Current and Future Trends in the Development of Integrated Methodologies for Assessing Non-Point Source Pollutants

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The role of Geographic Information Systems (GIS) and related technologies for assessing the environmental impacts of agricultural and urban non-point source pollutants is examined. The development of several new digital databases, advent of Global Positioning System (GPS) receivers, continuous yield sensors, remote sensing techniques, and continued migration to powerful desktop computers has caused an explosive growth in the number and variety of environmental applications of GIS during the past few years. These advanced technologies offer at least five advantages at scales ranging from individual farm fields to the entire globe. First, they can be used to generate and synthesize new information quickly and cheaply. Second, they may contribute input data for non-point source pollution models. Third, they can be used to document data sources and methods of integration explicitly. Fourth, they provide improved diagnostics for error detection and accuracy assessments. Fifth, they can be used to prepare maps and tables that meet specific needs. However, these potential advantages are currently offset by the difficulty of moving geographic data and model inputs and outputs between different structures and resolutions, our lack of knowledge of statistical methods for summarizing spatial patterns, the difficulty and cost of field validation, and the failure to integrate economic optimization techniques with spatial process models to evaluate the environmental and economic impacts of current and alternative land use practices. Finding ways to increase our knowledge in these areas is vital because the continued development of these advanced technologies will only improve environmental management to the extent that we can utilize the outputs to build sustainable agricultural and urban systems which match land use with land capability.

INTRODUCTION

This chapter examines the role of Geographic Information Systems (GIS) and related technologies for assessing the environmental impacts of agricultural and urban non-point source pollutants. These technologies offer powerful new tools for the collection, storage, management, analysis, and display of map-related information. They are part of what *Openshaw* [1997] refers to as our increasingly "information rich" world. These technologies can be distinguished from other information technologies because of their recency as well as the actors and subject matter involved.

The early GIS software consisted of standalone toolboxes developed by a series of specialized companies (Environmental Systems Research Institute Inc., MapInfo Corporation, Strategic Mapping Inc., etc.). The promotion of their product lines focused on the unique characteristics and challenges of geographic data processing. *Goodchild* [1996] noted several qualities that make geographic data special. First, the real world is infinitely complex and must be approximated in any digital database. Second, there are

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an infinite number of alternative representations for geographic phenomena. Third, geographic data are voluminous and incompatible with other types of information. Fourth, and perhaps most importantly, the ways in which people think and reason about space may not match the digital data structures used in modern geographic information technologies.

Geographic information technologies are also relatively new (compared to other information technologies) and still near the lower end of the growth curve measured in terms of: (1) applications; and (2) their influence as tools on the ways in which scientific inquiries and assessments are conducted [*Goodchild*, 1996]. Environmental modeling has a much longer history. Models have been used to either: (1) increase our understanding of cause-effect relationships in the physical world; or (2) provide a predictive tool for management. However, the rapidly expanding number and variety of GIS-based modeling applications have usually combined this pair of objectives, and utilized data collected and stored at a variety of scales and resolutions.

The choice of project goals and data resolution will have a large impact on the final outcome(s). *Wilson et al.* [1993, 1996] and *Inskeep* et al. [1996] demonstrated how the Chemical Movement through Layered Soils (CMLS) model can be used with a series of digital climate and soil databases to predict the likelihood of contamination of groundwater from spraying noxious weeds in counties. The project outcomes included a workshop for county weed supervisors where the model predictions were delivered as a series of maps showing leaching hazard overlaid on major roads and hydrologic features. The presentation emphasized the ways in which the research project had been organized and how the results could and should not be used. The audience, in contrast, wanted immediate assistance in the form of directions for spraying one side of the road versus the other that eliminated weeds and minimized the threat to groundwater. The failure to deliver this level of assistance can be traced to the differences between research and management models and the need for much finer resolution data to be able to offer the type of assistance that was requested. Non-point source pollution modelers have worked at the molecular, pedon (plot), polypedon (field), watershed, county, region, country, and global scales [*Bouma*, 1997; *Wilson*, 1998]. Anticipation of project objectives and knowledge of data availability will inevitably color any assessment of current and future trends in the development of integrated methodologies for assessing non-point source pollution.

GEOGRAPHIC INFORMATION TECHNOLOGIES

Geographic information technologies have evolved tremendously during the past few years. Table 1 lists the major trends identified in the most influential news stories published in GIS World from January 1996 to July 1997 [*Danielson*, 1997]. Numerous government policy shifts, market consolidations, new data delivery programs, satellite data expansion, and initiatives to improve interoperability are emphasized. However, the computer hardware and software environments have changed as well. These changes and their implications for GIS-based modeling assessments of non-point pollution are discussed in the following subsections.

Geographic Information Systems

Four major sets of changes have reshaped GIS software. First, many GIS software products have migrated from UNIX workstations to PCs running Windows95 and WindowsNT. Second, most GI software providers have developed Web-based map analysis and display tools. Examples include Autodesk's MapGuide, ESRI's MapObjects Internet Map Server for ARC/INFO and Internet Map Server for ArcView, Intergraph's GeoMedia Web Map, and MapInfo's ProServer products. Third, there has also been a shift from generic toolboxes to modular software. This trend is perhaps best exemplified by ESRI, Inc. which has launched a series of new products (ArcView and its extensions including Spatial Analyst and 3-D Modeler; MapObjects; Spatial Database Engine; etc.) to complement ARC/INFO since 1990. Finally, the shift to PCs and modular systems has helped to stimulate the development of customized software linking specific tools and applications. The launch of the CROPSIGHT (Applications Mapping Inc., Frankfort, IL), FARMTRAC (Farm Works Software, Inc., Hamilton, IN), VISAG (Crop Growers Software, Bozeman, MT) and VISION (Rockwell International, Cedar Rapids, IA) precision farming systems in the past few years exemplify this last trend.

Global Positioning Systems

Global Positioning Systems (GPS) constitute another tremendously important innovation because they provide measurements of geographic positions based on analysis of signals from a constellation of orbiting satellites. Differential GPS (DGPS) uses stationary and roving GPS receivers and constitutes an important component of most precision farming applications of GIS. The National Environmentally Sound Production Agriculture Laboratory (NESPAL) in Georgia, for example, specifies four or more ground control points in fields, measures their locations to < 0.1 m with DGPS, and reproduces these points in all GIS layers [*Usery et al.*, 1995]. The field and map locations can be matched in real time because field locations can be measured to < 1 m with a GPS attached to a variable-rate

applicator using a known base station and signal with differential correction [*Schueller and Wang*, 1994; *Usery et al.*, 1995]. Hand-held GPS have also been used with laptop GIS in field surveys [*Carver et al.*, 1994] and one study has examined the effects of GPS intensity and pattern on computed topographic attributes [*Wilson et al.*, 1998].

Automated Data Collection

GPS can also be combined with a series of automated data collection devices to collect spatially distributed information. Continuous yield sensors combine accurate location information collected using a GPS with the results of a variable-rate flow sensor to provide information about this year's crop performance [*Havermale*, 1998]. Sensors have so far been developed for corn, wheat, cotton and peanuts [*Usery et al.*, 1995]. Other instruments operate from the ground surface and build up a remotely sensed image of subsurface layers. Some instruments operate over a short range (ground penetrating radar, electromagnetic induction, etc.) and others operate over a long range (aerial photography, Doppler radar, satellite imagery, etc.). These techniques have been combined with DGPS and used to gather accurate information about the field variability of numerous soil and biological attributes. *Corwin* [1996] lists the remote sensing techniques that are most likely to help with the determination of subsurface transport parameters and non-point source pollution levels.

Satellite Data Expansion

The number and variety of data provided by airborne and space-borne sensors are likely to increase tremendously in the next decade. The early sensors, such as Landsat MSS (1972) and SPOT (1986), were limited to the visible/near infrared portion of the electromagnetic spectrum, and provided data resolutions (10-100 m over days or weeks) that were too coarse for many non-point source pollution applications. The ERS-1 satellite launched in 1991 provided synthetic aperture radar (SAR) imagery of the earth's surface in all weathers and was similar to the Landsat sensors except that it also provided information about the backscattering of the surface in the microwave region of the electromagnetic spectrum [*Wilkinson*, 1996]. The ERS-2, JERS-1, RADARSAT and SPOT-5 satellites, MODIS and MERIS medium resolution imaging spectrometers, and various multiple look-angle sensors will provide information for many more spectral bands at finer spatial resolutions and with improved radiometric calibration in the next decade [*Wilkinson*, 1996].

These new opportunities will require new exploratory data analysis and data mining techniques as well as improved virtual reality and 3-D visualization tools [*Wilkinson*, 1996]. Past attempts to process satellite imagery have incorporated some combination of spatial generalization and classification with the aim of preparing thematic maps for entry into a GIS. The cost and difficulty of these tasks has limited the accuracy and spatial extent of these applications [*Woodwell et al.*, 1984; *Skidmore and Turner*, 1988].

The latest spatial generalization techniques have used edge detection and region growing to create regions with a

Table 1. Geographic Information Industry Trends [after *Danielson*, 1997].

Market Consolidation and Curtailment
Autodesk, Bentley unveil GIS products
U.S. Army Construction Engineering Research Lab (CERL) ends GRASS development
University Consortium for Geographic Information Science (UCGIS) is formed
Sony acquires Etak
ESRI acquires Atlas GIS
ESRI teams with IBM and Informix to spatially enable databases
GDS slashed in convergent group reorganization
GIS Interoperability
Intergraph and Oracle to define object linking and embedding (OLE) standards for GIS data server
Windows use to increase among GIS users
Vendors unite to develop OpenGIS specifications
Microsoft named principal member of OpenGIS Consortium
Satellite Technology Expansion
RADARSAT successfully launched
Space Imaging granted FCC license for satellite systems
Clinton Administration signs GPS directive guaranteeing GPS access
U.S. to discontinue GPS signal downgrade
U.S. seeks international GPS agreements
Data Delivery Diversification
CD-ROM sales soar
Autodesk acquires Argus
Library of Congress to put "Americana" maps on Internet
National Imagery and Mapping Agency (NIMA) posts digital terrain data on Internet
National Center for Geographic Information and Analysis (NCGIA) to develop WWW-based GIS Core Curriculum
Government Policy Shifts
Department of Defense and Central Intelligence Agency to form new imaging agency
Congress supports use of private firms for surveying and mapping
U.S. Army uses GIS in Bosnian corridor
GIS programs suffer losses in Clinton budget

high degree of homogeneity [*Wilkinson*, 1996]. Edge detection algorithms search for edges or discontinuities in an image and region growing algorithms start from seed points and add pixels until a discontinuity is identified. These techniques, like the spatial filters (i.e., numerical techniques that remove entropy from neighborhoods around pixels) that preceded them, have met with mixed success [*Wilkinson*, 1996].

Recent work on classification techniques has focused on the use of spatial and textual information from image space, knowledge-based and evidential reasoning methods, and artificial neural networks [*Wilkinson*, 1996]. The use of various types of ancillary data with traditional classification methods has produced only modest improvements in classification accuracy [e.g., *Niemann*, 1996; *Wheatley et al.*, 1998]. Knowledge-based, evidential-reasoning methods weigh evidence consisting of ancillary data, heuristics, and facts (which may be very simple or complex) and assigns classes accordingly [e.g., *Coughlan and Running*, 1996; *Gahegan and Flack*, 1998]. However, these methods are often expensive to implement because of large setup costs. Neural networks consist of interconnected networks of simple processing elements that can be used to classify or cluster data. These methods make very few statistical assumptions about input data, can utilize parallel processing, and represent a very promising approach as we search for methods that can find and extract patterns from the new remote sensing data sets that will become available in the next few years [*Wilkinson*, 1996].

New GIS-Based Digital Data Sets

The number and variety of environmental GIS data sets has also increased tremendously during the past few years. The continuing development of digital Soil Survey Geographic Database (SSURGO) products for counties and other soil survey areas has important implications for GIS-based non-point source pollution modeling applications. The SSURGO database reproduces the soil mapping units portrayed at scales of 1:15,000-1:20,000 on county soil survey maps and records the attributes by soil layer (horizon) for 1-3 soil series in each mapping unit. *Wilson et al.* [1996] examined the impacts of using these data in place of the State Soil Geographic Database (STATSGO) that is currently available. *Foussereau et al.* [1993], *Maclean et al.* [1993], *Rogowski and Hoover* [1996], and *Rogowski* [1997] have proposed several options for combining these data with other data sets to predict continuous changes in soil attributes. In addition, several new approaches for predicting soil attributes that abandon the traditional soil survey paradigm altogether have been proposed and are discussed in the next section.

Improved estimates of land cover have also been generated. Many GIS-based modeling applications have exploited the tremendous potential of Landsat TM and SPOT imagery to provide spatially distributed estimates of land cover during the past decade [*Wilson*, 1998]. However, the large volumes of data and complexity of data acquisition and analysis make this approach prohibitively expensive for all but small areas [*Woodwell et al.*, 1984]. Recent attempts to prepare land cover assessments for large areas (e.g., multiple counties, states, continents) have focused on the potential application of meteorological satellite data for such ventures [*Loveland et al.*, 1991].

Loveland et al. [1995] have generated a multi-level, digital, geographically referenced land cover database for the continental U.S. that serves as a prototype for a global land cover database currently under development. The database is based on the statistical analysis of multi-date, Advanced Very High Resolution Radiometer (AVHRR) satellite data complemented by elevation, climate, ecoregion, and other digital geographic data sets. The prototype has a spatial resolution of 1 km^2 and divides the continental U.S. into 159 seasonal land cover classes representing alpine tundra (4), western forest (43), shrubland (18), grassland (17), cropland (56), eastern forest (16), coastal wetland (3), barren land (1), and water (1) cover types. However, these data should be used with care at the local (county and larger) scales until a more rigorous accuracy assessment is completed [*Wilson*, 1998].

The third and final set of new data products will result from the Digital Orthophoto Quadrangle (DOQ) program of the United States Geological Survey (USGS) [*http://nsdi.usgs.gov/nsdi/products/doq.html*]. This program aims to produce digital orthophotos for the continental USA at a resolution of 1 m and positional accuracy of 6 m. These photographs will help tremendously with the verification and integration of other data and the visualization of the results of GIS-based modeling applications

New Data Delivery Options

The development of new data delivery options as well as new satellite sensors and other data capture tools have encouraged many of these efforts to develop new data sets. Some of the new delivery options are linked to continuing developments related to CD-ROMs and disk drives. Others are linked to the World-Wide Web (WWW) and the role of GIS in massive, far-reaching, and ongoing information technology (IT) developments, such as digital libraries, data marts, data warehouses, data mining, and universal networking [*Openshaw*, 1997].

These new opportunities elevate the importance of metadata or information about where and when and how

the data were collected and by whom. The Federal Geographic Data Committee [*FGDC*, 1994] has proposed a national spatial data infrastructure (NDSI) and specified guidelines for describing the minimum metadata required for different types of GIS information. This metadata information is required for users to decide if a particular data set is adequate for their particular purpose(s).

Consequences

The technological developments summarized in the previous subsections have a number of important consequences for environmental applications of GIS. At one level, GIS users in new markets such as precision agriculture have complained that existing GIS: (1) are difficult to use, (2) include numerous superfluous functions, and (3) lack several other important functions [*Usery et al.*, 1995]. However, the latest precision farming software may convert generic GIS and database solutions into user-friendly farm management systems, but they still lack the required functionality (statistical tools). At another level, there has been an explosive growth in the number and variety of new data capture techniques. There is some evidence that these innovations are rapidly exceeding the pace of developments with GIS and related data analysis techniques, and several commentators have speculated that this state of affairs is likely to produce an "information rich" but "knowledge poor" world [*Bouma*, 1997; *Openshaw*, 1997]. The remainder of this chapter, therefore, seeks to situate these technological developments in a broader environment of innovations and explore the implications of these changes for GIS-based modeling assessments of non-point source pollution.

OTHER INNOVATIONS

The flow and transformation of information from observation (reality) to geographic data model, process data model, and better (knowledge-based?) resource management is key here. The outcomes depend on the data representations, GIS functions, and model development tools used for GIS non-point source pollution modeling applications. New developments in these areas are discussed in more detail in the three subsections that follow.

Data Representations

Goodchild [1996] wrote that "data modeling is a complex and often subtle process that extends from the design of surveys and instruments for capturing raw data through the various manipulations that occur before the data are finally ready to be analyzed or displayed [or used in non-point source pollution models]". The choice of data model is one of the most important and fundamental questions raised by the development and exploitation of GIS because these systems offer numerous choices and each of the sampling and processing decisions that are made will affect the types of applications that can be supported.

The options currently implemented in GIS databases are based on either the field or entity views of spatial variation [*Goodchild*, 1992, 1996]. The field view is used more frequently for environmental applications, and GIS databases currently provide six methods of discrete, digital representation as follows:

- a regular rectangular array of cells with the average value recorded in each (*raster model*);
- a regular rectangular array of sample points (*grid* model);
- an irregularly spaced set of sample points (*point* model);
- a polyline representation of a set of isolines (*contour* model);
- a set of planar enforced irregular polygons with the average value recorded in each (*polygon* model);
- a set of planar enforced irregular triangles in which the variation is assumed to be planar (*triangulated irregular network* model) [Figure 1; *Goodchild,* 1996].

The *raster* and possibly the *grid* field data models are suited to environmental modeling applications because these models are roughly equivalent to the processes of discretization and numerical approximation used in environmental process modeling [*Burrough*, 1996a; *Goodchild*, 1996; *Maidment*, 1996a].

Kemp [1997a, 1997b] recently advocated the design of a level of user interaction that would focus on the user's concept of the field and hide lower level issues of field representation as far as possible. *Kemp* [1997a] proposed a series of rules to guide conversions between data models based on the number of spatial elements per unit area (i.e., the relative size or spacing of the spatial elements). *Kemp* [1997b] described several field variables whose values can be used to select appropriate conversion procedures when working with two or more spatial data models. These ideas need to be developed further, since the choice of and conversion from one field model to another is fraught with difficulties [*Heuvelink*, 1996]. *Custer et al.* [1996] and *Stillman* [1996], for example, evaluated different methods of converting *point* precipitation data to the *contour* and *raster* data models.

Custer et al. [1996] estimated average annual precipitation for a mountainous area in Montana during the period 1961-90 with thin plate splines [ANUSPLIN; *Hutchinson*, 1991, 1995] and compared the output to a

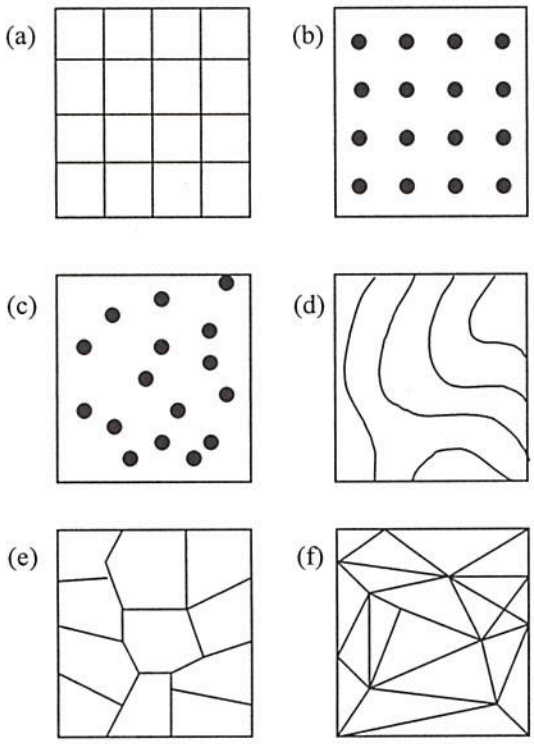

Figure 1. Schematic diagram showing raster (a), grid (b), point (c), contour (d), polygon (e), and triangulated irregular network (f) data models currently implemented in GIS databases.

hand-drawn map. Input data included latitude, longitude, and elevation from a 3 arc-second USGS DEM and precipitation data at 96 climate stations. The two maps were similar in appearance and statistical analysis revealed that 53 percent of the 5,760,000 cells showed no difference and another 33 percent of the cells varied by one contour interval. *Stillman* [1996] compared ANUSPLIN, MTCLIM-3D [*Running and Thornton*, 1996], and PRISM [*Daly et al.*, 1994; *Daly and Taylor*, 1996] model performance and found that the models produced statistically similar monthly mean precipitation estimates for a 60,000 km^2 study area covering parts of Idaho, Montana, and Wyoming during the period 1961-90. The largest differences occurred in mountains where the density of climate stations was lowest and topographic variation was greatest. These variations were substantial and could have a large impact when used as model inputs on model performance at hillslope and catchment scales. These results also demonstrate that most interpolation procedures will only perform satisfactorily when there are adequate input data.

These issues are important because the representational choices will influence the ways in which scientific investigations are carried out and the quality of the outputs [*Burrough*, 1996b; *Heuvelink*, 1996]. The challenges with scale and resolution noted earlier recur here, and the scientist must somehow integrate the natural scale of the phenomena of interest, the measurement scale, geographic data modeling scale, process modeling scale, and management scale.

Reconciling these different scales and resolutions can be extremely difficult (Figure 2). Numerous natural scales and levels of aggregation characterize the phenomena of interest in non-point source pollution applications (Figure 3). The measurement scale can vary from a few millimeters of soil or a few square millimeters in area to a satellite pixel of up to 5 km x 5 km [*Burrough*, 1996a]. The geographic modeling scale varies with the choice of data model [*Kemp*, 1997a]. However, square grids measuring 30 m or 100 m on a side are frequently used for environmental modeling applications because these resolutions match those used for digital elevation model data sets distributed by the United States Geological Survey [*Wilson*, 1996]. The modeling scale varies from one model to the next and is tied to the levels of spatial and temporal aggregation built into a model's assumptions [*Maidment*, 1996a; *Wilson*, 1996]. In addition, the shortest critical space and time scales incorporated in a model will affect the way the model is built and optimized, and the type of data that is required [*Burrough*, 1996a]. The management scale may vary from a farm field to a large river catchment, and will seldom match any of the other scales noted above.

Three observations are warranted with respect to this state of affairs. First, there remains an urgent need for new measurements that yield areal distributions or at least reliable totals or averages of hydrologic variables such as precipitation, evapotranspiration, and soil moisture

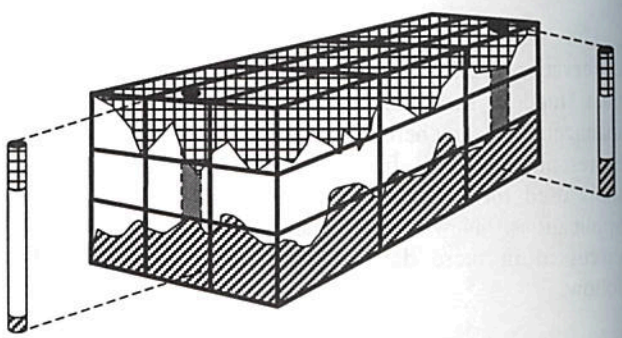

Figure 2. Schematic 3D diagram of a landscape showing why the conversion of single measurements to block averages is nontrivial [after *Burrough*, 1996a].

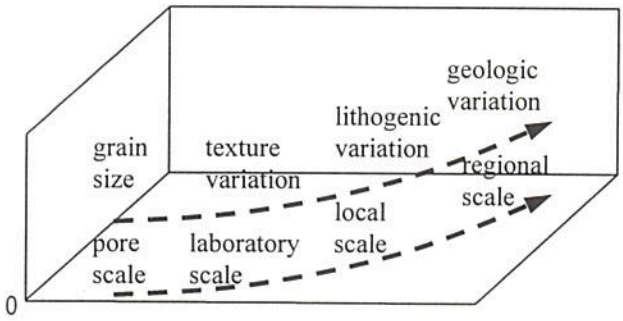

Figure 3. Scales and levels of aggregation commonly used in non-point source pollution modeling studies [*after Burrough*, 1996a].

[*Klemes*, 1986; *Corwin*, 1996]. Second, there is a need for further work on GIS-based spatial interpolation techniques because the quality of the predicted values will ultimately depend on the number and distribution of data points, the spatial correlation structure and how well this is known, and the method used for interpolation [*Burrough*, 1996a; *Heuvelink*, 1996]. Third, the uncertainty should be examined more carefully when using generalized as opposed to measured data [*Loague*, 1994; *Corwin*, 1996]. Simple models such as CMLS [*Nofziger and Hornsby*, 1986] require at least a dozen input parameters and more sophisticated models such as LEACHM [*Wagenet and Hutson*, 1989] require substantially more parameters or variables that are usually extremely difficult and time consuming to measure [*Inskeep et al.*, 1996; *Maidment*, 1996b]. Soil survey data are a special problem in this respect, and some new approaches for improving these data are discussed in the next section.

GIS Functions and Data Analysis Tools

There has been a steady increase in the number and variety of functions incorporated in GIS that may be used for non-point source pollution modeling applications in recent years. This trend is best exemplified by the GRASS GIS environment whose open architecture is particularly suited to the rapid prototyping of new functions to support environmental modeling applications [*Goodchild*, 1996; *Lovejoy et al.*, 1977; *Wilson and Lorang*, 1998; *see Mitasova et al.*, 1996 and *Mitas et al.*, 1996 for specific examples].

The inclusion of several new terrain analysis tools, kriging, and related geostatistical techniques represent very important innovations in this respect. The inclusion of the ANUDEM [*Hutchinson*, 1989] elevation gridding procedure in ARC/INFO (Versions 7.0 and higher) and development of a series of new terrain analysis tools in TAPES [*Wilson and Gallant*, 1997] and GRASS provide important new opportunities for GIS-based non-point source pollution modeling.

ANUDEM and TOPOGRID (as it is called in ARC/INFO) take irregular point data or contour data and create square-grid DEMs. The procedure automatically removes spurious pits within user-defined tolerances, calculates stream lines and ridge lines from points of locally maximum curvature on contour lines, and (most importantly) incorporates a drainage enforcement algorithm to maintain fidelity with a catchment's drainage network [*Hutchinson*, 1989]. The increased availability of GPS-derived elevation data and difficulty of using published USGS DEMs for hydrologic studies documented by *Hammer et al.* [1994], *Zhang and Montgomery* [1994], *Hodgson* [1995], and *Mitasova et al.* [1996] suggest an important role for these types of tools in the future.

Several recent projects have explored the consequences of choosing one or more of these tools. *Bolstad and Stowe* [1994] evaluated the accuracy of elevations, slopes, and aspects computed from USGS 7.5 minute quadrangle-based DEMs and SPOT-STX DEMs. Their results showed that the Gestalt Photomapper-derived USGS DEM provided a better representation of microtopography. *Gao* [1996] examined the impact of DEM resolution on the accuracy of terrain representation and slope gradients in three distinctive study areas. The results showed that representation accuracy decreased moderately at intermediate resolutions and sharply at coarse resolutions in all three types of terrain. Resolution changes also had a large impact on computed slope gradients. One would expect even larger impacts for topographic attributes that are calculated as second derivatives, such as plan and profile curvature [*Moore*, 1996]. *Carrara et al.* [1997] defined a series of objective criteria for evaluation of the quality of digital terrain models (DTMs) derived from contour lines. These criteria were used to evaluate four different interpolation procedures: the *r.surf.contour* procedure in GRASS (Version 4.1), the MDIP procedure developed by Carla' and Carrara [*Carla' et al.*, 1997; *Carrara*, 1988], the ArcTin procedure in ARC/INFO (Version 7.0), and the Terrain Modeler procedure in Intergraph's MGE GIS (Version 5.0). The first two procedures generated square-grid DEMs and the last two procedures generated TINs. These methods were applied to three sample areas and the results showed that the MDIP and Terrain Modeler techniques performed best in that they produced terrain models that reflected the ground surface as expressed by the input contour lines.

The Terrain Analysis Programs for the Environmental Sciences (TAPES) calculate a series of spatially distributed hydrological, geomorphological, and ecological variables in natural landscapes from contour- and grid-based DTMs.

These programs utilize the UNIX operating and X window systems. They were originally developed by *Moore* [1992] and have been subsequently modified and added to by various contributors. The grid-based versions of these programs include TAPES-G [*Gallant and Wilson*, 1996], DYNWET, [*Barling et al.*, 1994], EROS [*Wilson and Gallant*, 1996], and SRAD [*Wilson and Gallant*, 1998].

TAPES-G calculates slope, aspect, upslope contributing area, curvature (profile, plan, and tangential), flow direction, and flowpath length. A depressionless DEM can be created and the user can select one of four alternative methods for estimating upslope contributing area. The options are the D8 [deterministic eight node; *O'Callaghan and Mark*, 1984] and Rho8 [random eight node; *Fairfield and Leymarie*, 1991] single flow direction algorithms, the FD8/FRho8 multiple flow direction algorithm [*Freeman*, 1991; *Quinn et al.*, 1991], and the DEMON stream tube algorithm of *Costa-Cabral and Burges* [1994]. The choice of flow routing algorithm can have a large impact on computed topographic attributes [*Wolock and McCabe,* 1995; *Desmet and Govers*, 1996, *Wilson and Repetto,* 1998], although more work is required to know which of these algorithms works best in specific environments [*Wilson*, 1998]. This is an active area of research, and modified forms of the FD8/FRho8 algorithm and a new grid-vector multiple flow routing algorithm were recently proposed by *Quinn et al.* [1995] and *Mitasova et al.* [1996], respectively.

DYNWET calculates topographic wetness indices based on either a steady-state or quasi-dynamic subsurface flow assumption. EROS calculates soil loss and erosion potential. SRAD calculates short- and long-wave radiation fluxes, energy balances, and indices. Stream networks, subcatchments, and the spatial distribution of individual topographic attributes can be plotted interactively or copied to the ARC/INFO GIS for further analysis and display [*Wilson and Gallant*, 1997]. These tools have been used to predict selected soil attributes [*Moore et al.*, 1993a, 1993c], soil erosion and deposition [*Moore and Wilson*, 1992, 1994], soil water distribution and the location of ephemeral gullies [*Moore et al.*, 1988, 1993c], and land cover [*Moore et al.*, 1993b].

Several new sets of tools have also been added to the GRASS GIS (*http://www.cecer.army.mil/grass*) in recent years. One set can be used to create spline-based DEMs with tunable tension and smoothing [*Mitasova and Hofierka*, 1993]. This set of tools is similar in function to ANUDEM and TOPOGRID. A new vector-grid multiple flow routing algorithm has also been developed that can be used to direct the flow of water across the landscape [*Mitasova et al.*, 1996]. This new algorithm requires further testing, although it will almost certainly produce superior results in upland areas compared to the D8 single flow direction algorithm that is still used in many GIS. Finally, a series of new procedures have been developed for calculating continuous forms of several secondary terrain attributes that can be used for modeling soil erosion and deposition [*Mitasova et al.*, 1996]. *Mitas et al.* [1996], for example, solved the 2D continuity equation for steady-state overland flow and the appropriate equations for the sediment flux in complex terrain in the GRASS GIS. These equations were then used with the GIS tools to simulate the impact of complex terrain and various soil and land cover changes on the spatial distribution of soil erosion and deposition.

These new terrain analysis tools can be used to predict soil attributes as well as the movement of water and contaminants through landscapes. In one such study, *Bell et al.* [1994] developed a soil-landscape model that used multivariate discriminant analysis and class frequency information to predict soil drainage class from parent material, terrain, and surface drainage feature variables for the unglaciated ridge and valley physiographic province of Pennsylvania [*Bell et al.*, 1992]. The terrain and surface drainage model inputs were generated using a series of operations found in many GIS, from published DEMs (30 m resolution) and hydrography (as represented on 1:24,000 scale topographic maps). Combinations of the landscape variables were defined by overlaying the digital maps and applying the soil-landscape model to create maps of soil drainage class probability and most likely soil drainage class (Figure 4).

The predicted soil drainage class map agreed with the county (1:20,000 scale) soil survey for 67 percent of the study area and with 69 of 72 (95 percent) randomly selected field locations. The largest discrepancies between the model and soil survey maps occurred in areas predicted as somewhat poorly drained to moderately well drained by the model and well drained by the soil survey (cf. Figures 4b and 4c). These techniques offer as many as four advantages [*Bell et al.*, 1994]. First, they consistently assign soil drainage class based on landscape attributes. Second, they record metadata and decision criteria used for drainage class assignments. Third, they estimate the uncertainty associated with the drainage class assignments (Figure 5a). Fourth, these techniques generate a digital database for GIS applications (Figure 5b).

This application is also indicative of the shift in conceptual paradigms of soil survey and mapping that has occurred during the past 30 years [*Burrough et al.*, 1997]. The early models, exemplified by the STATSGO and SSURGO databases, used crisp classes in attribute space linked to crisply delineated mapping units in geographical space. A series of recent models has utilized fuzzy

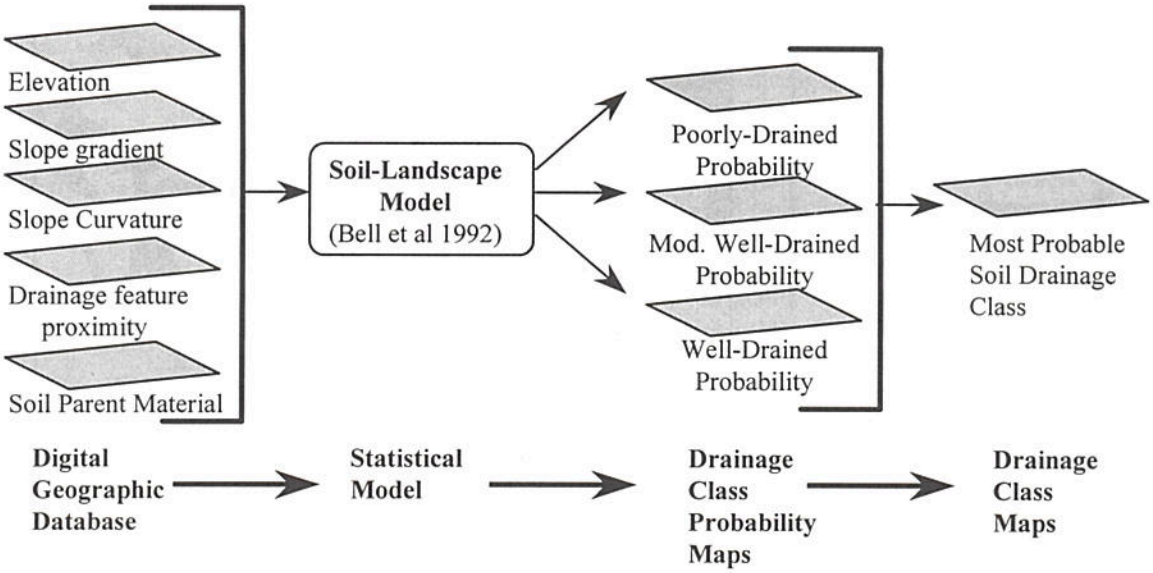

Figure 4. Procedure used to create drainage class maps using soil-landscape model [after *Bell et al.*, 1994].

classification and geostatistical interpolation for simultaneously handling continuous variation in both attributes and location. The basic strategy was recently described by *McBratney and Odeh* [1997], and can be summarized as follows.

The observations in fuzzy classifications are grouped into continuous classes based on continuous class membership values that vary between 0 and 1 depending on their degree of closeness to pre-defined classes or class centroids (class means). The values vary with the membership functions (MFs) used in assigning membership values and the attribute space between the individuals and the centroids of the classes. Two different but complementary approaches are used to group individuals into fuzzy sets of classes [*McBratney and Odeh*, 1997]. One is based on fuzzy c-means (FCM, also known as k-means) partitioning of observations in multivariate space into naturally occurring groups. Membership of an extragrade class is sometimes used to accommodate outliers [*De Gruijter and McBratney*, 1988]. The second approach is based on the Semantic Import (SI) model where a MF is defined without reference to the data. The class limits are specified based on experience or conventionally imposed definitions before individuals are allocated on the basis of how closely they match the requirements of the class [*Burrough et al.*, 1997; *McBratney and Odeh*, 1997].

The first approach is illustrated by *Irvin et al.* [1997], who used continuous (fuzzy set) and unsupervised (ISODATA) classification techniques to identify landform elements related to soil development processes in a 50 ha study area in southwestern Wisconsin. Each grid cell in a 10 m DEM was grouped based on its membership in a continuous landform class using the fuzzy k-means technique in MacFuzzy [*Ward et al.*, 1992]. The classes were determined by the natural clustering of the data in attribute space, based on elevation, slope, profile and tangential curvature, topographic wetness index, and incident solar radiation. The first five attributes were calculated with TAPES-G [*Gallant and Wilson*, 1996] and the final attribute was calculated using SOLARFLUX [*Rich et al.*, 1994], an Arc Macro language routine that is implemented in the GRID module of ARC/INFO. The ISODATA [*Tou and Gonzales*, 1974] algorithm is one of the most widely used unsupervised clustering algorithms for satellite image classification. The ISODATA classification of the topographic attributes in this study was performed with the ISOCLUSTER and MLCLASSIFY functions in the ARC/INFO GRID module. The computer-based classifications produced with these methods not only followed the subjective manual landform delineation, but they also provided more quantitative and detailed information.

The second approach is illustrated by *Zhu* [1997, 1998 - this publication], who developed a fuzzy-logic based similarity model and used it to represent soil information in the Lubrecht Experimental Forest of western Montana. The similarity model combined a similarity representation component and a raster representation scheme. The similarity representation component used a set of

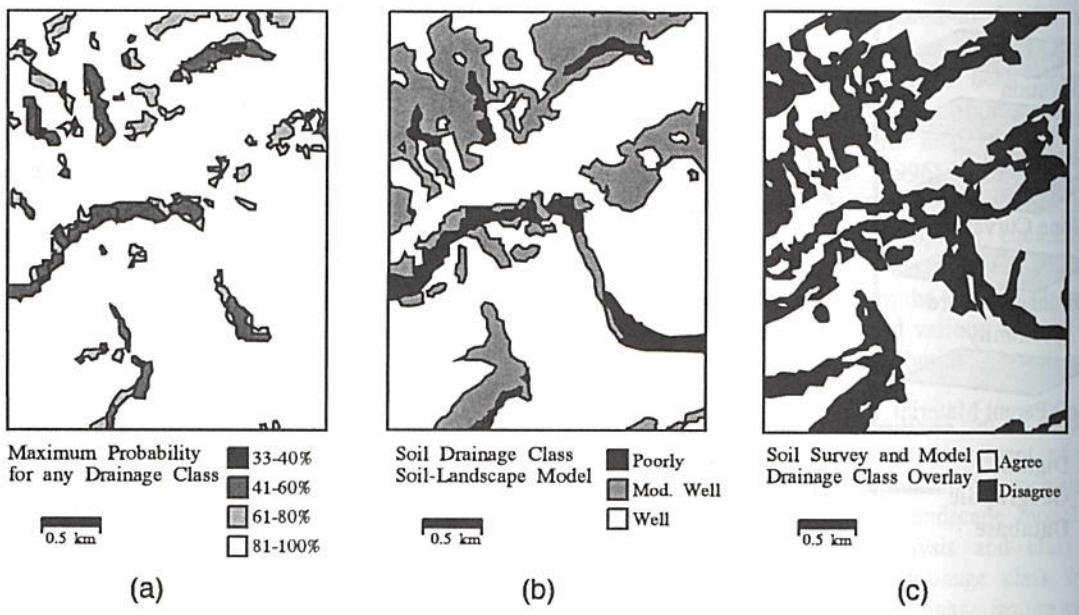

Figure 5. Maximum probability of any soil drainage class (a), soil drainage class map generated by soil-landscape model (b), and areas of agreement and disagreement between soil-landscape model and soil survey map of soil drainage class (c) at Licking Creek study site [after *Bell et al.*, 1994].

prescribed soil taxonomic categories as the central concepts of fuzzy soil classes and represented a soil at a given location as a set of similarity values relative to these central concepts (Figure 6). The sum of the values in the soil similarity vector can vary from 0 to n (where n is the number of classes and the local soil displays high similarity values to a number of similar soil classes). Values approaching 0 occur where a local soil is very unique and does not bear much similarity to any of the prescribed soil classes. The soil series was used as the soil taxonomic unit in this study and knowledge of the relationships between individual soil series and a set of six environmental variables was obtained from a local soil expert through the use of an iterative and structured interview process [Figure 7; *Zhu*, 1997]. Elevation, slope, aspect, and profile curvature were estimated from a 30 m USGS DEM, canopy cover was estimated from Landsat TM imagery, and soil parent material was derived from a geological map of the area. The fuzzy inference engine was then used to calculate each of the similarity values for the soil at a location to each of the prescribed soil series (Figure 7). These similarity values formed a soil similarity vector that was combined with a raster representation scheme and used to represent the soil information as an array of soil similarity vectors [*Zhu and Band*, 1994; *Zhu et al.*, 1996, 1997, 1998 - this publication].

Zhu [1997] claimed two advantages for this approach. First, the soil information can be represented at the resolution of the raster data model rather than the soil

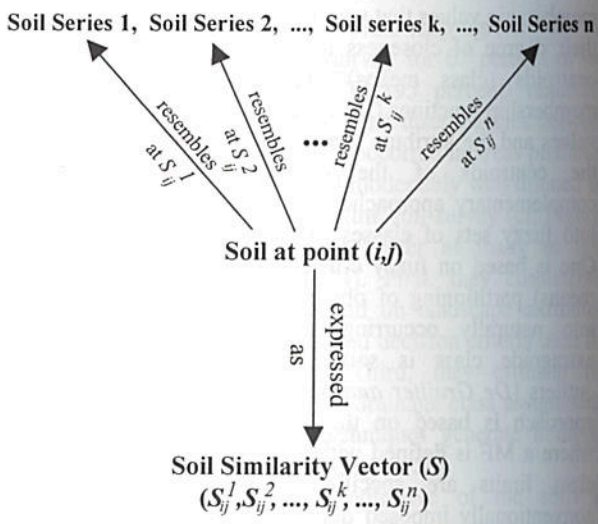

Figure 6. Fuzzy representation of soil information [after *Zhu*, 1997].

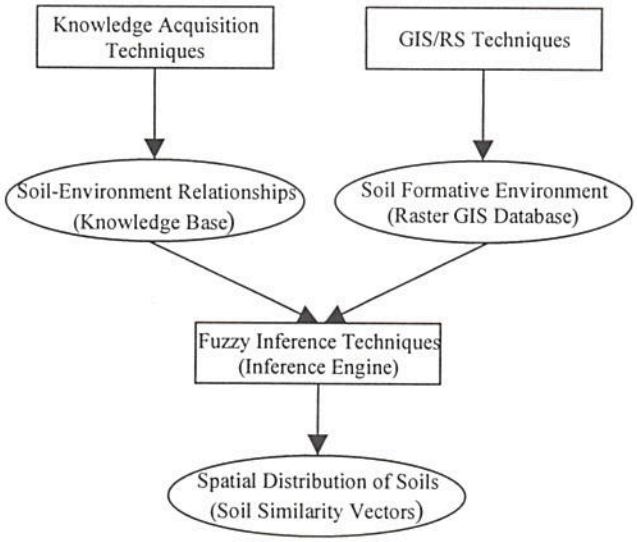

Figure 7. The general approach for deriving soil similarity vectors advocated by *Zhu* [1997].

mapping units used in the conventional soil survey. Second, the soil properties at a given location can take intermediate values compared to the typical values of the prescribed soil types. Hence, the results of applying this method to a 37.5 km^2 study area in the Lubrecht Experimental Forest showed that the information represented in this model has a higher resolution at both the spatial and attribute levels compared to the conventional soil map of the area.

This type of approach can also be implemented with the points, lines, and polygons that characterize the vector data model. *Wang et al.* [1990] proposed a fuzzy relational data model that is easily implemented in the ARC/INFO GIS by viewing membership grades as domains of relations. They represented areas as vectors in feature space and used the distance between the area vector and the class as a measure of their similarity. *Wang et al.* [1990] performed a land suitability assessment for five land uses in Indonesia to illustrate their approach. The membership functions in this case study were obtained from published literature and evaluated with the physiographic characteristics expressed in a series of thematic maps to assign absolute and relative suitability ratings for the five crops.

The approach employed by *Wang et al.* [1990] is very similar to that of *Zhu* [1997] except that it works with points, lines, and polygons instead of raster cells. It is also similar to the prototype soil information system with fuzzy retrieval capabilities of *Kollias and Voliotis* [1991] in that it is based on a fuzzy relational database model and supports fuzzy database queries.

Many of these applications have combined soil profile data with topographic attributes derived from DEMs and satellite data inside GIS to generate spatially distributed predictions of one or more soil properties. In addition, several of the applications illustrate how the fuzzy membership values for soil profiles (point observations) can be interpolated to continuous surfaces (maps) in a GIS to produce new kinds of maps if the classes in attribute space are spatially contiguous.

However, the spatial interpolation methods and cartographic representation techniques must be chosen carefully. *De Gruijter et al.* [1997], for example, combined the fuzzy k-means with extragrades classification method with newly developed spatial interpolation and cartographic representation methods. Their interpolation of soil profile data was performed with compositional kriging, which is a straightforward extension of ordinary kriging applied to compositional data (i.e., fuzzy memberships and other data sets in which all variables measured on an individual are non-negative and add to a fixed total). They argued that this particular spatial interpolation method is superior to ordinary and co-kriging because it satisfies four key requirements. First, each of the individual estimates will be greater than or equal to 0. Second, the memberships sum to 1.0 at each estimation point. Third, the estimates are unbiased and finally, the variance of the estimation errors is minimized [*De Gruijter et al.*, 1997].

Several techniques have also been proposed and used to produce cartographic representations of these continuous classifications. The map in Figure 8, for example, shows the core areas of continuous classes and the extragrade with the white areas between the cores as the intragrades (i.e., individuals that have less than 0.5 degree of membership to any of the continuous classes). Alternatively, separate maps can be produced for each class [*McBratney et al.*, 1992]. This approach retains much more information about the distribution model but at the cost of a loss of a coherent overview of all classes simultaneously [*De Gruijter et al.*, 1997].

De Gruijter et al. [1997] proposed a pixel mixture cartographic representation technique to avoid these problems. They generated a grid of colored pixels within each cell whereby the individual colors represented individual classes and the proportions of pixels with the same colors matched the memberships predicted for that cell. This method was implemented in the PC-RASTER GIS [*van Duersen and Wesseling*, 1992] and used to show the internal variation within individual classes and the gradual transitions between soil types as well as the similarities between the continuous classification and the existing soil map.

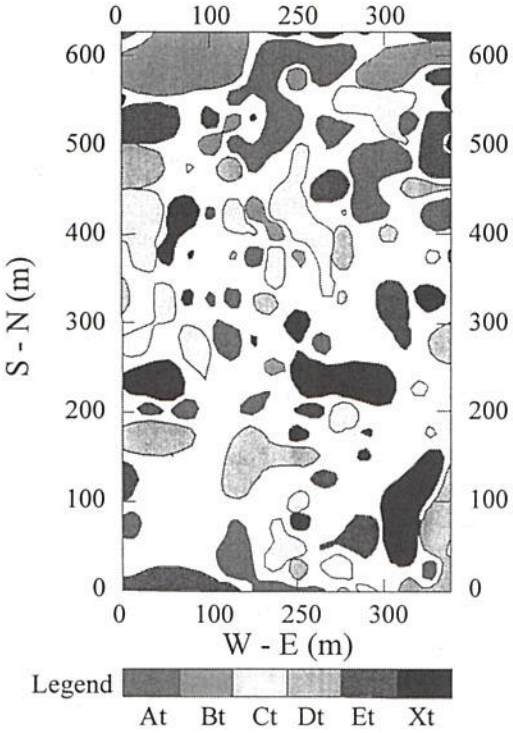

Figure 8. Composite map showing the core areas of continuous classes of textural profiles. The first five legend classes labeled *At* through *Et* indicate unique soil textures and *Xt* is the extragrade class [after *McBratney and Odeh*, 1997].

Burrough et al. [1997] reviewed many of the same concepts and proposed a confusion index to distinguish those regions of the map where two or more class membership values are very similar from those regions where one class dominates. The values of this index vary between 0 (when one class dominates and there is little confusion) and 1 (when the membership values for two or more classes are near equal and there is confusion about the class to which a site belongs). The index utilizes the spatial correlation structure of the continuous classes to distinguish those parts of the landscape where quantitative, numerically defined soil attribute classes are spatially contiguous and those areas where the classes are spatially complex or overlapping. *Burrough et al.* [1997] illustrated both of these results using study areas in Venezuela and Canada.

The knowledge gained from these applications and the incorporation of kriging and other geostatistical methods in several GIS means that it is now possible to perform several types of spatial interpolation and to determine which approach is most sensible for any given application [*Burrough*, 1992; *Burrough et al.*, 1997]. In addition, this state of affairs also means that the values of soil properties obtained when a GIS is queried are increasingly likely to be estimates derived by methods of spatial interpolation such as kriging from actual data stored in the GIS. These estimates are obtained with error because uncertainty of prediction (cast in statistical terms) and uncertainty of interpretation (when the complexity of the processes produces a confusion index approaching 1) both affect the output of the GIS [*Davis and Keller*, 1997; *Lark and Bolam*, 1997].

Lark and Bolam [1997] suggested that the uncertainty of prediction and of interpretation for a soil property at a site could be represented by a 'weighted' membership in a fuzzy set. They divided the range of values of the selected property into discrete intervals, and estimated the conditional probability that the true value of the property lies within each interval by disjunctive kriging. The weighted membership was obtained by summing over all intervals the product of the conditional probability and the value of the MF corresponding to the mean value of the soil property for that interval. Values of the weighted membership close to 0 or 1 are generated at specific locations whenever the uncertainties of prediction and interpretation are low, and values close to 0.5 are generated whenever the uncertainty of prediction and/or interpretation prevents an unambiguous conclusion. *Lark and Bolam* [1997] demonstrated the importance of this statistic with reference to two data sets, and described several situations where it may be preferable to develop methods for using information on the two sources of uncertainty separately.

The fuzzy methods may also help with the processing and interpretation of existing GIS data layers [*Wang and Hall*, 1996; *Davis and Keller*, 1997]. In one recent study, *Wang and Hall* [1996] used fuzzy representation of geographical boundaries to address the problem of misrepresentation of continuously distributed phenomena created by the use of crisp polygon boundaries (typical of vector GIS) where gradual changes in thematic properties are likely to occur. They defined the MF of the boundary fuzzy set in terms of the first-order derivative of the property of interest, and showed how this approach could be used to minimize the degree of error in polygon generalization by approximately 50 percent. *Wang and Hall* [1996] concluded that their method could improve processing accuracy, assist with the mapping of transition zones, and provide increased flexibility and realism in the way this information is conveyed to the computer during processing.

Overall, these results indicate that the shift from crisp to fuzzy classification and representation paradigms is likely to have an enormous impact on future GIS-based non-point source pollution modeling applications. These methods are likely to influence the ways in which soil and other types of

environmental information are captured and displayed in the future. These changes are likely to improve both the model inputs and the ways in which uncertainty and error in model inputs and outputs are handled. Two recent modeling applications described by *McBratney and Odeh* [1997] illustrate these possibilities, and the major components are highlighted here.

Bardossy and Disse [1993] and *Bardossy and Duckstein* [1995] fuzzified the commonly used finite-element solution of the Richards equation [*Richards*, 1931] to simulate water movement through the vadose zone of the soil. This equation can be solved so long as you know or can estimate the moisture content (θ), the hydraulic conductivity ($K(\theta)$), and the matric head ($\psi(\theta)$, which is also a function of moisture content). The hydraulic properties of a soil can be described by the curves of $\psi(\theta)$ and $K(\psi)$ using van Genuchten's equations [*van Genuchten*, 1980]. However, these equations require five variables for each spatial unit as inputs that are difficult to measure or estimate. These variables are the residual water content (θ_r), saturated water content (θ_s), saturated hydraulic conductivity (K_s), van Genuchten's shape parameter (n), and van Genuchten's scale parameter (α).

Bardossy and Disse [1993] used two linear coefficients, K_s and θ_s, with a series of rules based on the moisture condition in the immediate neighborhood of each location to describe vertical movement in the vadose zone. Their fuzzy rule-based model outperformed the finite-element model soiutions generated with both Richards equation and the *Green and Ampt* [1911] model [*Bardossy and Duckstein*, 1995]. The *Green and Ampt* [1911] model requires the same five inputs as the Richards equation.

The fuzzy Richards model can also be extended to three dimensions to predict flux in lateral as well as vertical directions. *McBratney and Odeh* [1997] suggested that further work is required to evaluate the impacts of incorporating the fuzzy rule-based approach in more complex models, such as LEACHM [*Wagenet and Hutson*, 1989].

The concepts and methods discussed in this section can be implemented with current GIS and are likely to transform the ways in which non-point source pollution models are constructed and applied in the next few years. Viewed this way, they represent innovations that can be implemented immediately. Few of the ideas related to three-dimensional data structures, hierarchical data structures, dynamic segmentation, and temporal change that were discussed by *Goodchild* [1996] in his review of recent innovations can be implemented in currently available GIS software. Indeed, *Goodchild* [1996] thought that progress in these areas was unlikely until the conceptual discussion of data models can be raised from the raster-vector debate that has dominated GIS database assessments for the past decade to the level of the entity and field models discussed earlier.

New GIS-Based Modeling Opportunities?

There have also been numerous attempts to develop models inside GIS. *Wesseling and van Duersen* [1995] programmed a complex series of dynamic mass transport and mass balance processes in an advanced, GIS-compatible model building language developed from map algebra [*Wesseling et al.*, 1996]. *Mitas et al.* [1996] programmed a similar series of tools in the GRASS GIS and used them to model spatially distributed soil erosion and soil deposition in a series of catchments. In other developments, *Takeyama and Couclelis* [1997] have developed map algebra extensions of cellular automata [*Wolfram*, 1984] that are capable of expressing a variety of dynamic spatial models and spatial data manipulations in a common framework. *Raper and Livingston* [1995] have implemented a series of object-oriented geomorphological models that combine functions and data. Object orientation does offer greater ease in transferring data from one system to another and increased interoperability between systems. Some proponents of object orientation have argued this approach matches the ways in which people think and reason about space more closely than the entity and field data models discussed earlier [*Goodchild*, 1996].

Burrough [1996a] noted that this type of embedded coupling means the data do not have to be transferred and data structures do not have to be reconciled prior to modeling. These advantages must be weighed against the added cost of programming and the knowledge that the final models may still be too simplistic and unskilled users may be uncritical of the results [*Burrough*, 1996a]. This state of affairs characterizes many of the attempts to implement GIS-based soil erosion models to date [*Wilson and Lorang*, 1998]. There is also the danger that fieldwork for model calibration, validation, and scientific investigation will be neglected if model building is too easy [*Burrough*, 1996a].

The addition of flowchart generators such as STELLA II [*HPS*, 1995] and Cantata (part of a suite of tools known as Khoros [*KRI*, 1996]) to GIS analytical engines represents another important innovation. The flowchart generators will automatically build the model program once the user has specified all the steps and data that are to be used. *Wesseling and Heuvelink* [1991] used this type of approach to investigate error propagation in empirical models. Many of the existing flowchart generators cannot handle complex

data types, such as multidimensional arrays, and they must be linked to a GIS to retrieve one cell or a group of cells at a time for processing [*Haddock and Jankowski*, 1997]. The VEEGRID visual programming environment proposed by *Haddock and Jankowski* [1997] overcomes many of these problems and illustrates how visual programming tools can be used to create flowchart-like models of spatial phenomena using GIS data. Similar types of tools have also been utilized in geographic modeling systems, which aim to provide libraries of landscape simulation components from which watershed simulation models will be assembled to represent user-specified processes and problems in catchments of interest [*Costanza*, 1996; *Maxwell and Costanza, 1996; Leavesley et al.*, 1996a, 1996b]. However, these innovations raise some of the same questions as embedded coupling in that it is not clear who will do what and how well they can do it.

CONCLUSIONS

This chapter has taken a broad view of GIS and offered an assessment of the potential of using the latest GI technologies as one of the building blocks for developing new or improved non-point source pollution models.

Four observations stand out with respect to computer technologies themselves. First, GI technology providers are focused on developing niche implementations and on identifying new customers. Second, this is a very exciting and potentially productive state of affairs for targeted audiences such as farmers and consultants interested in precision agriculture [*Berry*, 1998; *Mangold*, 1998]. One problem is that environmental modeling is not viewed as a separate and viable market niche. However, environmental modelers have benefited from development aimed at other markets. This assessment is probably not true of the GRASS GIS, where the modular structure and availability of source code have favored its use in many of the most recent environmental modeling applications [e.g., *Mitasova et al.*, 1996; *Mitas et al.*, 1996; *Leavesley et* al., 1996a; *Lovejoy et al.*, 1997]. However, a series of new tools and functions have been added to other GIS that can be used in non-point source pollution assessments [*Maidment*, 1996b; *Wilson and Gallant*, 1997]. The third observation is that there are lots of exciting developments connected with new technology and data access on the World-Wide Web. These innovations can only increase in number and importance in the immediate future since a series of new research initiatives launched by the National Science Foundation aim to develop "knowledge-rich" approaches that build on the "information-rich" world of GIS for example. Fourth, the manager or scientist in 2010 is likely to have a 5 GHz computer with a terrabyte of local storage and 5 GB of main memory on their desk. This computer will have been purchased for about $5,000 and it will be connected to the WWW with a 100 Gbit network connection. Environmental modelers will get a modest boost from these hardware and network innovations in the next few years.

Looking at the present, there are a number of important developments that have gathered pace in the past few years which offer new opportunities for developing improved tools for conducting non-point source pollution assessments. One is undoubtedly the tremendous increase in the number and variety of short-range and long-range remote sensing instruments. Another is the new opportunities afforded by the development and testing of new GIS software tools [*Wilkinson*, 1996]. The terrain analysis tools emphasized in this chapter reflect their importance for predicting the movement of water and contaminants in landscapes as well as the experience and interests of the author. A third development has been the increased popularity of fuzzy classification and geostatistical interpolation for simultaneously handling continuous variation in both attributes and location. These concepts and the accompanying tools have been applied most often to soil attributes but they are equally adept at describing other types of environmental variation [*Burrough*, 1996b]. In addition, these terrain tools and fuzzy classification methods are easily incorporated in GIS and offer advantages in terms of generating better model inputs, process descriptions, model outputs, and error assessments.

The recent work of *Bardossy and Disse* [1993], *Bardossy and Duckstein* [1995], *Mitasova et al.* [1996], and *Mitas et al.* [1996] illustrate the potential benefits of using these types of innovations to develop new and improved spatially distributed models. These applications also illustrate the increasing number of opportunities for developing and implementing non-point source pollution models inside GIS.

To make faster progress, knowledge-rich software tools and human-use systems need to be developed that make effective use of the spatial data riches that exist because of GIS and related technological advances. *Openshaw* [1997], for example, has recently advocated that new tools incorporating artificial intelligence and computational intelligence are required to uncover the processes that generate the patterns in these new digital data products. *Bouma* [1997], in contrast, stressed the human element and advocated a future in which soil scientists operate as 'knowledge brokers' with 'T-shaped skills' that can support both general assessments (synthesis) and detailed investigations (new research).

This state of affairs implies that we equip the next generation of scientists with broad as well as deep

knowledge and skills, and the ability to communicate the goals, methods, results, and utility of their research at varying levels of certainty to a variety of stakeholders. Some non-point source pollution problems do not require GIS and/or models [*Lovejoy*, 1997], and those that do require technologically sophisticated solutions need innovative applications so that the model results can be interpreted and used appropriately. Given this state of affairs, this chapter has hopefully demonstrated why technology, by itself, is a necessary but not sufficient component in successful non-point source pollutant assessments.

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