as an object for mankind, purely a matter of utility. This metaphysical belief has lead to widespread degradation of soil-landscapes, some of which have subsequently been deemed inhabitable for many generations.

Philosophies contrasting such self-centered views of soil-landscapes emphasize stewardship and cooperation with nature and perceive humans as managers or stewards of soil-landscapes. Socrates and Plato pointed out that it is humanity's responsibility to care for the welfare of resources.[5] There are different traditions of stewardship. One perceives humans as part of soil-landscapes seeking harmonized coexistence, whereas the other tradition perceives man as steward "to develop land and to perfect it."[2] Eastern philosophies emphasize stewardship in which men should take all responsible steps not to destroy any living beings or nonliving objects. Here the interdependence between everything that exists is stressed. While some deemphasize the responsibility of humans by putting the future of nature and soils in God's hands, others emphasize a deep spiritual concern for wildlife, soils, and water resources.

Growing concerns about environmental quality, degradation of ecosystems, aforestation, and human-induced erosion and pollution lead to the necessity of a holistic perception of soil-landscapes. From this viewpoint, soils are viewed as part of an ecosystem, stressing their important functions as buffers interfacing land use activities and water resources. More radical conservationists emphasize the protection of natural ecosystems, excluding any kind of human interference. Others seek a balanced ecosystem where humans are an integral part of the system willing to make genuine sacrifices to protect natural soil-landscapes. The ability to preserve the diversity of vegetation, habitats, and wildlife species is dependent on the preservation of pedodiversity. Shifting human-centered to enviro-centered perspectives is vital for conservation management.

Soil scientists have focused on two contrasting concepts to study soil-landscapes, both of which are equally important.[6] The reductionist approach promotes ever more detailed studies of soil characteristics and pedological processes derived from field investigations in pedons, along transects and laboratory studies. The other approach develops and enunciates an integrative, unifying point of view encompassing and integrating previous observations and results. With the advent of geographic information systems (GIS), the latter approach has focused on integrating a variety of environmental factors that correlate with soil attributes. McKenzie and Austin[7] outlined this concept of environmental correlation predicting soil characteristics (e.g., clay content) with more readily observed environmental variables (e.g., terrain attributes) as predictors.

1.3 WHAT ARE SOILS, LANDSCAPES, AND SOIL-LANDSCAPES?

Soil is the material that forms at the interface of the atmosphere and the lithosphere that is capable of supporting plants. It is the unconsolidated mineral or organic material on the surface of the Earth that has been subjected to and shows effects of genetic and environmental factors of climate (including water and temperature effects), macro- and microorganisms, conditioned by relief, acting on parent material over a period of time.[8,9] A *landscape* is the fundamental trait of a specific geographic area, including its biological composition, physical environment, and anthropogenic or social patterns.[10] Ruhe[11] defines landscape from a geomorphologic perspective as "a collection of spatially related, natural landforms, usually the collective land surface that the eye can comprehend in a single view." *Land* is the entire complex of surface and near-surface attributes of the solid portion of the surface of the Earth, which are significant to human activities.[8] All land and water resource data have a spatial and temporal dimension with variable scale, extent, and resolution. Commonly, soil-landscape datasets are managed in soil information systems (SISs) and analyzed using GISs.

The pedon serves as the mapping unit for soil taxonomic classifications and site-specific pedological studies focusing on profile dynamics. In contrast, sustainable land resource management is focused on the landscape-scale balancing economic profitability, stewardship of natural resources, and social equity concerned with the quality of life.[10] Sustainable management is important to maintain the functions of a soil-landscape for economic, recreational, biological, cultural, aesthetic, and social values. An integrative, synergistic ecosystem approach is rooted in understanding system components and behavior, including soils. Deductive science generated extensive knowledge of how individual parts function (e.g., pedological processes). Yet understanding how the parts interact as a whole requires a holistic perspective. Soil-landscape modeling attempts to integrate soils, parent material, topography, land use and land cover, and human activities. The goal of soil-landscape modeling is to gain an understanding of the spatial distribution of soil attributes, characteristics of soils, and their behavior through time. Soil-landscapes can be defined in terms of (1) geomorphology and topography, the form and shape of a landscape; (2) land cover, the aboveground characteristics; (3) land use, the functions that a landscape performs; (4) soil attributes, the belowground characteristics; and (5) genesis, the formation of soil attributes due to pedological processes. According to Dijkerman,[12] there are various, sometimes overlapping purposes of soil maps and soil-landscape models, including:

- Observational — used to sample subsets of a population of soil bodies or to study their behavior
- Experimental — used to study the effect of controlled situations
- Descriptive — used to characterize the system under study
- Explanatory — used to understand relationships and behavior of the soil system
- Predictive — used to forecast relationships, attributes, and behavior of the soil system
- Scale — used to represent the system
- Idealized — used to simplify the system
- Analog — used to extrapolate and transfer knowledge

1.4 GEOGRAPHIC SPACE

Soils are natural bodies with attributes varying continuously in the space–time continuum across landscapes.[13] Soil attributes are variable in the horizontal and vertical dimension, forming three-dimensional soil bodies that change over time due to pedological processes.[14] Commonly, soil attributes are anisotropic vertically and laterally. Soils coevolve through the interaction of physical and chemical weathering, erosion and deposition, lateral and vertical transport processes, and biological processes. To capture changes of soil attributes, models have been developed that segregate the soil continuum.[15] Such models are formal abstractions of soil-landscape reality that formalize how geographic space is discretized into smaller spatial units for analysis and communication. Generally, it is necessary to divide geographic space into discrete spatial units, and the resulting tessellation is taken as a reasonable approximation of reality at the level of resolution under consideration. There are two types of spatial discretization methods used for soil-landscape modeling: (1) the crisp soil map unit model and (2) the continuous-field or pixel (square grid cell, raster) model.

1.4.1 Crisp Soil Map Unit Model

This model has its roots in empiric observations combined with 19th-century biological taxonomy and practice in geological survey. Traditional soil-landscape models use crisp map units, which are defined by abrupt changes from one map unit to the other.[16,17] Each soil map unit is associated with a representative soil attribute set.[18] Horizons of these soil map units differ from adjacent and genetically related layers in physical, chemical, and biological attributes such as texture, structure, color, soil organic matter, or degree of acidity. As such, soil horizons and profiles of these attributes correspond to discrete, sharply delineated (crisp) units, which are assumed to be internally uniform. A soil surveyor uses his tacit knowledge, intuition, and understanding of soils to delineate these crisp map units. Factors such as topography, geology, geomorphology, vegetation, and historic information guide the identification of these so-called natural breaks, which become map unit boundaries. Variation within the classes is acknowledged, but is described qualitatively and usually in vague terms. The rationale for employing a crisp model is that if the variation within the classes is less than that in a soil region at large, then using the class mean of the soil attributes of interest as a predictor should be more precise than the regional mean. The model only has merit if the variance within the classes is less than the total variance.

Peuquet,[19] Goodchild et al.,[20] and Burrough and McDonnell[21] define crisp mapping units as *entities* or *objects* (Figure 1.1). These objects represent soil-landscape phenomena that are defined by the geographic location (where things are) and its attributes (what is present). On choropleth soil maps, the geographic locations of soils are defined in reference to other geographic features (e.g., other soils or landmarks) within geographic space. Crisp sets allow only binary membership functions (i.e., true or false); an individual is a member or is not a member of any given set as defined by exact limits. McBratney and de Gruijter[22] and Heuvelink and Webster[23] pointed out that crisp sets do not allow ambiguities, and they are too inflexible to take into account genuine uncertainty. Though the crisp data model is practical, it ignores spatial variation in both soil-forming processes and in the resulting soils.[24] The validity of the crisp soil model has been questioned and critically discussed repeatedly.[25–28] Butler[29] emphasized that successful classification of soils at the local level must represent what can be mapped at the chosen scale and is determined by the local landscape. Major drawbacks of the crisp soil model are that it ignores spatial autocorrelation within and across map units and assumes the same variation of attributes across space. Commonly, SIS such as the State Soil Geographic (STATSGO) Database, Soil Survey Geographic (SSURGO) Database, and Soil Data Mart (SDM) adopt the crisp soil map unit concept.[30] Thousands of soil maps exist that are based on this model.

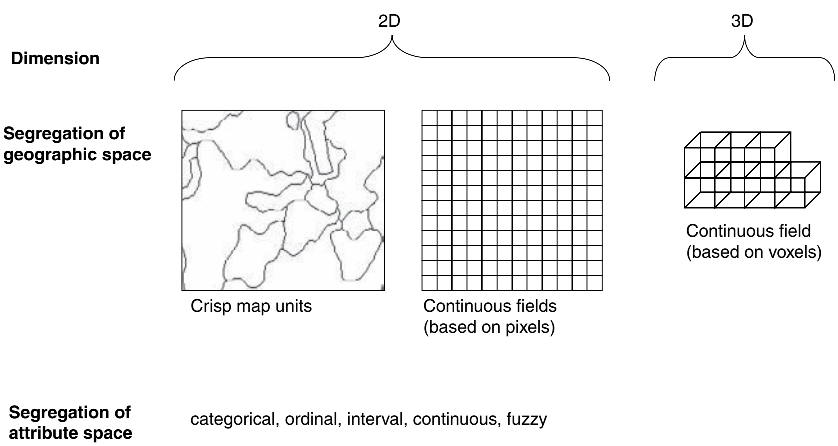

FIGURE 1.1 Models to segregate geographic and attribute space.

1.4.2 Continuous Field (Pixel Model)

The continuous-field model displays the real world as a set of pixels or voxels (volume cells) (Figure 1.1). Burrough and McDonnell[21] argue that the continuous-field model is adequate for modeling natural phenomena that do not show obvious boundaries (e.g., soils). This spatial model has the potential to describe the gradual change of soil attributes formed by a variety of pedological processes within a domain. The spatial resolution or pixel size depends on the spatial variability of soil attributes. Geostatistical techniques have been applied in numerous studies to interpolate point observations and construct soil attribute pixel maps.[17,31,32] It is challenging to optimize the density and spatial distribution of observations across a domain to characterize soil-landscape reality without knowing the underlying spatial variability of soil attributes and operating pedological processes. If the spatial resolution of the continuous-field model is finer than the crisp soil map units, the former provides more detailed site-specific information. Comparisons between crisp and continuous pixel-based soil models have been presented by Heuvelink and Huisman[33] and Hengl.[34] In order to bridge the gap between the conventional crisp and the continuous-field model, several models have been proposed to deal with the situation in which there are discrete (abrupt) and continuous (gradual) spatial variations in the same area.[16,33,35–39]

1.4.3 Two-Dimensional vs. Three-Dimensional Geographic Space

Brady and Weil[40] point out that soils are three-dimensional bodies. However, soils are commonly represented in the form of two-dimensional maps.[41,42] In crisp soil maps, each map unit is associated with attribute tables that store the soil attribute datasets and metadata (reports) that describe the soil attributes. In pixel-based soil maps, each grid cell carries the code of a specific soil attribute value. Commonly, different grid themes are used to represent different soil attributes. Other soil-landscape representations use a 2 1/2-D design superimposing land use, soil maps, or other thematic maps over a digital elevation model (DEM) to produce a three-dimensional view.[43,44] Since this technique describes patterns on two-dimensional landscape surfaces rather than the spatial distribution of subsurface attributes (e.g., soil texture, soil horizons), it fails to address three-dimensional soil-landscape reality. McSweeney et al.[45] pointed out that two-dimensional soil models are lacking the ability to address three-dimensional soil-landscape reality. Only recently have three-dimensional reconstruction and scientific visualization techniques emerged to produce three-dimensional soil-landscape models. For example, the Cooperative Research Center for Landscape Evolution and Mineral Exploration (CRCLEME) constructed a three-dimensional regolith model of the Temora study area in Central New South Wales, Australia.[46] A three-dimensional soil horizon model in a Swiss floodplain was created by Mendonça Santos et al.[47] using a quadratic finite-element method. Sirakov and Muge[48] developed a prototype three-dimensional Subsurface Objects Reconstruction and

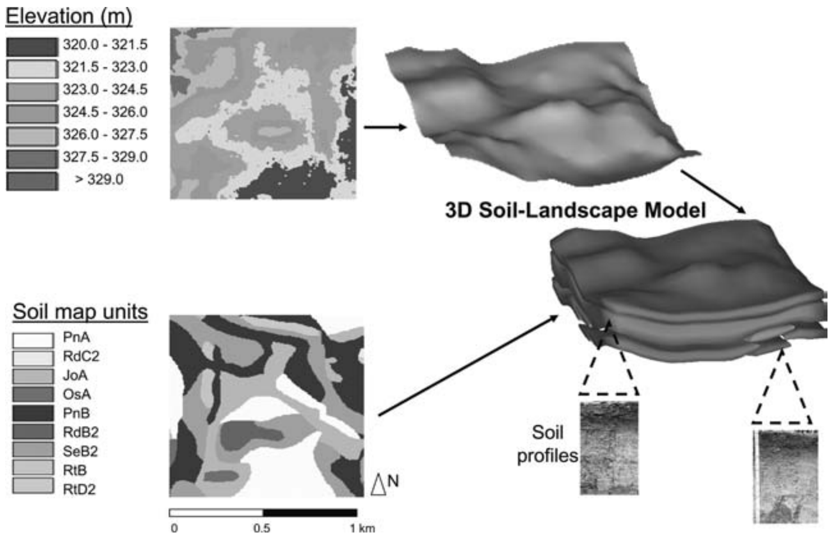

FIGURE 1.2 Elevation and soil data were used to create a three-dimensional soil-landscape model for a site in southern Wisconsin. (Reprinted from S. Grunwald and P. Barak, *Syst. Analy. Modeling Sim.,* 41, 755–776, 2001.) (See color version on the accompanying CD.)

Visualization System (3D SORS) in which two-dimensional planes are used to assemble three-dimensional subsurface objects. Grunwald et al.[14] presented three-dimensional soil-landscape models at different scales for sites in southern Wisconsin (Figure 1.2). Geographic reconstruction and scientific visualization techniques suitable for soil-landscape modeling were presented by Grunwald and Barak.[49] While complex, domain-specific prototype three-dimensional soil-landscape models have been developed, they have not been widely adopted yet for the following reasons: (1) input data requirements, (2) models are labor intensive to produce, requiring specialized software and programming skills, (3) lack of training and education, (4) preference of users for traditional crisp soil maps, and (5) lack of realistic abstraction of soil-landscapes.

1.5 ATTRIBUTE SPACE

Soil-landscape models employ different concepts to segregate attribute space. Some models focus on soil attributes while others aggregate soil attributes to form soil classes or taxa. The latter ones have been adopted to develop soil taxonomies in many different countries.[50] The rationale for adopting soil classes is that the soil cover can hardly be apprehended in its entirety. Hence, a subdivision is required in order to understand the different components of this continuum and to understand the relationships with the factors of their formation. There are problems with this approach, such as the establishment and ordering of classes and the ranking according to the importance of soil characteristics from high to low hierarchical levels, which vary widely among different soil taxonomies. The

U.S. Soil Taxonomy is a system developed using morphogenetic indicators (diagnostic horizons and attributes) as class criteria.[18] It is one of the most detailed soil taxonomies, which currently consists of 12 orders, 63 suborders, 319 great groups, 2484 subgroups, about 8000 families, and about 19,000 soil series in the U.S.[40,51]

Dudal[52] pointed out that existing soil classification systems enabled us to explain and characterize soil diversity in function of different sets of soil-forming factors. However, with the increasing demand for targeted soil information related to specific sites or specific purposes (e.g., assessment of phosphorus loads, forest management), technical soil surveys focusing on mapping of soil attributes rather than aggregated soil taxa are better suited. Dudal[52] stressed that due to the availability of GIS, there is no need to provide end users with aggregated soil taxa datasets. Burrough[53] points out that users can extract and aggregate soil attributes from GIS and soil datasets on demand targeting a specific application. In short, preference is given to raw field observations of soil attributes stored in a GIS rather than grouping of soil attributes to form soil classes.

Traditionally, soil mapping involves the collection of soil morphological attributes (e.g., soil texture, structure, consistency) derived from field observations and physical, chemical, and biological attributes derived from laboratory analyses. Often the sample support is small and samples are referred to as point observations. Such point observations made with augers or at excavated pits are labor intensive and costly. Emerging *in situ* techniques such as ground penetrating radar,[54] electromagnetic induction (EM),[55,56] profile cone penetrometers,[57,58] remote sensing,[59] and soil spectroscopy[60] are nonintrusive and allow for rapid data collection. While these new techniques are typically associated with greater uncertainty, they have the capability to complement traditional auger-based field observations.

Realistic soil-landscape reconstruction is highly dependent on soil and ancillary variable collection. The following criteria impact the soil-landscape modeling process:

1. **Attribute type**: Boolean (e.g., presence of redoximorphic features — yes or no, hydric or nonhydric soils), categorical (e.g., soil structure categories), ordinal (e.g., drainage classes ranging from very poor drainage to excessively well-drained soil), interval (e.g., soil texture), and continuous (e.g., bulk density in mg m^{-3}).
2. **Content of attributes**:
    a. **Soil attributes**: Describe soil characteristics.
        i. **Morphological, physical, chemical, and biological attributes**: Soil attributes are variable in geographic space. Soil attributes with a short range (small spatial autocorrelation) vary at close distances, whereas soil attributes with long range (large spatial autocorrelation) vary over long distances. The spatial autocorrelation of attributes is domain dependent. For example, the variability of a soil attribute (e.g., soil nitrogen) observed in a loess landscape is likely to differ from the same attribute observed in a fluvial landscape.

ii. **Soil classes**: Have a specific range in one or more particular attributes, such as texture, structure, drainage, acidity, or other. According to Wilding et al.,[61] attributes that are measured and closely calibrated to a standard (e.g., texture, color, pH, etc.) are commonly less variable than qualitatively assessed attributes (soil structure, consistency, porosity, root abundance, etc.).

b. **Topographic attributes**: Describe terrain characteristics.

i. **Primary topographic attributes**: Specific geometric attributes of the topographic surface calculated directly from a digital elevation model (DEM); these include slope, aspect, upslope drainage area, maximum-flow path length, profile curvature, plan curvature, and others.[62]

ii. **Secondary topographic attributes**: Secondary, or compound, attributes involve combinations of primary attributes and constitute physically based or empirically derived indices that can characterize the spatial variability of specific processes occurring in landscapes.[63] Examples of secondary attributes include the topographic wetness index, stream power index, and sediment transport index.

c. **Topographic classes**: A group of topographic attributes lumped into classes that form land surface classification systems. Ruhe[11] developed geomorphic slope units in a catenary way. Huggett[64] categorized terrain into four different basic slope shapes based on the convexity and concavity of the terrain. Conacher and Dalrymple[65] segregated three-dimensional units of a catena resulting in the nine land surface units based on soil morphology, mobilization, and transport of soil constituents, and redeposition of soil constituents by overland flow and throughflow or by gravity as mass movement. Pennock et al.[66] segregated terrain based on curvature, flow lines, and landscape position.

d. **Parent material**: The unconsolidated and more or less chemically weathered mineral or organic matter from which the solum of soils is formed by pedogenic processes.

e. **Land cover and land use**: Land cover describes the coverage of the land surface by vegetation, structures, pavement, or others. According to Turner and Meyer,[67] land cover is the biophysical state of the Earth's surface. In contrast, land use describes the function that land performs. Land use involves both the manner in which the biophysical attributes of the land are manipulated and the intent underlying that manipulation — the purpose for which the land is used.[67]

f. **Time**: Synoptic soil sampling provides a snapshot of the characteristics and distribution of soils within a soil mapping region. Repeated soil sampling (soil monitoring) provides information about soil attribute variability through time. Commonly, stable soil attributes (e.g., soil texture, particulate phosphorus) show less variation with time, whereas dynamic soil attributes (e.g., soil nitrate–nitrogen, soil temperature, water content, hydraulic conductivity, biological activity, exchangeable cations) are highly variable in time.[61]

3. **Sample support**: The volume of material or area of a sample. Observations that are made on small volumes of material (1 cm^3 to a few cubic meters), or areas of a few centimeters to a few meters, are considered point observations.[17]
4. **Geographic extent of observations**: Range from the molecular system, peds /aggregates, horizons, pedons, polypedons (multiple pedons), catena, to soil regions. The organization hierarchy of soil systems was outlined by Hoosbeek and Bryant.[68] McBratney et al.[69] provide an overview of small- and large-scale digital soil maps categorized by cartographic scale, pixel size, nominal spatial resolution, resolution *loi du quart*, and extent.
5. **Total number of observations**: Within the soil mapping region.
6. **Density of observations**: Varies from sparse to exhaustive (high-density, continuous) sampling. For example, profile cone penetrometers collect soil attributes (e.g., penetration resistance, soil moisture) continuously in small depth increments (e.g., 1 or 0.5 cm) along soil profiles. Satellite images provide exhaustive datasets covering large soil mapping regions with high spatial resolutions. For example, Landsat Enhanced Thematic Mapper (ETM) images have a grid resolution of 30 m. Hyperspectral images, such as NASA's Airborne Visible/Infrared Imaging Spectrometer (AVIRIS), with 224 contiguous spectral channels (bands), have a spatial resolution of 20 m, and IKONOS images have a resolution of 1 m in the panchromatic and 4 m in the multispectral resolutions. In contrast, auger-based point sampling is labor intensive and costly, and often fewer observations are collected to represent the soil-landscape.
7. **Sampling design**: Brus and de Gruijter[70] discuss model-based and design-based sampling. The design-based sampling approach is rooted in classical sampling theory where sample locations are selected by a predetermined random procedure. For example, simple random sampling and stratified random sampling are considered design-based sampling methods. Apart from measurement error, sampling is the only source of stochasticity considered in the design-based approach. This implies that the unknown value at any given location and time is considered fixed, not random. In the model-based approach, the soil-forming process that has led to the field of values of a particular attribute in the soil mapping region is modeled as a stochastic process. This implies that the sample does not necessarily have to be selected by a random procedure.

Sampling schemes comprise transect, random, stratified random, clustered, targeted, and grid sampling. Ideally, for mapping and subsequent analysis, observations should be located spatially distributed over the soil mapping area. Sampling schemes can take prior information into account derived from qualitative or quantitative soil maps, earlier point observations, or sampling barriers.[71]

1.6 PEDOMETRICS

Soil-landscapes are complex and diverse due to pedogeomorphological and hydrological processes acting over hundreds and thousands of years. These soil-forming and -destroying processes operate simultaneously in soils, and the resulting profile reflects the balance of these processes — present and past. The spatial distributions of subsurface attributes and processes in natural environments often vary at granularities ranging from pedons, hillslopes, to regions. Reconstructing soil-landscapes requires an interdisciplinary holistic approach. Pedometrics attempts to integrate knowledge from numerous disciplines, including soil science, statistics, and GIS (Figure 1.3). *Pedometrics* is a term coined by Alex McBratney — a neologism, derived from the Greek words πεδοζ (soil) and μετρον (measurement). Pedometrics is defined as the application of mathematical and statistical methods for the study of the distribution and genesis of soils (http://www.pedometrics.org).

Quantitative models that describe soil-landscapes are rooted in conceptual (mental) models. These conceptual soil-landscape models have currently evolved into complex quantitative models that utilize advanced mathematics and statistics, emerging soil mapping techniques, and computers that are capable of processing huge multidimensional datasets. Pivotal events that shaped soil-landscape modeling history are summarized in Figure 1.4.

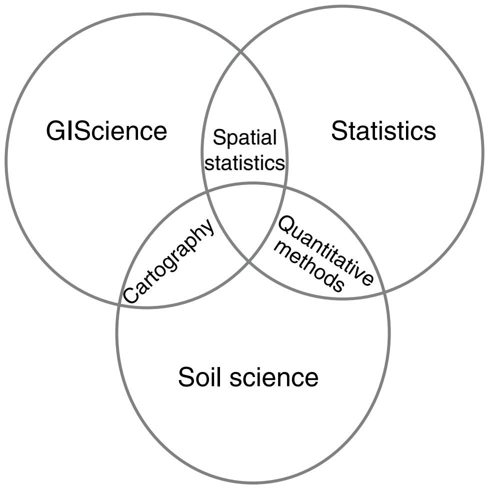

FIGURE 1.3 Pedometrics can be considered an interdisciplinary science integrating soil science, GIScience, and statistics (available from http://www.pedometrics.org).

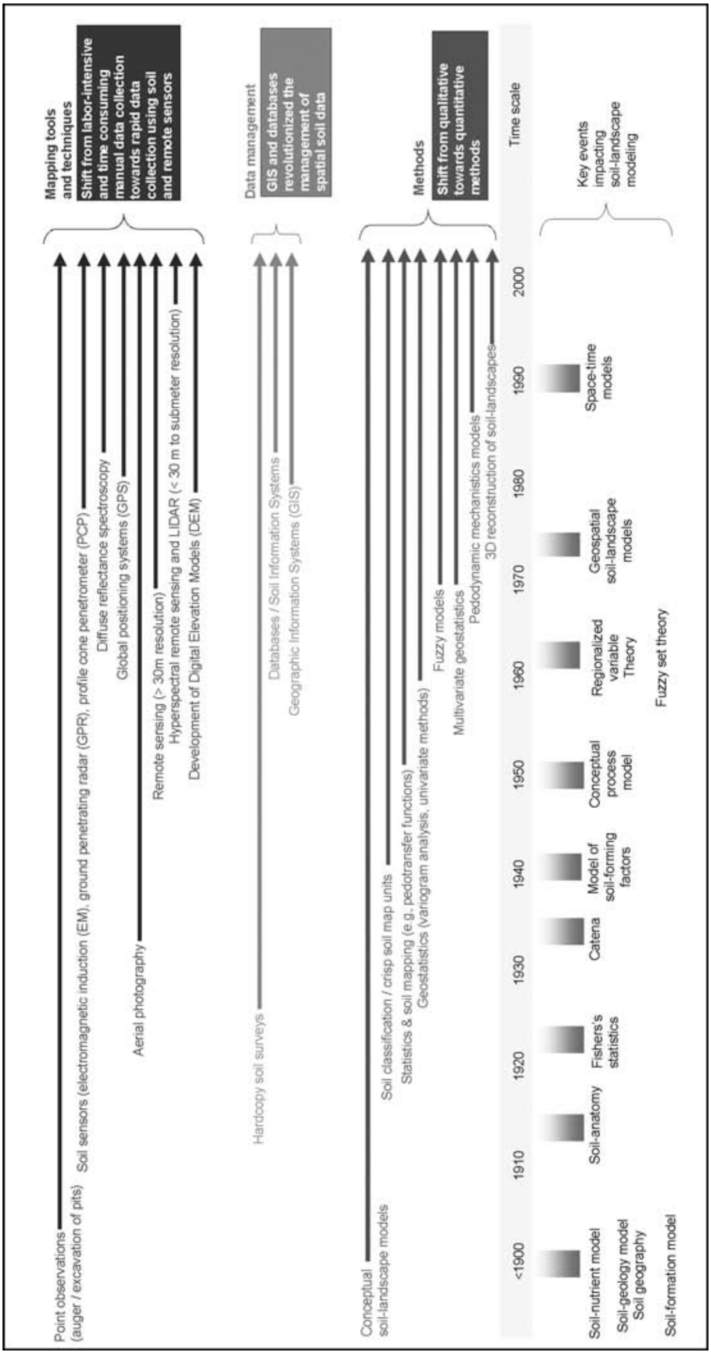

FIGURE 1.4 Pivotal events that shaped soil-landscape modeling history. Time periods and placement of events are approximate. (See color version on the accompanying CD.)

Since the 1980s, a dramatic change has taken place in our thinking about the utilization of natural resources. There has been an increased awareness of ecosystem health and environmental quality, and rate of resource consumption.[72] While soil survey in its traditional role is diminishing, the need for soil information is becoming more important in terms of sustainable land management and cycling of biogeochemicals. Pedometrics and environmetrics have grown closer. Environmetrics aims at fostering the development and use of statistical and other quantitative methods in the environmental sciences, environmental engineering, and environmental monitoring and protection. Spatially explicit, continuous, and quantitative soil-landscape data are required to assess environmental quality.

1.6.1 Jenny's Soil Factorial Model

Soil mapping first relied merely on the intuition of soil surveyors to read a soil-landscape. Soil factor equations were introduced by Dokuchaev in Glinka[73] and affirmed and popularized by Jenny.[74,75] Jenny's model of soil-forming factors is rooted in previous work by Dokuchaev and describes soil as a function of climate, biological activities, topography, parent material, and time (Figure 1.5):

$$S = f\,(cl, o, r, p, t) \tag{1.1}$$

where

S = soil attribute
cl = climate factor
o = organisms (biotic factor)
r = relief (topographic factor)
p = parent material
t = time

Hudson[76] discussed the two reasons for the success of the soil factorial concept:

1. "A large number of adherents were excited by the idea that this apparently simple concept could be used as the basis for accurately locating soil boundaries and delineating bodies of soil anywhere in the world."
2. "There are no details. Nothing is stated, e.g., about the mechanics how soils vary, or which attributes vary in different climates. Lacking specifics it pointed the way to a wide variety of interesting problems for practitioners to solve."

Jenny[77] called the factors in Equation 1.1 independent variables. Independence inherently implies that factors change without altering other soil attributes. These independent variables define the soil system; i.e., for a given combination of cl, o, r, p, and t, the state of the soil system is fixed (only one type of soil exists under these conditions). In this interpretation of soil-forming factors, the

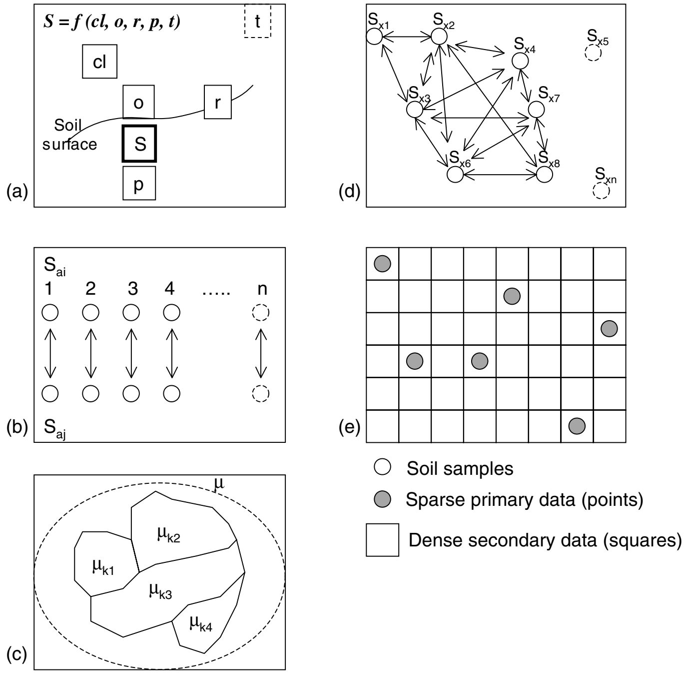

FIGURE 1.5 (a) Jenny's soil factorial model. (b) Pedotransfer functions without consideration of spatial autocorrelation. (c) Soil classification model. (d) Univariate geospatial model acknowledging spatial autocorrelation. (e) Multivariate geospatial model acknowledging spatial autocorrelation and covariation.

notions of "forming" or "acting" that connoted causal relationships have been replaced by the less ambiguous conceptions of "defining" or "describing" (*f* stands for "function of" or "dependent on"). Jenny[77] pointed out that in selecting *cl*, *o*, *r*, *p*, and *t* as the independent variables of the soil system, we do not assert that these factors never enter functional relationships among themselves. But he placed emphasis on the fact that the soil formers may vary independently and may be obtained in a great variety of constellations, either in nature or under experimental conditions.

Jenny's factorial model has been adopted in numerous soil survey programs worldwide that rely on tacit knowledge of soil surveyors. Jenny showed that the relationship between a certain soil property and a state factor can be investigated in a region in which one state factor is dominant compared to the combined contributions of the other state factors. These special cases are, depending on the dominant state factor, climo-, bio-, topo-, litho-, or chronofunctions. The conceptual factorial model Jenny developed provides the framework to develop quantitative descriptions of soil-landscapes.

Knowledge of the soil attributes produced by the interaction of environmental variables (geological, topographical, climatological, and biological variables) allows for the prediction of soil characteristics. The qualitative application of the factors of the soil formation model has been, and still is, the guiding paradigm of national soil survey programs around the world. Tacit knowledge of the soil surveyor is the basis for delineating soil boundaries. Soil surveyors use the qualitative model of soil-forming factors for mapping soils and rely on environmental factors as explanatory variables (e.g., landforms, local drainage, vegetation, parent material, etc.). Soil distribution is predicted on the basis of environmental correlation. These mental models can be complex and have considerable predictive power, but the results are not amenable to rigorous checking, repetition, and rational criticism by others unless the survey is repeated. It is difficult to distinguish between evidence and interpretation in survey reports. The quantification of soil-forming factors has been of major interest with the advent of digital terrain modeling and emerging mapping techniques such as remote and soil sensing. For example, Pennock et al.[78] related landform element complexes to physical (e.g., bulk density), chemical (e.g., inorganic carbon content), and biochemical (e.g., soil organic carbon) soil quality indicators. Hairston and Grigal[79] investigated relationships between topographic position and soil water, soil nitrogen, and tree growth on two regional landforms in Minnesota. Osher and Buol[41] related soil attributes to parent material and landscape position in eastern Madre de Dios, Peru, using 14 soil profiles. McKenzie and Austin[7] presented a quantitative approach to medium- and small-scale surveys based on soil stratigraphy and environmental correlation in the lower Macquarie Valley in Australia. The authors used a generalized linear model and a comprehensive set of soil attributes (e.g., soil morphological attributes, bulk density, texture, pH, electrical conductivity, cation exchange capacity) to characterize the soil region. Numerous studies showed that topography can be easily quantified and used successfully as a predictor of soil attributes. In reality, it is very difficult to assign quantitative values to some factors, particularly parent material and the biota. Processes of soil formation occur over timescales of tens to thousands of years. Hence, time is one of the factors that is very difficult to quantify. For example, Holzhey et al.[80] suggested that it took between 21,000 and 28,000 years to form the thick spodic horizons in North Carolina. Morrison and Frye[81] suggest that the formation of Churchill Geosol in Nevada can be envisaged as taking about 5000 years.

1.6.2 Catena Model

The catena[82] is a fundamental concept that explains the pattern of soils on hillslopes. Milne[82] coined the term to describe a repeating sequence of soils that occur from the top of a hillslope to the adjacent valley bottom. The catena concept includes both surficial stratigraphy and internal hillslope structure and lithology. Milne pointed out that soil formation along a hillslope is influenced by the parent material and pedological processes (e.g., erosion that redistributes soil material downslope). The catena is defined as a sequence of soils of about the same age, derived from similar parent material, and occurring under similar climatic conditions, but having different characteristics due to variation in relief and drainage.[15]

Bushnell[83] coined the term *toposequence*, which is often used synonymously with catena; however, the original meanings are not identical. A toposequence is a sequence of related soils that differ, one from the other, primarily because of topography as a soil formation factor. It is argued that changes in soil morphology can be mainly attributed to elevational position and local hydrology.

Huggett[64] further developed the catena concept, proposing that the basic three-dimensional unit of the soil-landscape is the first-order valley basin. The functional boundaries of this soil-landscape are defined as the atmosphere–soil interface, the weathering front at the base of the soil, and the drainage divides of the basin. Huggett[64] pointed out that the topographic boundaries of a drainage basin define the physical limits and directions of the basin, and thus control geomorphic processes such as erosion, deposition, surface runoff, and lateral subsurface flow. This conceptual model emphasizes soil hydrology and functional boundaries for soil mapping.

Sommer and Schlichting[84] presented a methodology of grouping catenas into three major categories: (1) transformation catenas, showing no gains or losses of the element or soil component under study; (2) leaching catenas, with losses in at least part of the catena and no accompanying elemental gains in other parts; and (3) accumulation catenas, showing gains in at least part of the catena but no losses elsewhere in the catena. Catenas that cover geomorphic units of distinctly different ages belong to the chronocatenas, a subcategory of either the transformation, leaching, or accumulation type. Though the catena concept acknowledges the continuum of soils along a hillslope, typically discrete entities (pedons) are identified and soils are segregated into crisp entities. Park et al.[85] presented a process-based terrain characterization model for a toposequence in southern Wisconsin. Its basic proposition is that soil distribution can be most efficiently identified by the separation of units where similar hydrological, geomorphological, and pedological processes occur.

1.6.3 Prediction of a Soil Attribute from Other Soil Attributes

Soil-landscape modeling history was also shaped by the theory formalized by Fisher,[86] who emphasized the importance of random selection to ensure that estimates are unbiased. This resulted in the applications of many design-based soil sampling schemes. First, ordination techniques, multiple discriminant analysis, and other clustering and data fragmentation techniques were introduced, rooted in classical statistical theory.

Empirical observations recognized that selected soil attributes are interdependent. For example, drainage in soils is highly dependent on soil texture, soil structure, and bulk density. These relationships between collocated soil attributes can be identified using a training (calibration) dataset to develop pedotransfer functions (PTFs). Wösten et al.[87] described two types of PTF, namely, class and continuous PTFs predicting soil classes (e.g., textural classes, horizons) and continuous variables (e.g., hydraulic conductivity). McBratney et al.[88] considered the variable type of the predictor and predictor variables to distinguish different types of PTFs, ranging from hard and fuzzy classes, continuous or fuzzy variables, to mixed-class continuous variables.

Statistical methods such as multiple regressions, artificial neural networks, or classification and regression trees (CARTs) are commonly used to formalize the relationships to predict soil attributes or soil classes (Equations 1.2 and 1.3). The functions are commonly used to predict soil attributes at unsampled locations. Pedotransfer functions are attractive because they provide a way to predict soil attributes that are costly and labor intensive to collect from a new suite of soil attributes that are cheap and rapid to collect. Most PTFs consider observations as independent and ignore the spatial autocorrelation of soil attributes (Figure 1.5):

$$S_{aj} = f(S_{ai}) \tag{1.2}$$

$$S_{cj} = f(S_{ci}) \tag{1.3}$$

where

S_{aj} = soil attribute j
S_{ai} = soil attributes ($i = 1, 2, \ldots, n$)
S_{cj} = soil class j
S_{cj} = soil classes ($i = 1, 2, \ldots, n$)

Pedotransfer functions define relationships between different soil characteristics and attributes, such as the moisture retention characteristics and the pressure head–hydraulic conductivity.[89] Rawls et al.[90] estimated soil water properties and Grunwald et al.[58] soil physical properties using cone index data collected with a profile cone penetrometer.

1.6.4 Soil Classification Models

Running parallel with, but without any formal connection, soil systematics was developing its own course. Its origins were intuitive and its proponents were trying to justify it, seeking to give it the same genetic respectability that biological and geological classifications seemed to have achieved. The lack of efforts to introduce statistical measures in soil survey programs is evident. For example, in current soil surveys in the U.S., no statistical techniques are used to optimize soil sampling designs and to document collected soil data (e.g., the variation of a soil attribute within a soil map unit). Nevertheless, soil classification systems still prosper around the world, supported by national soil surveying efforts to produce crisp soil maps.[50]

Adopting the classificatory approach, we assume that observations are taken from a statistically stationary population (i.e., the mean and variance of the data are independent of both the geographic location and the size of the support).[21] Other assumptions include that (1) the variations in the value of S

within the map units are random and not spatially contiguous, (2) all mapping units have the same within-class variance, which is uniform within the polygons, (3) all attributes are normally distributed, and (4) the most important changes in soil attribute values take place at boundaries, which are sharp, not gradual. Classification by homogeneous polygons assumes that within-unit variation is smaller than that between units. This conceptual model is commonly used in soil and landscape mapping to define homogeneous soil units, landscape units, ecotopes, etc. The model can be formalized using the following equation:

$$S(x_0) = \propto + \quad {}_k + \qquad (1.4)$$

where

$S(x_0)$ = value of the soil attribute at location x_0

μ = general mean of S over the domain of interest (soil mapping region)

α_k = deviation between μ and the mean μ_k of unit (class) k

ε = residual (pooled within-unit) error or noise

According to Webster,[91] there are three major types of classification models:

1. Intuitive classification models: The soil surveyor identifies class boundaries based on tacit knowledge.
2. Systematic classification (mathematical classification) models: Classification of multiple soil and environmental properties into classes, e.g., using multiple discriminant analysis, hierarchical clustering, or CART.
3. Spatial fragmentation classification models: Incorporation of the spatial position of observations into the grouping algorithm. Problems with the classificatory approach include a mismatch between multivariate and geographic space, where the geographic boundaries do not necessarily match with the attribute boundaries.

The value of the soil attribute classes in these models can be hard or fuzzy. Fuzzy sets were first introduced by Zadeh[92] and can be used to describe the uncertainty of data and boundaries between categories. Fuzzy methods allow the matching of individuals to be determined on a continuous scale instead of on a Boolean binary or an integer scale. In contrast to crisp sets, a fuzzy set is a class that admits the possibility of partial membership. Fuzzy c-means partition observations in multivariate space into relatively stable, naturally occurring groups.[93] Fuzzy set theory provides a rich framework to describe the vagueness of (spatial) data and information. McBratney and Odeh[94] provided an overview of applications of fuzzy sets in soil science that includes a numerical classification of soil and mapping, land evaluation, modeling and simulation of soil processes, fuzzy soil geostatistics, soil quality indices, and fuzzy measures of imprecisely defined soil phenomena.

1.6.5 Geospatial Models

Geospatial models predict soil attribute values at unsampled locations using soil attribute observations that are spatially distributed throughout the soil mapping domain. Global interpolation methods use all available observations to provide predictions for the whole area of interest, while local interpolators operate within a small zone around the point being interpolated to ensure that estimates are made only with data from locations in the immediate neighborhood.

Trend surfaces are the simplest geospatial model that requires fitting some form of polynomial equation through soil (or environmental) attribute values. These are least square methods that model the long-range spatial variation. Such models assume that the spatial coordinates are the independent variables and S (attribute of interest) is the dependent variable (Equation 1.5).[91] As trend surfaces are simplified representations of reality, it is difficult to ascribe any physical meaning to complex, higher-order polynomials. Therefore, the main use of trend surface analysis is not as an interpolator, but as a way of removing broad features of the data prior to using some complex local interpolator. The concept is based on partitioning the variance between trend and the residuals from the trend.

$$S(x_0) = \sum_{u=0}^{U} a_u f_u(x_0) + \tag{1.5}$$

where

a_u = unknown coefficients to be found by analysis
f_u = known functions of spatial position (x_0)
ε = uncorrelated error term

Local, deterministic interpolation methods focus on modeling short-range (local) variations. The interpolation involves (1) defining a search neighborhood around the point to be interpolated, (2) finding the observations within this neighborhood, (3) choosing a mathematical function to represent the variation over this limited number of points, and (4) evaluating it for the point on a regular grid. The procedure is repeated until all the points on a grid have been computed.[21] Local interpolation methods such as nearest neighbors (Thiessen or Vornonoi polygons), inverse distance weighting (IDW), and splines are described in Burrough and McDonnell.[21] Splines (local fitting functions) estimate values using a mathematical function that minimizes overall surface curvature, resulting in a smooth surface that passes exactly through the observation points, while at the same time ensuring that the joins between one part of the curve and another are continuous. Local interpolators in their simplest form are based on a linear interpolator, in which the weights are computed from a linear function of distance between sets of data points and the point to be predicted (Equation 1.6). The assumption of IDW is that the value of an attribute at an unsampled location is a distance-weighted average of data points occurring within a local neighborhood surrounding the unvisited point:[95]

$$\hat{S}(x_0) = \bullet_{i=1}^{n} \;\; {}_i * S(x_i) \qquad \bullet_{i=1}^{n} \;\; {}_i = 1 \tag{1.6}$$

where

$\hat{S}(x_0)$ = predicted soil attribute value at unsampled location x_0
λ_i = weights
$S(x_i)$ = observed soil attribute value at locations x_i

Mercer and Hall in Webster[91] in 1911 at Rothamsted, UK, discovered that soil attributes show two distinct sources of variation: an autocorrelated component and a random one. The advent of computers and software starting in the 1960s and regionalized variable theory formalized by Matheron[96] resulted in the exponential growth in geostatistical applications applied to soil science. This spatial area evolved from variogram analysis, ordinary kriging, indicator kriging, and universal kriging to more advanced multivariate geostatistical applications, such as cokriging, regression kriging, and spatial stochastic simulations.[91,97] It was recognized that more complex spatial patterns could be modeled by treating soil variables as regionalized variables (Figure 1.5).

Since the environment and its component attributes, such as soil, result from many interactive physical, chemical, and biological processes that are nonlinear or chaotic, the outcome is so complex that the variation appears to be random.

If we adopt a stochastic view, then at each point in geographic space there is not just one value for an attribute, but a whole set of values. Thus, at a location x_0 a soil attribute, S, is treated as a random variable with a mean (μ), variance (σ^2), and cumulative distribution function (cdf). The set of random variables, $S(x_1)$, $S(x_2)$, … $S(x_n)$, constitutes a random function or a stochastic process.[17] Regionalized variable theory assumes that the spatial variation of any variable Z can be expressed as the sum of three major components (Equation 1.7)[21]: (1) a structural component, having a constant mean or trend that is spatially dependent; (2) a random, but spatially correlated component, known as the variation of the regionalized variable; and (3) a spatially uncorrelated random noise or residual term. The deterministic component m is dependent on some exogenous factors such as the *cl*, *o*, *r*, *p*, and *t* factors and can be described by a trend model, e.g., via universal kriging.

$$Z(x_0) = m(x_0) + \quad (x_0) + \tag{1.7}$$

where

$Z(x_0)$ = value of a random variable at x_0

$m(x_0)$ = deterministic function describing the structural component of Z at x_0
$\varepsilon'(x_0)$ = stochastic, locally varying but spatially dependent residual from $m(x_0)$ — the regionalized variable
ε'' = a residual, spatially independent noise term having zero mean and variance
x_0 = geographic position in one, two, or three dimensions

Observations obtained close to each other are more likely to be similar than observations taken further apart from each other. This spatial autocorrelation of $\varepsilon'(x_0)$ is described by the semivariance γ. If γ is plotted as a function of the lag distance h, the semivariogram $\gamma(h)$ is obtained. In Equation 1.8, one implicit assumption is that the semivariance depends only on the separation distance h and not on the positions x_0 and $x_0 + h$ (stationarity assumption). $\gamma(h)$ is estimated as

$$(h) = \frac{1}{2N(h)} \bullet_{i=1}^{N(h)} [Z(x_0) \quad Z(x_0 + h)]^2 \tag{1.8}$$

where
γ = semivariance
h = distance (lag)
N = total number of datapairs

Regionalized variable theory is described in detail by Goovaerts,[31] Webster and Oliver,[17] and Chilès and Delfiner.[32] The semivariogram provides input for kriging, which is a weighted interpolation technique to create continuous (soil) prediction maps. Major limitations of the univariate geostatistical technique of kriging are due to the assumptions of stationarity, which are not often met by the field-sampled datasets and the large amount of data (>100 observations; better, >150 observations) to define the spatial autocorrelation.

1.6.6 Multivariate Geospatial Models

Jenny's factorial soil-landscape model inherently acknowledged relationships between soils and *cl*, *o*, *r*, *p*, and *t* factors. Univariate geostatistical models recognize spatial autocorrelation. We can unify both concepts to develop multivariate geospatial models considering spatial covariation and autocorrelation, forming complex models that describe soil-landscape reality (Figure 1.5).

McBratney et al.[69] expanded Jenny's model by explicitly introducing the spatial position *n* [*x, y* coordinates] and soil attributes (*s*) to predict a soil attribute (S_a) or soil class (S_c). They stressed the quantification of factors in Equations 1.9 and 1.10 using DEMs, remote sensing, soil sensing, and other emerging soil mapping techniques:

$$S_a[x, y, \sim t] = f(s[x, y, \sim t], cl[x, y, \sim t], o[x, y, \sim t], r[x, y, \sim t], p[x, y], a[x, y], n) \quad (1.9)$$

$$S_c[x, y, \sim t] = f(s[x, y, \sim t], cl[x, y, \sim t], o[x, y, \sim t], r[x, y, \sim t], p[x, y, \sim t], a[x, y], n) \quad (1.10)$$

where
- S_a = soil attribute
- S_c = soil class
- s = soils, other attributes of the soil at a point
- a = age, the time factor
- n = space, spatial position defined by the x coordinate (easting) and y coordinate (northing)

McBratney's model includes soil as a factor because soil can be predicted from its attributes, or soil attributes from its class or other attributes. The factor s can be derived from a prior map, remote sensing, proximal sensing, or expert knowledge. Implicit in the SCORPAN model are the spatial coordinates x, y and an approximate or vague time coordinate $\sim t$. This time coordinate can be expressed as "at about some time t." McBratney et al.[69] stress that Equations 1.9 and 1.10 are empirical in nature; i.e., there has been evidence of relationships between factors. They caution that the direction of causality is not defined. For example, vegetation is dependent on soil while soil is also dependent on vegetation. Another issue of using an empirical rather than a deterministic model is the nonuniqueness of S_c and S_a. For example, the soil attribute S_a at a specific geographic location and time might be explained by different factor combinations of s, cl, o, r, p, and a.

Below the SCORPAN model is extended to represent soil classes and attributes in three-dimensional geographic space considering the depth coordinate (z) explicitly:

$$S_c[x, y, z, \sim t] = f(s[x, y, z, \sim t], cl[x, y, z, \sim t], o[x, y, z, \sim t], r[x, y, z, \sim t], p[x, y, z, \sim t], a[x, y, z], [x, y, z]) \quad (1.11)$$

$$S_a[x, y, z, \sim t] = f(s[x, y, z, \sim t], cl[x, y, z, \sim t], o[x, y, z, \sim t], r[x, y, z, \sim t], p[x, y, z, \sim t], a[x, y, z], [x, y, z]) \quad (1.12)$$

This three-dimensional SCORPAN model was adopted to reconstruct soil-landscape models in three dimensions in southern Wisconsin[14] (Figure 1.2) and for a space–time simulation of water table dynamics in a flatwood landscape in northeast Florida.[98] We can extend the three-dimensional SCORPAN model even further by including scaling behavior of factors. Multiscale soil-landscape models do exist, but they are difficult to reconstruct with the present soil mapping technology and knowledge.

Hybrid modeling applications combine environmental correlation and geostatistics.[93] Hybrid techniques assume that soil variation is composed of deterministic and stochastic (empirical) components. With the advent of high-resolution and high-quality proximal sensing techniques of soil, land use/land cover, and topographic attributes such as electromagnetic induction (EM), soil video imaging systems, time domain reflectrometry, airborne gamma-radiometry, and multispectral remote sensing, we are capable of rapidly collecting and integrating multiple exogenous variables to predict soils. For example, Odeh et al.[99] used a DEM to predict soil attributes (depth to solum, depth to bedrock, topsoil gravel content, subsoil clay content) comparing multilinear regression, ordinary kriging, global universal kriging using restricted maximum likelihood, cokriging, and regression kriging. The latter methods are multivariate geostatistical hybrid techniques.

Cokriging is a multivariate extension of kriging that often combines a sparsely measured primary variable (or target variable) with a denser set of a secondary variable that is spatially cross-correlated (Figure 1.5).[100] Typically, the more expensive-to-measure target soil variable is predicted using the cheaper-to-measure soil, vegetation, topographic, or other variables. For example, soil texture (target variable) is predicted using slope or other topographic attributes derived from a high-resolution DEM.

Regression kriging is a hybrid method that uses multiple regressions, regression trees, generalized linear models, or others to describe the deterministic component in Equation 1.7. The residuals are modeled as the spatially varying but dependent component. Regression kriging was employed by Knotters et al.[101] to predict soil layer depths and by Carré and Girard[102] to predict soil types. According to Odeh et al.,[103] regression kriging performed better than multilinear regression, ordinary kriging, universal kriging, and isotopic and heterotopic cokriging to predict depth of solum, depth to bedrock, topsoil gravel, and subsoil clay.

Kriging with an external drift uses an ancillary variable to represent the trend $m(x_0)$ in Equation 1.7, which is modeled as a linear function of a smoothly varying secondary (external) variable instead of a function of the spatial coordinates. This method requires that the relation between primary trend and secondary variable is linear and makes physical sense.[97] Other multivariate geostatistical techniques are described in Goovaerts,[31] Chilès and Delfiner,[32] and Wackernagel.[100]

1.6.7 Space–Time Models

Other soil-landscape models stress the time component. Simonson's process model explained soil formation by the interaction of four processes: additions, removals, translocations, and transformations.[104] This model stresses pedological processes rather than the resulting soil attributes. For example, the eluviation of aluminum and iron from top O, A, and E horizons and the immobilization of these metals in short-range-order complexes with organic matter in the underlying B horizon is a process known as podzolization. Other conceptual pedogenic process models are based on a mass balance approach considering the accumulation of gains and losses of elements or tracers within a soil-landscape with defined boundaries.[105,106] Both models provide an important conceptual framework for understanding soil formation. However, neither model establishes functional boundaries for segregating the soil continuum into natural landscape units.

Since the 1990s, models that explicitly include time have been developed, including time series analysis (Equation 1.13), state–space modeling, space–time geostatistics, and spatial state–space approach, the last one based on physical laws and observations.[23] Time series analysis is based on an empirical statistical approach. In the simplest case, the measured series is treated as the realization of a stationary random process $Z(t)$:

$$Z(t) = m + \quad (t) \tag{1.13}$$

where

$Z(t)$ = realization of a stationary random process
m = global mean
t = temporally autocorrelated random residual with a mean of zero and variance characterized by its autocovariance function $C(s) = Cov[(t), (t + s)]$, where s denotes the lag and t is time

Several methods have been proposed to integrate both spatial and temporal variability into one model (Equation 1.14). Hoosbeek et al.[107] treated time as a third dimension added to two-dimensional space. They plotted a spatiotemporal semivariogram of leaching simulated with a mechanistic model (decision support model for agrotechnology transfer [DSSAT]). Journel[108] discussed possible problems associated with integrating spatial and temporal dimensions into one semivariogram model and pointed out that although some directional dependence (anisotropy) may exist, spatial phenomena in general show no ordering, whereas a notion of past, present, and future exists for temporal phenomena. Measured data may represent a unique realization for the past and present, but in the case of the future, a truer stochastic dependence exists. Because of this inequality, the additive space–time model cannot be used for interpolation. However, it is useful for describing and depicting the combined spatial and temporal variability of soil data:

$$Z(x_0, t) = m(x_0, t) + \quad (x_0, t) \tag{1.14}$$

where

$Z(x_0, t)$ = random variable dependent on location x_0 and t
$m(x_0, t)$ = deterministic trend (in the simplest case a constant equal to a global mean)

The linkage between hydrology and soil formation has been acknowledged in numerous studies.[109, 110] Though the conceptual soil-landscape models recognize dynamic hydrologic flow as a major soil-forming factor, the attempt to segregate soils rather than to address their continuity has resulted in numerous soil classification systems. Since almost all hydrologic models use stochastic or mechanistic methods to describe water flow, the development of pedology and hydrology has split into different directions.

Pedodynamic-deterministic modeling of soil processes is focused on predicting future conditions of the soil. Heuvelink and Webster[23] pointed out that calibration and validation of these models are delicate and scale dependent. Equation 1.15 formalizes the concept of process-based deterministic models:

$$Z(t) = f(t) \tag{1.15}$$

where
$f(t)$ = physical-deterministic part of the model

Quantitative soil process models, also referred to as pedodynamic models, are defined by "the quantitative integrated simulation of physical, chemical, and biological soil processes acting over short time increments in response to environmental factors."[111] Quantitative simulation models are based on the assumption that the state of each system at any moment can be quantified, and that changes in the state can be described by rate or differential equations. State variables are variables such as soil organic matter and have dimensions of length, number, volume, weight, energy, or heat content. Driving variables quantify the effect of external factors on the system and are not influenced by processes within the system. Their values must be monitored continuously (e.g., meteorological variables). Rate variables indicate the rate at which state variables change. Their values are determined by the state and driving variables according to equations that are based on process knowledge.[107] Hoosbeek and Bryant[111] developed the ORTHOD model, which simulates hydrology and pedologic processes (e.g., solute movement, microbial decomposition or organic matter, mineral dissolution, adsorption, ion exchange, and the precipitation of amorphous aluminum silicates), which lead to the formation of Typic Haplorthods. This model is specifically focused on one soil type out of thousands of others. A rudimentary mechanistic model for soil production and landscape development was proposed by Minasny and McBratney.[112] Their quantitative soil process model was constrained to the processes weathering and erosion.

Quantitative soil process models are computationally complex. The deterministic modeling approach requires a complete understanding and mathematical formulation of pedogenesis. In addition, the interaction between processes occurring over long periods has to be understood before such models can be developed. More research is necessary to unravel the mysteries of soil phenomena through time.

The time dimension is different from the space dimension because time has a direction, it moves forward only, processes take place in a sequence, and phenomena are almost never isotropic in the space–time domain. In the real world, the assumption of temporal stationarity is never a trivial one, and in many instances, it cannot be simply modeled by direct applications of kriging (interpolation) in the space–time domain. In contrast, mechanistic models often fail because we lack (1) a complete understanding of the physical, chemical, and biological ecosystem processes; (2) an appreciation for proper scaling issues; and (3) adequate input data to run our models. No matter how complex the mechanistic model structure, typically there are deviations between model predictions and independent observations. Alternative models are mixed pedodynamic-deterministic/stochastic models (Equation 1.16) where partial process knowledge is integrated with a stochastic component:[23]

$$Z(t) = f(t) + \quad (t) \tag{1.16}$$

Even more complex models acknowledge that the state at time t depends on state at time $t - 1$, which is considered in the Kalman filtering[113] state–space approach. The strength of the state–space approach lies in its ability to merge the formulation of pedodynamic-deterministic models with observations.[23] Applications of soil-landscape models that consider the variation of soil attributes in space and through time are still rare due to data input requirements.

1.7 CRITICAL REMARKS

In many countries around the world soil survey programs are still actively employing the factorial soil-landscape paradigm using tacit knowledge of soil surveyors. At the same time, many issues related to environmental quality, site-specific farm management, and land resource management have emerged that cannot be addressed successfully with available two-dimensional crisp soil taxa maps. The demand for quantitative soil-landscape models that focus on the prediction of soil properties rather than soil classes is increasing. There are slow but persistent shifts from qualitative to quantitative soil-landscape modeling providing digital, accurate, precise, and nonbiased information about soils. The philosophical soil-landscape paradigms rooted in empiricism, which emerged in the early 20th century, are still valid, and in fact, they form the cornerstone to reconstructing soil-landscapes with pedometrics.

In this chapter numerous quantitative soil-landscape modeling techniques have been presented that use a holistic approach to integrate numerous environmental factors. Hence, the term *environmental soil-landscape modeling* was proposed to emphasize that soil predictions are interdependent on environmental factors such as *cl*, *o*, *r*, *p*, and *t*. In addition, we can incorporate knowledge of how soil attributes behave in space and through time to improve reconstructing soil-landscapes.

While soils and soil attributes generally vary continuously across soil-landscapes and change through time, we measure the soil at only a finite number of geographic locations and at times with only small supports. Predictions are made from observation datasets to predict soil attributes at unsampled geographic locations. Because no measurement and model is perfect, uncertainties exist that need to be quantified. An inherent goal is to reduce prediction errors and uncertainty of quantitative soil-landscape models.

Recently, soil proximal and remote soil mapping techniques have improved greatly. Soil information systems are slowly migrating from entity to raster-based implementations. Hardware and software no longer impose limitations on developing quantitative soil-landscape models. Advanced statistical and mathematical techniques are available to test and compare conceptual soil-landscape models using stochastic simulations.[33] Virtual soil-landscapes and space–time applications can be implemented lending techniques developed in computer science.[14]

Phillips[114] argues that aggregate or probabilistic predictions are possible, but not deterministic predictions of individual soils. This implies that we currently cannot predict individual soil attributes accurately; instead, we can only predict broad-scale general behavior. In short, despite the fact that no two pedons are exactly alike, similarities do exist and commonalities can be identified. Phillips showed that intrinsic variability within homogeneous landscape units is more important in determining the pedodiversity of the study area than is the extrinsic variability associated with measurable differences in topography, parent material, and vegetation/land use. Despite the fact that our soil mapping techniques have improved tremendously, a completely deterministic approach to reconstruct soil-landscapes seems to be currently out of reach.

Although generic relationships between soil attributes and environmental factors have been identified, they are domain dependent. The relationship between soil and slope might be strong in one landscape setting but weak in another. Similarly, many soil attributes are nonstationary; their spatial variation and covariation with exogenous environmental attributes are domain dependent and potentially change through time. Therefore, no universal equation exists that fits all soil-landscapes. Rather, we have to strengthen our efforts to develop quantitative soil-landscape models that are customized based on our observations. Comparative studies that test different statistical and mathematical modeling techniques are desirable to improve our understanding of soil-landscapes.

Scaling behavior of soil and environmental factors confounds quantitative relationships between factors. Scale-dependent characteristics include (1) attributes and processes emerge at different scales, (2) nonlinear behavior of processes, (3) threshold dependency to trigger a process, (4) nonsimilarity of soil attributes and processes at different scales, (5) varying dominant processes at different scales, and (6) response to external disturbances interrelated to intrinsic processes. It is too simple to assume that we can describe soil regions by aggregating pedon descriptions.

The predicament entailed by the complexity of soil-landscapes requires a synergistic approach, integrating knowledge not only from pedology, but also geography, mathematics, computer science, ecology, hydrology, and others. Interdisciplinary collaboration will be key to reconcile deductive and inductive science to take soil-landscape modeling to the next level.

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