

# Progress in Soil Science

# Progress in Soil Science

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Progress in Soil Science series aims to publish books that contain novel approaches in soil science in its broadest sense – books should focus on true progress in a particular area of the soil science discipline. The scope of the series is to publish books that enhance the understanding of the functioning and diversity of soils in all parts of the globe. The series includes multidisciplinary approaches to soil studies and welcomes contributions of all soil science subdisciplines such as: soil genesis, geography and classification, soil chemistry, soil physics, soil biology, soil mineralogy, soil fertility and plant nutrition, soil and water conservation, pedometrics, digital soil mapping, proximal soil sensing, soils and land use change, global soil change, natural resources and the environment.

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Editors

# Digital Soil Mapping

Bridging Research, Environmental  
Application, and Operation

 Springer

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*Cover image:* Digital soil map illustrating the distribution of 24 soil classes in the Big Wash watershed in the Great Basin region of southwestern Utah, USA (adapted from Figure 15.2b, Chapter 15 from this book).

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# Foreword

Digital Soil Mapping is by now a well-established branch of soil science, with regular meetings and a very active working group of the International Union of Soil Sciences (IUSS). Meetings of the group bring together scientists dealing with digital soil mapping in the broadest sense. These meetings allow for exchange of information among scientists on their research topics and are excellent opportunities for assessing the status of this relatively young area of research in soil science.

The chapters in this book were selected from papers presented at the 3rd Global Workshop on Digital Soil Mapping (DSM 2008) that was held in Logan (Utah, USA). The theme of the workshop was *Digital Soil Mapping: Bridging Research, Production, and Environmental Application*.

There is great interest in transferring the scientific achievements of the past years of digital soil mapping into operational data and information systems responding to the increasing demands for high quality soil data and information. The past collection of soil data was largely driven by a mono-functional view of soil as the basis for agricultural production. Under the leadership of the Food and Agriculture Organization of the United Nations (FAO) substantial progress has been made in collecting soils data and information in all continents, particularly in developing countries. Standardized systems for soil classification and soil profile description have facilitated the interoperability of information systems across national borders, paving the way for the creation of digital soil databases at global and continental scales based on advanced GIS technologies. Good examples of such systems are SOTER (SOil and TERrain Digital Database) coordinated by FAO and the European Soil Information System (EUSIS) of the European Union (EU).

The relatively recent recognition of the multi-functionality of soils, including important ecosystem services and socio-economic benefits, has emphasized the inadequacy of existing soil information systems worldwide. Traditional soil survey, based on soil profile descriptions, soil classification and extrapolation of data on a soil-landscape model developed by expert judgment, cannot respond to the new requirements coming from user communities other than agriculturalists.

New soil data and information are needed to address the emerging concerns about the functioning of soils systems in the delivery of services required by modern societies. Data on soil contamination, soil biota and their diversity, soil stability (landslides), soil hydraulic functions, soil carbon pools, soil erosion, salinization,

etc. are needed by policymakers dealing with the urgent priorities related to climate change, natural and man-made hazard prevention, food and feed health as well as food security, and bio-energy production.

The emergence of new legal frameworks for soil protection at national, regional, and global levels has made traditional soil survey techniques incapable of responding to stringent legal requirements. The delineation of areas with different soil properties needs to have a solid scientific and geostatistical basis so that it can be used by legislators. Priority areas for soil protection cannot solely be delineated on the basis of expert judgements, but must be based on quantitative data that can withstand legal challenges in court. For example, the EU Soil Thematic Strategy requires the delineation of priority areas for the various threats to soil functions. These delineations have legal and financial implications that affect landowners. Therefore, the definition of these areas requires the highest quality of soil data as well as solid scientific methods for producing soil data. Digital soil mapping will thus play a key role in implementing this legislation in the European Union. Similarly at the global scale, soils play a critical role in the implementation processes of Multilateral Environmental Agreements (MEAs). The United Nations Framework Convention on Climate Change (UNFCCC), the Convention on Biodiversity (CBD), and the United Nations Convention to Combat Desertification (UNCCD) increasingly recognise the crucial role of soils. Updated and accurate global soil data and information are urgently required for these emerging needs, such as information on soil organic carbon pools and their dynamics over time. Also, the specific initiative within the Group of Earth Observation (GEO) to establish a Global Soil Information System (GLOSIS) as part of the Global Earth Observation System of Systems (GEOSS) is a response to these new requirements from policymakers.

The digital soil mapping community has taken up the challenge to foster the development of a new generation of digital soil information at local, national and global scales. The establishment of the *GlobalSoilMap.net* consortium, pooling together the major players in digital soil mapping in the world, has initiated a process that will deliver a new digital soil map of the world at fine resolution. The first node getting active in the *GlobalSoilMap.net* project is the Africa Soil Information Service (AfSIS), coordinated by the Tropical Soil Biology and Fertility Institute of CIAT (CIAT-TSBF) and financed by the Bill and Melinda Gates Foundation. The experience of transferring digital soil mapping technologies into practice on such a scale is useful in making digital soil mapping operational at continental and global scales.

The chapters in this book provide a very useful and comprehensive overview of the status of digital soil mapping and are a further step in developing this branch of soil science. I strongly recommend their consultation and reading.

# Preface

This book contains papers presented at the 3rd Global Workshop on Digital Soil Mapping held in Logan, Utah, USA, 30 September–3 October 2008. The workshop was organized under the auspices of the International Union of Soil Sciences Working Group on Digital Soil Mapping, and was hosted by Utah State University. The organizing committee was chaired by Dr. Janis Boettinger, professor of Pedology in Utah State University's Plants, Soils, and Climate Department. Financial and in-kind support for this workshop was provided by Utah State University and the US Department of Agriculture Natural Resources Conservation Service. Approximately 100 participants from 20 countries presented and discussed nearly 70 papers during the four-day session, demonstrating the global engagement in digital soil mapping.

The theme of this workshop was *Digital Soil Mapping: Bridging Research, Production, and Environmental Application*. Advances in digital soil mapping technology and methods occur at a rapid pace, facilitating the development of digital soil information with increasing precision for many areas around the world. In many cases we are fortunate to have a wealth of legacy soil data to work with. Legacy soil data can be used to improve digital soil mapping models and, in turn, digital soil mapping models can be used to help modernize and harmonize legacy soil data. Digital soil mapping has evolved to the point where it is has entered the operational realm, as a tool for improving accuracy, consistency, and efficiency of production soil mapping. At the same time, there is still a need for innovative soil information products to support environmental applications. Credible and innovative research is the basis for the development of digital soil mapping and soil assessment protocols. Development of practical soil mapping and environmental applications drives the need for continued progress in the field of digital soil mapping. With this workshop, we hoped to recognize these distinct foci within the realm of digital soil mapping.

We have selected 33 papers from the Logan workshop that focus on digital soil mapping research, environmental application, and operation. Part I is an introductory chapter which provides context for the whole book. The remaining papers are organized into the following parts: (II) Research; (III) Environmental Application and Assessment; and (IV) Making Digital Soil Mapping Operational. Within the research section, papers are grouped by three key topics: (A) Environmental Covariates and Soil Sampling; (B) Soil Sensors and Remote Sensing; (C) and Soil Inference Systems. Mapping and modeling of organic carbon is the primary focus

of the section on environmental application and assessment and of major interest to the global soil science community as well as policy makers. Digital soil mapping in a production setting is presented with case studies from New Zealand, the European Union, Canada, the United States, and the *GlobalSoilMap.net* project.

This book complements and extends the ideas presented in *Digital Soil Mapping – An Introductory Perspective*, edited by Lagacherie, McBratney, and Voltz, (2007) and *Digital Soil Mapping with Limited Data*, edited by Hartemink, McBratney, and Medonça-Santos (2008). We hope that this book will inspire digital soil mapping researchers and practitioners at universities, agencies, and other organizations in their efforts to create and utilize soil information in a range of global issues like climate change, food production, energy, and water security. We are excited to see where global advancements in digital soil mapping research will take us in the project.

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**Part I**  
**Introduction**

# Chapter 1

## Current State of Digital Soil Mapping and What Is Next

S. Grunwald

**Abstract** Digital soil mapping (DSM) involves research and operational applications to infer on patterns of soils across various spatial and temporal scales. DSM is not solely focused to map soils and their properties, but often environmental issues such as land degradation and global climate change, require assessing soils in context of ecosystem change and environmental stressors imparting control on soil properties. In this section an overview is provided of state-of-the art DSM applications and their constraints and potential is discussed. Future trends and challenges to map soils using digital approaches are outlined.

**Keywords** Environmental covariates · Soil sensors · Soil inference systems · Legacy soil data · Environmental assessment

### 1.1 Introduction

Digital soil mapping has evolved as a discipline linking field, laboratory, and proximal soil observations with quantitative methods to infer on spatial patterns of soils across various spatial and temporal scales. Studies use various approaches to predict soil properties or classes including univariate and multi-variate statistical, geostatistical and hybrid methods, and process-based models that relate soils to environmental covariates considering spatial and temporal dimensions. A comprehensive overview of digital soil mapping was provided by McBratney et al. (2003) and Grunwald (2006). Discussions of state-of-the-art digital soil mapping applications at different extents, geographic settings, and model resolutions (grains) were provided by Lagacherie et al. (2007) and Hartemink et al. (2008).

Research-focused digital soil mapping contrasts with agency-operated soil surveys. The dichotomy between research and agency-operated digital soil mapping is due to different sets of qualities. The former strives to find the best method/model to

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estimate soil characteristics exploiting digital, quantitative and emerging technologies with rigorous errors and uncertainty assessments. The latter aims to implement a standardized mapping protocol to characterize soils across a soil survey region. Soil taxonomic mapping of soil map units and development of soil information systems have played major roles in agency-operated soil surveys covering regional, national, and global scales. Whereas historically soil data needs were driven by food and fiber production (agriculture-centered period), more recent needs for soil data are more diverse with pronounced environmental-centered drivers requesting high-resolution, pixel-based soil products, which are associated with error assessment.

Traditional soil surveys explicitly incorporate pedological knowledge into the soil survey product, but have become costly and time-consuming when compared to emerging digital soil mapping approaches, such as diffuse reflectance spectroscopy (Lagacherie, 2008). This has evoked the thought to investigate in more detail how research and operational soil mapping can be fused. Grunwald (2009) presented a comprehensive analysis of recent digital soil mapping literature and pointed out that merging of quantitative, geographic, and pedological expertise is required to link production-oriented and research-oriented digital soil mapping. There is no universal soil equation or digital soil prediction model that fits all geographic regions and purposes, which complicates matters.

At the 3rd Global Workshop on Digital Soil Mapping organized by the International Union of Soil Sciences, Soil Science Society of America and Utah State University, Logan, UT, September 30–October 3, 2008, researchers, agency scientists, and practitioners met to share knowledge on digital soil mapping. This book compiles the outcomes from this Workshop in form of 34 chapters.

## 1.2 Research

### 1.2.1 *Environmental Covariates and Soil Sampling*

The section “Environmental Covariates and Soil Sampling” presents various chapters that focus on how environmental covariates are used to model soil properties. Factorial soil-landscape models form the conceptual framework for relating environmental covariates to soil properties as formalized in the *CLORPT* model (*CL*: Climate; *O*: Organism, vegetation; *R*: Relief; *P*: Parent material; and *T*: time) (Jenny, 1941) and the *SCORPAN* model (*S*: soil property or class; *C*: Climate; *A*: Age or time factor; and *N*: Space, spatial position) (McBratney et al., 2003) that are used to predict soil properties/classes ( $S_p$ ). The *SCORPAN* model is made spatially and temporally explicit by predicting  $S_c$  (soil classes) or  $S_a$  (soil attributes) at a specific geographic location ( $x$  and  $y$  coordinates) and time. Grunwald (2006) extended the *SCORPAN* model by incorporating the vertical dimension ( $z$ ), or depth of a specific soil property. Similarly, “environmental correlation” describes a method of relating environmental attributes (or environmental covariates) to  $S_p$  (McKenzie and Austin, 1993).



Although these conceptual models are accepted widely for digital soil mapping, the strength of relationships between environmental covariates and soil properties of interest differ by geographic region, observation/derivation method used to map environmental properties, spatial and temporal scales, and the specific soil property under investigation. In a comprehensive review, McBratney et al. (2003) found that the key environmental covariates for inferring  $S_a$  or  $S_c$ , were  $R$  (80% of studies) followed by  $S$  (35%),  $O$  and  $P$  (both 25%),  $N$  (20%), and  $C$  (5%). In contrast, in a review of 90 digital soil mapping journal articles Grunwald (2009) found that the contribution of  $S$  was 51%,  $C$  6%,  $O$  34%,  $R$  24%, and  $P$  6% to predict soil properties and classes.

To further investigate the behavior between environmental covariates and soil properties of interest various studies are presented in Section A. Chapter 2 discusses the use of environmental covariates in the Western USA derived from digital elevation models (DEMs) and remote sensing imagery (ASTER and Landsat) to infer on topography, climate, geomorphology, parent material, soil, and vegetation properties. These environmental properties are incorporated into soil prediction models to support soil mapping efforts, in particular, in the western USA region which still lacks initial soil mapping on private and public lands. In Chapter 3 a suite of topographic and land cover attributes to infer on soil depth using a Generalized Additive Model and Random Forest in a watershed in Boise, Idaho, USA is used. The importance of incorporating age ( $A$  factor) explicitly into digital soil models are emphasized in Chapter 4 fusing geological maps, age point data, and remote sensing data to infer on geochronology using a decision-tree analysis. The author indicates that incorporating the  $A$  factor explicitly into soil-prediction models as a co-variant is rare.  $A$  has been more often incorporated in implicit form carried in the age of parent material ( $P$ ) and land form ( $R$ ). In Chapter 5 different terrain attributes by varying grid and neighborhood sizes and investigate their effect on subsequent modeling of soil attributes are derived. Their study highlights that terrain attributes are specific to geographic land surfaces. Disparate neighborhood sizes correlate strongest with specific soil properties (soil carbon, rock fragment content, and clay content) suggesting that there is “no optimal” neighborhood size to model different soil properties. In Chapter 6 authors go after finding the optimal sample size for digital soil mapping in arid rangelands in Utah, USA. They employ conditioned Latin Hypercube sampling on five environmental covariates and identify an optimal sample size of 200–300 which is approximately 0.05–0.1% of the available potential sampling points in the 30,000 ha study area.

### ***1.2.2 Soil Sensors and Remote Sensing***

Sensing of both soils and environmental covariates is widely used in digital soil mapping studies. Lab-based or in-situ diffuse reflectance spectroscopy have been employed in the visible, near-infrared, and mid-infrared range to infer on a multitude of soil properties with varying success (Reeves, 2010). Other soil sensors map penetration resistance using cone penetrometers, apparent electrical conductivity, or

magnetic susceptibility (Grunwald and Lamsal, 2006). Grunwald (2009) found that out of 90 reviewed digital soil mapping studies 39% utilized soil or remote sensors, out of which 23.3% used soil sensors to complement analytical soil data which are more costly and labor-intensive to derive. In 16.7% of the studies, visible/near-infrared, mid-infrared, and/or Fourier-transform spectroscopy were used to infer different properties including soil organic carbon (SOC), texture, and others. Remote sensing applications that map soil properties, landscape or soil map boundaries, or environmental covariates, such as vegetation or climatic properties, can be readily incorporated into digital soil prediction models. A variety of satellite images are used in digital soil mapping projects including Landsat Enhanced Thematic Mapper (ETM), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), Quickbird, IKONOS or others. These satellite images differ in their spatial resolution, spectral range and spectral resolution, which may affect the capabilities to infer on soil and environmental covariates. Remote sensing is confounded by the fact that the land surface is a mix of bare soil (with varying soil moisture content) and vegetation coverage which impact reflectance patterns sensed by aerial or satellite sensors. But aerial and satellite images provide dense grids of information across landscapes allowing to characterize SCORPAN factors.

Chapter 7 provides an overview of proximal soil sensors for digital soil mapping including electromagnetic induction, magnetic sensors, gravimeters, ground penetrating radar, magnetic resonance sounding, gamma-radiometrics, and diffuse reflectance spectroscopy. The use of hyperspectral imagery with 5 m spatial resolution to map clay content and calcium carbonate content in a Mediterranean region is presented in Chapter 8. In this chapter, special attention is given to derive soil data from a region that is partially covered by vegetation using hyperspectral images accounting for atmospheric effects. In Chapter 9 Quickbird imagery with 2.4 m spatial resolution are used to discriminate between different soil types including chernozem-like soils, light chestnut soils, and solonchaks (sodic soils). In Chapter 10 ASTER imagery with 15 m spatial resolution to infer on vegetation and correlate it to soil horizons are used in the North Cascades National Park in Washington State, USA. In Chapter 11 quantitative hydrologic parameters, such as root zone soil moisture obtained by land-surface energy models, are used for the identification of soil boundaries. They employ Landsat imagery with 30 m spatial resolution to infer on root zone moisture based on a multi-temporal analysis.

### ***1.2.3 Soil Inference Systems***

McBratney et al. (2002) provided an overview of soil inference systems, which take measurements we more-or-less know with a given level of (un)certainty, and infers data we do not know with minimal inaccuracy, by means of properly and logically conjoined pedotransfer functions (PTFs). In essence, the soil inference system has a source, an organizer, and a predictor. The inference system is a collection of logical rules selecting the PTFs with the minimum variance (McBratney et al., 2002).

In her recent digital soil mapping review study Grunwald (2009) found that the most popular soil inference methods (41.1%) were regressions followed by classification/discrimination methods (32.2%), and tree-based methods (e.g. Classification and Regression Trees, Random Forest) (13.3%). Other methods such as GIS-based modeling, neural networks, and fuzzy logic based models were less frequently used to predict soils. In her comprehensive review study, knowledge-based digital soil models that rely on expert knowledge were rare when compared to stochastic or deterministic methods to predict soils. Out of 90 reviewed journal articles 40.0% presented soil prediction results derived from only one method, whereas 60.0% used two or more quantitative methods to predict or model soil properties/classes. Grunwald (2009) found that 36.7% of 90 reviewed digital soil mapping journal articles used legacy data in their research.

In Chapter 12 Homosoil, a methodology for quantitative extrapolation of soil information across the globe is presented. Homosoil facilitates to map soils in places where soil information is difficult to obtain or does not exist. A major assumption of this conceptual approach is homology of soil-forming factors between a reference area and the region of interest. Gower's similarity index is used to quantify similarity in climate, physiography, and parent materials in a reference area and the rest of the world. In Chapter 13 Artificial Neural Networks and a Decision Tree model for predictive soil mapping based on the *SCORPAN* approach are employed in a poorly accessible 20 km<sup>2</sup> watershed in Thailand. In Chapter 14 a knowledge-based approach and a rule-based fuzzy inference engine, Soil Inference Engine (SIE), is used in two small watersheds in Vermont. In this study not only the predictive capability of the inference engine is evaluated to infer on soil series and drainage classes, but also the potential to transfer the prediction model to a watershed with similar landscape characteristics is assessed. In Chapter 15 Random Forest to predict soil classes using environmental covariates derived from Landsat ETM and a DEM in an arid region in Utah are employed. Chapter 16 explicitly incorporates legacy data into the soil predictive models (sand, silt, clay and organic carbon) implemented using Generalized Linear Modeling and Bayesian Belief Networks. Authors of this chapter emphasize the limitations of using legacy data that may not cover the existing feature space (i.e., the range of attribute values present in a given region) and may contain a mix of qualitative and quantitative data.

### 1.3 Environmental Application and Assessment

Historically, soil surveys have focused on soil descriptions and mapping of taxonomic soil data and standard soil properties. Recently, the emphasis has shifted from classification and inventory to understanding and quantifying spatially and temporally soil patterns to address environmental problems. This environmental-centered approach views soils as integral part of an ecosystem interacting with environmental factors generating complex patterns and processes that co-evolve through time. Environmental-centered digital soil mapping responds to critical societal needs including environmental quality assessment, soil degradation, soil quality,

and health as outlined in Hartemink (2006). Spatially-explicit soil carbon assessment over large landscapes has gained attention to help mitigate rising levels of greenhouse gases in the atmosphere.

In a review it was found that out of 90 investigated digital soil mapping studies, 40.0% focused on predictions of base soil properties such as texture, bulk density, and structure, 31.1% on soil carbon/global climate change, 24.4% on eutrophication/environmental quality assessment, 16.6% on hydrologic properties (such as soil moisture, saturated hydraulic conductivity, or soil water content), 8.9% on soil degradation (salinity, acidity, and erosion), and 15.6% on mapping of soil taxonomic/ecological classes (Grunwald, 2009). In particular, studies that focus on mapping of SOC and soil organic matter (SOM) are prominently represented in the recent digital soil mapping literature.

Chapter 17 addressed the problem of heavy metals in soils in a study site in the Italian Alps. They use multi-scale Support Vector Regression (SVR), a machine learning technique, to model distribution patterns of heavy metals. SVR is a non-parametric technique based on Structural Risk Minimization that aims to optimize model performance by minimizing both the error and the model complexity. Chapter 18 map carbon/nitrogen (C/N) ratio of forest soils aiming to evaluate soil functions and provide needed information to address climate change in Europe. Interestingly, in their study the classical Kriging approach performs better to model C/N ratios when compared to Neural Network modeling of C/N using environmental covariates. This may be explained by the scale of the “global soil mapping approach” extending over Europe. Chapter 19 compares various methods (Multiple Linear Regression, Universal Kriging, Regression Kriging, Artificial Neural Network–Kriging, Regression Tree, and Sequential Indicator Simulation) to model SOC in a province in China, with Regression Tree outperforming all other tested methods. In Chapter 20 SOM is estimated using Regression Kriging and various environmental covariates in central Italy. The topsoil SOC stocks are estimated using six different sets of SCORPAN factors implemented using Multi-linear Regression analysis and Regression Kriging in Rio de Janeiro State (Chapter 21). Chapter 22 assesses the extent of organic soils in Denmark using Decision Tree Modeling and Indicator Kriging, which classified 58 and 52% correctly, respectively. In Chapter 23 wind erosion is assessed in the Danube Basin using Regression Kriging and various environmental covariates bridging the gap between digital soil mapping and digital soil risk assessment.

## 1.4 Making Digital Soil Mapping Operational

Research-focused digital soil mapping contrasts with need-driven digital soil mapping and agency-operated soil surveys. Digital soil mapping studies are diverse with specialized, mathematical prototype models tested on limited geographic regions and/or datasets and simpler, operational digital soil mapping used for routine mapping over large soil regions.

Grunwald (2009) pointed out that numerous research-oriented digital soil mapping studies ranked high in terms of quantitative knowledge and expertise, but lacked pedological interpretations which may limit widespread adoption by practitioners. In her review study she documented various complex digital soil mapping methods, such as genetic programming, Simulation of Gaussian Fields, Markov Chain Random Fields, or mechanistic models, which require profound mathematical expertise. Minasny and McBratney (2007) suggested that for practical applications digital soil prediction methods, such as Regression Kriging, may be mathematically biased, however, they appear robust to predict soil properties in various soil regions. Both authors conclude that improvement in the prediction of soil properties does not rely on more sophisticated quantitative methods, but rather on gathering more useful and higher quality data.

There are multiple studies presented in this book that use Multivariate Regression, Regression Kriging, Tree-based models, or Neural Networks, which are methods that are versatile and easy to implement. In these studies much effort is invested in assembly of *SCORPAN* factors from various sources (legacy datasets, soil and remote sensors, derivatives from DEMs, and others). In many cases, data collection of environmental covariates is given more attention than the collection of soil samples. The presented studies further suggest that there is not one method emerging that performs best to estimate multiple soil properties/classes in different geographic regions. Factors that confound findings to estimate soil properties and classes include sampling design and sample density, quality and spatial resolution of soil and environmental covariates, scale (extent of study site, model grain), data aggregation, and integration methods. Critical is to evaluate the performance of soil prediction models using calibration and/or validation. Grunwald (2009) found that out of 90 investigated studies 21.1% used cross-validation, 46.7% used validation, and 35.6% did not use cross-validation, validation or any other performance test. Rigorous performance tests to evaluate soil predictions in various geographic soil-landscape settings are critical to minimize uncertainty in soil predictions at unsampled locations.

Chapter 24 presents the S-map designed to deliver a new digital soil map, database, inference system, and soil information system for New Zealand. The system builds on legacy data, older soil surveys, expert-knowledge, and digital soil mapping methods. Preliminary results contrast expert-clustering and data-driven clustering deriving soilscapes. Chapter 25 addresses the problem of legacy soil data harmonization and data base integration for a region covering the Hungarian-Slovakian border. They form an integrated database of profiles using pedotransfer rules and environmental covariates to employ Regression Kriging and Maximum Likelihood Classification to derive soil groupings, pH, and humus content. Chapter 26 provides an overview of how existing soil survey data and expert-knowledge is linked to implement digital soil mapping in Canada. Authors aim is to produce raster-based soil maps that utilize existing soil survey information managed by the Canadian Soil Information System (CanSIS). Chapter 27 demonstrates predictive ecosystem mapping for 8.2 million hectare of forestland in British Columbia, Canada. Their approach for operational modeling of ecological entities is based

on a combination of fuzzy membership functions and knowledge-based predictive rules. Chapter 28 presents an operational initiative facilitated by the Natural Resources Conservation Service building digital soil mapping capacity within the U.S. National Cooperative Soil Survey. In this pilot project ASTER satellite imagery and DEM data will be used to create soil predictive models in the Joshua Tree National Park, Mojave Desert. Complimentary, Chapter 29 presents a qualitative comparison of conventional soil survey product and one derived using environmental covariates and Random Forest to predict soil subgroups as part of the Mojave Desert initiative. In Chapter 30 the Optimum Index Factor (OIF) to multiple data types is applied to identify the optimum combination of bands from Landsat TM and DEM data. The OIF is used to determine which data layers, derived from elevation data and remote-sensing images, best represent the full range of biophysical characteristics in a study area in north-eastern Utah. The optimum data layers are combined into a multiband image used for classification and modeling, and ultimately to create a pre-map for the study area. Chapter 31 presents the TEUI-Geospatial Toolkit which is an operational GIS-based ecological inventory application used by the U.S. Department of Agriculture, Forest Service and other land management agencies. In Chapter 32 a GIS framework and rule-based system developed by experts is used to map shallow soil condition to model dust emissions in the arid southwest U.S. Chapter 33 describes the GlobalSoilMap project that aims to produce a new digital soil map of the world with a grid resolution of  $90\text{ m} \times 90\text{ m}$ . The global soil map will be freely available, web-accessible, and widely distributed. The first portion of the global soil map is focused on Sub-Saharan Africa. Chapter 34 provides methodologies for global soil mapping based on the current state of knowledge incorporating legacy data, extracting information from soil maps, combining soil maps and soil point data, SCORPAN, Kriging, extrapolating based on reference areas, and the Homosoil approach.

## 1.5 What Is Next in Digital Soil Mapping

The methodological digital soil mapping framework to map soils across the globe at fine grains ( $\leq 90\text{ m} \times 90\text{ m}$ ) has been formalized (compare Chapters 33 and 34; and McBratney et al., 2003). Research-oriented digital soil mapping studies presented in this book and digital soil mapping literature (Grunwald, 2009; Hartemink et al., 2008; Lagacherie et al., 2007) provide evidence that soil taxonomic data and soil properties can be predicted successfully using sets of environmental covariates as shown in various soil-landscape settings. Availability of high-resolution and hyperspectral remote sensing data, high-quality DEMs as well as soil sensors, and multi-sensor systems have facilitated to improve soil prediction models. In research-oriented digital soil mapping error and uncertainty metrics accompany soil estimates to document the quality of digital soil maps, which have often not been provided in transparent format by operational soil survey programs. The trend to formalize pedological expertise in form of quantitative soil prediction models of various types is continuing in the research community.