Applying Landscape Ecology to the Assessment of Nonpoint Source Pollution

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Abstract

Nonpoint source (NPS) pollution caused by human activities is difficult to manage not because of the deficiency of water- or land-treatment technologies, but because the sources of NPS pollutants are diffuse and the landscape across which NPS problems occur are spatially heterogeneous. Landscape ecology, which is concerned with the interaction between landscape structure and spatial processes such as water flow, could provide guidelines for NPS management. This research investigated how landscape ecology and NPS management can be cross-fertilized by reviewing principles for landscape decomposition and examining existing practices in NPS monitoring and modeling. It concludes that, on the one hand, hierarchy theory has suggested useful spatial frameworks for conducting NPS monitoring and modeling. On the other hand, NPS management that deals with diffuse sources from multiple scales could provide practical feedback to the evolving theory of landscape ecology.

I. INTRODUCTION

Nonpoint source (NPS) pollutants such as sediment, nutrients, pesticides, heavy metals, and pathogens have impaired the quality of U.S. water (USEPA [45]). NPS pollution is a human-induced problem. Although naturally occurring events such as forest fires and volcanic eruptions yield NPS pollutants, human activities including construction, transportation, and agricultural production are the major contributors of nonpoint source problems. These land-based or airborne pollutants of water are difficult to identify and control unless the interactions between human activities, terrestrial landscapes, and aquatic ecosystems are well understood.

Links between people, land, and water are not easy to establish due to the complexity of the environmental systems. Prior to any land-water relationship being established, changes in land uses and water quality need to be monitored or modeled. Because both monitoring and modeling are expensive and NPS pollutants are diffuse across the entire landscapes, issues as to what, where, and how to monitor or model are critical to the cost-effectiveness of NPS control. Ideally, information learned from field studies can be extrapolated to a larger geographical area, so that monitoring and modeling only need to be implemented at representative sites for particular problems.

Nonetheless, the validity of translating the land-water relationship from a field plot to a watershed across whichNPS problems occur is challenged by the scale problem, because the environmental systems including the land, the water, and human society do not behave linearly. Information obtained from a field scale often is not applicable to a broad scale. As with concerns over the fragmentation of habitats, depletion of the ozone layer, and global warming, to address the question of how human daily activities that are conducted in farms or metropolitan areas cause water pollution downstream demands water quality professionals and environmental scientists to think locally and globally.

In response to the need for understanding the interactions between spatial patterns and processes across a broad scale, landscape ecology has emerged as a new discipline (Urban *et al.* [42]; Turner *et al.* [41]; O'Neill *et al.* [35]). Landscape ecology is characterized as scientifically immature, however, and is seeking for unifying concepts and methodology (Wiens [47]). The experiences of dealing with nonpoint source problems could provide valuable insights into how environmental systems interact across the heterogeneous landscape over a range of temporal and spatial scales. On the other hand, management of nonpoint source problems requires scientific guidelines for accurately assessing the severity of NPS problems, which are negligible at the source areas but collectively significant at watershed levels. Landscape ecology is promising in providing theoretical frameworks for monitoring and modeling designs. Both landscape ecology and nonpoint source assessment could cross-fertilize from each other.

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The attempt of applying landscape ecology to nonpoint source assessment has been made without much success. For example, the use of landscape metrics such as diversity and contagion in water quality prediction is not reliable yet, although landscape indices are theoretically promising to "link small-scale ecological information with patterns at the landscape level" (O'Neill *et al.* [34]; Hunsaker and Levine [14]). To establish relationships between people, land, and water, as well as to make NPS problems manageable, most of NPS control programs are piecemeal and restricted to small areas. The small-scale information is hardly transferable to other areas due to spatial heterogeneity and non-linearity of the environmental systems. Improvement of cost-effectiveness of nonpoint source control lies in a better design of spatial monitoring and modeling. This review thus aims to investigate new avenues for cross-fertilizing landscape ecology and nonpoint source assessment by focusing the implication of hierarchy theory to NPS monitoring and modeling.

II. MULTIPLE-SCALE HETEROGENEITY IN LANDSCAPES

Landscapes perceived by human beings consist of a variety of natural and man-made features, such as topography, soil, vegetation, farms, commercial centers, and traffic flows. Although these landscape components are interwoven and interact with one another, they are most distinctive at various spatial and temporal scales and form different spatio-temporal patterns. Our ability to discern characteristic patterns and their underlying processes and to organize them into hierarchical levels are essential to understanding the complexity of landscape systems (Kotliar and Wiens [17]; Wu [50]; Malanson [24]).

A. Decomposing a landscape into multiple-scale systems

Although it has never been the case in which one can clearly identify the operational scales of individual landscape components and separate them crisply as demonstrated in Figure 1, it is possible to decompose interacting components hierarchically in time and space and construct a scaling ladder across multiple scales. Landscape systems are assumed to be hierarchically structured and decomposable, because nature, like biological and ecological systems, is hierarchically structured to foster evolution and to enhance the stability of systems (Wu and Loucks [49]; Wu [50]).

Landscape components within a hierarchically nested system hold the property of part/whole duality. Accordingly, subsets of the landscape that comprise a particular hierarchical level act as "wholes" for those components below, but as "parts" for those components above (Urban *et al.* [42]; Jensen *et al.* [15]; Wu [50]). Take the example of hydrological hierarchy. A watershed of 1 km^2 can be treated as the overall size of a case study, if the focus of this study is to investigate how water molecules are transported between vegetation and soil within a relatively homogeneous field. On the other hand, the same watershed can also be treated as one of thousand sampling units, if the study is designed to evaluate how diversity in land uses within each sampling unit collectively affects water quality of the entire drainage area, which encompasses an area of 1,000 km^2.

Components of hierarchically structured systems not only interact horizontally with other elements that operate at the same level, but also interact vertically with those operating at upper and lower levels. Even though the vertical interaction provides an avenue to extrapolate information on spatial patterns, processes, and their interactions across a range of scales, the extrapolation is not straightforward, because the multiple-scale systems do not behave linearly. Evidence has shown that besides dominant pattern and process, the mechanisms that control pattern-process interactions vary with scale. For instance, soil erosion is controlled by overland flows, topography and vegetation, as well as climate and lithology at the field, the catchment, and the national scales, respectively (Kirkby et al. [16]).

Because spatial patterns and processes are reproductive and positively correlated, dynamics of hierarchically structured systems vary with scale (Malanson [23]& [24]). Components at the top level generally operate across a broader spatial scale over a longer period than those below (See Figure 1). For example, climate changes exert impact over the entire world, but a detectable change may take centuries to occur. In contrast, treefalls occur frequently, but their im-

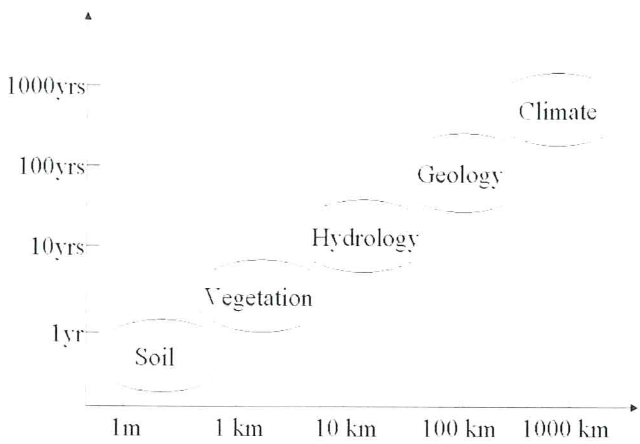

Figure 1. Hierarchical organization of environmental factors

pact on natural systems is limited to a local scale. The differences in dynamics in turn differentiate the roles played by components at varying hierarchical levels. Components that operate at higher-level are slow and appear as constants to phenomena occurring below. They provide context and impose top-down constraints to levels below. Conversely, components at lower-level are fast and appear as average conditions to phenomena taking place above. They provide mechanism and impose bottom-up constraints to those above (Urban *et al.* [42]; Wu and Loucks [49]). Nonetheless, to effectively deal with a multiple-scale system, one needs not to take care every single level equally, because interaction between components across a hierarchy decrease as the number of intervening levels increases. It is therefore suggested by hierarchy theory that simultaneously studying three adjacent levels including the focal level at which the phenomenon interested dominates and two immediately upper and lower levels will be sufficient to understand the behavior of complex systems (O'Neill [33]; Wu and Loucks [49]; Wu [50]).

Obviously, one would have to decompose a complex system into multiple scales before s/he can identify where the focal and adjacent layers are. The hierarchical structure of complex systems is a function of natural heterogeneity in the system, the extent of study area, data grain, and criteria used for classification (Kotliar and Wiens [17]). Criteria used to define the hierarchy levels could be a single component, such as temperature, elevation, and concentrations of nitrogen in water or a combination of multiple factors. For example, concerned with resource production capability and response potential to natural processes, Zonneveld [52] and Balley et al. [1] recommended using functional units, which are mapped by integrating several environmental factors, to characterize landscapes. Once criteria for classification are determined, statistical techniques including analysis of variance, spatial autocorrelation, semivairograms and analysis of fractal dimension can be used to to identify breaks in the data. Discontinuities in the data suggest changes in the system's behavior and indicate potential locations for the boundaries of characteristic scales (Bellehumeur and Legendre [4]; O'Neill and King [53]).

B. Relating Landscape Patterns and Spatial Processes at Multiple Scales

Case studies that deal with scaling issues expicitly will be reviewed to demonstrate the challenge of scale problem in resources manaement. For instance, to explore the relationships between landscape patterns and stream water quality, Hunsaker and Levine [14] first characterized landscape patterns by computing dominance, contagion, edge numbers, and the proportion of each land-use type within an Illinois watershed. These landscape indicators were then used as explanatory variables to predict concentrations of total nitrogen, total phosphorus, and conductivity in water. The result showed that both land-use proportions and indices of spatial pattern were useful in predicting water quality, but landscape metrics didn't account for much of the variation in water quality. Based on the same modeling approach, the authors constructed another set of regression models using land-use proportions and landscape indicators computed for 200- and 400-meter buffer zones and hydrological active areas around the stream corridors as the explanatory variables. R^2 values for buffer areas were found to be 10% lower than those for the entire watershed. The finding was contradictory to a conventional wisdom, which believes that land use types close to streams strongly influence water quality.

To examine the effect of scale on the statistical modeling, Hunsaker and Levine [14] went on and implemented a spatially distributed model to nested watersheds (ranging from 44 – 1000 km^2) in Texas. In contrast to the previous finding, the spatially distributed models indicated that proximity to streams was a critical factor in predicting annual nutrient loadings at the outlets of watersheds. The authors concluded that the discrepancy between watersheds in Illinois and in Texas mainly resulted from different modeling approaches and data resolutions used in each case study. A spatially distributed modeling approach based on fine-resolution data is necessary to model the interaction between stream quality and landscape characteristics surrounding the stream corridors. Hunsaker and Levine [14] thus suggested combining both lumped and distributed modeling approaches for modeling non-point source pollution in large river systems. The two-stage approach includes first implementing multivariate modeling to identify significant contributors of NPS pollution and then implementing distributed models for watersheds identified in the first stage to pin-point critical areas for NPS control.

Hunsaker and Levine's study [14] raised an inquiry: how can landscape indicators be used to improve the cost-effectiveness of nonpoint source management, if it is believed that land-cover types are closely related to water quality? In addition to questioning whether existing landscape indices adequately capture properties that are critical to nonpoint source pollution, the key issue that requires further exploration to address the above inquiry is the problem of scale. As demonstrated in the Wabash River study site in Illinois, spatial extent of the study area influences the quantified relationships between water quality and landscape patterns. Nevertheless, how scale influences the interaction between landscape patterns and stream quality is an on-going debate. Up to date, results of a series of studies on this topic show either stream corridors or the entire watershed is a better predictor for stream water quality (Lammert and Allan [19]; Roth *et al.* [39]; Omernik, *et al.* [29]).

In addition to the extent of study area and resolution of data, the size of sampling units is critical to scaling issues and deserves our special attention. Sampling units, whose size is between data resolution and the extent of study areas, serve as moving windows for the computation of landscape metrics. For instance, the Environmental Monitoring and Assessment Program (EMAP) initiated by the EPA to monitor the current status and trends in ecological resources across the nation, uses 40-km^2 hexagons as sampling units based on grid data that have cell size of 200 m on a side (Hunsaker, *et al.* [13]). For a case, in which resolution has been dictated by exiting databases, and specific extent is required to achieve research objectives, how sampling units are chosen may determine whether or not a hypothesis is supported or rejected. Obeysekera and Rutchey [28] coined the term "Model Grain" to emphasize the importance of choosing the optimal computational unit for ecological modeling.

No theoretical basis or elegant guidelines are available to guide the decision of sampling units (O'Neill, *et al.* [35]; Obeysekera and Rutchey [28]). Instead, experiments are conducted to help determine the so-called optimal model grain. For example, Obeysekera and Rutchey [28] analyzed the behavior of landscape across a range of scales in order to determine the optimal scale for implementing a landscape model in the Everglades. They first aggregated data produced by SPOT satellite, which has an original resolution of 20-by-20 m, to a 40-by-40 m resolution and continually increased by 40 meters up to 1000-by-1000 m. Secondly, they computed landscape indices including the proportion of land-cover types, diversity index, and fractal dimension for each of the 25 data resolutions. Upon seeing a rapid change in fractal dimension taking place around the resolution of 100-by-100 m, the authors suggested using 100 meters as the critical scale for patch characterization, because the rapid change in the relationship between parameter and area indicated the dominant process had changed (Obeysekera and Rutchey [28]). Likewise, summarizing from their experiences, O'Neill *et al.* [35] suggested that an ideal calculating unit should be 2 to 5 times greater than the largest patch on the landscape to prevent sampling biases.

III. APPLICATION OF LANDSCAPE ECOLOGY TO NONPOINT SOURCE POLLUTION ASSESSMENT

Nonpoint source (NPS) pollution, as defined by the Environmental Protection Agency (EPA), is a problem caused by diffuse sources that are not regulated as point sources, and normally is associated with human activities including agriculture, silviculture, and urban development (USEPA [43]). NPS pollutants originating from the terrestrial environment are generally carried into surface or ground water through diffuse transport paths including precipitation, atmospheric deposition, land runoff or percolation. The characteristics of watersheds therefore will influence the quality of surface or subsurface flows (Poiani, *et al.* [37]; Omernik [32]). Forman [11] thus suggested that a landscape urologist can diagnose the health of a drainage basin by analyzing the contents of a bottle of stream or lake water.

Forman's analogy [11] pointed out that site-specific sampling is an important tool for water quality assessment. However, the question has to be asked as to the geographic extent to which the information contained in a bottle of water can be extrapolated. The impact of rainfall on stream water quality differs vastly among landscapes because of heterogeneity in their structure and function. Extrapolation of water sampling should only apply to areas having similar hydrological response potential. Consequently, to enhance the cost-effectiveness of monitoring design, one has to understand the relationships between water quality and land attributes, as well as to know where the relatively homogeneous land areas are located.

In addition to monitoring, water quality modeling at a watershed scale is deemed as a powerful tool for nonpoint source pollution management. Unlike traditional water quality models, which are developed mainly to address the transport process of pollutants at a homogeneous field, nonpoint source pollution (NPS) models are designed to explore the interaction between landscape characteristics and water quality from a watershed perspective. Accordingly, NPS models are more spatially explicit than traditional models. In addition to representing the physical process of NPS pollution using mathematical formulae, NPS models require a detailed description of the terrestrial attributes so that link between land and water may be discovered. How to partition the spatially heterogeneous landscape into computational units that are meaningful to the phenomena being studied thus becomes *the* issue for NPS modeling.

The concepts of landscape classification and principles of hierarchy theory discussed above provide spatial frameworks for monitoring design and modeling implementation. I will explore the potential of applying landscape ecology theory to NPS assessment by examining the rationale that underlies existing monitoring and modeling practices. Prior to discussing spatial frameworks for monitoring and modeling I will review case studies to stress the interactions between terrestrial landscapes and aquatic environments.

Relationship between Land Characteristics and Water Quality

Stream water that collects nonpoint source pollutants from its drainage areas provides a good indicator of the cumulative impact of the entire watershed (Hunsaker and Levine [14]. Evidence has shown that patterns of water quality vary with terrestrial characteristics. For example, Larsen *et al.* [20] found that the highest water quality had consistently occurred in the southeastern region of Ohio throughout a 16-month sampling study. In contrast, the northwestern part of Ohio had consistently shown the lowest water quality. The differences in water-quality variables were attributed to varying land forms and land-use types. Due to past glaciation, the northwestern part of Ohio is dominated by flat land surface and a high proportion of cropland, which contributed to higher concentrations of nutrients and iron strength in stream water. Southeastern Ohio, on the other hand has a relatively high quality of stream water because of hilly land forms that in turn were mainly covered by woodland. Based on the correspondence between landscape characteristics and water quality, Larsen *et al.* [20] advocated the need for a land classification system and regionalized standards for water quality management.

Phillips and Bachman [36] presented another case study to demonstrate that correspondence between water quality and terrestrial characteristics exists not only among regions but also within a region. They sampled 29 basins in the Delmarva Peninsula during the spring of 1991 and found that areas where soils were poorly drained had higher concentrations of calcium, magnesium, potassium, alkalinity, chloride, and nitrate. In contrast, well-drained areas having a thick aquifer and long ground-water flow paths had higher concentrations of sodium and silica. The authors attributed this water-quality pattern to local geology.

Spatial heterogeneity that is inherent in landscapes exists within a smaller land area, and the watershed as well. A variety of nonpoint source pollution models such as ANSWERS, Areal Nonpoint Source Watershed Environment Response Simulation (Bingner [6]), AGNPS, Agricultural Nonpoint-Source-Pollution Model (Young [51]), and TOPMODEL, a topography-based hydrologic model (Nemani, *et al.* [27]), have been developed and widely used to identify critical areas within a watershed for NPS control. Cases of model application are presented in Moore and Nieber [26], Tim *et al.*[40] and Lo [21]. One of the assumptions underlying nonpoint source models is that interaction between environmental constraints, biotic processes, natural disturbances, and human activities make some sites more prone to nonpoint source pollution than others. Modeling is expected to distinguish areas that are more prone to pollution from those that are more sheltered.

In summary, water quality is closely related to terrestrial characteristics, which are spatially heterogeneous at varying levels of the landscape systems. Realistic goals for nonpoint pollution management should vary with the characteristics of the landscape surrounding the receiving water instead of enforcing a nation-wide water quality standard. Regionalization of the continental United States is deemed necessary to improve the management of nonpoint source pollution.

Ecoregions — Spatial Frameworks for Nonpoint Source Pollution Monitoring

Realizing the need for defining spatial frameworks for resource management, the Environmental Protection Agency (EPA) was motivated to delineate ecoregions throughout the conterminous United States in the late 1970s (Omernik and Griffith [31]). Ecoregions are defined as areas within which ecosystems, in terms of their types, quality, and quantity of environmental resources, are generally similar (USEPA [44]). The primary purposes for delineating ecoregions are to develop regional biological criteria and water quality standards, as well as to set management goals for nonpoint source pollution (Omernik [32]).

Because ecoregions are designed to reflect the overall response to natural or manmade phenomena, they are identified on the basis of perceived patterns of a combination of biotic and abiotic factors exerting influence on specific areas (Omernik [30]; Balley *et al.* [1]). Factors being considered and analyzed include climate, geology, vegetation, soils, hydrology, wildlife, and land use (Omernik [32]). Expert's judgment, in addition to map analysis and literature review, is sometimes helpful in determining the final boundaries of ecoregions (Bryce and Clarke [8]).

In response to the hierarchically nested ecosystems, ecoregions at a higher level are subdivided into several sub-regions to capture spatial variability missed at coarse scales (Bryce and Clarke [8]). Consequently, the conterminous United States has been divided into three levels of ecoregions. Levels I, II, and III contain nine, 32, and 78 classes, respectively (USEPA [44]).

To meet localized needs, parts of the United States have recently further divided the existing ecoregions into Level IV classification. For instance, the state of Iowa has further divided the Western Corn Belt Plains Ecoregion within Iowa into six subregions to facilitate the development of biological criteria for streams (Griffith *et al.* [12]).

Differing levels of ecoregions provide spatial frameworks for NPS management. Within each ecoregion, for example, principles regarding terrestrial and aquatic ecosystems established from site-specific studies can be reasonably extrapolated to the same ecoregion. This kind of extrapolation could greatly reduce the cost of NPS management, because six to ten years of monitoring data are required to establish relationships between changes in landscape and water quality, due to the nature of NPS problems and the environmental systems (Dressing, *et al.* [9]).

The delineation of ecoregions also helps environmental agencies define attainable goals of water quality management for each ecoregion. This definition is accomplished by referring to the least-disturbed stream conditions within the same ecoregion (Omernik [32]). By so doing, one takes the variability in landscapes into consideration so that water quality standards are achievable. On the other hand, to protect special resources, water quality standards may be set higher than the national average for some regions where water quality is exceptionally good.

The concept of applying hierarchy theory to delineating ecologically homogeneous land units has reinforced the necessity to define attainable water quality for individual ecoregions.

Computational Units — Spatial Frameworks for Nonpoint Source Pollution Modeling

Nonpoint source pollution modeling encompasses two major tasks: using equations to represent hydrologic processes and using maps to describe the spatial context within which hydrologic cycling takes place (Maidment [22]). Both hydrologic process and spatial context are complex and difficult to represent precisely in a modeling setting. Model developers have to decide either to emphasize physical process by simplifying spatial complexity or vice versa.

Due to the development of geographic information systems (GIS) and spatial data bases, as well as the availability of existing models, the priority of hydrologic modeling has recently been reversed (Maidment [22]). Spatial complexity, which used to be lumped, has gained increasing attention from hydrologic modelers. In contrast to traditional process-based modeling, Maidment [22] referred to spatially explicit hydrologic modeling as map-based modeling (Figure 2). In map-based modeling it is possible to depict the spatial process of nonpoint pollution. Map-based modeling therefore is regarded a promising tool for improving NPS management.

As previously mentioned, identifying critical areas within a watershed for treatment, and establishing links between landscape attributes and water quality are two of the primary objectives for implementing nonpoint source pollution models. However, the effectiveness of NPS modeling depends on how the modelers parameterize the watershed being studied. As with the classification of landscape units, the principles derived from hierarchy theory can provide insights into watershed parameterization. I will review existing case studies in NPS modeling to examine the discrepancy between theory and practical application. In particular, the following discussion will focus on three complementary aspects of model implementation. They are: 1) defining computational units, 2) determining optimal size of computational units, and 3) identifying controlling factors at different levels of the landscape hierarchy.

Defining Computational Units

Computational units are defined to create spatial frameworks for watershed parameterization. As different landscape patterns are perceived through different observation distances and tools, the shape and size of computational units could produce different model results that might confuse environmental policy makers.

A variety of spatial frameworks have been tested and applied in hydrologic modeling. Nonetheless, no absolute guideline exists for defining the optimal shape and size of computational units (Engel [10]). In terms of shape of computational units, for example, grid-cell, hillslope, triangulated irregular networks (TIN), and hydrologic response units (HRUs) have been developed to sample landscape attributes within watersheds. Each data type was designed to facilitate hydrologic modeling by improving the efficiency of data storage, the flexibility of resolution, the maintenance of linear features including channels and divides, or the capture of spatial variability in topography, soils, vegetation, or land use (Rokos [38]).

Each data representation type is strong in some

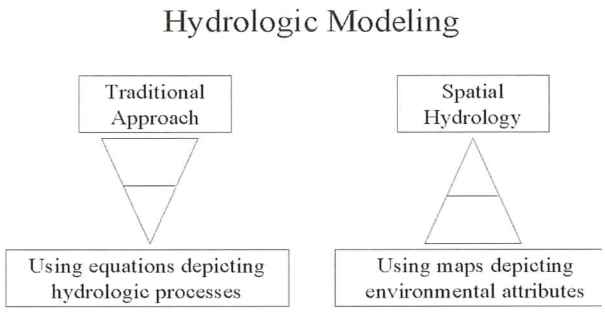

Figure 2. Shifting paradigms of hydrologic modeling

aspects, but weak in others. Modelers have to choose the one most suitable for a given model. As a result, each of the data models has been used in different hydrologic models. For instance, ANSWERS and AGNPS require users to partition watersheds into grids. Users overlay a grid of uniform cell size into thematic data layers such as topography, slope, or soils, and then extract a single value for each parameter in each cell. On the other hand, the hillslope, defined by Band and others [3] as "the drainage area contributing flow to a stream link from one bank," has been widely used to represent the spatial variability in mountainous landscapes. Hillslope is regarded as the most effective data type for modeling mountainous watersheds, where rapidly changing topography controls the characteristics of vegetation, soil, and microclimate because of its well-defined hydrologic and geomorphic boundaries (Band [2]).

Parallel to the way ecologists decompose the landscape into numerous functional units, computational units ideally should be defined based on their ecological function. In other words, ecological homogeneity, in addition to ease of computation, should be taken into consideration in watershed parameterization. Irregular shapes such as TIN, HRU, or hillslope all explicitly express the attempt to construct ecologically homogeneous land units for modeling. The grid-cell data type, although it was not originally designed to capture functional units, can be manipulated to minimize spatial heterogeneity in each cell by subdividing the grid into a finer cell size.

In addition to manipulating cell size, ecologically homogeneous computational units can be defined by using diagnostic criteria such as climate, soil, topography, or by examining the overall response of a system. The former can be exemplified by Rokos' [38] study; the latter by Wood *et al.*'s [48] study. Rokos used topography, vegetation, and soil as diagnostic criteria to construct TINs for a mountainous watershed in California. In contrast, Wood and others defined Representative Elementary Areas (REAs), the fundamental building blocks for watershed modeling, by analyzing the trend of runoff generation, which represented the overall response of a catchment to rainfall events.

As mentioned earlier, computational units are defined for parameterization. In order to account for spatial heterogeneity within a watershed, each parameter in each computational unit is represented by a single value. Whether the single value is representative of the actual condition is critical to the success of modeling. Therefore, the optimal size of computational units needs further consideration based on the spatial variability in the study fields.

Determining the Optimal Size of Computational Units

In any landscape, the larger the land units, the more heterogeneous they become. However, it is not cost-effective to parameterize a watershed into tiny units. An optimal size that compromises the costs of modeling and variability in landscape should be determined for parameter inputs.

From the perspective of landscape ecology, the optimal size for computational units can be determined by looking for boundaries that can minimize variability in ecological responses within, but maximize it between computational units (Band, *et al.* [3]; Nemani, *et al.* [27]). However, distinct boundaries seldom exist, because natural phenomena are not always decomposable (Urban, *et al.* [42]). In practice, NPS professionals commonly use the criteria of (a) goodness of fit, (b) diagnostic components, (c) trend of overall response, or (d) threshold values to determine "the" optimal scale for partitioning a watershed.

Goodness of fit here is used to measure the difference between modeling results and field data. Modelers may explore the optimal model grain through a trial and error process. Such an exploration includes the following steps. First, a set of grids that is divided into uniform but varying cell-sizes is designed. Second, each grid is overlaid onto individual layers of landscape attributes. Third, a single value representing the average condition of each landscape attribute within each cell is extracted and assembled into the format required by a particular model. Fourth, the selected model is realized at each cell-size. Fifth, results attained from each model simulation are compared with field data and the cell-size that generates the best-fitting result is chosen as the optimal computational size. Examples applying such a trial and error approach are presented in Brown *et al.* [7] and Vieux and Needham [46].

Rokos [38], as mentioned previously, used diagnostic components to determine the size of TIN for a mountainous watershed in California. The steps that Rokos took to generate TINs are as follows. (a) Using a topographic map to delineate watershed boundary and channel network. (b) Overlaying maps of soils and vegetation to define uniform polygons. (c) Determining elevation to the vertices of uniform polygons derived from soils and vegetation. (d) Constructing TINs using elevation points, drainage lines, and soil-vegetation polygons. The sizes of TINs generated through the above steps are virtually unique, and reflect the variability in soils, vegetation, and topography within the mountainous watershed.

Unlike Rokos, Wood *et al.* [48] used the overall response of a catchment to rainfall events to determine the size of Representative Elementary Areas (REAs) for a 17 km^2 catchment in North Carolina. Wood *et al.* [48] implemented TOPMODEL to the watershed and realized models for five rainfall events. They traced the changes in cumulative runoff volume calculated from TOPMODEL for each event as the size of subcatchment increased. Model results showed that the behavior of the subcatchment response changed at about 1200 pixels (about 1 km^2). For average areas under 1200 pixels, cumulative runoff volume fluctuated greatly, but runoff generation became stable for average areas above 1 km^2. Wood *et al.* [48] therefore determined 1200 pixels as the model grain.

Applying threshold values to determine the size of model grain presents a promising approach to examining scaling effects on hydrologic modeling. With the assistance of GIS, one can change the size of computational units within a stream network that is hierarchically nested by declaring different threshold values. For example, Band *et al.* [3] extracted different sizes of hillslope for modeling from DEM data. Prior to delineating hillslopes, which are the drainage areas contributing flow from one bank to a stream link, one has to extract stream networks from a DEM by computing the drainage area upslope of each outlet in the DEM. ARC/INFO computes drainage areas according to a threshold number of cells that is specified by the users. The threshold number of cells will be used to determine drainage areas, length of stream segments, and density of stream networks. As illustrated in Figure 3, a threshold of 100 cells generated a denser stream network than a value of 1000 cells. Assisted by GIS technology, one can easily compare the effects of scale on parameterization and model simulation.

Identifying Factors Controlling Hydrologic Processes at Different Scales

The generation and transport of NPS pollutants are influenced by a group of environmental factors that operate over various temporal and spatial domains. Knowing the operating domains associated with individual environmental factors will help establish cause-effect networks for nonpoint source problems, identify the extent to which a model can be reasonably extrapolated, and signal the need for model modification (Meentemeyer and Box [25]; King [18]). Moreover, different but complementary management goals can be developed for hierarchically organized environmental agencies, so that redundancy can be avoided and the cost-effectiveness of NPS management can be improved.

In general, controlling factors for a lower-level natural phenomenon are more complex than those for an ecological process operating at the top level of the landscape hierarchy. For example, the discharge of nitrogen at the watershed level was controlled by land use, fertilizer application, slopes, and soil types, while precipitation alone could explain most of the variation in nitrogen discharge at the continent level (Meentemeyer and Box [25]). Likewise, Nemani and others [27] found that evapotranspiration (ET) rates at the regional level were controlled by precipitation and temperature, while they were additionally controlled by microclimate and lateral distribution of soil water at the watershed level.

Environmental scientists inspired by hierarchy theory, which suggests that controlling factors vary with scales, strive to distinguish dominant controlling factors at different levels of the environmental hierarchy through experiment. Three empirical tests are commonly used to match patterns of spatial processes and agents of pattern formation They include:

(a). Performed Sensitivity Analysis. Wood *et al.* [48], for example, to identify dominant factors that control the size of the Representative Elementary Areas (REAs) in a 17 km^2 catchment in North Carolina. They began by holding soil and rainfall data constant and then ran the hydrologic model TOPMODEL to evaluate the effect of topography on model results. Subsequently, they held topography constant and ran the models repeatedly while altering the input values for soil and rainfall. They finally concluded that topography was the dominant factor that controls the size of REAs in the catchment studied.

(b). Arbitrary Thresholds. As mentioned earlier, Nemani *et al.* [27] investigated scaling by arbitrarily

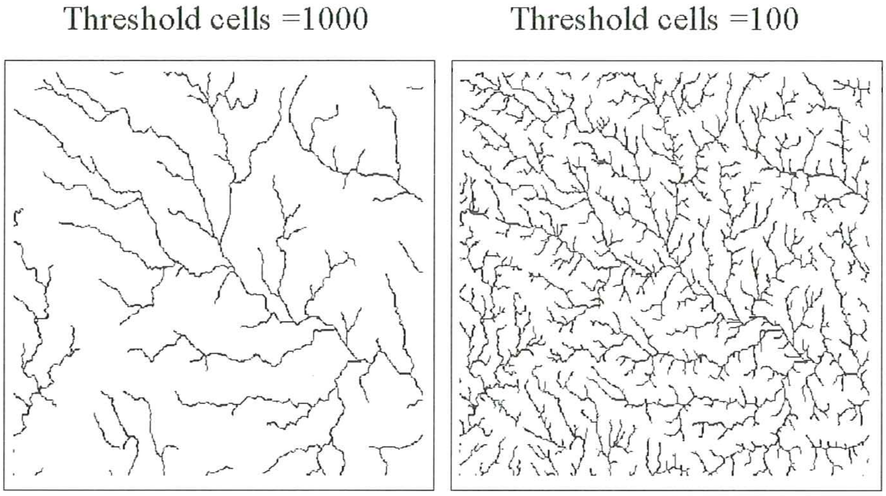

Figure 3. Stream density varies with threshold number of cells

partitioning the Seeley-Swan valley in Montana into 5 and 170 computational units representing the regional and watershed levels, respectively. They then implemented the Regional Hydrological Simulation System (RHESSys) to calculate evapotranspiration (ET) for the watershed using these two spatial configurations. After examining the variations in ET and individual parameters at both regional and watershed scales, the authors concluded that variation in ET at the regional scale was controlled by precipitation and temperature, while soil water content was the dominant factor for ET variation at the watershed scale.

(c). Trend Analysis. To examine the relationship between biomass index and elevation at varying scales, Bian [5] compared the patterns of both parameters in a series of scales by successively increasing grain size and data aggregation. She first derived the biomass index from remotely sensed images of the Glacier National Park, Montana, and elevation data from 1:24,000 digital elevation models (DEM) for the same area. Secondly, she performed simple linear regression models using biomass as the dependent variable, and elevation as the independent variable at each scale to test whether their spatial patterns match well. R^2 of the biomass index and elevation increased from 0.46 to 0.68, and 0.71 as data resolution changed from one-pixel (30-by-30 m) to 33-pixel, and 75-pixel, respectively. Bian's [5] example not only concluded that elevation became the dominant factor controlling biomass at a specific scale, but also illustrated the roles of additional factors that operate at smaller scales. Due to the property of containment that is inherent in hierarchical systems, the dominance of elevation was not clear until the agents operating at low-levels were filtered out as the scale of investigation increased.

The empirical studies reviewed above testify that there exists a close relationship between scales and controlling factors. However, efficient guidelines for investigating this relationship are not available now. Fortunately, GIS with its capability of data input, aggregation, and retrieval provides a powerful tool for future pursuit of this relationship.

IV. CONCLUSION

Nonpoint source (NPS) pollution that deteriorates the US water quality is a multi-scale problem. NPS pollutants generated from human activities are diffuse and negligible at their origins, but they are collectively significant at a watershed level, because they are accumulated across the terrestrial landscapes. Correctly assessing the cumulative impact of human activities taking place at the local scale on the nation's water quality requires strategic monitoring and modeling on both terrestrial and aquatic ecosystems.

A key issue involved in the strategic monitoring and modeling is how to decompose the landscape into functional land units. Theoretical basis for defining functional units and principles for partitioning the landscape can be found in hierarchy theory. I will thus conclude this study by summarizing principles of hierarchy theory and their application to the assessment of nonpoint source problems.

Principle one is to define functional units based on ecological homogeneity. Application of this principle includes the attempt to delineate ecoregions at varying hierarchical levels around the country to establish attainable goals for water quality management. Similarly, NPS modelers strive to construct ecologically homogeneous computational units by scrutinizing the distribution of diagnostic factors, or examining the overall response of a watershed to ecological events.

Principle two is to seek the optimal scale to isolate functional units so that heterogeneity can be minimized within a land unit, but maximized between units. Optimal scales can be considered in terms of extent and grain. Grain is the smallest land unit for data collection, while extent is the area over which information is collected or extrapolated. Because distinct functional units barely exist, NPS professionals usually determine the optimal scale through experiments.

Principle three is to identify controlling factors of ecological functions at varying scales of the landscape hierarchy. Individual environmental factors operating at different temporal and spatial scales exert different influences on ecological phenomena. In general, landscape components operating at levels that are lower than the one of interest serve as average conditions, while those operating at higher levels serve as constant. Both average and constant components have influences on the phenomena investigated but they are not controlling factors. Correctly identifying controlling factors and domains over which they are operating can help define boundaries for functional units, and optimal scales for data collection and information extrapolation. Similar to the choice of scales, controlling factors for spatial processes operating at varying levels are mainly identified through empirical experiments.

These three principles suggest spatial frameworks for decomposing the hierarchically nested landscape into functional land units that are manageable and conducive to establishing links between spatial patterns and spatial processes. The same principles thus provide guidelines to NPS practitioners for monitoring design and modeling operation. A common interest in understanding the interaction between landscape structure and spatial movements across the landscape has laid a foundation for cross-fertilization between landscape ecology and NPS assessment.

Cross-fertilization between landscape ecology and NPS management can be realized by tackling the challenge of "scaling up", i.e., extrapolating ecological information from local scales to landscape scales (King [18]). As previously mentioned, constrained by implementation costs, existing NPS monitoring and modeling are restricted to smaller watersheds. A promising way to improve the cost-effectiveness of NPS management is to translate the information gained from local studies across scales in the landscape. According to hierarchy theory, one can extrapolate information from local scales to a larger spatial extent by manipulating the grain and extent of observation (King [18]). Quantitative methods for data aggregation across scales exist. Yet, more applications of hierarchy theory and data aggregation are needed to consolidate the theoretical basis for scaling up. Given the common interest, the practice of assessing nonpoint source problems at different scales is possible to provide feedback on the applicability of theory.

In addition to decomposing the landscape into meaningful functional units, NPS professionals could endeavor to test the applicability of landscape indices to the problem of scaling up. As discussed in the context, landscape metrics are regarded as promising to establish quantitative relationships between spatial pattern and process, so that extrapolation of information can be safely exercised within a landscape hierarchy. However, the use of landscape indices in scaling up is limited due to the lack of full understanding of the association between landscape pattern, process, and measurement. The multi-scale issue of nonpoint source pollution again provides a wonderful example to improve our understanding of landscape indices, structure, and process.

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REFERENCES

[1] Balley, R.G., Jensen, M.E., Cleland, D.T. and. Bourgeron, P.S., 1994, Design and use of ecological mapping units. *In* M.E. Jensen and P.S.Bourgeron, (eds.) *Ecosystem Management: Principles and Applications Vol II.* General. Technical . Report. PNW-GTR-318. USDA Forest Service, Pacific-Northwest Research Station, Portland, Oregon.

[2] Band, L.E., 1989, Spatial aggregation of complex terrain, *Geographical Analysis,* 21(4):279 -293.

[3] Band, L.E., Peterson, D.L.,Running, S W.,Coughlan, J., Lammers, R., Dungan, J. and Nemani, R., 1991, Forest ecosystem processes at the watershed scale: basis for distributed simulation, *Ecological Modeling,* 56:171-196.

[4] Bellehumeur, C. and Legendre, P. 1998. Multiscale sources of variation in ecological variables: Modeling spatial dispersion, elaborating sampling designs. Landscape *Ecology,* 13(1): 15-25.

[5] Bian, L., 1997, Multiscale nature of spatial data in scal-

ing up environmental models. D.A. Quattrochi, and M.F. Goodchild (eds.) *Scale in Remote Sensing and GIS,* Lewis Publishers, New York, 13-26.

[6] Bingner, R.L., 1990, Comparison of the components used in several sediment yield models, *Transactions of the ASAE,* 33(4):1229-1238.

[7] Brown, D.G., Bian, L and Walsh, S.J., 1993, Response of a distributed watershed erosion model to variations in input data aggregation levels, *Computers & Geosciences,* 19(4): 499-509.

[8] Bryce, S.A. and Clarke, S.E., 1996, Landscape-level ecological regions: linking state-Level ecoregion frameworks with stream habitat classifications. *Environmental Management,* 20(3):297-311

[9] Dressing, S.A., Spooner, J. and Mullens, J.B., 1993, Watershed project monitoring and evaluation under section 319 of the Clean Water Act. Presented at the Watershed '93 Conference in Alexandria, VA.

[10] Engel, B.A., 1996, Methodologies for development of hydrologic response units based on terrain, land cover, and soil data. In M.F Goodchild, L.T. Steyaert and B.O. Parks (eds) *GIS and Environmental Modeling: Progress and Research Issues.* GIS World Books, Fort Collins, CO, 231-237

[11] Forman, R.T.T., 1995, *Land Mosaic: The Ecology of Landscapes and Regions.* Cambridge University Press, New York.

[12] Griffith, G.E., Omernik, J.M., Wilton, T and Pierso, S.M., 1994, Ecoregions and subregions of Iowa: A framework for water quality assessment and management, *Journal of Iowa Academy Science,* 101(1):5-13.

[13] Hunsaker, C.T., O'Neill, R.V., Jackson, B.L., Timmins, S.P., Levine, D.A. and Norton, D.J., 1994, Sampling to characterize landscape pattern, *Landscape Ecology,* 9(3):207-226.

[14] Hunsaker C.T. and Levine, D.A., 1995, Hierarchical approaches to the study of water quality in rivers, *BioScience* 45(3):193-203.

[15] Jensen, M.E., Bourgeron, P., Everett, R. and Goodman, I., 1996, Ecosystem management: A landscape ecology perspective, *Water Resources Bulletin,* 32(2):203-216.

[16] Kirkby, M.J., Imeson, A.C, Bergkamp, G. and Cammeraat, L.H. 1996. Scaling up processes and models from the field plots to the watershed and regional areas. *Journal of Soil and Water Conservation.* September-October: 391-396.

[17] Kotliar, N.B. and Wiens, J.A. 1990. Multiple scales of patchiness and patch Structure: A hierarchical framework for the study of heterogeneity. *Oikos,* 59: 253-260.

[18] King, A.W., 1991, Translating models across scales in the landscape. *In* M.G. Turner and R.H. Gardner (eds.) *Quantitative Methods in Landscape Ecology*. Springer-Verlag, New York.

[19] Lammert, M. and Allan, J.D., 1999, Assessing biotic integrity of streams: effects of scale in measuring the influence of land use/cover and habitat structure on fish and macroinvertebrates. *Environmental Management,* 23(2): 257-270.

[20] Larsen, D.P., Dudley, D.R. and Hughes, R.M., 1988, A regional approach for assessing attainable surface water quality: An Ohio case study. *Journal of Soil and Water Conservation*, March-April:171-176.

[21] Lo, K.F., 1995, Erosion assessment of large watersheds in Taiwan, *Journal of Soil and Water Conservation,* 50(2):180-183.

[22] Maidment, D.R., 1996, GIS and hydrologic modeling — An assessment of progress. *NCGIA Third International Conference/Workshop on Integrating GIS and Environmental Modeling.* 21-25 January, 1996. Santa Fe, New Mexico.

[23] Malanson, G. P. 1996. *Riparian Landscapes.* Cambridge University Press.

[24] Malanson, G.P. 1999. Considering complexity. *Annals of the Association of American Geographers*, 89: 746-758.

[25] Meentemeyer, V. and Box, E.O., 1987, Scale effects in landscape studies. *in* M.G. Turner (ed.) *Landscape Heterogeneity and Disturbance*, Spring-Verlay, New York.

[26] Moore, I.D. and Nieber, J.L., 1989, Landscape assessment of soil erosion and nonpoint source pollution, *Journal of the Minnesota Academy of Science,* 55(1):18-25.

[27] Nemani, R., Running, S.W., Band, L.E. and Peterson, D.L., 1993, Regional hydroecological simulation system: An illustration of the integration of ecosystem models in a GIS. pp 296-304. *In* Goodchild, M. F., Parks, B.O. and Steyaert, L.T. (eds.), *Environmental Modeling with GIS.* Oxford University Press, New York.

[28] Obeysekera, J. and Rutchey, K., 1997, Selection of scale for everglades landscape models, *Landscape Ecology,* 12(1):7-18.

[29] Omernik, J.M., Abernathy, A.R. and Male, L.M., 1981, Stream nutrient levels and proximity of agricultural and forest land to streams: some relationships, *Journal of Soil land Water Conservation*, July-August: 227 – 231.

[30] Omernik, J.M., 1987, Ecoregions of the conterminous United States, *Annals of the Association of American Geographers,* 77(1):118-125.

[31] Omernik, J.M. and Griffith, G.E., 1991, Ecological regions versus hydrologic units: Frameworks for managing water quality, *Journal of Soil and Water Conservation,* Sept-Oct:334-340.

[32] Omernik, J. M. 1995. Ecoregions: A spatial framework for environmental management. *In* W.S. Davis and T.P. Simon (eds.) *Biological Assessment and Criteria: Tools for Water Resource Planning and Decision Making.*

[33] O'Neill, R.V. 1988. Hierarchy theory and global change. In Rosswall, T., Woodmansee, R.G. and Risser, P.G. (eds) *Scales and Global Change: Spatial and Temporal Variability in Biospheric and Geospheric Processes.* John Wiley & Sons.

[34] O'Neill, R.V., Krummel, J.R., Gardner, R.H, Sugihara, G., Jackson, B, DeAngelis, D.L., Milne, B.T., Turner, M.G., Zygmunt, B., Christensen, S.W., Dale, V.H. and Graham, R.L., 1988, Indices of landscape pattern, *Landscape Ecology,* 1(3):153-162.

[35] O'Neill, R.V., Hunsaker, C.T., Timmins, S.P., Jackson, B.L., Jones, K.B., Riitters, K.H. and Wickham, J.D., 1996, Scale problems in reporting landcape pattern at the regional scale. *Landscape Ecology,* 11(3):169-180.

[36] Phillips, P.J. and Bachman, L.J., 1995, Hydrologic landscapes on the Delmarva Peninsula, Part 1: Drainage basin type and base-flow chemistry, *Water Resources Bulletin,* 32(4):767-778.

[37] Poiani, K.A., Bedford, B.L., Merrill, M.D., 1996, A GIS-based index for relating landscape characteristics to

potential nitrogen leaching to wetlands, *Landscape Ecology,* 11(4):237-255.

[38] Rokos, D-K. D., 1995, *A Geographically Distributed Approach to Hydrologic Modeling.* Ph.D. Thesis. The University of Iowa.

[39] Roth, N.E., Allan, J.D. and Erickson, D.L., 1996, Landscape influences on stream biotic integrity assessed at multiple spatial scales, *Landscape Ecology,* 11(3): 141-156.

[40] Tim, U.S., Mostaghimi, S and Shanholtz, V.O., 1992, Identification of critical nonpoint pollution source areas using geographic information systems and water quality modeling, *Water Resources Bulletin,* 28(5):877-887.

[41] Turner, M.G., Gardner, R.H., and O'Neill, R.V., 1995, Ecological dynamics at broad Scales, *Science & Biodiversity Policy* S-29 - S-35.

[42] Urban, D.L., O'Neill, R.V. and Shugart, H.H. Jr., 1987, Landscape ecology: A hierarchical perspective can help scientists understand spatial patterns, *BioScience,* 37(2):119-127.

[43] USEPA (U.S. Environmental Protection Agency), 1988, Nonpoint Source Guidance. *In Clean Water Deskbook.* Washington, D.C. Environmental Law Institute,169-192.

[44] USEPA (U.S. Environmental Protection Agency), 1996, Level III ecoregions of the conterminous United States. (http://www.epa.gov/ngispgm3/nsdi/projects/ecoreg.html).

[45] USEPA (U.S. Environmental Protection Agency), 1997, *NonPoint Source Pointers* (Factsheets). (http://www.epa.gov/OWOW/NPS/facts/index.html.

[46] Vieux, B.E. and Needham, S., 1993, Nonpoint-pollution model sensitivity to grid-cell size, *Journal of Water Resources Planning and Management, 119*(2):141-157.

[47] Wiens, J.A., 1999, Toward a unified landscape ecology, In Wiens, J.A. and Moss, M.R. (eds.) *Issues in Landscape Ecology,* The International Association for Landscape Ecology, 148-151.

[48] Wood, E.F., Sivapalan, M., Beven, K and Band, L., 1988, Effects of spatial variability and scale with implications to hydrologic modeling, *Journal of Hydrology,* 102: 29-47.

[49] Wu, J and Loucks, O.L. 1995. From balance of nature to hierarchical patch dynamics: A paradigm shift in ecology. *Quarterly Review of Biology* 70: 439-466.

[50] Wu, J. 1999. Hierarchy and scaling: Extrapolating information along a scaling ladder. Canadian *Journal of Remote Sensing* 25(4): 367-380.

[51] Young, R.A., Onstad, C.A., Bosch, D.D. and Anderson, W.P., 1987, AGNPS: Agricultural Non-Point-Source Pollution Model, A Watershed Analysis Tool, *Conservation Research Report* 35, USDA. 37.

[52] Zonneveld, I.S., 1989, The land unit — A fundamental concept in landscape ecology and its application, *Landscape Ecology,* 3(2):67-89.

[53] O'Neill, R.V. and King, A.W. 1998. Homage to St. Michael; or, Why Are There So Many Books on Scale? In Peterson D.L. and Parker, V.T. (eds), *Ecological Scale: Theory and Application.* Columbia University Press, New York.